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Modeling residential relocation choices: An egalitarian bargaining approach and a comparative study

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Abstract: Accompanying the rapid urban expansion and fast population growth is a progressive trend of residential relocation in developing countries, which necessitates a thorough understanding of households' relocation decisions. Previous studies generally treated home relocation as an individual or unitary household decision, ignoring the interactive and collaborative decision-making mechanisms that household members may adopt when making group decisions. In view of this research gap, this study examines the feasibility of applying the egalitarian bargaining approach to simulating households' group decisions concerning residential relocation and further compares its performance with the Nash bargaining and the conventional utilitarian approach. Moreover, the study experiments with the possibility of accommodating three possible group decision-making mechanisms using the latent class modeling framework. The proposed modeling approaches are applied to an empirical case study in Beijing. Results show that models based on the egalitarian and Nash bargaining principles have better model fits than the utilitarian principle, suggesting the importance of considering egalitarianism when modeling household members' collaborative choice on residential relocation. Moreover, the model based on Nash bargaining has the best model fit, indicating that instead of merely seeking egalitarianism or utilitarianism, household members are more likely to strike a balance between fairness and efficiency.

Keywords: Residential relocation, group decision, game theory, egalitarian bargaining, Nash bargaining

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1 Introduction

1.1 Research background

Residential relocation is the action of an individual/household residing in one dwelling moving to a new place. The new place can be a nearby location in the same neighborhood, a much farther location in the same city, or an even farther location in a different city or a different country. This study focuses on intra-city relocation of households. Rapid urban expansion and fast population growth are often accompanied by intensifying residential relocations in many big cities of emerging economies. For instance, Beijing, the capital city of China, has experienced rapid urban expansion with an average

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growth rate of 7.28% per year in built-up areas during the period from 1970 to 2013 and a trend of suburbanization since 1990 (Feng, Zhou, & Wu, 2008; Zhang, Li, Wang, Liu, & Yang, 2016). Accompanying the rapid urban expansion is residential relocation, which is among the important issues that land use and urban planning policies address. Such policies require a good understanding about how home relocation decisions are made by individuals or households, as well as how and to what extent factors like distance to workplace, distance to CBD, and housing price impact the choice of home locations (Ben-Akiva & Bowman, 1998; Bhat & Guo, 2004; Zolfaghari, Sivakumar, & Polak, 2012). Further, residential location/relocation choice models are important components of integrated land use-transport model systems, which help predict urban dynamics and how urban landscape is shaped over time (Waddell et al. 2003; Waddell, 2011; Moeckel, 2017).

1.2 Previous studies on residential relocation

Residential relocation decision may involve several dimensions, including when relocation takes place and to where as well as what type of new residence to choose (Rashidi & Ghasri, 2019). Methods for modeling choices related to residential relocation can be broadly classified into two main streams. The first stream is concerned about aggregate models that predict the percentage of households in a given neighborhood with likelihood to move, based on the built and socioeconomic environments at the aggregate level (e.g., neighborhood level). The second stream adopts the disaggregate approach and models home relocation decisions at individual or household levels (Kortum, Paleti, Bhat, & Pendyala, 2012). The present study belongs to the second stream and focuses on household-level decision making behaviors concerning residential relocation.

Among the disaggregate models, the binary discrete choice model is commonly used for modeling whether residential relocation took place over the past "x" years or not based on cross-sectional data (e.g., Ettema, Arentze, & Timmermans, 2011). The binary choice (move or no-move) is often modeled as a function of personal and household demographics and socioeconomic characteristics as well as neighborhood features of current home. Eluru et al. (2009) extended the binary choice model to a joint multinomial logit model combining the reasons for move and durations of residence preceding the move. The model is calibrated on data that capture information about residential moves over 20 years. By considering reasons for move as an endogenous variable, the results show that comparing with their counterparts, females are more likely to move due to family-related or personal reasons, larger households are less likely to move, and individuals that commute by transport modes other than private cars are more likely to move. To further investigate the underlying reasons that people choose to move their residences or not and demonstrate the endogeneity of primary reason for moving, Kortum et al. (2012) developed a joint model including a binary choice of whether or not to move and a multinomial choice concerning where to move to. Model results showed that a host of demographic and socio-economic attributes significantly influenced the choice of a particular residence. Lee and Waddell (2010) also made an attempt to develop a joint model of choices concerning whether to move or not and which location to move, applying the nested logit framework. A correction for sampling bias was introduced, because for the nested logit model, it is not possible to carry out random sampling of alternatives without introducing sampling bias. Rashidi, Mohammadian, and Koppleman (2011) employed hazard models examining the interdependencies among the timings of vehicle transaction, residential relocation, and job relocation. Specifically, they investigated the timing of home residential relocation, taking into consideration the hazard of husband and wife's job relocation. Still using hazard-based models, Rashidi and Ghasri (2019) developed a competing hazard-based model examining both the reason and timing of residential relocation. They treated residential relocation as a group decision making behavior of household members. They include factors that influence household joint decisions on matters such as large household purchasing; household saving, investment, and borrowing; social life and leisure activities; and child rearing; etc. Results showed that factors influencing these group decisions had also significant impacts on residential relocation.

Apart from these joint models that connect different dimensions of residential relocation choice, Habib and Miller (2009) developed the reference-dependent residential relocation choice model by using current residential location as the reference point. By considering reference dependence, it explicitly acknowledges the role of status quo and captures individuals' asymmetric responses towards gains and losses in making decisions on new residential location. Comparing to the conventional approach of modeling residential location choice, the reference-dependent approach provides more behavioral insights and performs better in terms of model fit. Chen (2009) developed a generalized extreme value model for the choice of residential relocation place, which accounts for spatial autocorrelation among neighborhoods. The influence of prior location on the choice of potential residential places was also considered by assuming that the preferences towards potential residential places were functions of the characteristics of the current and prior residential locations. The empirical results confirmed that previous housing experiences exerted influence upon new location choices. Similarly, López-Ospina, Cortéz, and Martínez (2017) developed a residential location choice model incorporating past experiences and the dynamics of socioeconomics. Previous experience was considered via a dynamic learning process.

All residential relocation studies reviewed above assume that an individual or a unitary household is the basic decision-making unit and no interactions or differences among household members exist when making relocation choices. Although household choices were treated as group decisions by Rashidi and Ghasri (2019), the model was still individual-based and interactions among household members were not explicitly considered. However, as empirically demonstrated by researchers (Mao & Wang; 2020; Mulder & Cooke, 2009), there are intra-household differences in the outcome of residential relocation. Residential relocation is a household-level decision that reflects not only the divergent needs, preferences and values of household members, but also negotiations and compromises among household members (Mao & Wang, 2020). Therefore, residential relocation choice should be regarded as a group decision made collaboratively by household members that incorporates their different needs, preferences and values. Thus far, very few studies have considered residential relocation as a group decision and explored how household members make interactive and collaborative decisions concerning residential relocation.

1.3 Previous studies on household group decisions

Many short- and long-term household choices are group decisions. Short-term decisions such as time allocation to daily activities, activity scheduling, and allocation of household responsibilities (e.g., allocation of maintenance tasks, escort of children) involves coordination between household members and have to be made jointly; long-term decisions like car ownership, employment, and residential location/relocation are mostly group decisions jointly made by household members.

In the transportation field, the study of households' choice behavior based on group decision theories only started in the 1990s when the activity-based modeling approach was high on the agenda of transportation research. Household time allocation was a frequently studied topic because of its involvement of different household members. A number of studies have adopted the group decision approach to investigate time allocation to independent, joint and allocated activities at home or out-of-home (Gliebe & Koppelman 2002; Kato & Matsumoto, 2009; Wang & Li, 2009; Zhang & Fujiwara, 2006; Zhang, Timmermans, & Borgers, 2005; Zhang, Timmermans, & Fujiwara, 2007). The group-decision approach was also applied to study household members' joint choices on daily activity participation, travel and social-recreational patterns (Bradley & Vovsha, 2005; Gliebe & Koppelman, 2005; Lim, 2015). Household members' joint decisions concerning trips for escorting children to and from school were modeled by Ermagun and Levinson (2016) and Weiss and Habib (2018). Apart from these short-term household decision problems, researchers also investigated household members' long-term collaborative decision-making on car ownership (Picard, Dantan, & de Palma, 2018; Zhang, Fujiwara, & Kuwano, 2007; Zhang, Kuwano, Lee, & Fujiwara, 2009) and residential location choices (Borgers & Timmermans, 1993; Chiappori, de Palma, Picard, & Inoa, 2012; Rivera & Tiglao, 2005; Timmermans, Borgers, van Dijk, & Oppewal, 1992).

The studies reviewed above used different types of group utility functions such as additive, multilinear, iso-elastic, and collective model to capture household members' group decision-making mechanism. They are often based on utility maximization decision theory and make use of different rules of aggregating household members' preferences to derive group utilities, which may account for the power differences of individual members in the group decisions. However, household group decision making is much more complicated than aggregating household members preferences and often involves interactions and bargaining among household members. It is thus necessary to explore methods from other theories (in particular, game theory could serve as a promising tool) for further study of household choice behaviors, as identified by Timmermans and Zhang (2009) and Zhang and Daly (2009). Game theory, alternatively named interactive decision theory, makes use of mathematical models to study the conflict and cooperation between intelligent and rational decision-makers whose interests are interlinked or interdependent (Roger, 1991). In a nutshell, game theory is concerned with the study of multi-person decision problems (Gibbons, 1992). Although game-theoretic approaches have been applied to study household group decision making problem (e.g., Yao, Wang, & Yang, 2017), more studies, especially attempts to apply other decision theories (other than utility maximization theories), are needed.

1.4 Research motivation

Households are usually comprised of a single family involving a group of people united by kinship. Household members care about mutual benefits and may pay special attention to equity when collaboratively making household decisions, especially when more and more wives go into the workforce and increase their family status in the modern society (Tereškinas, 2010; Ogolsky, Dennison, & Monk, 2014). They are becoming more important in their family and have more influence (or decision power) in family decision-making. Because of the enduring impacts of residential location on all household members and everyone's interests and desires need to be taken care of, it is highly likely that household members interact with each other and make compromises to reach decisions about residential relocation. For example, for two-worker households, if the potential place for home relocation is very close to the workplace of one member, but very far from that of another member, this place is unlikely to be accepted by both of them.

In view of the above, this research makes an attempt to apply the egalitarian bargaining solution from cooperative game theory (Kalai, 1977; Roth, 1979) to study household decisions concerning residential relocation. We shall also conduct a comparative study to reveal whether utilitarianism or egalitarianism dominates group decision-making by applying the egalitarian bargaining, the Nash bargaining, and the conventional utilitarian approaches to develop models. These three approaches differ in their solution principles in terms of the degrees of concerns for equity and efficiency. Details about these three approaches will be introduced in section 2. In reality, households differ in their members in terms of socio-demographic backgrounds and personalities, who may vary in their concerns for fairness and efficiency. Thus, they may use different group decision mechanisms in making household choices such as residential relocation choice. To accommodate such heterogeneities in group decisions, we shall apply the latent class modeling framework to identify households with different concerns about fairness and efficiency.

2 Model formulation

2.1 Construction of value functions for different principles

Let $s=\{a,b,c\}$ represent household group decision making based on egalitarian bargaining, Nash bargaining, and utilitarian principles, respectively. The egalitarian bargaining and Nash bargaining are two important game-theoretic approaches from cooperative game theory, while the utilitarian approach belongs to the stream of decision-theoretic aggregation approaches. Both these streams of methods can be adopted to model group decision-making problems, but they differ in terms of theoretic foundations and decision mechanisms, and the threat point[1] plays an important role in cooperative bargaining approaches. The decision-theoretic aggregation approaches primarily emphasize on the specification of how a group should behave so that its actions are in consistency with some postulates of rationality. By contrast, in cooperative game-theoretic approaches, rationality postulates are imposed on individuals instead of the group and the allocation of payoffs among individuals is a main concern (Corfman & Gupta, 1993).

The egalitarian bargaining solution is based on the principle of maximizing the minimum of surplus utilities and the outcomes tend toward equality. It is in close connection with Rawls' (1971) theory of justice by concerning for the least advantaged person (Kalai, 1977; Roth, 1979). This solution selects the weakly efficient agreement using max-min rule (maximizing the minimum of surplus utilities), putting more attention on fairness (Hinojosa & Mármol, 2011). Moreover, it is in good conformity with experimental findings that suggest bargainers do make interpersonal comparisons and outcomes tend toward equality (Corfman & Gupta, 1993). The egalitarian bargaining solution can be obtained by maximizing the following function,

$$\pi_g^{a,j} = \min_i \left\{ \frac{1}{\omega_{g,i}^a} \left(u_{g,i}^{a,j} - u_{g,i}^{a,0} \right) \right\} \tag{1}$$

where $\pi_g^{a,j}$ represents household g's value function for choosing relocation alternative j when using the egalitarian solution principle. $\omega_{g,i}^a$ is the relative weight (power) of household member i (from household g) in collaborative decision-making. If $\omega_{g,i}^a$ is different across household members, then it is generalized to the weighted egalitarian (or proportional) solution (Bossert & Tan, 1995).

$u_{g,i}^{a,0}$ is reference utility level, which is set as the residential utility at original residence in this study. This is behaviorally appealing because previous studies have demonstrated that previous residence tended to serve as an important reference and play a critical role in the selection of new residence (Chen, 2009; Habib & Miller, 2009; López-Ospina et al., 2017). Notation $u_{g,i}^{a,j}$ represents household member i's (from household g) residential utility for choosing relocation alternative j based on egalitarian principle. It is a function of individual/household level and residential attributes,

[1] Threat point refers to the point of payoffs that players will receive if they fail to reach an agreement in decision-making.

$$u_{g,i}^{a,j} = f(\boldsymbol{\gamma}_{i,a} \cdot \boldsymbol{\chi}_{g,i}) \tag{2}$$

where $\boldsymbol{\chi}_{g,i}$ is the vector of individual/household level attributes and residential attributes, and $\boldsymbol{\gamma}_{i,a}$ is the associated parameters to be estimated using egalitarian principle.

The Nash bargaining solution is the best-known and most widely used cooperative game-theoretic approach. It is based on the principle of maximizing the product of players' surplus utilities, applicable to bargaining scenarios when negotiators with personal preferences are motivated to achieve proportionate cooperation (MacCrimmon & Messick, 1976). The Nash bargaining solution is "between" the utilitarian and egalitarian points (Rachmilevitch, 2016). Therefore, it balances fairness and efficiency, which is a tradeoff and compromise between egalitarianism and utilitarianism. Moreover, the Nash bargaining solution is demonstrated to be more utilitarian than egalitarian (Rachmilevitch, 2016). That is, it puts more emphasis on utilitarianism than egalitarianism. The Nash bargaining solution can be obtained by maximizing the following expression (also called Nash product),

$$\pi_g^{b,j} = \prod_i (u_{g,i}^{b,j} - u_{g,i}^{b,0})^{\sigma_{g,i}} \tag{3}$$

where $\pi_g^{b,j}$ represents household g's value function (also called Nash product) for choosing relocation alternative *j*, corresponding to using the Nash bargaining solution principle. $\sigma_{g,i}$ is household member *i*'s (from household g) bargaining power in collaborative decision making. The bargaining solution is claimed to be symmetric when players have equal bargaining power, and asymmetric otherwise. $u_{g,i}^{b,0}$ is the threat point utility for household member *i* (from household *g*) in the case that family members fail in consensual decision-making, which is set as the residential utility at original residence in this study. In this way, the original residence is accommodated as a reference point for seeking new residences.

The utilitarian solution approach has been previously adopted for modeling residential location choice that considers different household members as collaborative decision makers. It selects an agreement point under which the sum of the player's utilities is maximized (maximizing the sum of weighted utilities). It is a conventional approach that has been widely used to model household members' collaborative decision making on activity participation, time allocation, residential location. For residential relocation choice problem, the mathematical formulation is to choose a potential relocation alternative *j* that maximizes the following group utility,

$$\pi_g^{c,j} = \sum_i \omega_{g,i}^c \, u_{g,i}^{c,j} \tag{4}$$

where $\pi_g^{c,j}$ represents household g's value function (also called group utility) for choosing relocation alternative j when using the utilitarian solution principle. $\omega_{g,i}^c$ is the relative weight related to individual *i*'s preference. It is later noticed and analyzed by researchers that the additive formulation only deals with the efficiency of group's choice (utilitarianism philosophy), without capturing group's equity concern for fair distribution of benefits among group members (Diamond, 1967; Keeney & Kirkwood, 1975). That is why the corresponding solution is called (weighted) utilitarian solution (Hinojosa & Mármol, 2011; Argenziano & Gilboa, 2015; Rachmilevitch, 2015, 2016).

Taking a look at the above mathematical formulations for three different group decision principles, it can be found that the egalitarian principle shows the most concern for equity but least concern for efficiency. On the contrary, the utilitarian principle shows the most concern for efficiency but least concern for equity. As for the Nash bargaining principle, its concern for efficiency and equity is between these two principles. In addition, an advantage regarding the mathematical formulation of Egalitarian max-min principle is that it allows for direct interpersonal comparisons, which could not be realized by the utilitarian principle or Nash bargaining principle.

2.2 Accommodation of heterogeneity

As declared by Curry, Menasco, and van Ark (1991), it is hard to determine a priori criterion for selection among the possible group decision mechanisms, because the choice should be made based on a good match between model and problem and on relevant empirical evidence. Latent class (LC) choice models are particularly suitable to investigate and accommodate the existence of decision rule heterogeneity, and they have played a dominant role in the investigation of decision rule heterogeneity in transportation studies. Specifically, the heterogeneity can be accommodated by classifying individuals/households into unobserved groupings (latent classes) with similar (more homogeneous) patterns (Berlin, Williams, & Parra, 2014). Latent class discrete choice modeling approach is appropriate for this analysis under our hypothesis that household members with different socio-demographic backgrounds and personalities will have different decision mechanisms in their consensual decision-making on residential relocation choice. Apart from the commonly used socio-demographic attributes for determining class membership probability, this research incorporates personality attributes as well. It is obvious that household members' personality characteristics are very likely to influence the decision rules of the household (Krueger, 1985). For example, household members that are more concerned for others may show higher tendency towards egalitarianism in collaborative decision making. The following logit model is specified to determine how these attributes affect the class membership probability (Bhat, 1997; Boeri, Scarpa, & Chorus, 2014; Charoniti, Rasouli, & Timmermans, 2016; Walker & Li, 2007),

$$M_{gs} = \frac{exp(\mu_s+\tau_s \cdot \boldsymbol{Z_g})}{\sum_{s,}^{S} exp(\mu_{s'}+\boldsymbol{\tau_s}} \tag{5}$$

where M_{gs} denotes household g's membership probability to class s. μ_s is the class-specific constant. $\boldsymbol{Z_g}$ is a vector of variables characterizing household g's class membership probability and $\boldsymbol{\tau_s}$ is the associated parameters. For determining number of classes s, it is related to the number of group decision-making mechanisms. In our study, it is assumed that there three group decision-making mechanisms, indicating s=3. As for class assignment, after estimating the parameters associated with latent class model, households can be assigned to their most likely latent class. Specifically, based on the class membership probability calculated by equation (5), households can be assigned to the latent class with the highest probability.

In estimation, only S-1 set of coefficients can be interpedently estimated to avoid identification problem (Boeri et al., 2014). Set the coefficients of one arbitrary class to 0, namely μ_{s1} =0 and $\boldsymbol{\tau_{s1}}$ =0, so that for this class s_1 the membership probability is

$$M_{gs1} = \frac{1}{1+\sum_{s,}^{S-1} exp(\mu_{s'}+\boldsymbol{\tau_{s'}} \cdot \boldsymbol{Z_g})} \tag{6}$$

Taking class membership probability M_{gs} as one component, the probability that household g chooses relocation alternative j can be calculated by the following equation,

$$P_g^j = \sum_{s=1}^{S} M_{gs} \cdot P_{gj/s} \tag{7}$$

where $P_{gj/s}$ is the class-specific choice probability, namely, the probability that household g belonging to class s chooses alternative j.

3 Model estimation

In consideration that the min-type value function is intractable for the estimation process, an approximation will be carried out. Approximate the min-type value function by the following smooth function (Boyd & Vandenberghe, 2004; Tsoukalas, Parpas, & Rustem, 2009),

$$\pi_g^{a,j} = -\frac{1}{p} \ln\left[\sum_i \exp\left(-\rho \frac{1}{\omega_i}\left(u_{g,i}^{j} - u_{g,i}^{0}\right)\right)\right] \tag{8}$$

The larger ρ>0, the closer the approximation is to the minimum.

Assume Gumbel distributed additive error terms to the value functions in equation (3), (4) and (8) respectively, then the class-specific choice probability $P_{gj/s}$, namely, the probability that household g chooses alternative j using group decision mechanism s can be calculated as,

$$P_{gj/s} = \frac{\exp(\pi_{gj}^{s})}{\sum_k \exp(\pi_{gk}^{s})} \qquad \forall s = a,b,c \tag{9}$$

The choice likelihood for household g on the condition that household g belongs to segment s can be calculated as

$$L_{gs} = \prod_{j=1}^{J}\left(P_{gj/s}\right)^{\delta_{gj}} = \prod_{j=1}^{J}\left(\frac{\exp\left(\pi_{gj}^{s}\right)}{\sum_k \exp\left(\pi_{gk}^{s}\right)}\right)^{\delta_{gj}} \qquad \forall s = a,b,c \tag{10}$$

where δ_{gj} equals 1 if household g chooses alternative j and 0 otherwise.

The likelihood function of observing a vector of choices for all decision-makers in the sample is,

$$L = \prod_g \sum_{s=1}^{S} M_{gs} L_{gs} = \prod_g \sum_{s=1}^{S}\left[\frac{\exp(\mu_s + \boldsymbol{\tau_s} \cdot \boldsymbol{Z_g})}{\sum_{s'}^{S} \exp(\mu_{s'} + \boldsymbol{\tau_{s'}} \cdot \boldsymbol{Z_g})} \prod_{j=1}^{J}\left(\frac{\exp\left(\pi_{gj}^{s}\right)}{\sum_k \exp\left(\pi_{gk}^{s}\right)}\right)^{\delta_{gj}}\right] \tag{11}$$

The equation (11) is characteristic of finite probability mixture models, making the maximization of the likelihood function using the traditional Newton or quasi-Newton computationally unstable (Bhat, 1997; McLachlan & Basford, 1988; Redner & Walker, 1984). Therefore, the expectation-maximization (EM) algorithm is adopted for estimation. It is an iterative optimization approach broadly applicable to the computation of maximum likelihood estimates, especially useful in various incomplete ("missing" or "hiding") data problems (McLachlan & Krishnan, 2007). Over the years, the EM algorithm has gained popularity in estimation of latent class models owing to its stability, simplicity and easiness for implementation, while missing data for the EM algorithm are the class membership of each agent (Sun, Arentze, & Timmermans, 2012; Train, 2008). For latent segment logit model, Zenor and Srivastava (1993) demonstrated that the estimates from EM algorithm provide the best latent partitioning for any desired number of segments (Zhang et al., 2009). The EM algorithm comprises two steps, the E-step and the M-step.

Let q_{gs} be the discrete latent variable that equals to 1 if household g belongs to latent segment s and 0 otherwise. The first step for implementing the EM algorithm entails writing the complete log-likelihood function assuming that discrete latent variable q_{gs} is observable (El Zarwi, 2017). Then the likelihood function could be written as

$$L = \prod_{g} \prod_{s} \left[\frac{exp(\mu_s + \boldsymbol{\tau_s} \cdot \boldsymbol{Z_g})}{\sum_{s'}^{S} exp(\mu_{s'} + \boldsymbol{\tau_{s'}} \cdot \boldsymbol{Z_g})} \prod_{j=1}^{J} \left(\frac{exp(\pi_{gj}^{s})}{\sum_k exp(\pi_{gk}^{s})} \right)^{\delta_{gj}} \right]^{q_{gs}} \tag{12}$$

Take logarithmic form, the complete log-likelihood function can be broken into two separate parts as follows[2],

$$lnL = \sum_{g} \sum_{s} q_{gs} ln \frac{exp(\mu_s + \boldsymbol{\tau_s} \cdot \boldsymbol{Z_g})}{\sum_{s'}^{S} exp(\mu_{s'} + \boldsymbol{\tau_{s'}} \cdot \boldsymbol{Z_g})} + \sum_{g} \sum_{s} \sum_{j} q_{gs} \delta_{gj}\, ln \frac{exp(\pi_{gj}^{s})}{\sum_k exp(\pi_{gk}^{s})} \tag{13}$$

Using Bayes' Theorem, at the (t+1) iteration, the updates for expected membership q_{gs}^{t+1} of household g belonging to segment s can be computed by the following E-step,

$$q_{gs}^{(t+1)} = \frac{\frac{exp\left(\mu_s^{(t)} + \boldsymbol{\tau_s^{(t)}} \cdot \boldsymbol{Z_g}\right)}{\sum_{s'}^{S} exp(\mu_{s'}^{(t)} + \boldsymbol{\tau_{s'}^{(t)}} \cdot \boldsymbol{Z_g})} \prod_{j=1}^{J} \left(\frac{exp(\pi_{gj}^{s})^{(t)}}{\sum_k exp(\pi_{gk}^{s})^{(t)}} \right)^{\delta_{gj}}}{\sum_s \left[\frac{exp\left(\mu_s^{(t)} + \boldsymbol{\tau_s^{(t)}} \cdot \boldsymbol{Z_g}\right)}{\sum_{s'}^{S} exp(\mu_{s'}^{(t)} + \boldsymbol{\tau_{s'}^{(t)}} \cdot \boldsymbol{Z_g})} \prod_{j=1}^{J} \left(\frac{exp(\pi_{gj}^{s})^{(t)}}{\sum_k exp(\pi_{gk}^{s})^{(t)}} \right)^{\delta_{gj}} \right]} \tag{14}$$

After deriving the expressions for updates in the E-step for q_{gs}^{t+1}, we can proceed with the M-step. In M-step, the expectation of membership q_{gs}^{t+1} is treated as known value. Compute the first-order conditions for the complete log-likelihood function with respect to the unknown parameters,

$$lnL = \sum_{g} \sum_{s} q_{gs} ln \frac{exp(\mu_s + \boldsymbol{\tau_s} \cdot \boldsymbol{Z_g})}{\sum_{s'}^{S} exp(\mu_{s'} + \boldsymbol{\tau_{s'}} \cdot \boldsymbol{Z_g})} + \sum_{g} \sum_{s} \sum_{j} q_{gs} \delta_{gj}\, ln \frac{exp(\pi_{gj}^{s})}{\sum_k exp(\pi_{gk}^{s})} \tag{15}$$

It is worth noting that Bhat (1997) proposed another perspective of constructing the complete log-likelihood function, which turned out to be the same to the expression in equation (15). His philosophy is to derive the necessary first-order conditions for maximizing the log-form of likelihood function expressed in equation (11) with respect to the parameters to be estimated respectively, and then construct the complete log-likelihood function for estimating all the parameters through a combination of several MNL log-likelihood functions.

Based on equation (15), we can obtain the following updates for unknown parameters in the M-step:

$$\mu_s^{(t+1)}, \boldsymbol{\tau_s^{(t+1)}} = argmax \sum_{g} \sum_{s} q_{gs}^{(t+1)} ln \left(\frac{exp\left(\mu_s^{(t)} + \boldsymbol{\tau_s^{(t)}} \cdot \boldsymbol{Z_g}\right)}{\sum_{s'}^{S} exp(\mu_{s'}^{(t)} + \boldsymbol{\tau_{s'}^{(t)}} \cdot \boldsymbol{Z_g})} \right) \tag{16}$$

[2] The estimates for each separated model of group decision making mechanism can be obtained in this way: for all households, set q_{gs}=1 for that particular mechanism and q_{gs}=0 for the other two mechanisms, and then solve the log-likelihood function in equation (12).

$$\boldsymbol{\gamma}_{\boldsymbol{i,s}}^{(\boldsymbol{t+1})} = argmax \sum_{g} \sum_{s} \sum_{j} q_{gs}^{(t+1)} \delta_{gj} \, ln\left(\frac{exp\left(\pi_{gj}^{s}\right)^{(t)}}{\sum_k exp\left(\pi_{gk}^{s}\right)^{(t)}}\right) \tag{17}$$

Thus, the new guess for the model parameters can be obtained. The EM algorithm keeps iterating between the E-step and M-step, until the convergence is reached.

4 Empirical case study

4.1 Data source and sample formation

The primary data source used for this study is a panel data drawn from a two-wave (before and after home relocation) household activity-travel diary survey conducted in Beijing. The usage of panel data enables the consideration and incorporation of effects from previous residential location on choice of new location. The dataset includes information on residential location, built environment, household/individual level socio-economic, demographic, and personality characteristics, etc. Respondents were home movers recruited through a multi-stage stratified sampling method to ensure that the samples were in proportion to the total numbers of three types of home movers (renters, new property buyers and second-hand home buyers) in each district of Beijing. The first wave was collected from November 2011 to June 2012, with 1243 individuals from 467 households sampled from 12 urban and suburban districts successfully completing the questionnaire survey through face-to-face interviews. The second wave was collected from April to August 2013, after respondents had been living in their new homes for more than 6 months. There are 587 respondents from 229 households taking part in the second wave data collection. Only dual-head households with full information in both waves are used to form the final sample of the empirical case for this study, which involves 166 dual-head households. The sample size is relatively limited because of difficulties in approaching home movers in a large quantity. Considering that children in many cases neither have the capacity nor the power to influence household decisions and following the normal practice of studies on household decision problems in literature, this empirical study assumes that only husband and wife are involved in the household decision making concerning residential relocation choice.

Table 1 presents the characteristics of the households participating in the two-wave survey. It can be noted that, in comparison with female heads, male heads are more likely to be full-time workers. Moreover, among employed spouses, female heads tend to have relatively shorter home-work distance than male heads. Another interesting information revealed in Table 1 is that about 33.1% households changed their car ownership status after relocation and approximately 23% households become car owners following their relocations.

Table 1. Sample profile of individual and household level characteristics

Variable	Classification	Individual characteristics			
		Male head		Female head	
		Frequency	Percentage	Frequency	Percentage
Education	Junior secondary or lower	33	19.9%	38	22.9%
	High school	80	48.2%	76	45.8%
Employment status	University or above	53	31.9%	52	31.3%
	Full-time worker	142	85.5%	111	66.9%
	Other	24	14.5%	55	33.1%
Home-work distance	Null	24	14.5%	55	33.1%
	<10km	50	30.1%	58	34.9%
	10-20km	57	34.3%	34	20.5%
	20-30km	27	16.3%	14	8.4%
	>30km	8	4.8%	5	3.0%
		Household characteristics			
		Frequency	**Percentage**		
Household size	2	65	39.2%		
	3	41	24.7%		
	>=4	60	36.1%		
Presence of child					
under 11	No	127	76.5%		
	Yes	39	23.5%		
Monthly household income	<=5999	18	10.8%		
	6000-9999	57	34.3%		
	10,000-19,999	68	41.0%		
	>=20,000	23	13.9%		
Housing price	<=19999	25	15.1%		
	20000-29999	32	19.3%		
	30000-39999	61	36.7%		
	>=40000	48	28.9%		
Change in household car ownership	No car --> Car owner	38	22.9%		
	Car owner --> No car	17	10.2%		
	Car owner --> Car owner	58	34.9%		
	No car --> No car	53	31.9%		

Note: the statistics are mainly based on the second wave of the survey.

The second source of data is obtained from the Beijing City Lab[3], including parcel level data as well as housing price information in Beijing. The parcel level data includes information about geographic location, density, land-use, shape area, POI (point of interest), etc., which are gathered from 2010 to 2012. Details about the data information is introduced by Liu and Long (2016). The housing price

[3] Website: https://www.beijingcitylab.com/data-released-1/data1-20/

information was Crawled from *Ganjiwang* website (a popular housing website in China) on October, 2013, which includes housing prices for 7832 housing projects in Beijing.

There are 12,348 parcels in Beijing. A random sampling approach is applied to construct the choice set, which is a common way to handle the huge number of choice alternatives in location studies (e.g., Ben-Akiva & Bowman, 1998; Guevara & Ben-Akiva, 2013; Guo & Bhat, 2007; Habib, Miller, & Mans, 2011). The constructed choice set includes the chosen relocation alternative and nine randomly selected non-chosen relocation alternatives. As demonstrated by McFadden (1978), if the model underlying the choice process is multinomial Logit model, then consistent estimation can be obtained under random sampling of alternatives from the global choice set.

4.2 Specification of variables

Following the normal practice of studies on household decision problems in literature, we involve male and female head as decision makers in this empirical case study. For husband and wife respectively, the vector of individual/household level attributes and residential attributes $\boldsymbol{\chi}_{g,i}$ include: distance to workplace, distance to CBD, ratio of housing price to household income, land use mix and land-use density. Distance to workplace is closely linked with workers' daily commuting distance, and would certainly be a very important factor in the choice of potential relocation places. Previous studies have identified that distance between home and the urban center (CBD) was an important determinant of travel distance (e.g., Hickman & Banister, 2004; Naess, Roe, & Larsen, 1995).

It has been observed that price-sensitivity reduces with rising income, therefore, the ratio of housing price to household income is adopted and a logarithmic form is taken to reflect the diminishing marginal effect (Schirmer, van Eggermond, & Axhausen, 2012; Walker & Li, 2007). The log-form ratio has been used by other researchers as well (e.g., Habib & Miller, 2009)

The land-use mix index M of a parcel is calculated by (Liu & Long, 2016)

$$M = -\sum_{n=1}^{N} p_n * ln(p_n) \tag{18}$$

where N is the number of POI types in the parcel, and p_n is the proportion of POI type n among all the POIs in the parcel. In the data, there are 8 types of POI: commercial sites, office building/space, transport facilities, government, education, residence communities, green space, others. The land-use mix index reflects the POI diversity. It can be noted that a more balanced distribution of the POI types will induce higher value of land-use mix index.

Land-use density is defined as the ratio between the counts of point of POIs in or close to a parcel to the parcel area. Therefore, the unit of land-use density is POI count per km². The density is further standardized to range from 0 to 1 (refer to Liu & Long, 2016, for detailed information).

The vector of variables characterizing household g's class membership probability $\boldsymbol{Z}_g$ is supposed to include: personality attributes of husband and wife, age of husband and wife, employment information of husband and wife. In the activity-travel diary survey, personality attribute was obtained by asking the respondent to select a scale option for rating question "I think I am highly concerned for and kind to almost all people", with rating scale from 1 to 7. Where 1 is "totally disagree" and 7 is "totally agree." For employment information, an indicator is included to denote whether husband and wife are in the same employment status (both employed or both unemployed).

The relative weight (power) of household member i (from household g) in collaborative decision making w_{gi} or household member i's (from household g) bargaining power in collaborative decision making $\sigma_{g,i}$ are supposed to be determined by the wage rate of husband and wife.

4.3 Results of model estimation

The results of estimation for relocation choice models based on three different decision principles respectively are presented in Table 2. Goodness-of-fit of the three models is assessed by likelihood-ratio test, and the models are compared with a null (simple) model which assumes all the parameters to be 0. The value of likelihood ratio LR=-2[L_{null} - L_{final}] follows a χ2 distribution with 12 degrees of freedom. For a significance level of α=0.05, the critical value of chi-square distributed statistic χ_r^2 (α) is 21.0261. As shown in table 2, the likelihood ratio (LR) is significantly larger than this critical value, indicating that the proposed model fits the data significantly better than the null (simple) model. In addition, the value of adjusted likelihood ratio index ρ^2 is between 0.2 to 0.4, suggesting that all these models present excellent fit (McFadden, 1977).

Statistical metrics like AIC&BIC and adjusted ρ^2 show that the model based on Nash bargaining principle has the best model fit, indicating that it can best represent household relocation choice behavior in the dataset. Nash bargaining solution is between" the utilitarian and egalitarian points. This suggests that instead of merely seeking for egalitarianism or utilitarianism, household members in the randomly sampled data are more likely to strike a balance between fairness and efficiency when choosing potential relocation places. In comparison with that of utilitarian principle, models using egalitarian principle and Nash bargaining principle provide obvious improvement in model fit, suggesting that it is important to consider egalitarianism when modeling household members' collaborative choice on residential relocation.

The estimated results are in line with expectations. Some insights can be obtained from the estimated coefficients and *t* values for these three types of models. It is obvious that both heads would significantly prefer shorter distances between the potential relocation place and their workplaces. The negative influence of home-work distance on residential utility has been evidenced by other studies as well (e.g., Bürgle, 2006; Fatmi, Chowdhury, & Habib, 2017). Distance to workplace is valued more negatively than distance to CBD. Distance to CBD is revealed to have non-significant and negative impact on residential utility, this kind of negative relationship is supported by previous studies (e.g., Fatmi et al, 2017). An underlying reason might be that households living closer to CBD have better access to amenities and more convenience when conducting activities to meet personal and household needs (Tana, Kwan, & Chai, 2016). However, this kind of influence is not that powerful in comparison with that of home-work distance. The negative impact of ratio housing price to household income suggests that household members would prefer to reduce the proportion of income spent on housing (Bürgle, 2006; Guo & Bhat, 2007; Habib & Miller, 2009). Higher values of land-use mix index and land-use density both tend to increase the pleasure of living.

For the three models with different group decision mechanism, willingness-to-pay (WTP) measures concerning different attributes that characterize residential relocation choice are presented in Table 3. WTP is obtained as the ratio of the marginal utility of the attribute to the marginal utility of purchase price (Train, 2009). In general, the WTP measures vary between household heads and between group decision models, with the discrepancy between male and female heads larger than that of different models. With regard to the distance to workplace attribute, the Nash bargaining model's WTP is more balanced than the other two. Female heads' WTP is higher than that of male heads, indicating that they are generally willing to pay a relatively larger amount of money for a marginal decrease in home-work distance. For land-use attributes, in comparison with female counterparts, male heads are found to value more about the increase of land-use mix and less about the increase land-use density, suggesting that males may care more about the balance of POIs and females may care more about particular POIs when choosing relocation alternative. Another finding about land-use attributes is that the gap between spouses' WTP turns out to be relatively larger in utilitarian model than the other two, a possible reason is that spouses stick more to their own preferences and care less about other household members in this decision context.

As described earlier, in reality, household members with different socio-demographic backgrounds and personalities will have different decision mechanisms in their consensual decision-making on residential relocation choice. It is necessary to accommodate the differences through a more complicated model. In this study, the latent class choice framework is adopted to accommodate heterogeneous group decision principles into the modeling framework. In consideration that there are 48 parameters to be estimated for the latent class choice model, the small sample size (166 randomly sampled households) is only used as an indicative test study for this complicated model[4]. It shows that Nash bargaining principle has a latent membership probability of 62%, egalitarian bargaining principle has a latent membership probability of 27%, while the utilitarian principle has a latent membership probability of 11%. To some extent, this result supports the information obtained from Table 2, which shows that the Nash bargaining principle has the best model fit, while the utilitarian principle has least model fit. The detailed result is not presented here due to data limitation, and we acknowledge that it will be better if the proposed models can be estimated by panel data with larger sample size.

Table 2. Results of estimated relocation choice models for three separated decision mechanisms

Variables	**Egalitarian principle**		**Nash bargaining principle**		**Utilitarian principle**	
	Male head (t-stat)	**Female head (t-stat)**	**Male head (t-stat)**	**Female head (t-stat)**	**Male head (t-stat)**	**Female head (t-stat)**
location attribute						
distance to workplace	-0.1484 (-3.1715)	-0.1504 (-4.2431)	-0.0871 (-3.0432)	-0.1439 (-6.1016)	-0.1047 (-3.8265)	-0.1346 (-4.0958)
distance to CBD	-0.0029 (-0.4273)	0.0013 (0.9740)	-0.0302 (-2.4412)	-0.0112 (-1.4984)	-0.0799 (-1.4810)	-0.0471 (-0.9402)
housing price/income (log)	-4.3618 (-3.2001)	-2.1324 (-2.6284)	-0.5184 (-5.8627)	-1.3581 (-7.9629)	-0.2305 (-0.5889)	-1.0467 (-2.9663)
housing price	-0.6063 (-2.3409)	-0.3932 (-1.5671)	-0.3395 (-2.8712)	-0.4159 (-3.5223)	-0.5107 (-3.1776)	-0.3463 (-2.0511)
land-use mix degree	2.8588 (5.2493)	1.4013 (3.4638)	1.6264 (4.2734)	1.3195 (2.5709)	2.4838 (6.3064)	0.9318 (1.4882)
land-use density	1.8397 (3.1664)	1.4506 (2.1306)	1.0532 (1.5682)	1.4221 (2.4624)	0.9425 (0.8192)	1.1436 (2.8135)
Number of observations	166		166		166	
Null-log likelihood (L_{null})	-382.2291		-382.2291		-382.2291	
Final-log likelihood (L_{final})	-257.2615		-251.2615		-270.9625	
Likelihood ratio (LR)	249.9352		261.9352		222.5332	
Adjusted Rho-square	0.2955		0.3112		0.2597	
Akaike Information Criterion (AIC)	538.5230		526.523		565.9251	
Bayesian Information Criterion (BIC)	575.8669		563.8669		603.2689	

[4] It should be noted here that the sample size of 166 households is sufficient for estimating separated decision models, with 12 parameters for each model. As stated by many researchers (e.g., Bentler & Chou, 1987; Chankuna, Sriboon, & Wiboonuppatum, 2014; Kline, 2015; Nunnally, Bernstein, & Berge, 1967), for the ratio of sample size to number of free parameters, a ratio of at least 10:1 may be more appropriate for arbitrary distributions.

Table 3. WTP for male and female heads across three group decision models

	Egalitarian principle		**Nash bargaining principle**		**Utilitarian principle**	
	Male head	**Female head**	**Male head**	**Female head**	**Male head**	**Female head**
Reduce of distance to work-place by 1km	24.48	38.25	25.66	34.60	20.50	38.87
Increase of land-use mix index by 1%	4.72	3.56	4.79	3.17	4.86	2.69
Increase of land-use density by 1%	3.03	3.69	3.10	3.42	1.85	3.30

5 Conclusion

This study applied the egalitarian bargaining approach from cooperative game theory to model households' group decisions about home relocation and compared its performance with that of the Nash bargaining and utilitarian modeling approaches. Special attention was paid to the importance of utilitarianism versus egalitarianism in household collaborative decision-making. The study acknowledged that households differed in their members in terms of socio-demographic backgrounds and personalities, which might lead to variations in the concerns for fairness and efficiency. Thus, the three different possible group decision mechanisms in making residential relocation choice were considered. The latent class modeling framework was employed to address the issues of heterogeneities in group decisions and identify households with different concerns about fairness and efficiency. The study design and proposed models were applied to an empirical case study involving two-wave panel data collected in Beijing.

The results showed that models based on egalitarian and Nash bargaining principles provided improvements in model fit when compared with a model based on the utilitarian principle. This indicates that it is important to consider egalitarianism when modeling household members' collaborative decisions on residential relocation. Furthermore, model based on Nash bargaining principle showed the best model fit. This suggests that instead of merely seeking for egalitarianism or utilitarianism, household members in the randomly sampled data are more likely to strike a balance between fairness and efficiency when making the joint choice of destination for residential relocation. In other words, household decisions about residential location are not based on utility maximization as the conventional modeling approach suggests, but to compromise between utility maximization and equal share of benefits among household members. The modelling approach proposed by this study can be used to assist planners, researchers and policy-makers to develop relevant policies on land use to foster a more sustainable urban development. For example, with better understanding and representations of household relocation choice behavior, researchers and policy makers are likely to produce more accurate predictions of the medium-term dynamics of urban area, and gain a deeper knowledge about how the urban landscape is shaped over time. This will facilitate the design of residential policies that aim to spatially redistribute households toward desired objectives and make the goals more attainable.

Overall, the group decision-based approach challenges the mainstream of studies that treat household decisions, such as residential location, as an individual decision of the household head, which is not true in reality. Findings of this study suggest that policy makers should be aware of the importance of "differences" between not only people of different social groups, but also people of the same households. Therefore, household-based approach should be adopted to develop policy interventions. Results presented in Table 2 and Table 3 show that household members have divergent needs, preferences and values towards attributes of residential relocation, indicating that the final residential relocation choice is a compromise made by household members. Therefore, the needs and opinions of different household members should be considered when modeling residential relocation choice. As for policy implications, these findings suggest that the same policy may generate different impacts to people even from the same household who have different opinions and priorities regarding improvements in residential satisfaction. For example, policies that aiming at improving job-housing imbalance may be more powerful in boosting females' residential satisfaction. Additionally, policies aiming at increasing land-use mix may increase males' residential satisfaction to a higher extent, whereas female's residential satisfaction may benefit more from improvement in land-use density.

Some directions for future research can be identified. Firstly, to capture heterogeneity in households' group decision, this research adopted the commonly used latent class method. However, latent class models may not be able to address the issues that taste heterogeneity, heteroscedasticity and decision rule heterogeneity are confounded (van Cranenburgh & Alwosheel, 2017). Other methodologies for modeling group decision heterogeneity are worthwhile to be explored for future studies, such as artificial neural networks, which are well-known for being highly effective in solving complex classification problems (van Cranenburgh & Alwosheel, 2017; Zhang, 2000). Secondly, interactions between long-term residential relocation and short-term daily activity-travel choices could be incorporated and examined by developing integrated models. Since residential relocation involves long-term commitment while activity-travel pattern involves short-term commitment, dynamic modeling framework that is able to address the change of habitual activity-travel patterns within the relocation time-span (the time duration from one relocation to the other) should be explored. Thirdly, the sample size of the empirical case in this study was relatively small, especially for latent class modeling that incorporates different group decision rules. It would be desirable in future to test the modeling approaches proposed in this study with panel data of larger sample size so as to calibrate full-fledge models with empirical data. Fourthly, it is worthwhile to design and explore more possible specifications of the group utility function, such as adding the utility of original residence to equation (4) based on the underlying assumption that group members are motivated to maximize their weighted utility surplus, which provides a possible way of introducing reference dependence into the utilitarian framework.

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