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Exploring the impact of residential relocation on modal shift in commute trips: Evidence from a quasi-longitudinal analysis

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ABSTRACT

A growing number of studies have been devoted to the effects of residential relocation on travel behavior. However, most of these studies only focus on the direct effects of personal and system characteristics; while, residential relocation may trigger several interrelated changes in activity-travel behavior and mobility resources. This paper studies the mode choice of commuters who used active transport before relocating. Results from a Bayesian network (BN) analysis, trained on retrospective data collected in Nanjing, China, are presented. The constructed BN identifies significant statistical associations between modal shift and selected explanatory variables, which include movers' socio-demographic characteristics, relocation-related attributes, and changes in built environment. Specifically, car ownership, income, additional car purchase, specific housing type and size, relocation type, change in commute distance, convenience of subway/bus for commuting, and distance to subway station are found to be important factors when deciding to switch from private car to public transit.

1. Introduction

Recently, many major cities in China have witnessed large-scale urban sprawl. The explosive population growth and the rapidly increasing and often unaffordable housing prices in city centers have caused residents to change their living environment and to relocate to the suburbs. Relocation may trigger people to re-evaluate their current activity-travel patterns and to reconsider their current choices. To the extent that residential relocation does not coincide with a parallel change of workplace, residential relocation likely involves longer commuting distances or travel times. Moreover, the pattern of suburbs is spatially more diffuse and densities are typically lower. Consequently, many suburbs are logically better fit for car use (Raphael and Rice, 2002).

Thus, people, who were active commuters (walkers or cyclists) before residential relocation, may reconsider their travel mode choice and shift to car use. In that case, suburbanization has detrimental effects on transport mode choice and therefore the environment and health. Evidence suggests that commuters who moved are more likely to change their commuting behavior than those who did not (Dargay and Hanly, 2007; Prillwitz et al., 2007). Following the outward relocation wave, the commuting distance/time of most residents living in suburban communities has increased due to the job-housing imbalance. Consequently, a motorizing trend is observed in many Chinese cities, further amplified by the raise of income levels (Cervero, and Day, 2008; Wang and Zhou, 2016). Because, compared to other countries across the world, the share of active travel modes in Chinese cities is traditional relatively high, cities in China are more likely to experience this motorization trend more intensely, with stronger negative externalities such as worsening traffic conditions, deteriorating air quality and increased energy consumption. Therefore, it is of paramount importance to understand the process of modal shift after relocation.

To investigate the determinants of behavioral change, a growing body of research has employed mobility biographies, emphasizing that key life course events, such as job change and residential relocation, may lead individuals to reconsider and even reshape their travel habits (Van der Waerden et al., 2003; Lanzendorf, 2003; Scheiner and Holz-Rau, 2013a; Oakil et al., 2016; Clark et al., 2016). This approach assumes that through learning and adaptation, people adjust their travel behavior to cope with

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the difficulties they face and ultimately developed habitual activity-travel patterns. Supply conditions of the transportation system and the urban context are important factors for the definition of choice options and constraints (Rasouli and Timmermans, 2014). Over time, they develop routines that best suit their needs, subject to the constraints they face. Dramatic changes in these equilibrium conditions may trigger them to change partly or fully their activity-travel patterns. Changes in built environment seem correlated with changes in travel behavior (Handy et al., 2005; Scheiner and Holz-Rau, 2013b; Panter et al., 2014; Van de Coevering et al., 2015). However, although these studies have successfully identified general determinants of behavioral changes, only few studies have focused on modal shifts of previously active transport commuters after relocation.

Therefore, this study sets out to elucidate the complex relationship between residential relocation and modal shifts using a retrospective survey administered in Nanjing, China. The central questions to be addressed in this study are: (1) How does residential relocation affect long-term mode choice of active commuters? (2) Do socio-demographic and relocation-related characteristics of commuters before and after relocation influence transport mode choice for commuting trips of movers who used to commute by active transport modes before relocation? To answer these questions, we use a slightly more complex method of analysis than commonly applied in studies about the relationship between the built environment and travel behavior to account for the potentially complex direct and indirect relations between moving house and travel choices that may prevail. While many previous studies on behavioral change have applied statistical methods (such as probit, binary logit, and logistic regression) that allow estimating only direct effects (Dargay and Hanly, 2007; Cervero and Day, 2008; Panter et al., 2014; Oakil et al., 2016; Clark et al., 2016), the complexity of adjustments to residential relocation made us decide to construct a Bayesian network (BN). This method allows extracting direct and indirect relationships from the selected variables. An inference analysis based on the resulting network structure quantifies the impacts of these variables on modal shift.

The contribution of this paper to the literature is two-fold. First, the study adds empirical evidence to the still relatively limited number of studies on modal shifts for the work commute after relocation. Second, the focus on Nanjing, China expands the understanding of dynamics in modal shift to the relocation with respect to previous studies developed in European settings. Large cities in China are significant different from western developed regions; the populations are much larger, socio-demographic characteristics show higher variability; differences in mobility resources differ substantially. In other words, the inherently more varied geography of the location under study makes this analysis particularly relevant and offers opportunities to identify key influential factors for policy analysis and identification.

2. Literature review

This study aims to explore the relationships between modal shifts of active commuters, changes in the built environment, socio-demographics and relocation-related attributes in a relocation context. Using a socio-ecological framework, we consider three types of factors that influence long-term change in commute behavior.

2.1. Built environment

Relocation often implies significant changes of the built environment characteristics experienced by commuters; this creates new opportunities or imposes constraints and might induce residents to alter their modal choice after relocation (Næss, 2005; Aditjandra et al., 2016). In the Chinese context, suburban areas are not well connected by public transportation and offer much less opportunities for active transport modes. It is well known that facilities for active transport provided in a new neighborhood are positively associated with walking and cycling (Giles-Corti et al., 2013). This finding is congruent with a more general literature that people living in neighborhoods with better walking or cycling facilities such as cycle routes, sidewalks and secure cycle parking are more inclined to use active transport (Pucher et al., 2010; Susilo et al., 2012). By contrast, Winters et al. (2010) found that built environments with high arterial accessibility stimulate people to substitute active travel for car travel. Other studies have emphasized the role of changes in public transport quality. Lo et al. (2011) and Scheiner and Holz-Rau (2013b) found that the provision of effective public transit services in a new neighborhood is positively associated with the use of public transit. Similarly, Cervero and Day (2008) and Aditjandra et al. (2016) concluded that short walking distances to bus stops, metro stations or subways are more likely to attract more travelers.

However, there is also conflicting evidence. For example, Ma et al. (2014) and Feng (2016) found that physical neighborhood form and a well-supplied cycling environment have very limited effect on active travel. These findings are consistent with an abundant literature suggesting that urban form is at best a modest contributor to travel behavior (Maat and Timmermans, 2009; De Vos et al., 2012). Upon reflection, beyond the questionable methodological underpinnings of particularly much early work on the influence of built environment on activity-travel behavior, several considerations may explain these apparent contradictions. First, it should be realized that the overall distance or travel time between home and work might prohibit the use of active transport modes. Particularly, in the context of residential relocation, this may be a primary reason because typically distances tend to increase after relocation to suburban areas. Second, people show a tendency to maximize the overall utility of their daily activity travel patterns (Rasouli and Timmermans, 2014). Unless their local neighborhood provides at least the same facilities of the same quality as competing destinations, which is rarely the case, people tend to visit other neighborhoods and use modes other than walking and cycling. Only if people cannot act on their preferences due to budget or spatial-temporal constraints, the built environment may exert a strong influence on activity-travel choices.

Recent studies have emphasized the importance of perception in quasi-longitudinal comparisons to better interpret the contribution of the built environment on travel decisions (Ewing and Handy, 2009; Panter et al., 2014). Using multivariate regression analysis, Panter et al. (2014) assessed how perceived and cognitive changes in the built environment impact travel mode choice and concluded that improved perception of public transport convenience or cycling safety may help promote active commuting. The formation of cognitions takes time and therefore behavioral change tends to involve a time lag after physical change. Goodman et al. (2014) argued that new high-quality routes for walking or cycling provided in a neighborhood only exert some influence on active travel after two years.

2.2. Individual and household characteristics

Apart from the built environment, socio-demographic characteristics influence travel behavior (e.g., Ewing and Cervero, 2010; Akar et al., 2013), reflecting that people with different socio-demographic profile have a certain tendency to have different needs and face different constraints. Studies addressing the relationships between land use and travel behavior demonstrated that besides residential density, socio-demographic characteristics including income, car ownership, and household composition played a significant role in affecting car use (Cao et al., 2009; Hickman et al., 2010; Milakis, 2011). Maat and Timmermans (2009) found that single workers are more likely to use a car. Having a child also stimulates car use for commuting trips because people often combine the work commute with escorting children to school (Tyrinopoulos and Antoniou, 2013). Using longitudinal data, race and household composition were significant predictors of post-move walking (Wells and Yang, 2008). Christiansen et al. (2014) concluded that besides living in high walkable neighborhood, holding a tertiary education and being part of a young adult group were associated with higher odds ratios

of cycling in a Danish sample.

Clark et al. (2016) and Oakil et al. (2014), examining the effects of life events on the decision to switch transport mode, concluded that acquiring additional cars and acquiring a driver's license expanded the choice sets and consequently influence commuter mode choice. Life events involving demographic changes such as changes in household composition, may lead to a change in transportation needs and then intervene in family members' daily travel behavior, including the mode choice decision (Scheiner and Holz-Rau, 2013b). Oakil et al. (2016) found that 'child birth' may result in increased car ownership and increased demand for children's school travel, in turn increases the tendency of switching to car commuting.

Thus, although several studies have reported evidence about the significance of individual and household characteristics in dynamic activity-travel behavior decisions, one should realize that these variables have little theoretical meaning in their own right. Rather, these characteristics act as moderator variables, which influence the demand for travel, discriminate between different lifestyles and different environmental attitudes and correlate with budget and other constraints that influence activity-travel behavior.

2.3. Residential relocation-related attributes

Even if individuals would prefer using active transport modes, attributes of their environment after relocation may limit their opportunities. Scheiner (2006) claimed that relocation-related attributes have better interpretability in travel behavior than conventional socio-demographic characteristics of a person. Residential relocation as a life event brings changes in daily life and creates new circumstances for individuals that directly affect their activity-travel behavior. Oakil et al. (2011) stated that housing size, housing type and commute distance are important aspects considered in households' decision on how to allocate investments of time and money between transport and housing. For instance, some residents in Beijing reported that they would rather suffer the long distance commute but enjoy the better housing in suburbs than renting old houses in the city center close to their work. Thus, it seems that households do not make travel mode decision in isolation, but rather trade-off owning/renting a house in the city center close to work and owning/renting a better house in a suburb using the car to commute to work. The majority of households tend to derive a higher utility from suburban residential living environments than the disutility of commuting long distances by car. Evidence shows that commuters who live farther away from their workplace are more inclined to use their car for work, if they have one (Oakil et al., 2014; Dong et al., 2016).

Policy interventions related to transport costs, such as a one-month free public transport card (Thøgersen, 2009) and the daily rewards for drivers who drove during off-peak hours (Ben-Elia and Ettema, 2011), also influence commuters' travel behavior. However, such policies do not seem to have a long-lasting effect; initially people are stimulated to participate in such new policy schemes but after some time they realize the disadvantages and fall back into their old routines (Khademi and Timmermans, 2014). Because such policies do not exist in our study area, they were not included in our study.

In conclusion, residential relocation may lead to a dramatically different choice context, characterized by different opportunities and constraints. Relocation may also reflect changing needs and resources. Both may trigger or force individuals to reconsider their current mode choice. One would expect a shift if it is the only realistic option or if it would better reflect their preferences. Relocation may result in substantially longer distance making active modes no longer feasible. Relocation may also imply moving to residential areas that are more appealing for using slow modes. Consequently, understanding the dynamics of transport mode choice after relocation requires a framework of analysis of sufficient complexity to disentangle to direct and indirect interdependencies in the data.

Ignoring the methodological limitations of some previous studies, the mixed evidence from Europe, Australia and USA does not necessarily generalize to China. In many Chinese cities, the urban sprawl and the launch of housing reform policies have caused dramatic, large-scale suburbanization, involving active and passive relocation (Wu, 2004). China's case is more varied in all its determinants, making it an interesting case to study. Therefore, this paper examines whether changes in the (perceived) built environment and changes in socio-demographics can explain shifts in commute mode choice after relocation, with a special focus on active modes.

3. Data

3.1. Study area

In order to collect the necessary data, we administered a survey among relocated residents in Nanjing, the provincial capital of Jiangsu in Southeast China. Nanjing is the fourth most densely populated city in China with an urban population of 8.23 million inhabitants (Nanjing Statistical Bureau, 2016). To alleviate the pressure in the center, three new towns (Xianlin, Jiangning, and Hexi), occupying approximately 24% of the urban area were built. Fig. 1(a) shows the basic geography information of the three new towns. To meet the growing housing demand, many housing projects with affordable mortgages/rents were recently developed. Many residents relocated to these new towns. The transactions records in the real estate market from 2007 to 2012 confirm the high residential mobility in Nanjing, along with a substantial increase in car ownership from 66,900 in 2003 to 1.17 million in 2013 (Qin et al., 2016). The share of cars in the new towns is higher: 35% in Jiangning Newtown, 19% in Xianlin Newtown, compared to 14% in the urban center (Yang and Qian, 2015).

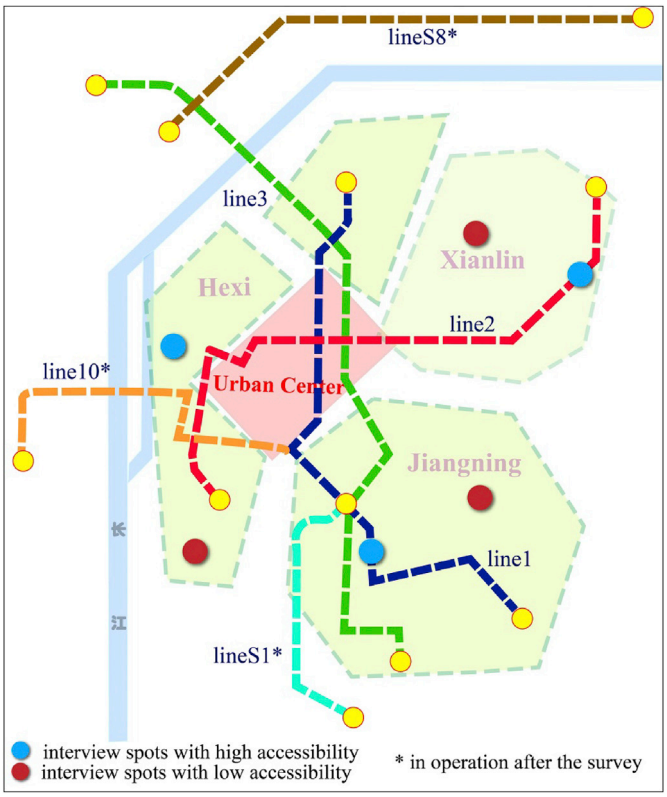
3.2. The survey and data

The questionnaire, designed to collect the necessary data, consists of two parts. The first part measures changes in built environment perceived by respondents and also collects basic socio-demographics information. The second part asked respondents about changes, if any, in their commuting mode choice before and after relocation, and included a series of relocation-related questions.

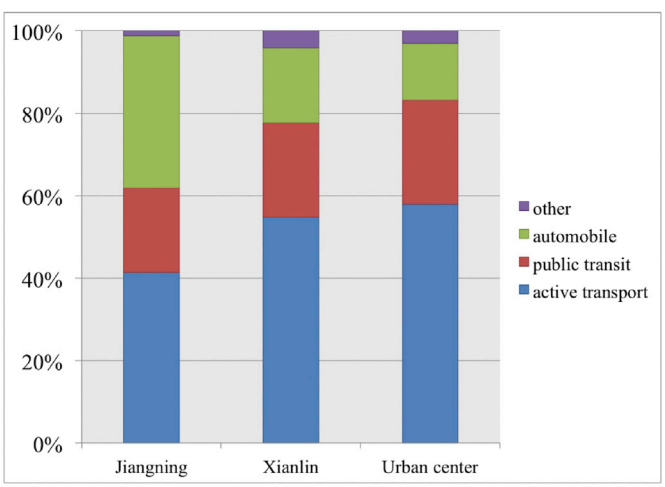
We administered the survey in the spring of 2014 in three new towns. To ensure the availability and reliability of the data, in each new town we selected several typical neighborhoods with a high move-in rate as our survey locations. The selection considered differences in housing types, geography, and transportation accessibility. Due to the difficulties of organizing a household survey in China, and the low response rate of home interviews, interviews took places in neighboring public places such as parks and plazas. We invited respondents at random to participate in the survey. In total, 550 respondents who relocated completed the questionnaire. After checking the surveys, we used the data of 497 respondents for analysis. To analyze the modal shifts away from active transport, we selected the sub-sample of 258 individuals who were active transport users before their residential relocation. Most respondents are 30 years or older; 50.4% is male, and 39.1% owns a car. The dynamics in modal split after relocation are as follows: 37.2% shifted to public transit, 24.8% switched to the car, while the remaining 38% continued to use active modes for their commuting trips. Table 1 presents some descriptive statistics of the explanatory variables.

3.2.1. Measurement of perceived changes in the built environment

To measure the perceived changes in the built environment, respondents were asked to indicate how the characteristics of the built environment in their current neighborhood differ from those in their previous neighborhood on a three-point scale, ranging from 1 ("improved") to 3 ("worsened"). Ten characteristics were included: bus service coverage, distance to the nearest bus stop, convenience of bus commuting, distance to the nearest subway station, convenience of



(a) Urban area of Nanjing (2016)



(b) Modal share in Nanjing (2014)

Fig. 1. Basic information about Nanjing.

subway commuting, the daily traffic on roads, the accessibility of arterials or freeways, sidewalks throughout the neighborhood, bike or e-bike routes beyond the neighborhood, and safety of bike or e-bike parking. Note that the former five items indicate changes in the experienced quality of public transport in the neighborhoods. While admittedly, the three categories are rather crude, this approach has the advantage that it only captures differences between neighborhoods to the extent respondents discriminate and attach meaning to the differences in the selected neighborhood characteristics.

Table 1 presents the mean values of all perceived changes in the built environment. In terms of public transport, all perceived changes except

Table 1
Variables used in the BN (N = 258).

Variable	Description
Personal and household characteristics	
Income	Income per month: < 4000 yuan (47.3%), >4000 yuan (52.7%)
Car	Car ownership: no car (60.9%), one or more cars (39.1%)
Add cars	Bought additional car(s) after relocation: Yes (30.6%), No (69.4%)
H_composition	Household composition: 1–3 persons (64%), >3 persons (36%)
Childbirth	Have new born baby: Yes (20.5%), No (79.5%)
H_workstatus	Household working status: ≤1 worker (11.6%), 2 workers (71.3%), ≥3 workers (17.1%)
Residential relocation-related attributes	
Housetype	Housing type: commodity housing or villa (46.9%), other (53.1%)
Housesize	Size of house: < 80 m^2 (65.9%), >80 m^2 (34.1%)
Payment	Paid in full or in part (71.7%), renting or other (28.3%)
Relotype	Relocation type: active (51.9%), passive (48.1%)
Relodirection	Relocation direction: move outward (55.4%), other (44.6%)
Chan_hsize	Change in house size: increased (66.3%), No (33.7%)
Chan_ cdistance	Change in commute distance: increased (47.7%), No (52.3%)
Travel behavior	
Postmode	Travel mode of previously active commuters after relocation: active transport (38.0%), public transit (37.2%), private car (24.8%)
Perceived changes in built environment (mean value)	
Bus_coverage	Number of bus lines or bus service coverage (2.41)
Dis_busstop	Distance to the nearest bus stop (2.32)
Bus_commute	Convenience of bus commuting (2.51)
Dis_subway	Distance to the nearest subway station (1.89)
Subway_commute	Convenience of subway commuting (2.03)
Traffic_onroad	Daily traffic on road especially during peak hours (2.11)
Arterials	Accessibility of arterials or freeways (1.95)
Sidewalks	Sidewalks throughout the neighborhood (1.91)
Bikeroutes	Bike or e-bike routes beyond the neighborhood (1.99)
Safeparking	Safe neighborhoods for bike/e-bike parking (2.03)

Note. The numbers for public transit service and built environment are mean values from a 3-point scale ranging from "improved" (1) to "worsened" (3).

distance to the nearest subway station are higher than 2, indicating that most public transit services in the respondents' current neighborhoods are experienced worse than in their previous neighborhoods. The worst service aspect is the convenience of bus commuting (2.51), followed by bus service coverage (2.41), closeness to the nearest bus stop (2.32), and convenience of subway commuting (2.03). Other characteristics are valued equally. These findings support the view that public transport availability and service delivery tend to play a less important role in residential relocation decisions.

3.2.2. *Individual and household characteristics*

Data on socio-demographic variables that were collected included income, car ownership, household composition, and household working status. In addition, questions were asked about whether respondents had new-born babies and whether they bought additional cars after relocation. The data indicate that 52.7% earns an income more than 4000 yuan per month, while 47.3% has a monthly income less than 4000 yuan; 39.1% of the households possesses one or more cars; 64% has one to three family members, while 36% has four or more members in the household; most households (71.3%) have dual workers. As for socio-demographic changes, after relocation 30.6% of the households bought additional cars and 20.5% had a new-born baby, suggesting that the relocation decision in these cases was triggered by this life event.

3.2.3. *Residential relocation-related attributes*

Attributes related to residential relocation included current housing type, size of the house, house payment, direction of move (whether the resident moved from the city center to the outlying area or not), and relocation type. Relocation type mainly measures the willingness of resident's relocation. Additionally, we collected data on the difference in commuting distance and change in house size. Table 1 shows that 46.9% of previously active commuters now lives in commodity housing or villas. Only 34.1% lives in residences with a size more than 80 m^2; 71.7% of the

households purchased their current residence in full or in part; 51.9% moved to their residence actively, meaning that they left their previous residence actively and chose their current residential location for their own needs (such as marriage, for a better school, working, or for a better living environment); 55.4% of households moved outward and the other relocated within the same region or moved inward. In terms of dynamics, two thirds live in a larger residence and 47.7% reported that their commute distance increased.

4. Methodology

4.1. The BN

Following Verhoeven et al. (2006), we constructed a BN to capture the underlying direct and indirect relationships between the selected variables and to assess their influence on mode shift of commuters, who previously used active transport modes. The choice of a BN is mainly motivated by the inherent complexity of the adjustment process occurring after residential relocation. BN is a data-mining technique. Formally, BN is a directed acyclic graph (DAG), where nodes represent variables and arrows represent conditional dependencies among these variables (Pearl, 1988; Nielsen and Jensen, 2009). Both the conditional dependencies and the network structure can be learned from the data using one of the algorithms that are available in software packages or toolboxes.

As discussed, input to the BN are the socio-demographics, residential relocation-related characteristics, perceived changes in the built environment and travel mode choice. Socio-demographics are included to consider possible differences in underlying needs and constraints. We incorporated perceived changes in the built environment in the Bayesian network to vary differential assessment of various factors stimulating or discouraging the use of different transport modes. The relocation-related attributes were selected to reflect our contention that transport mode choice decision is not made in isolation but that people tend to find the combination of job, residence, and transport mode, considering budget and other constraints that give them maximum satisfaction.

To detail the choice of BN, first, Bayesian networks can incorporate different types of information, including empirical data, theoretical relationships, and expert knowledge. Consequently, the researcher has more control over the model and does not need to rely only on statistical evidence that may be biased, particularly for small samples and complex interdependencies. Second, a BN has the ability to deal with the uncertain and complex relationships hidden in the data. As shown in Table 1, a large group of variables that is assumed to have direct or indirect relationships with the shift in transport mode of respondents using active transport modes before relocation is included in this study. As the variables included herein are often strongly correlated and the relationships between them are uncertain, the inclusion of these correlated variables and the specification of an appropriate structure for these interactions becomes rather challenging for the mainstream choice models. BN is proficient in addressing these difficulties, because it can simultaneously derive and represent the underlying relationships using a network-learning algorithm. Third, Bayesian networks have shown competitive performance in predicting relationships among variables compared to classical discrete choice models in many application domains (Chen et al., 2015). Finally, once the model is extracted, the easy updating of causal relations makes inference analysis straightforward.

Further details about BNs, particularly with respect to the learning the structure of the network, can be found in Pearl (1988). The potential of the approach in transportation research has been demonstrated in a variety of different studies (e.g., Janssens et al., 2006; Uusitalo, 2007; Arentze and Timmermans, 2009; Karimnezhad and Moradi, 2017; Wu et al., 2016). All these studies apply Bayesian network to other types of research problems. Verhoeven et al. (2006) is a more related study in that they also consider the effects of life trajectory decisions on transport mode choice.

4.2. BN learning and model specification

The first step in the formulation of a BN is to learn the structure of the network, i.e. the set of direct and indirect relationships, from the data. Network learning involves two main steps: building the network structure and estimating the conditional probability tables (CPTs). To learn the structure, we applied the three-phase dependency analysis (TPDA) algorithm developed by Cheng et al. (2002). The algorithm adds or removes links between pairs of variables using the conditional independence (CI) test that calculates the mutual information for each pair of variables (X, Y) as expressed in the following equation:

$$I(X,Y) = \sum_{x,y} P(X,Y)\log\left(\frac{P(X,Y)}{P(X)P(Y)}\right) \tag{1}$$

where, $I(X,Y)$ measures the closeness between X and Y, $P(x, y)$ indicates the joint probability of observing X and Y, $P(x)$ is the probability of observing X and $P(y)$ is the probability of observing Y. In the algorithm, the conditional independence between all pairs of variables will be tested. If a pair of variables has the mutual information greater or less than the entropy, links between them will be added to or removed from the current network structure. This procedure would be repeatedly performed until no additional links are able to add or remove. For a more detailed explanation on TPDA readers could refer to the study by Arentze and Timmermans (2009). The second step is to estimate CPTs for the resulting structure. In this study, we used a sequence of stepwise iterations embedded in the commonly used EM algorithm (Expectation Maximization) and a more detailed description on this algorithm can be found in the paper of Lauritzen (1995).

To ensure that the network is consistent with our expectations and does not only depend on statistical correlations, before the network learning, we predefined constraints on the links between some variables based on our domain knowledge. Because this study is supposed to predict modal shift after relocation and investigate its relationship with personal, household, and relocation-related characteristics, and perceived changes in the built environment after the move, we predefined the following constraints. First, the built environment variables were categorized into two sets (one regarding public transport and the other involving traffic facilities) and were used as explanatory variables. Therefore, we did not allow any links between the variables of each set in the BN model. Moreover, as socio-demographic variables such as income, household car ownership, household working status, and child birth are difficult or impossible to change due to the factors in the other groups, we precluded any influences from latter set of variables to the socio-demographics. This constraint guarantees that the socio-demographics are the control variables so that a change of other variables does not influence the socio-demographics in the inference analysis.

4.3. Model assessment

Following the above processes, we constructed the network using PowerConstructor and then compiled the corresponding network in Netica for better visualization (Cheng et al., 2002; Norsys Software,

Table 2
Confusion matrix (N = 258).

Observed			
Active transport; 98 (38.0%)	Public transit; 96 (37.2%)	Private car; 64 (24.8%)	Predicted
80	21	3	Active transport; 104 (40.3%)
13	65	1	Public transit; 79 (30.6%)
5	10	60	Private car; 75 (29.1%)
Overall accuracy = 79.4%			

2006). Because the database is rather small, we applied the method of "Leave-one-out" (Moore and Lee, 1994), which involves repeated learning from 257 records out of the available 258 records and subsequently testing it on the remaining 258th record. Table 2 shows the overall BN estimation results for the dataset and its corresponding confusion matrix. The estimated probability distribution (40.3% for active transport, 30.6% for public transit, and 29.1% for car transport), is reasonable close to the observed shares (38.0% for active transport, 37.2% for public transit, and 24.8% for car). The overall estimation accuracy of the BN reaches 79.4%, indicating that the result is acceptable. The confusion matrix gives the number of misclassified transport modes after relocation. The numbers on the main diagonal indicate the number of correctly predicted transport modes for the work commute trips after relocation. The off-diagonal numbers indicate the distribution of misclassified transport modes. Table 2 shows that the extracted BN by far correctly predicts the chosen transport mode for the commute trip. For

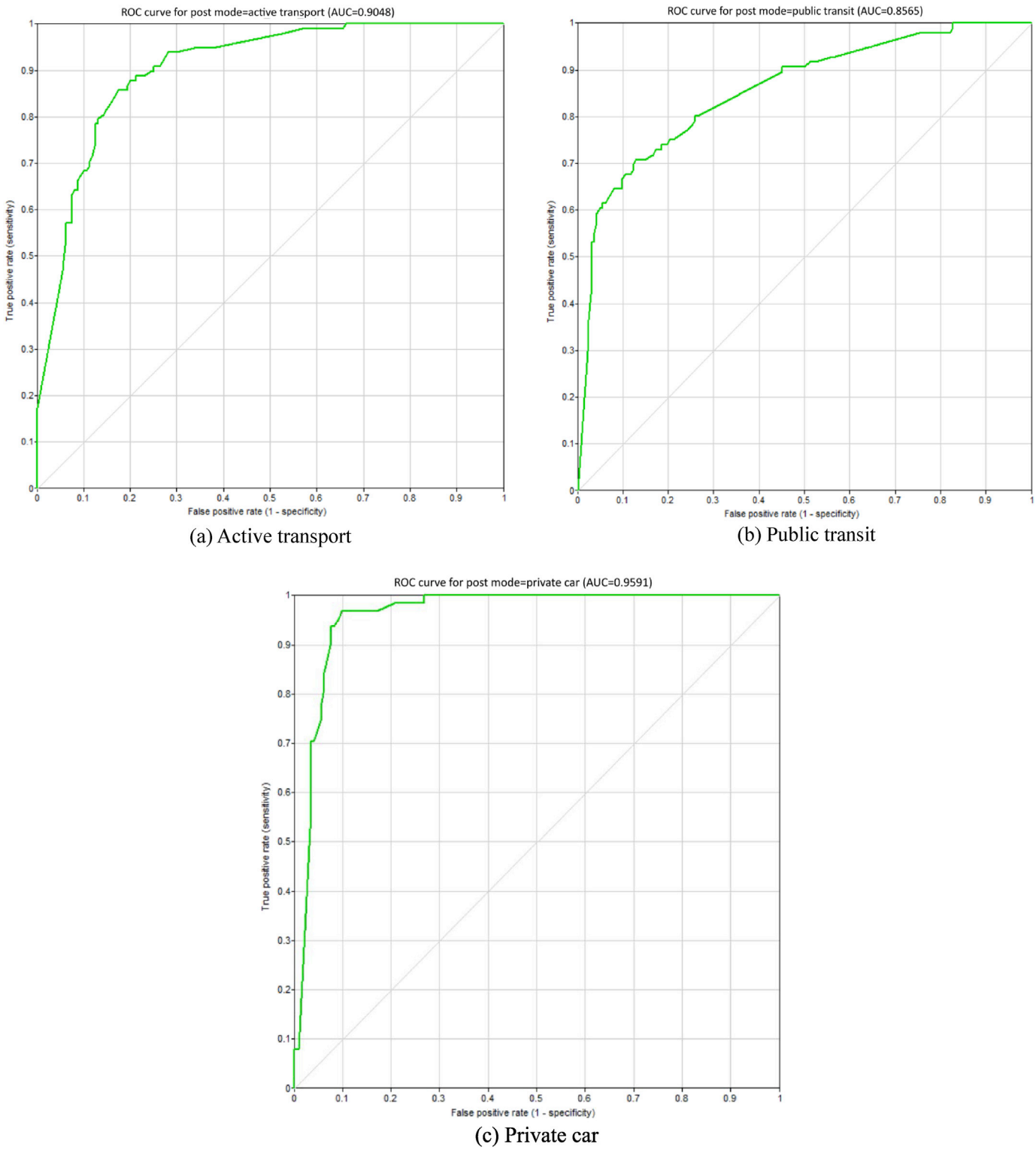


Fig. 2. ROC curves for modal shift.

instance, almost all cases for private cars are predicted correctly by the network.

To assess the overall performance of the resulting BN model, we applied a Receiver Operating Characteristic (ROC) curve analysis. Fig. 2(a, b, c) present the ROC curves for the modal shifts. All curves are located above the diagonal lines, meaning that this BN works rather well for these modal shifts (Fawcett, 2004). Another commonly used index, which usually goes along with ROC, is the area under the ROC curve (AUC). It quantifies the overall performance of the BN taking values between 0 and 1. Values close to 1 mean better performance. The calculated AUCs from highest to lowest are: 0.9591 for private car, 0.9048 for active transport, and 0.8565 for public transit. Based on the three AUCs the weighted average is 0.9002, calculated as $AUC_{overall} = \sum_{i=1}^{3} AUC_i p(i)$. It indicates that the performance of the constructed BN is acceptable (Akobeng, 2007).

5. Model results

Fig. 3 shows the extracted network structure. As we expected, many socio-demographic variables are closely associated with the perceived built environment and relocation-related attributes. The results present a direct relationship between modal shift and car ownership, current housing type, change in commute distance, and perceived change in the convenience of bus commuting. Moreover, results indicate a direct relationship between commute distance and modal shift, which is in line with previous studies (Cervero and Day, 2008). All other characteristics have indirect and mediated associations with modal shift.

Fig. 4(a and b) show the inference results for variables that might influence the travel decision of active transport commuters in switching to public transit or to private car after relocation. The inference analysis is made through the setting of specific evidences for related variables. The corresponding effects are updated in the whole network by Bayes' Rule and then their contributions to modal shift with certain travel mode can be quantified. For each variable, the evidence setting is proceeded by predefining its probability with 100% in its specific value, which certainly results in a new probability distribution of modal shift. The comparison with the original probability that captures the changes in each travel mode exactly implies the impact of these variables with specific values on the model shift. For instance, "-10.6%" in the first row in Fig. 4 means that when a probability of 100% is assigned income >4000 yuan, the probability of a modal shift from active transport to public transit after relocation reaches its minimum value, with a decrease of 10.6%, compared to other states of income. It implies that an increasing income will decrease the propensity of modal shift to public transit after relocation.

5.1. Shift from active transport to public transit

Fig. 4(a) shows the inference range of each factor on the modal shift to public transit. Car ownership, change in commute distance, and additional car purchase are the best indicators of this modal shift. They are followed by income, built environment variables (distance to subway station and convenience of subway commuting or bus commuting), and relocation-related attributes (housing type, house size, and relocation type). Changes in house size, accessibility of arterials, sidewalks, and working status do contribute to the shift to public transit but to a lesser extent, while the remaining variables have only minor effects. Below, these findings are discussed according to the nature of the explanatory variables.

5.1.1. Perceived changes in built environment

The results show that better transit accessibility and services generally have a significant effect on the modal shift towards public transit. Both walking distances to subway stations and the convenience of subway commuting are significantly associated with this modal shift with an influence of 27.9%–45.4% and 28.0%–44.6% respectively. Commuters living in neighborhoods with longer walking distances to bus stops are less likely to shift to public transit after relocation. This supports the viewpoint of Næss (2005) that the development and integration of the public transit system should be given priority. To make public transit more accessible and encourage more people to use public transit for commuting, new transport modes for short distance could serve as the access mode around the residents' new residences or worksites. For instance, community buses operated in residences or worksites aiming to improve transit accessibility and bicycle sharing services are providing fast and convenient access and egress services for rail transit commuters. Other aspects of the built environment have small effects.

5.1.2. Personal and household characteristics

Fig. 4(a) shows that commuters' modal shift to public transit is strongly influenced by the availability of private cars. Households with

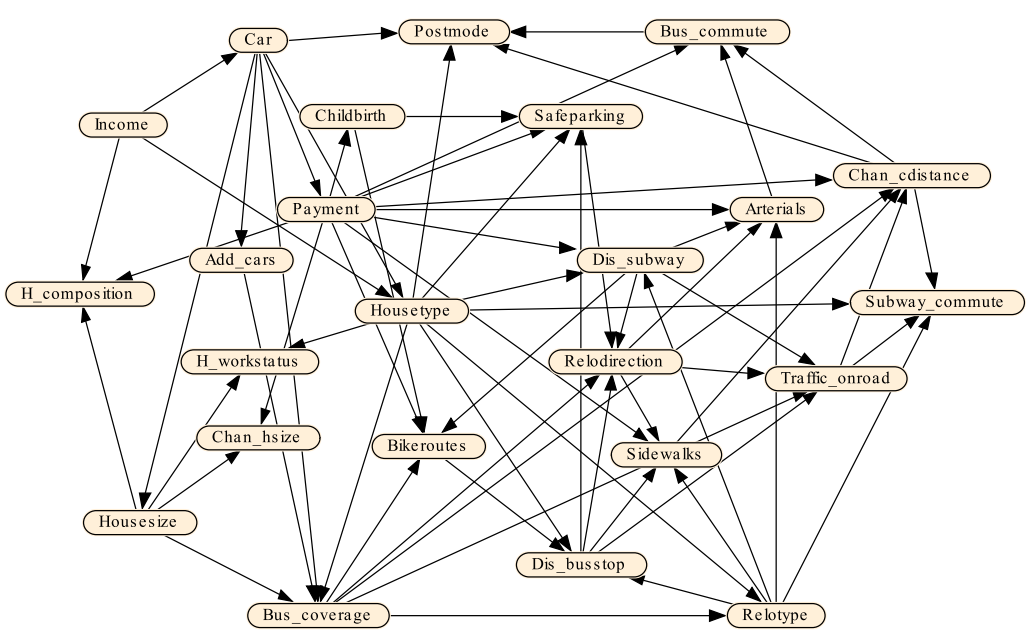
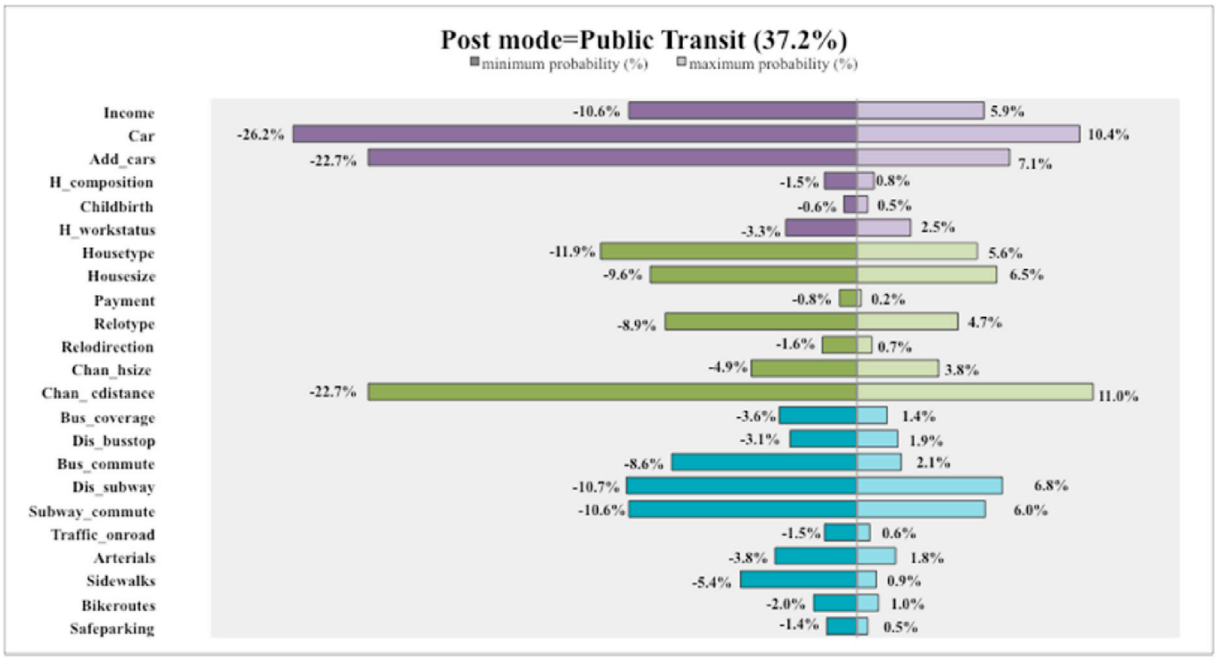


Fig. 3. The Bayesian network.

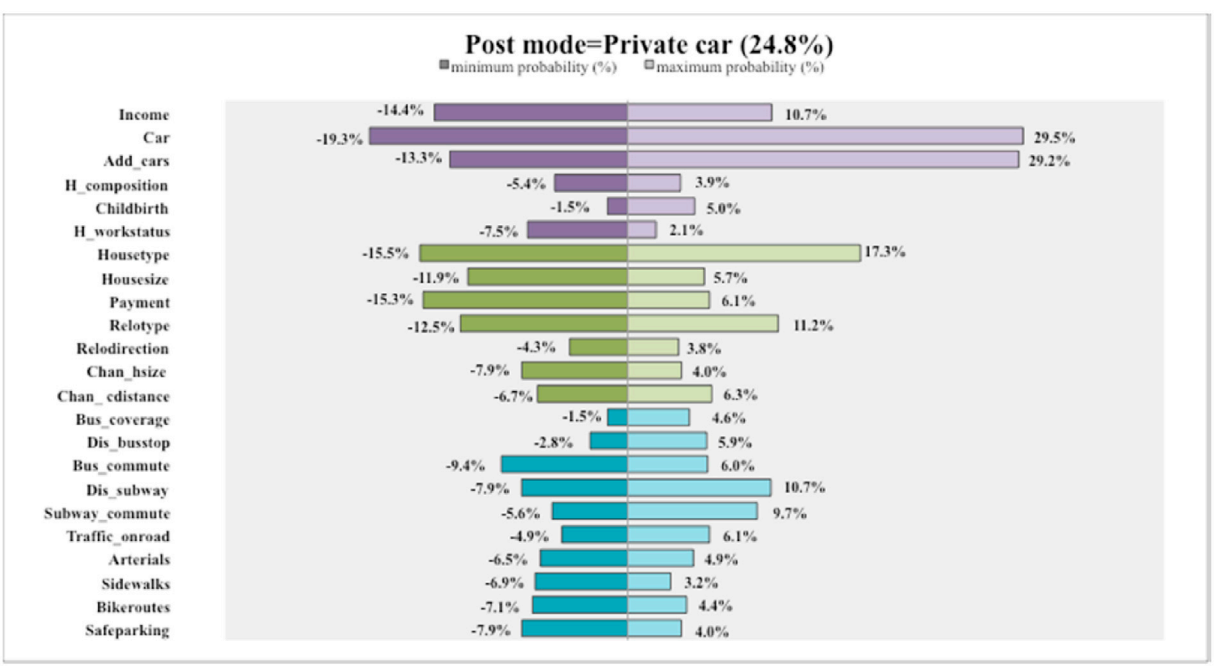
private cars or acquiring an additional car after relocation are unlikely to switch to public transit and will use less public transit, whose percentage of use will decrease by 26.2% and 22.7% respectively. Respondents with an income over 4000 yuan are less likely to shift to public transit after relocation. Variables describing the household structure, such as household composition, household working status, and childbirth, barely affect the shift toward public transit.

5.1.3. Residential relocation-related attributes

Commute distance is the primary contributor for this shift: the longer the distance, the higher the probability that residents use public transport after relocation. Its negative effect on active transport is consistent with the fact that a greater commute distance after relocation is beyond the serving range of active modes. Meanwhile, the efficient and cheap delivery services provided by the subway system in Nanjing meet the commute needs of a certain percentage of the sample. Household demand for commodity housing or villas and housing with more than 80 m^2 after relocation has negative effects on this modal shift with odds of −11.9% and −9.6% respectively. Households who can afford the costs of a more spacious housing are less likely to switch to pubic transit with a negative



(a)



(b)

Fig. 4. (a) Probability changes of modal shift to public transit. (b) Probability changes of modal shift to private car.

effect of 9.6%. Residents who relocated for their own needs depend less on public transit (−8.9%). The demand for specific housing initially stems from the unbalanced development of the land use pattern, which in turn leads to a significant difference between housing in the city center and the suburbs. Reasonable guidance of land use, especially related employment and residential development, is assumed to somewhat ease this trend and reduce unexpected modal shifts. The direction of the move and house payment have the smallest effects on modal shift.

5.2. Shift from active transport to private car

Fig. 4(b) shows changes in the posterior probability of shifting to private car with respect to its initial value. The top nine factors that contribute most to this change are in order of importance: car ownership, additional car purchase, housing type, income, relocation type, house payment, house size and distance to the nearest subway station.

5.2.1. Perceived changes in built environment

Fig. 4(b) shows that the built environment characteristics have clear impacts. The likelihood of switching to car increases for active commuters as the distance to the subway station increases and the perceived convenience of the subway or bus deceases. If buses or subways are perceived more accessible, the likelihood of this modal shift among former active commuters decreases by 5%–9%. However, if subway services are perceived less accessible, nearly 10% will turn to private cars for commuting. A well-built subway system is a promising competitor of private cars for long-distance commute. With the exception of public transport factors, the remaining built environment variables shown in Fig. 4 have similar effects of around 11%. Good traffic conditions would encourage 6.1% of former active commuters to travel by car. The provision of better infrastructures like sidewalks, bike routes, and bike parking in the neighborhood are negatively associated with car use after relocation, with a modest influence of around 7%. This finding is consistent with the study by Pucher et al. (2010) that the supply of secure and sheltered bike parking around residences or worksites and safe bike routes could to some extent support bicycle commuting. Moreover, the implementation or the expansion of bicycle sharing services is expected to decrease this shift to motorized mode for medium-to short-distance commute to work. As to the accessibility to arteries, a worsening accessibility of arterials or freeways would reduce car use by 6.5%.

5.2.2. Residential relocation-related attributes

Most variables of this category affect the modal shift to private car for the commute trip. Individuals living in commodity housing or villas are more likely to use a private automobile to commute (−15.5%–17.3%). People who paid the current house in full or in part are inclined to choose the private car to reach the work place (−15.3%–6.1%). Relocation type, with an effect ranging from −12.5% to 11.2%, is another important factor. People who actively moved prefer to switch from their previous mode to a private car for commuting. Commuters now living in a smaller residence than before seem not capable of shifting their commute mode. Moreover, the medium effect of changing commute distance implies that the groups who could afford car usage or have a strong desire for car ownership are less sensitive to the changing job-housing balance than the low-income group.

5.2.3. Personal and household characteristics

Not surprisingly, the results show that the purchase of a second (new) car, current car ownership, and personal income strongly influence a modal shift to the car after the relocation. Increased personal income, possibly coinciding with car ownership means that people will use the car. Variables describing household structure including household composition, household working status, and childbirth, have a relatively small impact on modal shift to using private cars. A noticeable finding here is the negative effect of households with three or more workers (−7.5%) on commute mode switching from bicycle to private car. This means that these households are less likely to shift to the private car for commuting after relocation. The effects of the remaining attributes in this category are negligible. The results suggest that license plate control and traffic management of private car may curb the trend of further motorization through the limitation of the private car purchases and usage, conditional on how many people buy and extra car. Moreover, measures that reduce the attractiveness of car driving such as reducing access to cars to the city center and increasing the costs of driving by charging high parking fees may help slow down the motorizing shift. On the other hand, in western countries, it did not stop people using their car if they could afford to pay for these extra charges. Hence, such pricing policies have an equity issue.

6. Conclusions

The aim of this study was to explore the relationships between residential relocation and shifts in transport mode choice for the work commute of respondents who were walking or biking to work before their relocation. The study contributes to the limited prior research on the topic. Because the reasons for moving house may vary and the ways of people in adapting their activity travel behavior to this newly experienced situation may vary, a set of factors and their independencies may be involved. Therefore, a BN that allows the estimation of these underlying direct and indirect effects was constructed. Data obtained from a survey among 258 relocated residents in Nanjing about residential relocation and perceived changes in built environment characteristics, conducted in 2014 was used to extract the network. In line with the socio-ecological framework, a network including both direct and indirect relationships between all variables was established. The wide variation in determinants in Nanjing makes the study highly valuable compared to studies in Europe, USA, and Australia.

The network structure extracted from the data demonstrated that the modal shift of previously active commuters is directly associated with the change in commute distance, car ownership, current housing type, and perceived changes in the convenience of bus or subway commuting. Results seem to suggest that if the relocation coincides with increased income, people who can afford it will likely buy a private car and use it, particularly if the commuting distance is too high to walk or bike. The influence of the built environment on this group seems asymmetric. The presence of a high-quality environment does not trigger these people to use public transport; the lack of good quality such as easy accesses to subway station and extensive convenience of bus commuting or subway commuting triggers them to avoid it.

A second segment of the respondent is primarily driven by constraints. If they cannot afford to buy or use a private car, they depend on public transport when the commute distance is too high. The results demonstrate that perceived changes in the built environment are only important for some respondents, and then again their influence is modest.

Our findings have some interesting implications for urban and transportation planning. First, residential relocation of a certain share of the sample manifests improved living conditions. If they can afford a car, they tend to use it, irrespective of the commute distance. The car is a status symbol of accumulating wealth, but of course at the same time is also more convenient. This case resembles most dominant behavior observed in several European studies. The urban form has a very modest role in changing the behavior of this group to environmentally friendly transport modes. The only thing that seems to matter is changing attitudes, implying that most effective policies for this segment relate to the promotion of attitudinal change. If the commuting distance prevents using active modes, another segment faces the choice of either public transport or cars. Provision of high-quality public transport may then postpone people from choosing the car once they can afford it.

Only the segment where relocation does not increase commuting distance and distance within the reach of active transport modes may benefit from the local provision of infrastructure stimulating the use of

active modes. In order to stimulate the use of slow transport modes among residents and encourage public transit usage, planners should design neighborhoods with infrastructures tailored to commuters' needs. However, even for this group, the impact is modest.

By inference, the right job-housing balance and concentrations of residents and job at transport nodes seem the most effective policy that may somewhat counterbalance increasing car ownership and use. Furthermore, for long commute distances, a combination of improving public transit services and implementing reasonable restrictions on car use may stimulate public transit use as much as possible.

Although this study has given some insights on the modal shift of active commuters in response to residential relocation, further studies are still needed to explain their travel behavioral changes. First, new advanced techniques for data collection are required to supplement the current data in studying their travel pattern dynamics. For instance, the behavioral changes in commute time and cost, the key attributes of commute trip, have not been addressed in this study due to the quality of retrospective data. In the survey, many respondents reported that recalling the detailed trip information on time and cost before relocation was much more difficult. Second, investigations on how these previous car commuters changed their travel pattern and car usage after relocation are of great necessity because knowledge on these causal relations is beneficial to develop effective initiatives and countermeasures to reduce their car usage.

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