INVESTIGATING THE MODE SWITCHING BEHAVIOR FROM DIFFERENT NON-CAR MODES TO CAR: The Role of Life Course Events and Policy Opportunities

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ABSTRACT

Life course events could lead to a habitual change of mode choice, and sometimes it is from non-car modes to car, which is not a desirable outcome from a sustainable view. This research intends to study in-depth the mode switching behavior from each of the different non-car modes to car, in order to identify opportunities for policy intervention to hold back such a habitual change towards car usage. Retrospective commute mode choice and various life course event data over four observation periods are collected. A mixed binary logit regression model is developed at first to study the mode switching behavior from car to non-car modes followed by a set of “mirror models” (also mixed binary logit) which evaluate the mode switches from non-car modes to car. It is found that different non-car mode users do have different mode switching behavior by observing their distinct reactions to life course events, especially towards getting married, having the first child and different degrees of commute distance change. A thorough discussion on the policy implications of these findings is provided in the end.

Keywords: Life course event, Mode switch, Retrospective data, Commute mode choice, Binary logit, Policy implication

INTRODUCTION

Mode choice analysis is a popular topic in travel behavioral research, and most of the existing works have focused their analysis at a tactical level by studying how individual travelers make trade-offs among different attributes. It is indeed a widely used tool for travel demand management; however, there are also findings revealing that choice behavior could be habitual and the mode use decision may not be affected by the surrounding tactical-level conditions (1, 2, 3). With such an understanding, many works have incorporated dynamic elements in their models, i.e. taking into account the influence of mode choices observed in earlier periods/states on the current mode choice behavior (4, 5, 6, 7), and in most cases such influence turned out to be significant.

The revealed importance of mode choice habit could bring substantial challenges to effective travel demand management. For instance, reducing car usage is practically a common pursuit in today's world. However, if policy efforts only focus on tactical-level mode choice behavior, the expected modal shift from car to more sustainable modes may not occur due to the behavior could be dominated by the mature car use habit. So, what could be the solutions? In other words, can the choice habit be somehow changed?

Research has proposed and shown that life course events could potentially lead to a change of mode choice habit. There could be a variety of life course events, for example household or family related (getting married, child birth, etc.), employment related (income change, employer change, etc.), residential or contextual related (home relocation, trip distance change, etc.) (8). A number of studies have attempted to investigate the connections between those events and long-term mode switching behavior, e.g. switching to and away from car as a regular commute mode (9, 10), to and away from bicycle (11, 12) and a shift towards multimodality (13). In addition, the impacts of life course events have also been explored on other types of travel behavior such as car ownership changes (14, 15, 16, 17, 18) and commute distance changes (19, 20).

Nevertheless, the challenge still remains. It is probably desirable to see a switch away from using car following the occurrences of some life events; however, meanwhile, switching to car is also a possible outcome and in fact, several results have indicated that switching from non-car modes to car was more frequently observed than the opposite (9, 10). Thus, in such a case, it is crucial if efforts could be made to hold back any mode switches to car that are induced by life course events; since otherwise, once car is picked up and over time its usage becomes habitual, it would be even more difficult to alter the mode choice behavior (2). This is a subject that has not been properly looked at and the following question still remains to be answered: given the presence of life course events that could result in the mode switches from non-car modes to car, what could be the counter-measures to hold back such a change?

This research aims to offer some direct insights to the above query by delivering a mode switching analysis. The case study is in a Chinese city, Taiyuan. A retrospective mode choice survey was conducted to collect the citizens' regular commute mode information in 2006, 2008, 2010 and 2012, totally four observation periods. A variety of life status data in the corresponding observation periods was also collected. A binary logit regression model is developed first to study the mode switching behavior from car to non-car modes followed by a set of "mirror models" which evaluate the mode switches from different non-car modes to car. The mirror models could reveal any differences in mode switching behavior among different non-car mode users, and hence more targeted policy implications could be derived.

The remainder of the paper is structured as follows. The next section provides the information of the retrospective survey and the descriptions of life course events and observed mode switching pattern. Following that is the details of model formulation. The model estimation results come next and a thorough discussion of policy implications is presented in the end.

RETROSPECTIVE SURVEY AND DATA

This research uses a retrospective survey data to study the effects of life course events on mode switching behavior. The survey is part of the Taiyuan citizens' travel behavior survey which took place in 2015 at a Chinese city, Taiyuan (21). Respondents were asked to recall their most frequently used commute mode in the year of 2006, 2008, 2010 and 2012, and also provide a variety of information about their life status in the same years. The survey approached 15,000 Taiyuan citizens; however, for the retrospective part, the number of responses that we keep in the final sample for this research is limited. This is due to 1. the difficulty in recalling past information in a retrospective survey (22, 23) so that a lot of missing values do exist and the corresponding observations are removed; and 2. we applied many other criteria to make sure the selected data is credible enough to enter the analysis, for instance, a person included in the final sample must has full observations across all four periods and must has become a resident in the city at least before the first observation period, etc. Relevant information has been gathered in the survey to ensure those criteria can be fulfilled. Eventually, we have 1,799 individual respondents with their all four-period commute mode choices (7,196 observations in total) ready to be used in the mode switching analysis. Some key information of this sample is presented in Table 1.

The sample is almost equally composed of male and female commuters. Age information is not collected in the retrospective survey. Household income has gradually increased over time. The proportion of people who live and work both in the central districts of Taiyuan city (there are 6 districts in Taiyuan and 2 are perceived as the central districts in the past decade) has remained stable and we found from the data that this is not due to the approximately same number of people moving in/out, but simply because most respondents in the sample have stayed within the central/outer district boundary. Many people got married, had child birth and received a fixed job during our study period. The distribution of commute distances is relatively stable over time; however, this time, it is revealed from data that such stability is caused by the occurrences of both commute distance increases and decreases, not because people have their home and work place locations unchanged (though, as mentioned earlier, most of them still stayed within the boundary of central/outer district). There is an increasing possession rate of car by household over time while the possession rates of electric bike and bike remained similar across different periods. Regarding the commute mode choices, car usage has been through a continuous increase from 2006 to 2012; by looking at the rest of modes, we can see the increasing demand for car came from bus, electric bike, bike and walk journeys. Meanwhile, taxi was rarely chosen for regular commute trips and its share remained low in all four periods.

Table 2 and 3 provide more specific statistics for a mode switching analysis with respect to life course event occurrences. In Table 2, we identified from data five critical life course events that could possibly result in mode switching behavior; they are "Get married", "Have the first child", "Engage in a fixed job", "Encounter a level jump of household income" and "Commute distance change". Over the entire study period (2006-2012), the percentages of respondents who have got married, had the first child birth and engaged in a fixed job are 28%, 24% and 12% respectively. The latter two figures (24% and 12%) are consistent with the statistics in Table 1 where the number of people having at least one child increased from 38% in 2006 to 62% in 2012, and having a fixed job increased from 72% in 2006 to 84% in 2012. However, 28% of people getting married is 5% higher than the yearly marriage statistics (from 61% in 2006 to 84% in 2012). The difference implies 5% people may have got divorced but such a life course event will not be studied in our models given its low occurrence rate. The survey captures household income in six levels: below ￥3k, ￥3k -￥6k, ￥6k -￥9k, ￥9k -￥15k, ￥15k -￥30k and above ￥30k. A jump to a higher household income level is another event that might make people reconsider their mode choice decisions. 26% of the sampled individuals have been through at least once such an income increase over the entire study period. Finally, commute distance change is broken down to two sub-cases, where 22% have experienced a distance increase and 14% have experienced a distance decrease.

To reveal the mode switching pattern, we convert the original sample data into a different format. Initially, each individual respondent has four mode choice observations from the four periods (2006, 2008, 2010 and 2012) respectively. Then, we formulate paired observations by capturing the mode choices in a precedent period and the period followed. As such, each individual respondent now has three paired observations (2006/2008, 2008/2010 and 2010/2012) to explicitly display any mode switching behavior. Table 3 offers an overview of the mode switching pattern over the entire study period (2006-2012). About 90% paired observations which had car as the commute mode in the precedent period still had car chosen in the period followed. As a comparison, for bus, electric bike, bike and walk that were chosen in the precedent period, the percentages of paired observations which had the same modes chosen in the following period were lower, though all of the numbers were still above 80%. Thus, there was slightly stronger adherence to car usage than to using the rest of modes. Besides, it is noteworthy that car would always be the most popular alternative if people would like to switch away from bus, electric bike, bike and walk in the period followed.

MODEL FORMULATION

Based on the data structure displayed in Table 3, we put the paired observations into five sub-datasets in which the commute mode choice in the precedent period is car, bus, electric bike, bike and walk respectively. These are the datasets that will be used in our mode switching analysis.

A binary logit regression model is developed at first to investigate the mode switching behavior from car (precedent period) to non-car (the following period). In fact, broader insights could possibly be obtained if the "non-car" alternative can be decomposed into the actual modes that are chosen in the following period (e.g. car-bus, car-electric bike…) and hence perform a multinomial logit regression. However, there are very limited mode switching events in this working dataset (i.e. the first row of Table 3), and as a result our modeling attempt with multinomial logit regression encountered a convergence issue. Eventually, a binary approach is adopted by following the similar practice in earlier studies (9, 10).

Next, a set of "mirror models" are developed to study the mode switching behavior from bus to car, electric bike to car, bike to car and walk to car. There are two considerations behind such a practice: 1. It is important to distinguish and verify if a factor that could possibly induce a mode switch, for instance, car to non-car, is due to preferring a non-car alternative or simply preferring a switch of mode. This is the information that must be clearly revealed to avoid ineffective or even erroneous policy measures that could be developed from the modeling results (i.e. if a factor induces a mode switch from car to non-car is however due to "preferring switch", in other words, this factor will have the same impact sign on non-car to car switch, then any policy making that aims to encourage car to non-car switch and targets at this factor could possibly also result in mode switch from non-car to car). Hence, these mirror models will help to check if a factor's impact on various mode switches to car is opposite or in the same direction to its impact on mode switch from car in the earlier model, and thus distinguish between "preferring mode" and "preferring switch" to better inform policy making. 2. Another benefit of a set of mirror models is that the differences in mode switching behavior among different mode users can be revealed, i.e. a factor may only have significant impact on some mode users and may be completely irrelevant to others. In other words, different and more targeted policy implications can be obtained when there is a need to persuade different non-car mode users not to switch to car as a regular commute mode.

Again, either binary or multinomial logit regression can be applied to set up the mirror models. Taking the bus user model as an example, the binary specification will classify the paired choice observations into two categories: bus to car and bus to non-car while the multinomial specification can handle more alternatives by for example further splitting the above "bus to non-car" into "bus to bus" (the majority) and "bus to the rest" (though only a tiny proportion). We tested both specifications and the most important part "bus to car" shared the same results in terms of factors' impacts on such a choice. Thus, we adopt the binary specifications for all the mirror models in order to simplify the result presentation in the paper while not losing any valid information and model explanatory power.

The variables that are used to explain the mode switching behavior include life course events (dynamic) and socio-economic factors (static). The life course events are those presented in Table 2; besides, for commute distance change (both increase and decrease), we generate three sub-groups, i.e. (change by) less than 2km, 2km to 5km and more than 5km to explicitly assess how different degrees of distance change in an urban context would possibly affect mode switches. All life course events are studied with their impacts on mode switch observations in the same years. Oakil et al. also explored lead (one year before) and lag (one year after) effects of life course events in their mode switching models (9). However, we do not incorporate such effects in the analysis given the 2-year observation interval in our data which means the lead and lag effects are likely to be trivial. Three socio-economic factors are studied; gender, household income and home & work place (see Table 1). Mode switch availability conditions are also applied to the models, and they appear as that car, electric bike and bike can be chosen as regular commute modes only if an individual's household owns the corresponding vehicle.

Finally, given the fact that an individual often has more than one paired observations in the datasets, a standard logit mixture approach (24, 25) is applied to all models to account for any potential intra-person correlation. Equation 1 presents the mathematical form of our mixed logit model. Model estimations are performed in BisonBiogeme (26).

$$U_{in} = \sum_{k=1}^{K} \beta_k X_{ink} + \sigma_i \eta_{in} + \varepsilon_{in} \qquad (1)$$

Where U is the utility associated with a mode choice, i is the choice alternative, n is the individual choice maker, X is the factor of explanatory variables and β is the estimated parameter. The intra-person correlation is captured by the error component η, and the impact is denoted by the standard deviation σ. ε is the error component i.i.d. Extreme Value and independent from η.

ANALYSIS FINDINGS AND IMPLICATIONS

Table 4 and 5 display the modeling results of mode switching from car and to car respectively. As an overview, the log-likelihood and the adjusted rho-square values imply a fairly good level of fitness of all the models. The parameter measuring intra-person correlation also has universal significance confirming the presence of individual-specific attribute which did post an unobserved effect on mode switching behavior.

Model Estimation Results

In Table 4, with respect to the mode switching behavior from car to non-car, almost all variables exhibit significant effects, except the life course event of having the first child, which has a negative impact sign and is the only variable not meeting the 90% significance level. For the rest of life course events, getting married and encountering a level jump of household income also manifest a negative effect which means both events are less likely to induce a shift to using non-car modes for regular commute. In comparison, positive effects on a switch from car to non-car are observed with the event of engaging in a fixed job and all three cases of a commute distance decrease. For the socio-economic factors, males and commuters from richer households would prefer to stick with car rather picking up any alternatives; however, if both the home and work place are inside the central districts of the city, people might be more willing to switch their commute modes away from car.

So far, we only described some facts of the modeling results without further elaboration. This is because a single model studying only car to non-car mode switching behavior cannot firmly tell whether the factors' impacts are due to "preferring mode" (i.e. different utilities on car and non-car modes) or "preferring switch" (i.e. different utilities on embracing changes and living with status-quo). Thus, we now introduce the results of the mirror models in order to further unveil the mode switching behavior.

Table 5 shows the parameter values in the mirror models. Unlike the earlier "car to non-car" model in which most variables exhibit significant effects, there are many more insignificant variables in each of the four mirror models and are thus dropped out to avoid any model convergence problem. However, despite that part, the remaining significant variables do display a consistency in terms of their impact signs across the different mirror models and the analyses below will demonstrate whether these effects are due to "preferring mode" or simply "preferring switch".

Preferring Mode

Several life course events are associated with mode preference. Getting married could significantly affect the mode switches from electric bike, bike and walk to car where bus to car is the only model in which the significance is lost. By comparing these positive impact signs with the negative impact sign in the earlier model, it can be identified that getting married is likely to make people start moving away from non-car modes to using car for regular commute; while if car users get married, they would possibly prefer sticking with car without switching to any non-car alternatives. The same conclusion can be made for having the first child and encountering a level jump of household income where both events also have positive effects on the mode switches to car in the mirror models and the effects are opposite to which in the earlier model where negative signs are observed. However, it should be noticed that having the first child is only significant in inducing bus users to switch to car whereas a surge in household income has a universally significant effect in all four mirror models. Another type of life course event that belongs to "preferring mode" rather than "preferring switch" is the change of commute distance. Different degrees of commute distance increases are positively associated with the mode switches to car in the mirror models whereas a mode switch from car to non-car in the earlier model is positively associated with commute distance decreases.

For socio-economic factors in the mirror models and the earlier "car to non-car" model, opposite impact signs are found on household monthly income and home & work place location, which means both of these factors are associated with mode preference. Specifically, car commuters with higher household income would like to stick with car usage and non-car commuters with higher household income would prefer switching to car; for those settled themselves in the central districts, they are more willing to accept a mode switch from car to non-car while the switch from non-car to car turns out as a less appealing option.

Preferring Switch

Only one life course event and one socio-economic factor seem to be associated with such a type of behavior. In the earlier model, engaging in a fixed job could possibly lead to a mode switch from car to non-car; in the mirror models, the effect also has a positive impact sign though it is significant only in the walk to car model. The implication would be that receiving a fixed job (i.e. from self-employed or student) may induce a switch of commute mode; however, both switching to and away from car could occur, possibly depending on the more specific travel needs which cannot be clearly identified from the available information in our survey. Similarly, male commuters are found with negative impact signs throughout the earlier "car to non-car" model and the subsequent mirror models which could possibly imply their relatively strong "reluctant to switch" characteristic compared to female commuters.

Discussions and Policy Implications

Like many travel behavioral studies, the modeling outputs could offer a bunch of insights to enrich the current literature. However, to what extent the insights could actually be taken away to inform policy making is always skeptical since in many cases the findings cannot be transferred into practical application due to various constraints. Thus, next, we will discuss each of the key factors in our models and evaluate their potentials in helping design policies with an objective to keep commuters away from car use. It should be clarified that our aim is not to make any specific policy proposals as it is beyond the scope of this work.

Getting Married

There could be various reasons explaining why such an event would possibly induce a mode switch to car, for example due to a car purchase activity which occurs frequently by getting married and thus resulting in an easy car access (18), or due to a need to save commute journey time when starting to undertake additional family roles and will thus switch to car given its stronger mobility, etc. In fact, the latter hypothesis could possibly reflect the results of our mirror models in which getting married would make the users of electric bike, bike and walk switch to car, whereas its effect on bus users, who are probably more satisfied with the mobility of their status-quo mode, did not reveal any significance. Such a result could offer an opportunity for policy intervention. Although we cannot halt the mode switch to car by manipulating the occurrences of life course events, policy making could potentially step in from a tactical angle by encouraging the mode switch to bus; so that when the users of electric bike, bike and walk get married, they could possibly find their travel needs can also be satisfied by switching to bus. A very common policy practice to serve such a type of objective is the Voluntary Travel Behavior Change (VTBC) strategy (27, 28) which usually consists of informational and marketing efforts to encourage a behavioral change (10), for example in our case could be providing special rewards to new customers starting to use bus, in order to attract the regular electric bike, bike and walk commuters.

Having the First Child

Recall that the event does not have a significant effect on the mode switching behavior from car to non-car modes; however, positive and significant effect is observed in one of the switching to car models. Oakil et al. also had a similar discovery and one explanation they proposed was having child would lead to stronger demand for travel flexibility, e.g. for baby's regular check-up or day care drop off and pick up, which is something car can definitely offer (9). Moreover, further insight could possibly be revealed by comparing across the mirror model results. Having the first child is only significant in inducing bus and not the rest of mode users to switch to car, which implies that flexibility may not be the only concern in such a circumstance and the stronger willingness of bus users to choose car might be due to the dislike of public transport environment when traveling with baby in their commute trips (for drop-off and pick-up). Hence, encouraging new parents who used to commute by bus to switch to those non-car travel options could be a policy pursuit. For instance, subsidies could be offered to new parents for their purchases of cycling tools (e.g. e-bike or bike).

Engaging in a Fixed Job

Given the finding that employment status change could possibly lead to both switching to and away from car, we prefer not to derive any policy implications at this stage until further research unveils the intrinsic factors that might result in such an outcome. Distance could be one of those factors after observing the significant impacts of commute distance changes on mode switching behavior in our models (their policy implications will be discussed shortly). However, we did not study the potential interaction between the change of employment status and the changes of commute distance since there are not enough observations in the datasets. Besides, other intrinsic factors may exist and need to be investigated as well.

Encountering a Level Jump of Household Income

This is the only factor that has a universally significant effect in all four mirror models. However, from a practical perspective, this also implies none of the four modes can be a competitive alternative to car when commuters become richer (i.e. inferior goods) and therefore the room for policy intervention would be limited.

Changing Commute Distance

An increase in commute distance could make non-car mode users start to prefer car; however, different non-car mode users would be affected by different degrees of increase. Bus users tend to switch to car only if the distance increase is large (by more than 5km); the two cycling mode users tend to switch to car under a smaller threshold (by 2km to 5km); finally, commuters on foot can switch to car even when there is a relatively small degree of increase (by less than 2km). It seems that such a trend is in line with the mobility power of each non-car mode. As for the implications to policy making, bus users could potentially stay with bus if for example they can be rewarded for making long-distance bus journeys. One solution is introducing a flat or even a diminishing bus pricing scheme with respect to journey distance so that the incurred longer travel time by bus comparing to which by car can be compensated in terms of a cost saving, though whether the implementation is feasible or whether any side-effects would arise should be carefully studied by relevant research. By having a commute distance increase, persuading cyclists and on-foot commuters to stay with their original mode choices would be a trickier task since many more pain-points will get involved, e.g. physical fitness, comfort and safety concerns, which cannot be easily addressed by policy intervention. Thus, from a practical perspective, it might be more effective to encourage a mode switch to bus, for example via the aforementioned VTBC strategy by offering new-customer rewards to the cyclists and on-foot commuters who are willing to make a switch. Besides, for the two bicycle modes in particular, efforts could also be made towards the integration with public transport system (e.g. carrying foldable bikes on bus / placing bikes on the attached racks, both measures have already been adopted by many cities across the globe), which may offer another solution to handle a commute distance increase.

Socio-economic Factors
The three socio-economic factors in this research are studied in terms of their linear effects on mode switching behavior. A more sophisticated approach would be evaluating their interaction effects with life course events to better reveal the mode switching pattern, i.e. whether a socio-economic group would be affected more/less by a particular life course event and hence more realistic policy implications can be obtained (29). However, due to our data constraints that the number of interaction observations is very limited, only linear effects can be properly modeled. In fact, the data constraints by only having a small number of observations on life event or mode switch occurrences seem to be a universal issue given its presence in earlier studies as well (9, 10, 13). Future works that can overcome such a data challenge could potentially be of great contribution to mode switching research; meanwhile, a broader range of socio-economic factors, such as age, educational level and household size, could also be explored when relevant data is collected.

Beyond Life Course Events
Finally, apart from the above insights that have been explored, we would like to discuss any wider implications in light of the results obtained from this research. Since life course events were found being able to trigger the mode switches to/from car, it would be worth asking further that if there could be other types of events (i.e. not 'intrinsic' as those directly related to individuals) also having the similar effects, and more importantly, bringing more policy insights. By making hypotheses broadly, many substantial changes such as those in land uses, in transport network and other built environment conditions, in transport service accessibility and even any persistent changes in an area's general weather conditions, may all possibly result in changes in mode choice habits. In fact, if studies can capture some of these 'extrinsic' events in mode switching analyses, we expect there could even be more rooms for policy design, especially for countries like China (i.e. the case study), where the built environments, transport supplies and a lot other contextual aspects are currently in massive and rapid transitions and reforms; as such, interventions could have more opportunities to step in and hence pose an influence on people's mode choice habits. Moreover, when evaluating those 'extrinsic' events, their potential interactions with, not only the socio-economic factors but also the 'intrinsic' events (i.e. life course events), should be taken care of. For example, if a public transit station/stop was opened to use, car users who lived nearby might or might not switch to this public transport service, possibly depending on if they had children recently or if there were changes in their employment and income status, etc. Overall, more research would be needed to shed light on the expected interactions among these events.

CONCLUSIONS AND FURTHER RESEARCH OPPORTUNITIES

This work offered a mode switching analysis using a retrospective survey data. The impacts of a variety of life course events were investigated and the corresponding implications to policy making were discussed. The survey data had a panel structure by capturing a group of Chinese citizens' main commute mode choices in four observation periods. A mixed binary logit regression model was developed at first to study the mode switching behavior from car to non-car modes between a precedent period and the period followed. A set of "mirror models" were developed next to reveal the mode switches from each of the non-car modes to car. The mirror models also had a binary structure with the logit mixture to capture intra-person correlation.

It was revealed that getting married, having the first child and encountering a level jump of household income could induce a mode switch from non-car modes to car while car users who experienced these life course events would prefer sticking with car as their regular commute mode. Similarly, an increase in commute distance would make people more likely to switch to car whereas a decrease would make people switch away from car. The only event that is not associated with a clear mode preference is engaging in a fixed job which could result in both switching to and away from car, and further research would be needed to explore any intrinsic factors that might result in such an outcome.

Moreover, the mirror models also revealed the differences in mode switching behavior among different non-car mode users, and corresponding policy implications were subsequently derived. To prevent the commuters using electric bike, bike and walk from switching to car when they get married, it could be useful to encourage the mode switches to bus which may also be able to satisfy their travel needs, since the bus commuters who get married are not found with the same level of desire to switch to car. Possible informational and marketing measures could be introduced to facilitate such a mode switch to bus. In comparison, bus users would be more willing to pick up car when they have the first child whereas the rest of non-car mode users seemed to be indifferent to such a switch towards car when experiencing a child birth. Thus, measures could step in to encourage an opposite switch this time (i.e. bus to cycles or walk) via for example subsidies to new parents for their purchases of cycling tools. Another event that could lead to useful policy implications was a commute distance change. Bus commuters would switch to car only if the distance increase is large (by more than 5km); e-bike and bike users would switch to car under a smaller threshold (by 2km to 5km); commuters on foot could switch to car even when there was a small increase (by less than 2km). As a result, a rewarding scheme would probably be needed for undertaking long-distance bus journeys to prevent bus users from switching to car; meanwhile, persuading cyclists and on-foot commuters to switch to bus rather than staying with their status-quo choices would also be recommended since an increase in distance could result in more pain-points that cannot be easily addressed by policy intervention (e.g. physical fitness, comfort and safety concerns). Finally, when discussing these policy implications, attempts were also made to provide possible explanations for the differences in mode switching behavior among different non-car mode users (i.e. why an event could have a significant effect on some mode users and not on the others); however, similar to previous studies (9, 18), these explanations are still hypothetical and there could be a need to further disclose any profound causes behind, which leads to another opportunity for doing future research.

Several socio-economic factors were captured in this work. However, due to data constraints, their interaction effects with life course events were not analyzed. This is a subject that should definitely be explored in the future in order to acquire more in-depth implications to policy making. In the end, opportunities for studying a broader range of events (e.g. changes in land uses, transport supplies) were also identified and discussed.

ACKNOWLEDGEMENTS

We sincerely appreciate the support from Shanxi Transportation Research Institute in their funding and advice provided during the data collection. We would also like to express our gratitude to the following individuals who made the most significant contributions in the data recording task: Mr Li Peiyu from Shanxi Experimental Secondary School, Mr Hou Juntao from Peking University and Ms Zhao Helan.

AUTHORS' CONTRIBUTION

The authors confirm contribution to the paper as follows: study conception and design: W. Li, M. Kamargianni; data collection: W. Li; analysis and interpretation of results: W. Li; draft manuscript preparation: W. Li, M. Kamargianni. All authors reviewed the results and approved the final version of the manuscript.

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LIST OF TABLES

TABLE 1 Sample Descriptive Statistics

		N=1,799 in each year			
		2006	**2008**	**2010**	**2012**
Gender	Male	53%	53%	53%	53%
	Female	47%	47%	47%	47%
Household monthly income (after tax, in CNY)*	Below ￥3k	44%	40%	35%	31%
	￥3k - ￥6k	38%	40%	42%	44%
	Above ￥6k	18%	20%	23%	25%
Home & Work place	Both in central districts	29%	28%	27%	27%
	Either or both in outer districts	71%	72%	73%	73%
Marital status	Single	39%	32%	24%	16%
	Married	61%	68%	76%	84%
Number of children (under 12)	None	62%	57%	47%	38%
	At least one	38%	43%	53%	62%
Employment status	Have a fixed job	72%	77%	80%	84%
	Self-employed or student	28%	23%	20%	16%
Commute distance	Within 2km	17%	17%	16%	16%
	2km to 5km	20%	20%	18%	17%
	Beyond 5km	63%	63%	66%	67%
Household car	percentage of possession	34%	38%	45%	50%
Household electric bike	percentage of possession	46%	48%	49%	50%
Household bike	percentage of possession	68%	68%	68%	68%
Commute mode choice	Car	17%	20%	25%	29%
	Bus	27%	27%	25%	23%
	Electric bike	17%	16%	15%	14%
	Bike	23%	22%	21%	20%
	Walk	15%	14%	13%	13%
	Taxi	1%	1%	1%	1%

Note: age information is missing from the retrospective survey
* ￥1 ≈ $0.15

TABLE 2 Life Course Event Occurrences on Individuals over the Entire Study Period (2006-2012)

Life course event	% individuals been through the listed life course events (N=1,799)
Get married	28%
Have the first child	24%
Engage in a fixed job	12%
Encounter a level jump of household income (at least once)#*	26%
Commute distance increases (at least once)*	22%
Commute distance decreases (at least once)*	14%

Household income is measured in six levels in the survey: below ￥3k, ￥3k -￥6k, ￥6k -￥9k, ￥9k -￥15k, ￥15k -￥30k, above ￥30k (￥1 ≈ $0.15)

* Events that could occur more than once over the entire study period (2006-2012) in the given sample

TABLE 3 Mode Switching Pattern over the Entire Study Period (2006-2012)

Precedent period	The following period					
	Car	Bus	E-bike	Bike	Walk	Taxi
Car	89.5%	5.4%	0.9%	2.2%	1.9%	0.2%
Bus	11.1%	83.2%	1.7%	2.2%	1.5%	0.3%
E-bike	6.4%	2.7%	84.9%	5.8%	0.2%	0%
Bike	6.1%	4.3%	2.4%	86.0%	1.0%	0.1%
Walk	6.0%	3.8%	1.0%	1.0%	88.2%	0%

Note: we do not analyze the sticking to/switching away behavior when having taxi in the precedent period due to the very limited observations of having taxi as a regular commute mode (see also the "Commute mode choice" in Table 1)

TABLE 4 Mixed Binary Logit Regression Result: Mode Switch from Car to non-Car

	coefficient	t-statistic
(The alternative: "car to car" is normalized to the base)		
Constant	- 2.48	- 12.27
Intra-person correlation (standard error)	1.76	6.50
Static variables (socio-economic factors)		
Gender (male)	- 1.64	- 6.15
Household monthly income (Above ￥6k)	- 0.50	- 1.94
Home & Work place (both in central districts)	2.39	9.07
Dynamic variables (life course events)		
Get married	- 1.64	- 1.82
Have the first child	- 1.22	- 1.40*
Engage in a fixed job	2.97	5.22
Encounter a level jump of household income	- 2.17	- 2.64
Commute distance decreases by less than 2km	3.66	3.28
Commute distance decreases by 2km to 5km	2.73	3.09
Commute distance decreases by more than 5km	4.40	8.50
Model performance		
Number of obs.	1,110	
Initial log-likelihood	- 769.39	
Final log-likelihood	- 251.10	
$\overline{\rho^2}$	0.66	
$\overline{\rho^2}$ (constant only)	0.51	

* The only parameter not meeting the 90% significance level

TABLE 5 Mixed Binary Logit Regression Results: Mode Switches to Car

	Bus to car		E-bike to car		Bike to car		Walk to car	
	coef.	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**
(In each model, the alternative: "not switch to car" is always normalized to the base)								
Constant	- 2.24	- 10.58	- 0.74	- 2.55	- 2.74	- 8.44	- 4.88	- 4.32
Intra-person correlation (standard error)	1.45	4.30	1.93	6.27	0.84	3.15	2.11	7.74
Static variables (socio-economic factors)								
Gender (male)	-	-	- 3.90	- 3.74	- 1.68	- 2.93	- 4.17	- 3.42
Household monthly income (Above ￥6k)	0.90	3.10	-	-	1.27	2.50	3.99	3.42
Home & Work place (both in central districts)	- 1.09	- 3.24	- 2.79	- 3.30	-	-	-	-
Dynamic variables (life course events)								
Get married	-	-	2.63	3.08	2.81	4.45	7.23	4.78
Have the first child	2.14	5.78	-	-	-	-	-	-
Engage in a fixed job	-	-	-	-	-	-	4.95	2.85
Encounter a level jump of household income	2.35	6.89	2.96	3.13	1.89	2.89	2.76	2.23
Commute distance increases by less than 2km	-	-	-	-	-	-	4.69	3.04
Commute distance increases by 2km to 5km	-	-	5.49	2.29	4.19	3.83	-	- #
Commute distance increases by more than 5km	2.23	3.93	2.52	1.95	3.18	4.05	-	- #
Model performance								
Number of obs.	1,446		862		1,173		768	
Initial log-likelihood	- 362.52		- 114.37		- 225.97		- 175.37	
Final log-likelihood	- 175.88		- 52.80		- 72.33		- 23.53	
$\overline{\rho^2}$	0.50		0.48		0.65		0.83	
$\overline{\rho^2}$ (constant only)	0.11		0.07		0.23		0.31	

Note: insignificant variables are dropped out since there are many of them in each model and including them can lead to model convergence problem

Those two variables in the "walk to car" model have no displayed values not due to the effects are insignificant, but they have limited number of occurrences in the data and cannot be properly modeled