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Are People from Households with Children More Likely to Travel by Car? An Empirical Investigation of Individual Travel Mode Choices in Shanghai, China

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Received: 5 November 2018; Accepted: 30 November 2018; Published: 4 December 2018

Abstract: China is expected to have more children now that its family planning policy has been relaxed, and the influence of children on transportation and sustainability should not be neglected. This study uses econometric methods to explore the impact that the presence of children has on household car ownership, car-travel behavior of family members, and variability in their car-use frequency across weekdays and weekends. Models are estimated using multi-day travel patterns imputed from GPS-enabled smartphone data collected in Shanghai, China. Results indicate that: (1) households with children have more private cars than those without children, and the presence of preschoolers and pupils both increase families' demand for car ownership; (2) travel behavior of people from households with children is influenced subtly by the children's presence, which leads them to prefer to travel by car, although the presence of retired or unemployed household members can weaken that influence; and (3) car-travel frequency of individuals is significantly different between weekdays and weekends, with the presence of pupils in the household diminishing that variability and the presence of preschoolers enlarging it. Policymakers and transportation planners should be concerned about these issues and take appropriate measures.

Keywords: car-travel behavior; children; Hausman–Taylor estimation; variability; panel data; sustainability

1. Introduction

China has relaxed its family planning policy gradually during the last few years. Since 2015, each couple has been permitted to have two children, and at the first session of the Thirteenth National People's Congress in 2018 a delegate proposed ending the family planning restriction. Thus, China's families are expected to have more children in the coming decades. The impacts of children are not limited to just what economists and politicians have considered, since every child needs clothing, food, shelter, and to be educated, and each child will grow up and affect others. Indeed, family life and many aspects of society are affected by children, and transportation and sustainability are no exception. Most Chinese families regard children as treasures and want to give them the best they can. The car, which combines comfort and convenience, naturally becomes the first choice for travel with children, and the growing income of Chinese families has made that attainable. However, do families travel just by car more frequently with their children? That may be far from reality, and the travel behavior of family members is also likely to change when they are traveling without children. For instance, due to child-related matters, car purchases, or more taxi trips, may lead family members to be more accustomed to traveling by car with or without children. If this speculation is correct, the process of China's sustainable development will be influenced greatly by the additional children, and that will in turn affect the children's growing environment and living conditions [1]. Therefore, it is meaningful to explore how the presence of children in a household will impact the travel behavior of family members.

Some previous studies have discussed the impact of children on car travel behavior and are worth reviewing. Turning points in life, including important personal and family events, disrupt people's habitual behaviors and offer a valuable opportunity that may affect their adoption of sustainable mobility patterns [2,3]. The event of childbirth may be such an occasion and may cause changes in habitual travel behaviors [4]. Studies have shown that families with children tend to depend more on using cars [5,6]. However, research in developed nations highlights possible instances of households with young children transitioning away from dependence on cars and toward sustainable transportation [7]. This finding indicates that it is feasible for families with young children to use less car-oriented mobility practices.

For a long time, academia has assumed that people with the same sociodemographic characteristics perform similarly in their travel behavior [8]. Several cross-sectional studies have shown that the effects of sociodemographic variables influence certain aspects of people's travel behavior [9–11]. Households with children have diverse travel needs because of several spatial and time constraints [12]. Other literature has offered strong evidence that certain socioeconomic factors, such as gender, age, income, and so on, affect people's choice of transportation mode [13,14]. Meanwhile, household characteristics are positively associated with car ownership, and high-income households tend to own more automobiles [15]. Moreover, households with several private cars are likely to use cars more frequently and may show a stronger dependence on cars [16]. In addition, with the broadening research on travel behavior, an increasing number of scholars have begun to use panel data to explore the factors that affect transportation mode choices [17,18].

In recent years smartphones have become widespread, and thus the use of GPS-enabled smartphones has greatly reduced the costs and difficulties of collecting larger sample panel data. Meanwhile, the inherent changes in individual travel behaviors that previously could only be studied in developed countries have also been realized in developing countries [19]. Needless to say, the availability of multi-day travel data opens up new avenues for studying the dynamics of individual travel behavior [20]. Kang and Scott [21] explored day-to-day variability in time use for household members, while involving their interactive variations. Xianyu and her coauthors [22] are the first to apply a unique combination of methods and multi-day activity-travel data to analyze the degree of variability between travel days in China.

In this paper, multi-day activity-travel data were collected via a GPS-enabled smartphone. Using econometric methods including Hausman–Taylor (HT) estimation to analyze panel data with socio-demographic characteristics, this study explored in depth the impact of children on one family member's travel by car. At the same time, the different effects of preschoolers and pupils were studied. Three stages guided the analysis: (1) Does the presence of children affect private car ownership? (2) Do children have an influence on people traveling by car? (3) How do car-travel patterns vary across the days of the week? Do children influence the observed variability, and if so, to what extent?

The structure of the paper is as follows. In the next section, the data collection, central concepts, and descriptive statistics of the sample are outlined. Then, the methods used for modeling and measuring three stages are presented, and that is followed by a discussion of empirical results. Finally, conclusions are drawn and recommendations are provided.

2. Data and Preliminary Analysis

The data analyzed in this study were derived from a smartphone-based travel survey conducted in Shanghai from early December 2014 to early November 2015. We approached prospective respondents through market research agency. All respondents were recruited before the designated survey day and sent survey guidance and privacy documents. Next, the respondents downloaded onto their smartphones a specific application that was available for both Android and iOS platforms. Then, they were required to run that app for a week. The app assigned a unique identification number for each of the users. Respondents could log onto the survey's website to improve household and individual information based on that identification number. During the survey, each respondent opened the app before starting his or her first trip and uploaded GPS records after his or her last arrival at home every day. After the original GPS data were uploaded to the server, preprocessing was first performed to correct systematic and random errors. Subsequently, with the help of the ArcGIS database and household and individual information, main travel characteristics were identified and displayed on a map.

After that, respondents would receive their activity-travel diaries to validate and collect their activity-travel information, if needed. The purpose of this intervention was to ensure maximum accuracy of the actual travel information. More details about data collection can be found in the research papers by Xiao et al. [23], Zhou et al. [24], and Wang et al. [25]. Next, each travel segment was required to be identified. Subway, bus, car, electric bicycle, bike, and walking were considered as travel modes in this study. Special rules were employed to detect subway trips, because of their significant difference from the other travel modes. Subsequently, the method of random forest classifier was applied to divide the remainder of the five types of travel modes. For details about the identification methods, see the paper by Wang and his coauthors [26]. Thus far, more comprehensive multi-day travel data have been obtained. Each piece of travel data records the information about one trip. It specifically contains respondents' ID, date, day of the week, departure time, departure location, arrival time, arrival location, travel modes, whether traveling by car, travel purpose, travel distance, travel time, and so on.

Data for analysis included household and individual information and activity-travel diaries, derived from smartphone-based GPS data. A total of 260 respondents participated in the survey, although four of them were missing some household and individual information. Due to their small proportion in the sample, this paper excluded the data of those four respondents. In addition, we used electronic maps to supplement the missing values of the distance to nearest subway station and the nearest bus stop in the household information. In terms of travel data, for the case in which multiple travel modes are used for a single trip, the trip mode is identified by the one covering the longest distance [27]. Finally, individual, household and travel information were linked by the ID of respondents. Therefore, through the initial data processing, the data in this paper came from individual and household information of 256 respondents and their total of 4764 pieces of travel data. All 256 respondents were from different families.

Table 1 shows the household and individual information statistics of the sample. Probably because of the nature of smartphone use, the sample was dominated by the young and middle-aged group, who were an average age of 30.03 years old. Moreover, the sample was distributed among people from all walks of life, and the majority of participants had a fixed working time. Among their household attributes, 41.4% of the respondents came from households with underage children—that is, children between the ages of 0 and 12. Many of the respondents (30.5%) had preschool children (0 to 6 years old) at home. The group of respondents from households with pupils (7 to 12 years old) comprised 14.1% of the total. Among them, eight respondents had both preschool children and pupils, thereby accounting for 3.1%. The small proportion of duplicate data in the study had little effect on subsequent research and is not processed or presented here. Finally, more than 40% of the respondents had retired or unemployed adults in their home.

Table 1. Socio-Demographics of the Sample (N = 256).

Socio-Demographics	Definition	Percentage/Mean
Individual characteristics		
Gender	Male	40%
Age		30.03
Education		
	College and below	34.38%
	Bachelor degree	55.47%
	Master degree and above	10.16%
Occupation		
	Government employee	7.03%
	Teacher/Researcher	1.95%
	Manufacturing staff	23.05%
	Financial practitioner	5.47%
	Business staff	21.88%
	College student	7.42%
	Others	33.20%
Monthly income		
	¥5000 or less	40.23%
	¥5000–¥10,000	39.45%
	¥10,000–¥15,000	12.50%
	¥15,000 or more	7.81%
Weekly working hours		35.93
Fixed working time		71.48%
Transportation card ownership		92.97%
Household characteristics		
With child(ren)	Aged between 0 and 12	41.41%
With preschooler(s)	Aged between 0 and 6	30.47%
With pupil(s)	Aged between 7 and 12	14.06%
With free member(s)	Retired or unemployed adult(s)	41.82%
Number of family member(s)		3.16
With bike(s)		49.61%
With electric bicycle(s)		36.72%
With car(s)		42.58%
Distance to the nearest subway station (m)		1305.43
Distance to the nearest bus stop (m)		171.91

Note: In column 3, the figure represents percentage if it is with the symbol "%", otherwise mean.

As the economic center of China, Shanghai is densely populated. The city has more vehicles on the road during the morning and evening peak hours, and the key roads are prone to congestion. In previous studies, an electric bicycle was often classified as a bicycle and was seldom considered in the model framework [28,29]. However, that may be unreasonable in China. The popularity of electric bicycles in the past decade has led them to become an indispensable mode of transportation in most urban areas [30,31]. And in addition to the subway, the electric bicycle has become another type of transportation that people often use to guarantee their travel time [32]. Thus, our travel data can be divided into the six most widely used modes of transportation in China: subways (21.8%); buses (27.3%); cars (19.9%); electric bicycles (7.3%); bikes (7.7%); and walking (16.0%). We refer here to a car as a passenger car that can accommodate fewer than nine people, and in a broad sense that includes private cars, taxis, and so on. Travel modes other than cars can be considered as environmentally friendly modes, and the two primary modes can be divided into car travel (19.9%) and environmentally friendly travel (80.1%). Compared with the results of a 2011 diary survey [33], the rate of car use in our study reflects a significant increase. That change is reasonable, since our sample comes largely from the age group encompassing youth to middle age. We divided the travel data into five categories of outdoor activities: work (57.8%); personal business (18.1%); shopping (4.5%); dining out (9.9%); and recreation (9.7%).

In addition, we conducted Pearson correlation analysis on the dependent variables—car ownership, travel mode choice, differences in the frequency of car use within a specific pair—and the corresponding explanatory variables. It has been found that the Pearson correlation coefficients among these variables were generally less than 0.5. That is, the correlations between the variables were not obvious and the collinearity was weak. Further analysis using a collinearity test found that the tolerance values between the variables were all greater than 0.6, and the variance inflation factor (VIF) was approximately 1. Therefore, it is reasonable to believe that the selection of each variable and subsequent regression analysis can be performed on the sample data.

3. Methodology

Children's impact on family members' car travel behavior is explored in a three-step process. The variables of each sub-question have their own particularities. For example, the dependent variables of the first two problems are count variable and binary variable respectively. The core explanatory variables of the third problem do not change with time during the observation period. Thus, we choose the appropriate econometric models, which are briefly introduced below.

3.1. Poisson Regression Model

We used a Poisson regression model to test the impact of children on the number of private cars owned by a household. Since the dependent variable (the number of private cars in each household) is a count variable that takes a non-negative integer value, the Poisson or negative binomial regression model is a relevant statistical method. And the Poisson regression model was chosen due to the fact that the data set was free from the problem of over-dispersion [34]. The Poisson model assumes that the relevant count variable follows a Poisson distribution:

$$\mathrm{P}(Y = y_i) = \frac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i!} \quad y_i = 0, 1, 2 \ldots \tag{1}$$

where $\ln \lambda_i = x_i\beta + z_i$.

The term Y is the count variable taking positive integer values, which are the number of private cars owned by each household in this study; λ is the parameter of Poisson distribution; x is the vector of explanatory variables—that is, whether there is a child in each household; z is a vector of control variables, and β and γ are the coefficient vectors of the explanatory variable and the control variable, respectively.

3.2. Logistic Regression Model

The logit model, as a binary selection model, is often used to analyze the influencing factors of travel modes [35]. Here, we used it to detect the influence of children on people's travel mode choice. The utility that person i obtains from alternative q in trip j is specified as: $U_{ijq} = \alpha X_{ij} + \varepsilon_{ijq}$. Here, q stands for two alternatives of travel mode choice, that is, q equal one if person travels by car in the trip, and zero when the other eco-friendly traffic mode is selected; X_{ij} is the vector of explanatory variables in the aspects of household, individual and travel characteristics; α is the coefficient vector to be estimated; and the final term ε_{ijq} is a random error term. The following logistic probability model will be used for parameter estimation:

$$Prob\left(U_{ijq}\big|_{q=1} > U_{ijq}\big|_{q=0}\right) = \frac{e^{\alpha X_{ij}}}{1 + e^{\alpha X_{ij}}}. \tag{2}$$

3.3. Hausman–Taylor Estimation

For panel data, the fixed-effect model and the random-effect model are the most effective estimation methods when all of the time-varying explanatory variables are correlated with individual effects (fixed-effect model) and uncorrelated, with those effects (random-effect model). Both models have the disadvantage that it is impossible to estimate variable coefficients that do not change over time. However, these variables may be precisely the focus of research. Hausman and Taylor [36] proposed that in the case of a mixture of the two—that is, of some explanatory variables that are related to the individual effects and other explanatory variables that are not related—it is possible to use the instrumental variable method to obtain a consistent estimate of the coefficients of the variables that do not change with time.

Consider the following panel model:

$$y_{it} = X_{it}\beta + Z_i\delta + u_i + \varepsilon_{it}, \quad i = 1, 2, \ldots, \mathrm{N}; t = 1, 2, \ldots, \mathrm{T} \tag{3}$$

where X_{it} is the vector of explanatory variables that change with time varying, while Z_i is the vector of explanatory variables that do not change with time varying. The Hausman–Taylor estimation method divides the explanatory variables into two groups: $X = [X_1; X_2]$ and $Z = [Z_1; Z_2]$.

We next obtain Equation (4) as follows:

$$y_{it} = X_{1,it}\beta_1 + X_{2,it}\beta_2 + Z_{1i}\delta_1 + Z_{2i}\delta_2 + u_i + \varepsilon_{it}, \;\; i = 1, 2, \ldots, \mathrm{N}; t = 1, 2, \ldots, \mathrm{T}. \tag{4}$$

Here, X_1 and Z_1 are assumed to be exogenous variables and are not relevant to u_i and ε_{it}; X_2 and Z_2 are assumed to be endogenous variables, but they are related only to u_i and are not related to ε_{it}. The intra-group estimate will divide u_i off to obtain an unbiased estimate of β, but it is not possible to obtain an estimate of δ. In order to obtain a consistent parameter estimate of δ, we multiply $\Omega^{-1/2}$ at both ends of Equation (3) and then estimate the parameters by the instrumental variable method. The specific estimation steps are as follows:

1. The residual is obtained by the intra-group estimation method and is averaged in the time dimension—that is, $\hat{d} = \overline{y_{i.}} - X'_{i.}\hat{\beta}_\omega$.
2. Regression of $\hat{d}$ by two-stage least squares estimation (2SLS) first obtains a consistent estimator of δ. The instrumental variable used in this step is $A = [X_1, Z_1]$, and then $\hat{\delta}_{2SLS} = (Z'P_A Z)^{-1} Z'P_A \hat{d}$ can be obtained, where $P_A = A(A'A)^{-1}A'$.
3. By introducing $\hat{\beta}_\omega$ and $\hat{\delta}_{2SLS}$ into $y_{it} = X_{it}\beta + \varepsilon_{it}$ and $y_{it} = X_{it}\beta + Z_i\delta + u_i + \varepsilon_{it}$ separately, the respective variance-component estimations are obtained. Then, a consistent estimator of $\Omega^{-1/2}$ is obtained, the value of which is $\Omega^{-1/2}$. Next, we replace Equation (3) with Equation (4).
4. The instrumental variables $A_{HT} = \left[\widetilde{X}, \overline{X}_1, Z_1\right]$ are introduced, and two-stage least squares estimation is performed by using Equation (4) to obtain the HT parameter estimates of β and δ. Here, $\widetilde{X}$ is the value of the difference in the X (including X_1 and X_2) groups, and $\overline{X}_1$ is the mean of groups of X_1.

In this study, the concept of a day pair is defined. For each individual, one can make a total of 21 pairwise comparisons of daily activity travel in a full week [22]. Thus, the dependent variable is the variability in the proportion of car travel for each pair. In the Hausman–Taylor panel regression model, the time dimension is a pair. Variables that do not change over time, such as work, gender, age, and the like, are obviously exogenous variables. Children are endogenous variables because their presence may produce unobservable individual effects such as transactional diversity. If we wish to observe the effects of different pairs on car usage variability, we consider the pairs to be exogenous variables in the model that change with time varying. Meanwhile, we wonder whether children would exert a certain adjustment effect on car usage between weekdays and the weekend. Thus, the newly introduced interaction terms between the effects of children and pairs across weekdays and weekends are endogenous variables that change over time.

4. Empirical Results and Discussion

Considering that household ownership of a private car belongs to a specific attribute of the entire family, the explanatory variables here take household attributes into account without exception, including income level, family members, distance of the residential district from public transportation stations, and so on. First, it has been verified that the expected value of the dependent variable in model one is 0.449 and the variance is 0.295, which means the data set was free from the issue of over-dispersion. Thus, the Poisson regression model is the suitable statistical method. Table 2 shows the relationship between the presence of children in the family and the number of private cars owned by the family. The results of column (a) indicate that the estimated coefficient of children is 0.883 and is significant at the 1% level, which means the presence of children has a significant and positive influence on the number of private cars that a family owns. Controlling for variables of related factors, such as the number of bikes owned by the family, we find that families with children have more private cars, which agrees with the finding of Shen and his coauthors [37]. When studying the influence of children of different ages on car ownership, as column (b) in Table 2 shows, we find that the presence of preschoolers and pupils showed a significant, positive correlation with the number of private cars. That correlation is probably due to the fact that in a huge city like Shanghai, people pay more attention to their children's growth experience and hope to give them a better education and leisure experience, and private cars provide a specific comfort and convenient choice.

Table 2. Poisson Regression Result of Household Car Ownership.

Variable	Number of Cars Owned by the Household			
	(a)		(b)	
	Coef.	z	Coef.	z
With child(ren)	0.883 ***	3.89		
With preschooler(s)			0.618 ***	2.89
With pupil(s)			0.536 **	2.17
With free member(s)	0.098	0.45	0.029	0.14
Number of family member(s)	−0.012	−0.12	0.013	0.13
Number of bikes (owned by the household)	−0.040	−0.49	−0.029	−0.36
Number of electric bicycles (owned by the household)	−0.035	−0.40	−0.012	−0.14
Log (Distance to the nearest subway station)	0.031	0.23	0.027	0.20
Log (Distance to the nearest bus stop)	−0.088	−0.61	−0.082	−0.56
Monthly income of the respondent (base: ¥5000 or less)				
¥5000–¥10,000	0.507 **	2.14	0.581 **	2.49
¥10,000–¥15,000	0.620 **	1.99	0.584 *	1.87
¥15,000 or more	0.445	1.27	0.524	1.45
Constant	−1.350	−1.29	−1.325	−1.25
Number of observations (N)	256		256	
Pseudo R^2	0.072		0.060	
Log likelihood	−195.98		−198.61	

Note: ***, ** and *: significant at 1%, 5% and 10% respectively.

Strictly speaking, owning private cars does not mean that one would always travel by car. The construction of an environment-friendly society is inseparable from efforts of families possessing cars to reduce their car use. Therefore, based on the question one, we hope to further explore the influence of the presence of children on the people's travel mode choice.

A preliminary result without control variables in the logit regression, which is not reported here to save space, shows that people from households with children prefer to choose a car for their travels. Table 3 reports the study's results from controlling for the variables of household, individual, and travel characteristics and eliminating variables triggering multi-collinearity. From column (a) in Table 3, it is clear that the estimated coefficient of children is 0.494 and is significant at the 1% level, which means the presence of a child in a family does have a positive influence on the family's car use, and people from households with children are more willing to travel by car. Specifically, as column (b) in Table 3 shows, the positive influence of the presence of preschoolers and pupils on car use are also significant at the 1% level. Compared with people from households without children, people whose household has child member(s) may need to take children to travel activities, and the relatively convenient travel mode, the car, is unsurprisingly their first choice. Combining the above results, we find that the presence of children not only greatly enhances the probability of household car ownership, but it also subtly affects people's travel behavior. After all, the comfort and convenience of a car, which was originally selected to facilitate children's travel, is also convenient for other travel activities. Therefore, people from households with children travel by car more frequently.

Table 3. Logit Regression Result of Travel Mode Choice.

Variable	Travel Mode Choice (Dummy Variable: 1 for Car, 0 for Others)					
	(a)		(b)		(c)	
	Coef.	z	Coef.	z	Coef.	z
Household characteristics						
With child(ren)	0.494 ***	3.78				
With preschooler(s)			0.385 ***	2.86	0.359 ***	2.66
With pupil(s)			1.172 ***	5.94	1.320 ***	6.45
With free member(s)	0.362 ***	2.86	0.496 ***	3.79	0.539 ***	4.08
With pupil(s) * With free member(s)					−2.402 **	−2.23
Number of family member(s)	0.113	1.63	0.110	1.54	0.118 *	1.66
Number of bikes	−0.330 ***	−4.47	−0.367 ***	−4.63	−0.377 ***	−4.72
Number of electric bicycles	0.010	0.19	0.009	0.18	0.025	0.51
Log (Distance to the nearest subway station)	0.170 **	2.14	0.192 **	2.42	0.221 ***	2.75
Log (Distance to the nearest bus stop)	0.091	1.08	0.112	1.31	0.092	1.07
Individual characteristics						
Gender (male)	0.529 ***	4.71	0.625 ***	5.44	0.629 ***	5.47
Age	0.019 *	1.75	0.009	0.77	0.007	0.60
Transportation card (owned)	−0.605 ***	−2.97	−0.614 ***	−2.99	−0.605 ***	−2.94
Occupation (base: government employee)						
Teacher / Researcher	(empty)		(empty)		(empty)	
Manufacturing staff	0.095	0.49	−0.040	−0.20	−0.048	−0.24
Financial practitioner	0.758 **	2.26	0.424	1.24	0.361	1.05
Business staff	−0.681 ***	−3.13	−0.756 ***	−3.47	−0.758 ***	−3.48
College student	−1.550 ***	−3.49	−1.738 ***	−3.88	−1.731 ***	−3.86
Others	0.169	0.91	0.066	0.35	0.083	0.44
Monthly income (base: ¥5000 or less)						
¥5000–¥10,000	0.367 ***	2.84	0.429 ***	3.27	0.473 ***	3.57
¥10,000–¥15,000	0.340 **	2.04	0.444 ***	2.63	0.474 ***	2.80
¥15,000 or more	−1.462 ***	−3.76	−1.262 ***	−3.29	−1.194 ***	−3.13
Weekly working hours	0.007 *	1.72	0.006	1.63	0.007 *	1.67
Fixed working time (Yes)	−1.019 ***	−9.16	−0.977 ***	−8.83	−0.958 ***	−8.64
Travel characteristics						
Log (Distance)	0.184 ***	5.55	0.178 ***	5.34	0.178 ***	5.35
Purpose (base: work)						
Personal business	0.229 *	1.67	0.243 *	1.75	0.223	1.61
Shopping	−0.317	−1.10	−0.424	−1.44	−0.456	−1.54
Eating	0.112	0.64	0.140	0.80	0.129	0.74
Recreation	0.604 ***	3.76	0.588 ***	3.64	0.564 ***	3.49
Constant	−5.124 ***	−6.18	−5.060 ***	−6.03	−5.191 ***	−6.16
Number of observations	4764		4764		4764	
Number of groups (N)	256		256		256	
Pseudo R^2	0.134		0.141		0.144	
Log likelihood	−1308.59		−1296.96		−1292.78	

Note: ***, ** and *: significant at 1%, 5%, and 10% respectively.

In addition, it can be seen from the regression results of the control variables that the car is more popular in the long-distance travel or some entertainment activities. And people who are male, with upper-middle-income, or living far from the subway station are more likely to travel by car while certain characteristics, like possessing bikes or transportation cards, working as business staff or college students and fixed working time, are negatively correlated to the probability of travelling by car.

It is an important issue in Chinese families to take students, especially pupils, to and from school, and that is also a constant travel activity. Moreover, in many families such a travel activity is undertaken by retired or unemployed adults, if they are available, and we speculate that this fact may affect the influence exerted by a child's presence in a family. Therefore, we added an interaction term to test that effect, and the result is reported in column (c) of Table 3. The data reveal that the presence of pupils in the family leads the family members to travel by car more frequently, but the presence of retired or unemployed adults moderate that effect negatively.

Figure 1 is intended to illustrate the influence of pupils on the probability that people travel by car, and the role of free members in moderating this effect. The blue line in Figure 1 shows that for individuals from households without free members, presence of pupils makes them more likely to travel by car. Conversely, in households with free members, this probability is reduced, which indicates that free members have a strongly negative effect on the influence of pupils on car usage. The main reason can be explained as follows. When there are pupils but no retired or unemployed family members in the household, workers usually need to consider the activities of the children. Therefore, their trip chain of one day becomes more complicated by adding the middle ground such as the school. Meanwhile, their mobility will become slightly worse due to carrying children, especially in the bad weather or in the morning and evening peaks of working days in Shanghai. Although there is a risk of congestion, it is more convenient and comfortable to travel by car than other modes of transportation. Once there is someone within their households in charge of taking the pupils to and from school, the commuters' trip chain becomes simple and their mobility increases. At this moment, the advantage of car is no longer obvious. People are more likely to travel in a way that can effectively avoid road congestion and ensure arriving on time.

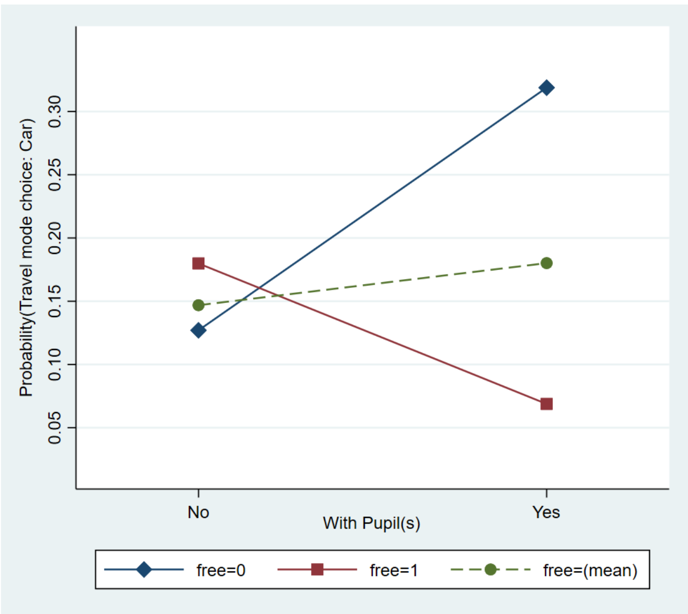

Figure 1. Moderating Effect of Free Member(s) on the Impact of Pupil Presence.

Except for the choice of travel modes for the single trip, more attention has been paid to the changing of travel patterns in multi-day trips [7,22]. Considering different activities across weekdays and weekends, is there a regular change in their car uses? If so, do children influence the observed variability? Thus, we turn to the third research question.

The day pair is redefined here to identify the difference in frequency of car use between weekdays and weekends. In each pair, the first element is car use frequency on a specific day, and the second element is overall car use frequency on weekdays or weekends. There are 10 different pairs for a full week, and the difference between Wednesday and weekdays is used as the base. The results from a Hausman–Taylor estimation are reported in Table 4, and we can see that the differences between weekdays and weekends are significantly positive at the 1% level, while the evidence of differences for weekday–weekday and weekend–weekend pairs are negative for both. We can conclude therefore that car-use behavior is quite different between weekdays and weekends, while any difference across weekdays or across weekends is negligible. That pattern is probably caused by the characteristics of a metropolis. The most important travel activity on the weekdays is commuting, and because road conditions in Shanghai are relatively poor during weekday morning and evening peaks, workers using cars to commute risk being stuck in traffic jams. As a result, people whose working time is fixed are less likely to travel by car on weekdays. In contrast, there are more leisure and entertainment activities on the weekend, and the road conditions then are relatively good. Thus, people are more likely to adopt travel by car on weekends because the car combines comfort and convenience. Of course, restrictions on private cars on the weekdays in Shanghai is another important factor. Meanwhile, it can be found from Table 4 that personal attributes such as gender, age, etc. do not significantly affect the variability in car use frequency, which further implies the universality of above patterns.

Table 4. Hausman–Taylor Estimation Result of Difference in Car Use Frequency.

Variable	Difference in Frequency of Car within a Specific Pair	
	Coef.	z
Pair of days (base: Wed to weekday)		
Weekday to weekday		
Mon to weekday	−0.000	−0.01
Tues to weekday	−0.001	−0.06
Thu to weekday	−0.008	−0.39
Weekday to weekend		
Mon to weekend	0.079 ***	3.28
Tues to weekend	0.114 ***	4.74
Wed to weekend	0.112 ***	4.54
Thu to weekend	0.119 ***	4.94
Fri to weekend	0.119 ***	4.89
Weekend to weekend		
Sat to weekend	−0.031	−1.27
Household characteristics		
With child(ren)	−0.068	−0.38
With free member(s)	0.010	0.16
Number of family member(s)	0.025	0.61
Number of bikes	−0.015	−1.26
Number of electric bicycles	0.010	0.47
Individual characteristics		
Gender (male)	0.024	0.73
Age	0.006	1.59
Transportation card (owned)	−0.063	−1.01
Occupation (base: government employee)		
Teacher/Researcher	−0.138	−0.96
Manufacturing staff	0.003	0.05
Financial practitioner	0.172 *	1.64
Business staff	0.033	0.49
College student	−0.010	−0.10
Others	0.053	0.85
Monthly income (base: ¥5000 or less)		
¥5000–¥10,000	0.004	0.09
¥10,000–¥15,000	0.098 *	1.92
¥15,000 or more	0.058	0.62
Weekly working hours	−0.000	−0.07
Fixed working time (Yes)	−0.001	−0.01
Constant	−0.159	−0.83
Number of observations	2164	
Number of groups (N)	256	
Prob > chi2	0.000	
σ_u	0.166	
σ_e	0.173	
rho	0.477	

Note: *** and *: significant at 1% and 10% respectively.

Further, we used interaction terms to explore the impact of the presence of a child in the household on the weekday–weekend day pair differences. The original definition of a day pair presented in the methodology section was applied here, and the pairs were divided into three types: weekday–weekday, weekday–weekend, and weekend–weekend. As the results presented in Table 5 show, the sign of the interaction term for preschooler presence in a family and weekday–weekend pair is positive, and its estimated coefficient is 0.067, which implies that the frequency difference of people whose household has preschooler member(s) is larger than those of households without preschoolers. This difference is reasonable because on weekdays most people go to work and don't go out with their preschool children, whereas on weekends they are likely to take part in recreational activities with those children, and that enlarges the difference of car use frequency between weekdays and the weekend. On the contrary, the sign of the interaction term for the presence of a pupil in a family and the weekday–weekend pair is negative, which indicates a negative moderating effect by school children. In a highly competitive city like Shanghai, school children are busy attending auxiliary classes or classes of interest and participating in many kinds of activities in addition to their compulsory education, both on weekdays and on weekends. As a result, their family members need to ferry them about and their car use frequency may always be high. Thus, the presence of pupils in the family decreases the difference in car use frequency of family members between weekdays and weekends, to some extent.

Table 5. Hausman–Taylor Estimation Result with Interaction Terms.

Variable	Difference in Frequency of Car within a Specific Pair	
	Coef.	**Z**
Pair of days (base: weekday to weekday)		
Weekday to weekend (D–E)	0.052 ***	2.70
Weekend to weekend (E–E)	0.072	1.47
Interaction terms		
D–E * With preschooler(s)	0.067 **	2.12
E–E * With preschooler(s)	0.004	0.05
D–E * With pupil(s)	−0.350 ***	−5.53
E–E * With pupil(s)	−0.259 *	−1.67
Household characteristics		
With preschooler(s)	−0.008	−0.24
With pupil(s)	−0.025	−0.44
With free member(s)	0.014	0.47
Number of family member(s)	−0.013	−0.74
Number of bikes	−0.008	−0.80
Number of electric bicycles	−0.011	−0.97
Individual characteristics		
Gender (male)	−0.053 *	−1.92
Age	0.007 **	2.13
Transportation card (owned)	0.090	1.60
Occupation (base: government employee)		
Teacher/Researcher	0.028	0.24
Manufacturing staff	0.019	0.36
Financial practitioner	−0.031	−0.37
Business staff	0.035	0.65
College student	0.132 *	1.66
Others	0.042	0.86
Monthly income (base: ¥5000 or less)		
¥5000–¥10,000	−0.035	−1.16
¥10,000–¥15,000	0.062	1.48
¥15,000 or more	0.187 ***	2.65
Weekly working hours	0.001	0.55
Fixed working time (Yes)	0.042	1.50
Constant	−0.297 *	−1.86
Number of observations	3109	
Number of groups (N)	256	
Prob > chi2	0.000	
σ_u	0.119	
σ_e	0.286	
rho	0.147	

Note: ***, ** and *: significant at 1%, 5%, and 10% respectively.

5. Conclusions and Recommendation

Using multi-day GPS-imputed travel data from families in Shanghai, China, this paper studied in depth the impact of children on household private car ownership, one family member's car-travel behavior, and the variability in the degree of car usage between workdays and weekends. In addition, the different effects of preschoolers and pupils were explored separately. This study differs from previous studies from the single perspective that children, used as only one factor in sociodemographic characteristics, have an impact on the travel of the entire family, via cross-sectional data. We expected to find out whether children's affairs caused the purchase of vehicles or the use of more taxi trips, and also whether the presence of children made family members more inclined to adopt the habits of car travel, thereby increasing car usage in their overall travel. Therefore, the method of Hausman–Taylor estimation was used to explore the effects of the non-time-changing children's factors in the panel data. In addition, the problem that only the effects of time-varying variables can be studied when using fixed or random effects models was solved. So far, this paper has formed a series of longitudinal, system-specific research systems, ranging from private car ownership to car-travel behavior to variability in the degree of car usage.

Several interesting conclusions can be drawn from this systematic study. First, the study shows that the presence of children in a household greatly increases the number of private cars owned by the household. Specifically, the presence of preschoolers and the presence of pupils each have a significant, positive impact, which indicates that there is a greater demand of car ownership for households with these two types of children. Second, the travel behavior of people from households with children is influenced subtly by the presence of their young family members, and that presence leads them to travel by car more frequently. After all, those families originally selected the comfort and convenience of a car to facilitate their children's travel, but a car is also convenient for other travel activities. On the other hand, the presence of a retired or unemployed member in the family can weaken the impact of a pupil's presence on the choice of travel mode. Because these household members with free time usually take charge of ferrying the children to and from school, they allow other members to choose other travel modes that are less likely to get them stuck in a traffic jam and also are eco-friendly and beneficial to sustainable development. Last, there is a significant difference in individuals' frequency of car use between weekdays and weekends. In addition, the presence of school children in the household diminishes that difference, while the presence of preschoolers enlarges it.

In developing countries with rapid economic growth, children will significantly stimulate the demand for household car ownership and will enhance family members' preference for cars as their travel mode. Countries or regions that urgently need to solve the problems of traffic jams and environmental pollution should take this into account when they formulate their birth policies. The good news is that the presence of retired or unemployed adults in the household will weaken the influence that children exert on the travel behavior of family members. From that perspective, this group of people with free time may not only contribute to their families but also may have a positive effect on sustainable development of the entire society. To make that effect more significant, relevant agencies should further improve the safety, convenience, and friendliness of public transportation, by doing such things as improving the comfort of transport stations by increasing the available number of elevators, adding more special boarding gates for young and old, and providing enough shade and natural cooling in summer. What's more, the results of our investigation on the frequency of car use also indirectly confirm the popularity of car use in travels with children. This popularity reflects that a gap still exists between the distribution of transportation infrastructure and the allocation of educational and entertainment resources in Chinese cities, and accordingly, urban designers and transportation planners still have a long way to go.

Of course, the impacts of the presence of children in a household are complicated, and many factors could moderate them. Only some of the impacts are investigated here with the help of econometrics, and this general issue should be analyzed comprehensively by different means in future research. For instance, this paper has explored the variability in car-use frequency across weekdays and weekends from the time dimension, however research questions in the spatial dimension should not be neglected, like the influence of children on people's travel routes planning and decision in different types of travel activities.

Author Contributions: Conceptualization, N.Y. and L.G.; Data curation, N.Y.; Formal analysis, N.Y. and L.G.; Funding acquisition, L.G. and Z.J.; Methodology, N.Y.; Resources, L.G. and Z.J.; Software, N.Y. and L.G.; Writing—original draft, N.Y.; Writing—review & editing, L.G., Z.J., and A.N.

Funding: This research was funded in part by the National Natural Science Foundation of China, grant number 51478266.

Acknowledgments: The authors are grateful to Zhizhou Jin and Bao Wang for their help in data collection and useful comments on the earlier version of the paper, and gratefully acknowledge the contribution of three anonymous reviewers to the consequent improvement of this research.

Conflicts of Interest: The authors declare no conflict of interest.

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