Investigation of Factors Influencing the Private Car Ownership in China: Evidence from the Panel Data

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Abstract: Influencing factors of private car ownership in China are investigated by adopting data in 32 provincial capital cities from 2001 to 2011. Aiming to capture the individual effects (heterogeneity), the fixed and random effect models are employed and compared, in which 10 explanatory variables are selected to include economic characteristics, urban characteristics, and transportation characteristics. Double natural logarithm model is employed to measure the elastic relationship between the private car ownership and regressors. According to the model results, the fixed effect model performs better than pooled regression model and the random effect model, which is reasonable considering the approach to sample and the purpose of respective model. Finally the influence of factors responsible for private car ownership variations is also presented and discussed in this paper.

Keywords: Private Car Ownership, Panel Data, Fixed Effect Model, Random Effect Model, Double Logarithm Model

1.INTRODUCTION

In recent years, China's national economy has achieved an impressive development in the background of economic globalization. At the meantime, the private car ownership is experiencing a sharp increase. Based on the data from *China Statistical Yearbook for Regional Economy*, by the end of 2012, the number of civilian vehicles breaks through 100 million, in which private car ownership occupies 88 million. Figure 1 illustrates the growth of Gross Domestic Product per capital and private car ownership per 1,000 people in China. On the one hand, vehicles have a positive effect on expanding the scope of the residents' activities, improving the level of residents' life, and promoting the economic and cultural interchange. On the other hand, a good many of vehicles cause serious traffic and social problems, such as congestion, accident, exhaust, and so on. Investigating the private car ownership and its determinants, therefore, is not only beneficial to forecast private car ownership and traffic demand, but also provides reference basis for determining fuel duty and strong support for making policies related to transportation, automobile industry, energy and environment.

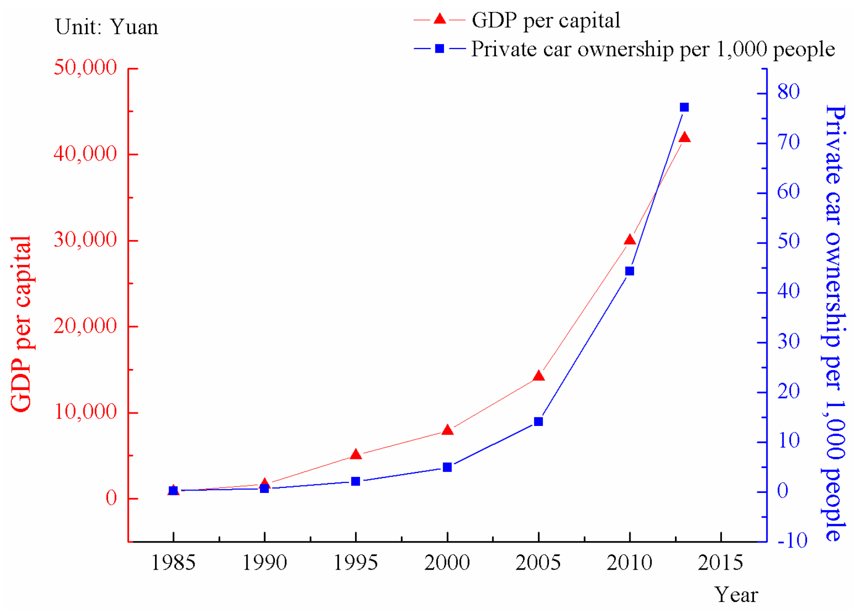

Figure 1. The growth of Gross Domestic Product per capital and private car ownership per 1,000 people in China (Data source, *China Statistical Yearbook 2014*)

Examining the determinants of private car ownership from macroscopic level has been one of the research topics for academia, public and private sectors over the world. There are a number of studies on the general relationship between the car ownership and various variables. Mogridge (1967) put forward a new approach to predict car ownership using Family Expenditure Survey (FES) for the first time by analyzing the relationship between household disposable income and the expenditure on car purchase. Factors influencing the car ownership in England, London, Kuwait, Yugoslavia, and Ireland were investigated separately (Buxton and Rhys, 1972; Fairhurst 1975; Stanovnik 1990; Said 1992; Nolan 2010). Results indicated that household characteristics, income per capital, permanent income, the prices of cars, population density, level of service for public transportation, and life cycles, were determinants of car ownership. Button *et al*. (1993), Dargay and Gately (1999), and Storchmann (2005) examined the degree of correlation between car ownership and income per capital using the statistical data from different countries. Dargay (2001, 2002) compared and analyzed the influence of asymmetry stemming from the change of car ownership with income and the difference in rural and urban areas with respect to car ownership.

Examining the determinants of car ownership in China has continuously attracted some domestic researchers' attention as well. Gong and Jin (2005) and Han and Li (2006) performed a quantitative analysis of the factors influencing car ownership with econometric model , in which Han and Li used the data from 1989 to 2004 from National Bureau of Statistics of the People's Republic of China. Gu *et al.* (2010) predicted the private car ownership using the Gompertz model with the longitudinal data from 31 Chinese cities. Huang *et al.* (2012) discovered that the economic factors were decisive in determining the private car ownership, and the level of urbanization had a significantly positive effect in prompting it while population density and level of service for public transportation played a negative influence, by adopting data from Statistical Yearbooks at all levels. Shen (2006), Deng and Hu (2010), Hao *et al.* (2011), Huo and Wang (2012), and Sun *et al.* (2013), proposed various models to predict car ownership. According to findings obtained by Shen (2006), the number of civil automobiles will reach 22.8 billion while private car ownership will be 14.7 billion by 2030.

In the current study, there are two main types of research. Some studies explored the impact of various factors on private car ownership with the family unit. The others focused on analyzing the influence factors in national or regional. In China, the researchers did a lot of work in predicting the private car ownership and dealing with the problems during the process of car development. Compared to the existing research, this paper examines the determinants of private car ownership in China using the longitudinal data from 2001 to 2011 from the perspective of cities (32). In the study, we investigated the impacts of some economic, urban, and transportation variables on the private car ownership so that some environmental and economic advice for Chinese governments can be put forward. Therefore, it has great significance for creating societies with less car dependence to study the changes of private car ownership as well as factors contributing to the variations. Figure 2 depicts the distribution of these 32 Chinese cities with their respective population scale in the general map of China. Additionally, in order to capture the growth situation of private car ownership in these 32 cities from a visual perspective, figure 3 is presented.

The remainder of this study is structured as follows. Section 2 is the description of the data followed by the framework of private car ownership models. Estimation results as well as some implications for policy makers are then presented. Finally, the paper offers some concluding remarks.

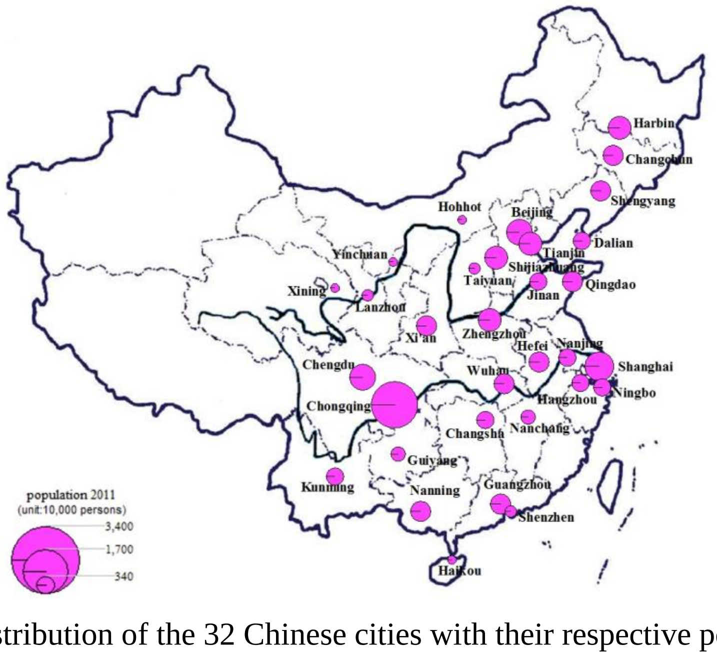

Figure 2. Distribution of the 32 Chinese cities with their respective population scale

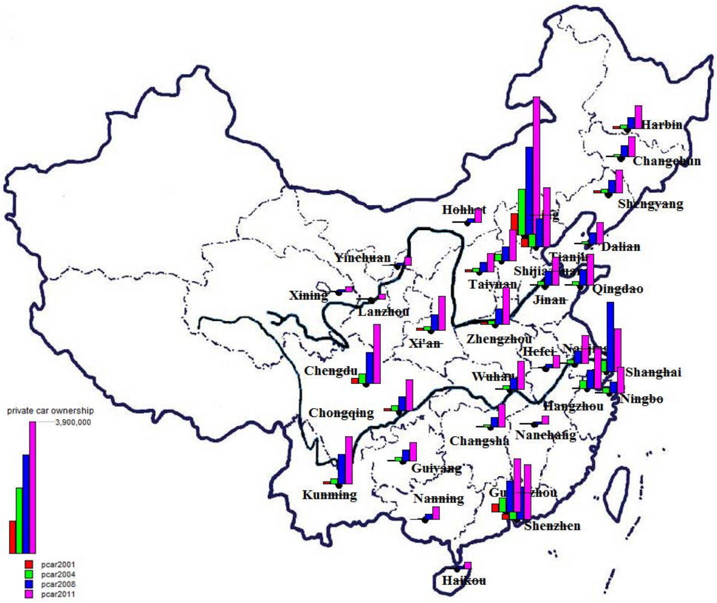

Figure 3. Growth of private car ownership for the 32 Chinese cities illustrated in this study

2.DATA

Data for this research are collected basically from *China City Statistical Yearbook* and *China Statistical Yearbook for Regional Economy*. And some supplemented data come from their respective statistical yearbooks or some sources online.

In our research, we will adopt the natural logarithm model which enables regression coefficients to be interpreted as respective elasticity as well. The dependent variable is Private Car ownership per ten thousand people (*PCar*) for each city, from 2001 to 2011. We also use 2001 as the base year to make adjustment for inflation in terms of economic attributes. In order to capture the relationships of the dependent variable with other factors, three categories of 9 independent variables are carefully picked as follows:

a) Economic characteristics: Gross Regional Product per capital (*GRP*), the Average Wage for employed workers (*AW*). The GRP equals to the gross regional production divided by the average of year permanent residents. The AW means the income level of workers and the higher the income level, the higher the purchasing power.

b) Urban characteristics: Urban Rate (*UR*), Population Density (*PD*). The UR is a measure of the development degree of a city, usually represented by the proportion of urban population to total population. The PD measured by persons of every square kilometer (p/sq. km) and can reflect the development model of urbanization, intensive or not.

c) Traffic characteristics: Road Area with Pavement per capital (*RAP*), measured by square meters, the actual number of operating Buses and Trolley buses per 10,000 persons at the end of the year (*BT*), the Total number of Buses and Trolleybuses (*TBT*), the Total Number of Passengers of buses and trolleybuses (*TNP*), the actual number of Taxi at the end of the year per ten thousand people (*PTaxi*), Highway Mileage per ten thousand people (*PHM*). The RAP and HM reflect the degree of highway development in a region, the higher values of which means the better environment. Note that *TNP* and *TBT* are not induced in the model separately. Instead, (*TNP/TBT*) is used to measure the level of comfort for buses and trolleybuses.Basic descriptive statistics are summarized in table 1. We describe means and standard deviations (in parentheses) for the whole sample.

Table 1 Descriptive statistics

Variable	**All sample**	**Variable**	**All sample**
1.PCar	999.0344	**7.AW**	14040.3
Std. Dev.	(942.3028)	Std. Dev.	(4702.2)
2.PTaxi	31.9096	**9.GRP**	18207.3
Std. Dev.	(13.67635)	Std. Dev.	(9023.0)
3.TNP/TBT	189918.9	**10.PD**	1619.195
Std. Dev.	(55730.0)	Std. Dev.	(1117.182)
4.BT	13.9	**11.UR**	0.5929
Std. Dev.	(14.9)	Std. Dev.	(0.2173)
5.PHM	29. 02259		
Std. Dev.	(16.7882)		
6.RAP	10.6		
Std. Dev.	(6.2)		

3.PANEL DATA MODEL

In order to capture the city-level heterogeneity (individual effects) of the samples, two most conventional approaches –the fixed and random effect models-are employed (Wen *et al.*, 2012, Woldeamanuel *et al.*, 2009, Bilotkach and Lakew, 2014).The fixed-effect model assumes that the unobserved individual effects may be correlated with regressors and allows each observation to process its own intercept by building a set of dummy variables while the random effect model captures the individual difference through error variance. Specifically, the random effect model assumes the unobserved effects are independent from regressors and have the same intercept. In terms of estimation methods, the fixed and random effect models can be estimated by standard least squares and generalized least squares procedures, respectively.

The fixed effect model with city as individual can be formulated as

$$\begin{aligned}\ln PCar_{it} = \alpha_i + \beta_1 \ln UR_{it} + \beta_2 \ln PD_{it} + \beta_3 \ln GRP_{it} + \beta_4 \ln AW_{it} + \beta_5 \ln RAP_{it} \\ + \beta_6 \ln BT_{it} + \beta_7 \ln(TNP / TBT)_{it} + \beta_8 \ln PTaxi_{it} + \beta_9 \ln PHM_{it} + \varepsilon_{it}\end{aligned} \tag{1}$$

Where *lnPCar*, *lnUR*, *lnPD*, *lnGRP*, *lnAW*, *lnRAP*, *lnBT*, *ln(TNP/TBT)*, *lnPTaxi*, and *lnPHM* are the dependent and independent variables described in the previous section, just adopting the natural logarithm form, α_i is city specific constant, ε_{it} is the error term and ε_{it} ~IID $(0, \sigma_{\varepsilon}^2)$.

F test can be applied to determine whether the fixed effect model is more proper than the pooled regression model with a single constant, which is estimated by ordinary least squares approach. Rejection of null hypothesis means fixed effect model performs better.

If the individual specific constant (v_i) is regarded as randomly distributed term, formulation of the random effect model can be expressed as

$$\begin{aligned}\ln PCar_{it} = \alpha + \beta_1 \ln UR_{it} + \beta_2 \ln PD_{it} + \beta_3 \ln GRP_{it} + \beta_4 \ln AW_{it} + \beta_5 \ln RAP_{it} \\ + \beta_6 \ln BT_{it} + \beta_7 \ln TNP_{it} + \beta_8 \ln PTaxi_{it} + \beta_9 \ln PHM_{it} + v_i + \varepsilon_{it}\end{aligned} \tag{2}$$

Where ε_{it} ~IID $(0, \sigma_{\varepsilon}^2)$ and v_i ~IID $(0, \sigma_{v}^2)$. Other variables remain the same as they were described previously.

The appropriateness of the random effect model versus the pooled regression model can be justified by the Lagrange Multiplier (LM) test, developed by Breusch and Pagan (1980). If the null hypothesis is rejected, then the random effect model is preferred.

The models adopted are determined by the purposes of the research. The aim of the fixed effect model is to compare subjects within the samples. The results obtained from the fixed effect model are just limited to these subjects and cannot be extended to the whole sample while the random effect model is employed to explore the characteristics of the general group which can be represented by samples. Therefore, conclusions could be expanded to a more general scheme. Generally speaking, the fixed effect model is more appropriate than the random effect model to compare individuals.

4.ESTIMATION RESULTS AND ANALYSIS

The estimation results are presented in table 2 with specifications for the fixed effect model and random effect model respectively.

The estimated results of F value2 (12.98) and R^2 value (0.755) indicates good model fit for the fixed effects model over pooled regression model for the entire sample. Analogously, the rejections of null hypothesis in LM test demonstrate that the random effect model has a stronger explanation for the relationship between regressors and the dependent variable than the polled regression model. In terms of appropriateness between the fixed effect model and the random effect model, however, the first one is favored for the entire sample based on results of hausman test.

From the regression results, we can see that the independent variables, *lnTaxi* is not significant. With the remaining independent variables, we get the revised result.

Table2 estimation results

VARIABLES		All sample		
		FE (1)	RE(2)	FE(revised)
lPTaxi		-0.034	-0.0.189	
	se	0.162	0.123	
l(TNP/TBT)		0.324**	0.230*	0.327***
	se	0.13	0.12	0.13
lBT		0.347**	0.389***	0.341**
	se	0.156	0.134	0.153
lPHM		0.872***	1.006***	0.873***
	se	0.0796	0.0703	0.0793
lRAP		0.803***	0.681***	0.804***
	se	0.117	0.109	0.117
lAW		0.926***	0.539**	0.931***
	se	0.266	0.233	0.264
lGRP		0.691***	0.436**	0.695**
	se	0.241	0.185	0.241
lPD		0.216*	0.161*	0.215*
	se	0.11	0.0861	0.11
lUR		1.294***	0.962***	1.315***
	se	0.281	0.199	0.262
Constant		-19.03***	-11.26***	-19.22***
	se	3.31	2.51	3.17
Observations		352	352	
R-squared		0.755		0.755
F value1		106.31		119.97
F value2		12.98		13.33
LM test		329.5		
Hausman test		27.87		
Number of city		32		

Notes: se means standard errors; *** p<0.01, ** p<0.05, * p<0.1;

F value (1) is to test the joint significance of explanatory variables;

F value (2) is to test the significance of individual effects (pooled regression model versus the fixed effect model);

LM test is used to judge the appropriateness of the random effect model versus pooled regression model;

Hausman test is employed to determine which one is favored between the fixed effect model and the random effect model.

Next, we will analyze the results of the fixed effect model (revised)for all sample from three perspectives: economic characteristics, urban characteristics, and transportation characteristics.

a) Economic characteristics

In general, the number of private cars per ten thousand people presents an upward trend as the urban economy grows. It increases as average wage of employed workers rises.

Specifically, the elasticity of it is 0.931 with 99% significance level, indicating that a 1% increase of Average Wage is associated with 0.931% rise in the private car ownership per ten thousand. Coefficient of lGRP is statistically significant at 99% confidence level with positive signs, which implies that GRP has a positive role in prompting the increase of private car ownership .

b) Urban characteristics

As for the influence of urban rate on private car ownership, it significantly stimulates the growth of private cars per ten thousand people with an elasticity of 1.315, which reveals that so far the sprawl of city enhances the private car ownership greatly with the elasticity over 1. Nevertheless, this is just an average effect among cities. We hope to find some variation between different city scales, which will be one of our future researches.

The regression result of population density suggests that it drives up the private car ownership substantially. Numerically, 1% increase of *PD* will lead to 0.215% increase of *PCar*. As for policy makers in China, they should see more than that. Whether there are any other developing modes in which *PD* contributes to the ridership of public transit, such as TOD (Transit Oriented Development) mode; thereby reducing the number of private cars owned by communities.

c) Transportation characteristics

From the result ,we can see that the *lPTaxi* is insignificant which can be justified by its little variation during the 11 years for each city.

The increase of (*TNP/TBT*), which can be used to measure the comfort level for public transportation, means that buses or trolleybuses are more congested than before. It is positive and 1% increase of (*TNP/TBT*) will lead to 0.327% increase of *PCar*. In addition, 1% increase of *BT* will lead to 0.341% increase of *PCar*.

In this study, the high value of elasticity for *HM* and *RAP*, both of which are associated with the positive sign, suggests that there is a very strong and positive relationship between the two indicators and the number of private cars individuals own. Numerically, 1% increase of *HM* will lead to 0.873% increase of private car ownership. 1% increase of *RAP* will induce 0.804% rise in private car ownership.

5.CONCLUSION

This paper focuses on exploring private car ownership through time by using panel data of 32 cities in China from 2001 to 2011 implementing the fixed effect and random effect model aiming to observe the individual effect. In order to create elastic relationship between private car ownership and its determining factors, double natural logarithm model is adopted, in which the explanatory variables were selected to include economic characteristics, urban characteristics, and transportation characteristics. The estimated results show that the fixed effect model is favored over the pooled regression model and the random effect model.

Based on the regression results, variables related to economy will stimulate the growth of private cars. *PD* contributes to the rise of private car ownership as well as *UR*.

When transportation attributes are concerned, *BT, TNP/TBT, HM* and *RAP* play a positive role in the rise of number of private cars. These effects are consistent with what people think.

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