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Generational Differences in Household Car Ownership

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ABSTRACT

The stagnation of car demand had been observed in many countries. A similar phenomenon had emerged in Taiwan. From the perspective of socio-demographic characteristics, this study employs quantile regression for count data to investigate generational differences in household car ownership in Taiwan. The results show that the socio-demographic characteristics affected household car ownership. Due to the seniority effects, households in the later life-cycle stages and households with a higher proportion of elderly members would reduce car demand. But, households with the middle-aged heads owned more cars due to their better economic ability. The income effects are greater for higher income households. Household car ownership varied across generations, which was related to the income effects, the life course, and household structure. Hence, the demographic changes and generational differences in travel preferences should be considered in urban transportation planning. Seamless transportation and senior-friendly facilities would be important for transportation demand management.

KEYWORDS

Car ownership, Socio-demographic characteristics, Count data, Quantile regression, Household structure, Poisson regression.

INTRODUCTION

For the past few decades, automobile demand has increased considerably with economic development and income growth. However, numerous researchers have noticed that after a long period of growth, car travel has shown a sign of levelling off or declining in many developed countries. This phenomenon is referred as “peak car”, describing the demand for car use has reached its peak. Goodwin and Van Dender [1] showed that young people had reduced car use and the changing propensity to drive was a widespread phenomenon. Metz [2] stated that personal car travel had ceased to grow in the developed economies due to demand saturation. Puentes and Tomer [3] indicated that per capita car use started to decline in 2004 in most American cities. Stanley and Barrett [4] pointed out that car use had a downward trend in Australian cities since 2004. Moriarty and Wang [5] demonstrated that per capita car travel had been fallen in Japan,

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America, and Australia since 2004. Kuhnimhof *et al.* [6] showed that a period of stagnation or decrease in per capita car travel began after the millennium in France, Germany, Great Britain, and America. Similar declining trends of per capita car travel in many European countries were evidenced in the study of Focas and Christidis [7]. Since car ownership is an important driver of car use and the determinants of car use may influence car ownership, some researchers have turned their attention to car ownership. They found that peak car phenomenon may not only exist in car use but also in car ownership. Particularly, the level of car ownership among young households has been declining [8, 9].

In Taiwan, a similar phenomenon of peak car has emerged in Taiwan for recent years. However, the trends of household car ownership may be diverse across generations. According to the statistics from the Directorate-General of Budget, Accounting and Statistics of Taiwan's central government, car ownership per household increased with a high annual growth rate of 15% during the 1980s and 1990s but the growth rate began to slow down after 2006. From 1980 to 2006, the number of cars per household increased from 0.05 to 0.7. After peaking in 2006, household car ownership stayed at a level of 0.7 during the period 2007-2017. In particular, young households obviously own fewer cars than before. From 2005 to 2015, car ownership among households with heads under the age of 40 had decreased from 0.82 to 0.78. However, car ownership among households with heads over the age of 40 still persistently increased from 0.63 to 0.69 during the same period. In addition, from 2005 to 2015, the share of carless households with heads over the age of 40 had decreased from 46% to 43%, while the share of carless households with heads under the age of 40 had risen from 31% to 34%. This phenomenon reflects that demographic factors would be important determinants of future vehicle demand. As Taiwan is facing radical demographic changes, such as low fertility rate, population aging, and household size declining, it is important to analyse the impacts of demographic changes on household car ownership and understand the possible trend of car ownership in the future. Therefore, this study analyses how household car ownership would be affected by socio-demographic characteristics and investigate generational differences in household car ownership in Taiwan over the period 1985-2015.

Many studies have explored the possible reasons of peak car phenomenon. The possible causes of peak car phenomenon can be attributed to economics factors (such as income and fuel prices) [10, 11], demographic factors [2, 3], urbanisation [12], user preferences [7], and changes in transport modes [7]. Although the peak car phenomenon has aroused a lot of attention, few studies have paid attention to the stagnation or declining trend of car ownership. Oakil *et al.* [8] and Klein and Smart [9] are two studies that focused on the decrease in car ownership among young households. Oakil *et al.* [8] showed that car ownership has declined among young Dutch households due to urbanisation and increasing singlehood. Klein and Smart [9] found that, in America, millennials own fewer cars than previous generations did when they were young. The dramatic decline in car ownership among younger Americans can be attributed to age and economic factors. Besides, Matas *et al.* [13] focused on the impacts of urban form and public transport on household car ownership. The results showed that spatial variables are crucial for car ownership in Spain. The improvement of job accessibility can result in a significant reduction in the level of car ownership.

However, some studies claimed that the aggregated member of cars will tend to increase in the future. Ritter and Vance [14] evidenced that despite the projected decrease in population, car ownership in Germany will continue to increase in the future. The most important reason is the steady increase in household income. Yagi and Managi [15] examined the demographic determinant of car ownership in Japan between 1980 and 2009. The results revealed that car ownership would be accelerated by the decrease in population and household size. Although the degree of public transit use can lower the level of car ownership, these effects are insignificant and limited. Therefore, the question about how the trend of car ownership will go in the future is still inconclusive. Nevertheless, previous studies have manifested the importance of socio-demographic factors in the trend of car ownership. Numerous studies have proven that socio-demographic factors have significant effects on household car ownership. Rith *et al.* [16] and Ao *et al.* [17] found that household characteristics influenced household car ownership. Rith *et al.* [16] evidenced that household income was the main factor of household vehicle ownership in Manila. Households inclined to acquire more vehicles owing to more working adults and older and well-educated household heads in families. Ao *et al.* [17] showed that household size, income, the number of members under the age of 18, and the number of members with driver's license positively affected household car ownership in China. Metz [2] indicated that demographic changes, such as population growth and aging, are more important than economic development and technological change. Matas and Raymond [18] and Berri [19] highlighted the importance of generation effects on car ownership. They confirmed that the generation effect existed and population aging would contribute to a reduction in the level of car ownership. In addition, Bussière *et al.* [20] demonstrated that the peak car phenomenon is projected to occur in developing countries due to the demographic transition, including a slowdown of population growth and population aging.

Although previous studies had stressed on the importance of the socio-demographic determinants for car ownership, these studies were based on the standard models, such as logit, probit, and poisson models, which neglected the possibility of heterogeneity and skewed distribution in the data. Moreover, socio-demographic determinants may have different effects depending on the level of car ownership. For instance, the effects of family size or household income on car demand may be different between these households with one car and these households with three cars. This paper employs quantile regression for counts model, developed by Machado and Santos Silva [21], to investigate the effects of socio-demographic determinants on household car ownership. This method uses the entire sample to estimate the effects of predictor variables on specific quantiles of a dependent variable. Few studies have considered the changes in the distributions of determinants when they explore household car ownership along the time dimension. Particularly, transport preference and travel behaviour may vary across generations. For instance, urban commuting behaviour may have altered nowadays. Keyes and Crawford-Brown [22] found that, in England, the higher income people tended to commute by train or active modes rather than the car. The determinants may have changed influences on commuting mode choice. Thus, taking account of the possible changes in the contribution of demographic determinants, this study considers the time dimension and uses the household data in 1985, 1995, 2005, and 2015 so as to investigate generational differences in household car ownership in Taiwan over the period 1985-2015.

METHODS AND DATA

This paper employs the Poisson and generalized Poisson regression models to estimate the effects of the predictors on household car ownership. In addition, to estimate different responses in different parts of the distribution, this study further uses quantile regression for counts model to investigate the effects of socio-demographic determinants on household car ownership. The information about household socio-demographic characteristics and car ownership is collected in Taiwan's Family Income and Expenditure Survey. Therefore, the cross-sectional household data from the databases can be used in this paper. The empirical methods and data are addressed in detail as follows.

Methods

As the outcome variable is count data which may tend to be non-normally distributed and positively skewed, the use of ordinary least squares regression would be inadequate. Poisson regression can provide more appropriate alternatives for analysing count data. The standard Poisson probability function of household car ownership (Y) can be written as follows:

$$\mathrm{P}(Y=y)=\frac{\mu^{y}\exp(-\mu)}{y!},\qquad y=0,1,2,\dots,\mu>0 \tag{1}$$

In the Poisson distribution, both the mean and variance of Y are equal to μ. However, the restrictive assumptions may not be suitable to handle some types of count outcomes. In practice, the variance can be either larger or smaller than the mean. When the variance exceeds the mean, it is referred as over-dispersion. The phenomenon with the variance less than the mean is under-dispersion. To deal with the estimation more flexible, Consul and Famoye [23] and Famoye [24] developed the generalized Poisson regression model that has statistical advantages over standard Poisson. It is applicable to model count data with either over-dispersion or under-dispersion. The generalized Poisson probability function of Y can be written as the following:

$$\mathrm{P}(Y=y)=\left(\frac{\mu}{1+\alpha\mu}\right)^{y}\frac{(1+\alpha y)^{y-1}}{y!}\exp\left[-\frac{\mu(1+\alpha y)}{1+\alpha\mu}\right] \tag{2}$$

The mean of Y is μ, and the variance of Y is $\mu(1+\alpha\mu)^2$. With the link function: $\mu=\mu(x) = \exp(x\beta)$, the mean of Y is related to the explanatory variables. In the function, x is a $(k-1)$ dimensional vector of explanatory variables and β is a k-dimensional vector of regression parameters. In the next step, the mean parameter μ can be expressed with the log link function: $\log(\mu) = x\beta$. The dispersion parameter is α. If α equals zero, the probability function reduces to the standard Poisson probability function. The positive value of α means count data with over-dispersion, while the negative value of α represents count data with under-dispersion. How to verify whether the generalized Poisson regression model is more suitable than the Poisson regression model? The null hypothesis $H_0{:}\alpha = 0$ can be tested by using the asymptotic Wald t-statistic. The use of generalized Poisson regression model can be supported if the null hypothesis is rejected. Alternatively, the goodness of fit of two models can be assessed by the likelihood ratio test.

The Poisson and generalized Poisson regression models can reflect the effects of individual factors on household car ownership. However, these methods can estimate mean effects but not provide information on the full probability response to the change in an explanatory variable. Therefore, this study further employs the quantile count model so as to allow for different responses in different parts of the distribution. The quantile regression has been widely applied in the studies since Koenker and Bassett [25] introduced the concept of quantile regression and developed the estimation of conditional quantile functions. The typical quantile regression, based on the distribution function of a continuous random variable, can be performed for analysing the impact of the regressors on each quantile of the distribution. Consider a dependent variable Y, and the θ quantile of the distribution of a random variable Y is denoted by $Q_Y(\theta|X)$. X is a vector of observable characteristics, and θ is a number between 0 and 1. $Q_Y(\theta|X)$ can be obtained by sorting the values of Y from smallest to largest. The parameter vector β can be estimated for any quantile θ by minimizing the following expression with respect to β [25]:

$$\min \sum_{i=1}^{n} \theta (Y_i - X_i' \beta)^2 \text{ for any quantile } \theta \in (0,1) \tag{3}$$

The different parameter vectors of β for a given θ can be obtained using linear programming algorithms. However, when the dependent variable is discrete and the quantiles are not continuous, the linear programming approach of typical quantile regression cannot be used for count data. To overcome this problem, Machado and Santos Silva [21] had developed the quantile regression for count data. This approach employed a specific form of jittering technique proposed by Stevens [26] to smoothen the data. The first step is to construct a continuous variable Z where $Z = Y + U$. U is a random variable uniformly distributed in the interval [0, 1] and independent of Y and X. Let $Q_Z(\theta|X)$ denote the θ quantile of the conditional distributions of Z:

$$Q_z(\theta|X) = \theta + \exp\left[X' \hat{\beta}(\theta)\right] \tag{4}$$

The additive term θ is set as the lower bound of $Q_Z(\theta|X)$. In the second step, the distribution of Z is smoothed and a monotone transformation $T(Z;\, \theta)$ can be obtained. The transformed quantile function is linear. The quantile regression can be expressed as follows:

$$Q_{T(Z;\,\theta)}(\theta|X) = X' \hat{\beta}(\theta) \tag{5}$$

where $\hat{\beta}(\theta)$ is the estimated vector of parameter at the θ quantile. When the process is performed, an important necessary condition is that at least one continuous explanatory variable must exist. The monotone transformation $T(Z;\, \theta)$ is specified as follows:

$$T(Z;\theta) = \begin{cases} \log(Z - \theta) & \text{for } Z > \theta \\ \log(\zeta) & \text{for } Z \leq \theta \end{cases} \tag{6}$$

where $0 < \zeta < \theta$. The quantiles are equivariant to monotonic transformations and invariant to censoring from below up to the quantile of interest. The estimator can satisfy the property of asymptotically normal. Any inference based on the t test and Wald test can be used. Ultimately, the θ quantile of Y can be transformed from the θ quantile of Z based on the relation:

$$Q_Y(\theta|X) = \lceil Q_Z(\theta|X) - 1 \rceil \tag{7}$$

The eq. (7) means that [α] returns the smallest integer greater than or equal to a. To sum up, the estimation technique is relied on adding an extra continuous "noise" term to the counts. Then, the transformed quantile function can be estimated since the dependent variable has been smoothened. The inferences are used as conventional methods. The quantile regression for count data has not been widely applied. Only few studies have adopted this approach in the issues of the health care [27], contract duration [28], and sparrow number investigation [29]. This study extends the application of quantile regression for counts to the analysis of household car ownership. This method can help us to investigate the determinants of household car ownership with a view of full distribution and evaluate the effects of predictor variables on different quantiles of a dependent variable.

Data

In this study, the household data are obtained from Taiwan's Family Income and Expenditure Survey. This is a nationwide cross-sectional survey that has been conducted annually by the government, but households are not tracked. There are approximately 15,000 households involved in this survey for each year. The database of Taiwan's Family Income and Expenditure Survey contains household information such as demographic characteristics, property and facilities, income and expenditure. The household data in 1985, 1995, 2005, and 2015 are used so as to analyse generational differences in household car ownership over the past three decades [30-33]. Table 1 reports the descriptive statistics for household car ownership. The mean value of household car ownership increased from 0.12 in 1985 to 0.71 in 2015. The share of carless households decreased from 88% in 1985 to 41% in 2015. There was no obvious difference in the distribution of car ownership between 2005 and 2015. Figure 1 shows the trend of the percentage of households that owned cars. It had increased from 5% in 1980 to 58% in 2002 and then kept at the level of 59% till 2015. These results also reflect the fact that the growth rate of car ownership had slowed down for the past decade.

Table 1. Descriptive statistics for household car ownership

Car ownership	1985		1995		2005		2015	
	Households	[%]	Households	[%]	Households	[%]	Households	[%]
0	14,467	88.08	7,639	51.94	5,740	41.96	6,735	40.75
1	1,915	11.66	6,471	44.00	6,690	48.91	8,070	48.83
2	39	0.24	547	3.72	1,116	8.16	1,531	9.26
3	3	0.02	45	0.31	111	0.81	169	1.02
4	0	0	2	0.01	20	0.15	22	0.13
5	0	0	2	0.01	2	0.01	1	0.01
Observations	16,424	100	14,706	100	13,681	100	16,528	100
Mean	0.12		0.52		0.68		0.71	
Variance	0.11		0.35		0.45		0.47	

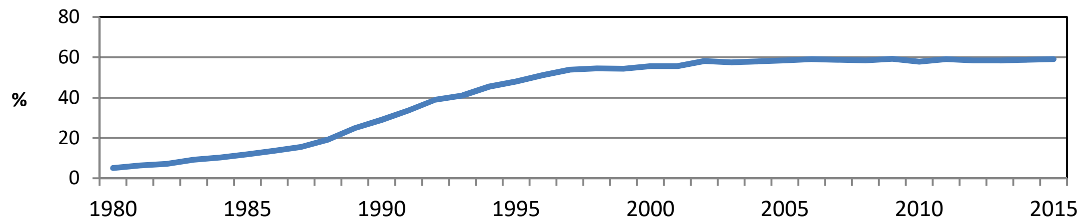

Figure 1. The trend of the percentage of households that owned cars

The explanatory variables are classified into four categories: household head characteristics, economic characteristics, demographic characteristics, and transport attributes. Household head characteristics include age, gender, education, whether the head is an employer or not, and marital status. The age of household head is a continuous variable, which captures the life-cycle stage of a household and generation effects. Gender is represented by a dummy variable that takes value 1 for male and 0 for female. Education level is an ordinal variable, measured by the highest degree that household heads obtain. This study assigns scores 1, 2, 3, and 4, respectively, to the four levels: less than junior high school, junior high school, senior high school, and bachelors or graduate degree. A dummy variable also is used to represent whether the head is an employer or not. It takes value 1 if household head is an employer and 0 if otherwise. This variable captures the difference of employment status that an employer with better economic ability and higher social-economic status may incline to own a car. Marital status is represented by a dummy variable, valued at 1 if the head has a spouse and 0 otherwise.

Economic characteristics contain household income, house ownership status, and the number of parking lots. An important variable to capture economic ability is household disposable income, which includes both regular and non-regular income after expenses, such as taxes, housing rent, interest and insurance payment. Household disposable income is transformed into a real term and deflated by the consumer price index, whose base year is 2016. The literature indicated that the car ownership level is positively related to household income [34, 35]. Rith *et al.* [16] pointed out that, as compared with the other socio-economic attributes, household income is found as the main factor of household car ownership. House ownership status is measured by a dummy variable, valued at 1 if the house is owner occupied and 0 otherwise. Owner-occupied households who possess property rights may have higher economic ability to own cars. The number of parking lots self-owned by a household is included in the model because easy car parking may be also a key point for households to own cars.

The variables of demographic characteristics capture the effects of household structure, including household size, the number of elderly members, and the number of children. Household size is defined as the number of household members, which may be positively associated with the demand for cars. The number of elderly members can represent the seniority effect on car ownership since the travel patterns may be different between order and younger generations. The elderly are defined as household members aged 65 years and older. Similarly, the number of children is considered as an explanatory variable. Due to generational differences, the households with children may have different travel patterns that influence their decision to buy cars. The children are defined as household members aged under 12 years.

Transport attributes include the number of motorcycles, public transit expenditure, and whether the household lives in the urban areas. In Taiwan, motorcycles are important means of transport due to the characteristics of relatively low prices and time-saving. The relationship between motorcycle and car ownership may be negative because household motorcycle ownership may substitute car ownership, however, since motorcycles also play a role to supplement the mobility, the relationship between household motorcycle and car ownership may be positively related [35]. Besides, previous studies demonstrated that the increase in public transport use can decrease vehicle ownership [18, 36]. Public transit expenditure can be used for measuring the dependency on public transit. As households depend on public transit much more, they may reduce their demand for cars. Public transit expenditure is deflated using the consumer price index, whose base year is 2016. Lastly, the model also considers the spatial effect and includes a dummy variable to represent whether the household lives in the urban areas. It takes value 1 if the household lives in the urban areas and 0 otherwise. The urban areas have different types of land development and high population density. Thus, households living in the urban areas may have different travel patterns and higher living standards. On the other side, households in the urban areas may own fewer cars if the public transit networks are well-developed. Previous studies found that people incline to have fewer cars if they are living in a high-density built environment [16, 37].

The descriptive statistics for explanatory variables are reported as Table 2. The statistics show that the age of household head, the number of elderly members, the number of motorcycles, the ratio of female-headed households, and the education level of household head exhibited an upward trend, while household size, the number of children and the ratio of household heads with a spouse gradually declined. It is worth noting that household income increased from 608 thousand NT dollars in 1985 to 1,225 thousand NT dollars in 2005, and then decreased to 1,179 thousand NT dollars in 2015. This phenomenon revealed the stagnation of real income in Taiwan for the past decade.

Table 2. Descriptive statistics for explanatory variables

Variables	1985 dataset		1995 dataset		2005 dataset		2015 dataset	
	Mean [N]	SD [%]	Mean [N]	SD [%]	Mean [N]	SD [%]	Mean [N]	SD [%]
Continuous/Numeric variables								
Age of household head	46.75	13.33	49.32	14.27	48.98	14.40	52.28	14.82
Household income (thousand NT dollars)	608.36	368.42	1,250.41	782.08	1,225.40	854.08	1,179.43	848.48
Number of parking lots	Na	Na	0.18	0.39	0.46	0.71	0.37	0.58
Number of motorcycles	1.02	0.86	1.26	0.96	1.36	1.03	1.51	1.08
Household size	4.59	1.94	3.92	1.73	3.39	1.58	3.09	1.49
Number of elderly members	0.22	0.51	0.34	0.62	0.46	0.71	0.59	0.77
Number of children	1.20	1.30	0.81	1.07	0.52	0.87	0.32	0.68
Public transit expenditure (thousand NT dollars)	7.74	9.77	11.23	15.14	9.06	13.90	9.61	14.94
Dummy/Categorical variables								
Gender of household head								
Male	13,748	83.7	11,119	75.6	10,660	77.9	11,637	70.4
Female*	2,676	16.3	3,587	24.4	3,019	22.1	4,891	29.6
Employer								
Yes	4,979	30.3	3,579	24.3	3,361	24.6	3,360	20.3
No*	11,445	69.7	11,127	75.7	10,318	75.4	13,168	79.7
Education level of household head								
Less than junior high school	9,497	57.8	6,589	44.8	3,419	25.0	2,976	18.0
Junior high school	2,083	12.7	2,240	15.2	2,210	16.2	2,460	14.9
Senior high school	3,637	22.1	4,024	31.4	5,945	43.5	7,168	43.4
Bachelors or graduate degree	1,207	7.3	3,302	8.6	2,105	15.4	3,824	23.7
Have spouse								
Yes	11,362	81.4	11,147	75.8	9,472	69.2	9,987	60.4
No*	3,062	18.6	3,559	24.2	4,207	30.8	6,541	39.6
Ownership								
Own	12,714	22.6	12,256	83.3	11,928	87.2	13,894	84.1
Rent*	3,710	77.4	2,450	16.7	1,751	12.8	2,634	15.9
Urban								
Yes	8,875	54.0	8,803	59.9	11,229	82.1	Na	Na
No*	7,549	46.0	5,903	40.1	2,450	17.9	Na	Na
Total observations	16,424		14,706		13,679		16,528	

SD means standard deviation.
* is used as the reference category.
Na means that the variable is not available in the dataset.

EMPIRICAL RESULTS

The empirical results include three parts. The first part is the estimation results of Poisson and generalized Poisson models. The second part shows the results of quantile regression for counts. The third part presents the further analysis for the generation differences in household car ownership.

Estimation results of Poisson and generalized Poisson models

Firstly, the Poisson and generalized Poisson models are used to estimate the effects of possible factors on household car ownership. This study focuses on the household datasets in 1985, 1995, 2005, and 2015, which represent four time points from different decades. Table 3 reports the estimation results of Poisson and generalized Poisson models. The results show that the dispersion parameters are significantly negative in all of the models, implying that count data have a feature of under-dispersion. These results support that the generalized Poisson regression model is preferred to the Poisson regression model. Since the adequacy of the generalized Poisson regression over the Poisson model has been confirmed, the following interpretation of predictors would be based on the results of generalized Poisson regression.

Among the household head characteristics, the variables of age, education level, whether the head is an employer, and whether the head has a spouse had significant effects for all of the four datasets. The age effects on household car ownership were negative, suggesting that the households headed by the younger generation tended to own more cars than the households headed by the older generation. The effects of education level were positive, implying that household heads with higher education attainment would have more cars due to their better social-economic status. Besides, household heads who are employers would own more cars than those who are employees. Household heads with a spouse would have more cars than household heads without a spouse.

As for the effects of economic characteristics, the variables of household income, house ownership, and the number of parking lots would have significantly positive effects for all of the four datasets. The level of household car ownership would rise as household income and the number of parking lots increased. Owner-occupied households inclined to own more cars since they had higher economic ability.

Table 3. Estimation results of Poisson and generalized Poisson models

Variables	1985		1995		2005		2015	
	Poisson	Generalized Poisson	Poisson	Generalized Poisson	Poisson	Generalized Poisson	Poisson	Generalized Poisson
Intercept	−4.3317** (0.1605)	−3.7925** (0.1696)	−1.9000** (0.0849)	−1.5472 (0.0479)	−1.3900** (0.0902)	−1.4316** (0.0510)	−1.5428** (0.0834)	−1.3154** (0.0406)
Age	−0.0074** (0.0023)	−0.0131** (0.0024)	−0.0046** (0.0012)	−0.0031** (−0.0007)	−0.0134** (0.0012)	−0.0079** (0.0008)	−0.0074** (0.0010)	−0.0054** (0.0006)
Gender	−0.2263** (0.0677)	−0.2854** (0.0675)	−0.0355 (0.0293)	−0.0130 (0.0176)	0.1455** (0.0319)	0.1164** (0.0148)	0.0996** (0.0243)	0.0733** (0.0134)
Education	0.4393** (0.0247)	0.3377** (0.0266)	0.1607** (0.0137)	0.0854** (0.0065)	0.1210** (0.0141)	0.1116** (0.0097)	0.1612** (0.0128)	0.0660** (0.0079)
Employer	0.3908** (0.0509)	0.3567** (0.0533)	0.0653* (0.0271)	0.0602** (0.0167)	0.1164** (0.0245)	0.0728** (0.0178)	0.1479** (0.0226)	0.1438** (0.0147)
Spouse	0.5643** (0.0900)	0.5615** (0.0924)	0.2141** (0.0367)	0.1351** (0.0167)	0.3725** (0.0326)	0.1405** (0.0118)	0.2953** (0.0260)	0.1797** (0.0117)
Income	0.0006** (0.0000)	0.0014** (0.0001)	0.0002** (0.0000)	0.0002** (0.0000)	0.0001** (0.0000)	0.0002** (0.0000)	0.0001** (9.21e-06)	0.0001** (0.0000)
Owner occupied	0.3948** (0.0615)	0.3264** (0.0630)	0.1644** (0.0384)	0.1555** (0.0230)	0.2008** (0.0399)	0.2181** (0.0222)	0.1432** (0.0332)	0.1128** (0.0167)
Parking lots	Na	Na	0.8029** (0.0257)	0.6698** (0.0220)	0.4722** (0.0145)	0.4454** (0.0119)	0.5026** (0.0133)	0.3904** (0.0110)
Household size	0.1471** (0.0170)	0.0841** (0.0187)	0.1803** (0.0101)	0.1241** (0.0039)	0.1160** (0.0103)	0.1624** (0.0064)	0.1198** (0.0094)	0.1647** (0.0066)
Number of elderly members	−0.1294* (0.0554)	−0.1030 (0.0579)	−0.1849** (0.0250)	−0.0233* (0.0112)	−0.1958** (0.0193)	−0.1582** (0.0080)	−0.1112** (0.0146)	−0.0561** (0.0087)
Number of children	−0.0044 (0.0233)	0.0164 (0.0247)	−0.0817** (0.0137)	−0.0732** (0.0062)	−0.0962** (0.0147)	−0.1098** (0.0110)	−0.0833** (0.0150)	−0.1260** (0.0114)
Number of motorcycles	−0.2360** (0.0307)	−0.2912** (0.0318)	−0.0681** (0.0138)	−0.0368** (0.0082)	0.0040 (0.0118)	0.0588** (0.0077)	0.0171 (0.0099)	0.0267** (0.0067)
Public transit expenditure	−0.0308** (0.0030)	−0.0694** (0.0055)	−0.0094** (0.0009)	−0.0007* (0.0003)	−0.0070** (0.0009)	−0.0055** (0.0004)	−0.0057** (0.0070)	−0.0015** (0.0001)
Urban	0.4322** (0.0531)	0.2003** (0.0559)	0.1064** (0.0263)	0.0325* (0.0149)	0.0421* (0.0294)	0.0618** (0.0167)	Na	Na
Dispersion parameter		−2.3568** (0.1644)		−0.1908** (0.0036)		−0.2429** (0.0040)		−0.2390** (0.0039)
Log likelihood	−5,407.39	−4,900.13	−11,424.91	−10,813.21	−11,796.15	−10,844.14	−14,646.69	−13,337.93
LR Chi-square	1,680.85**	1,436.93**	3,849.20**	3,821.98**	4,318.80**	5,395.86**	5,090.02**	6,549.05**
AIC	10,842.77	10,030.26	22,879.82	21,656.42	24,564.72	22,292.06	29,321.37	26,705.87
Pseudo R-squared	0.13	0.21	0.13	0.18	0.15	0.20	0.15	0.20

The value in the parenthesis is standard error. *, and ** represent 5% and 1% significance levels, respectively.
Na means that the variable is not available in the dataset. The 1985 database didn't collect the number of parking lots, and the 2015 database didn't collect the urban variable. The variables not available in the dataset would be excluded in the regression model.
LR Chi-square is the Likelihood Ratio Chi-square test that at least one of the predictors' regression coefficients is not equal to zero in the model. AIC means Akaike information criterion.

The effects of demographic characteristics were evident and important. Household size had significantly positive effects for all of the four datasets. The increase of family members would induce the demand for cars. Table 3 shows that, in the generalized Poisson model, the coefficient of household size had increased from 0.0841 in 1985 to 0.1647 in 2015. It is worth noting that the marginal effect of household size had increased with time. This result reflects the fact that household size had gradually decreased. Thus, the effects of household size on household car ownership would be stronger as the number of household members decreased. In addition, the number of elderly and children had significantly negative effects in 1995, 2005 and 2015, implying that households would own fewer cars if the dependent members increased. These results may be attributed to two possible reasons. First, the households with more elderly and children may have higher economic burden. Furthermore, the elderly and children are not the working group as a result of a lack of demand for cars.

Regarding the effects of transport attributes, the number of motorcycles had significantly negative effects in 1985 and 1995, but the effects were positive in 2005 and 2015. The negative relationship between motorcycle and car ownership indicated that household motorcycle ownership would substitute car ownership. According to Taiwan's Family Income and Expenditure Survey, during the period of 1980-2000, about 75% of households had at least one motorcycle, while only 29% of households had at least one car. Households would be able to own motorcycles but not afford to buy cars due to cost-saving incentives. However, as the income level gradually increased, household were able to own cars and motorcycles. In 2015, around 83% of households had at least one motorcycle, and 60% of households had at least one car. Since motorcycles could play a role to supplement the mobility, the relationship between household motorcycle and car ownership became complementary. Besides, the variable of public transit expenditure had negative effects on household car ownership, suggesting that the higher dependence on public transport would contribute to reduce the level of car ownership. In terms of the spatial effects, the urban variable had positive effects on household car ownership, indicating that households living in the urban areas would tend to own more cars than households living in the rural areas. The higher level of household car ownership in the urban areas may possibly be related to the higher living standards and meeting the demand to commute.

The estimation results of quantile regression for counts

Accounting for different responses in different parts of the distribution, this paper further employs the quantile count model to investigate whether the responses would be different between households with a high level of car ownership and households with a low level of car ownership. The quantile estimation is repeated for the 1985, 1995, 2005, and 2015 datasets. The results can help us to know how the effects of explanatory variables have evolved over time and understand which types of households own more or fewer cars. Table 4 reports the estimation results of quantile regression for counts. Since some households may not own any car, it would be meaningless to compute the model at a low quantile where the value of the outcome variable is zero. Therefore, the quantile regressions for the 50th, 75th, and 90th quantiles are estimated.

As for the effects of household head characteristics, the age effects were significantly negative in the all quantiles, indicating that families in a later stage of the family life cycle have fewer car demand than do younger families. The effects of education level of household head were significantly positive. Households with higher-educated household heads owned more cars than households with lower-educated household heads. It is worth noting that the education effects were greater in 1985 than those in other periods. The education effects were strongest in the 90th quantile of the 1985 dataset. However, for the 1995, 2005, and 2015 datasets, the education effects in the 90th quantile were weaker than the effects in other quantiles. These results mean that, in the early stages of economic development, the increase of education level may generate a stronger contribution to enhance economic ability and induce households' high demand for cars. But, along with income growth and education popularization, these effects may be weaker than before. Besides, the result also shows that households headed by an employer owned more cars than households headed by an employee. The household head with a spouse would tend to have more cars than the household head without a spouse.

Table 4. Estimation results of quantile regression for counts

Variables	1985			1995		
	50th	75th	90th	50th	75th	90th
Intercept	−4.5484** (0.3072)	−4.1660** (0.1879)	−4.6147** (0.2410)	−2.1281** (0.0792)	−1.8108** (0.0812)	−1.0062** (0.0607)
Age	−0.0170** (0.0026)	−0.0165** (0.0027)	−0.0184** (0.0037)	−0.0118** (0.0010)	−0.0134** (0.0010)	−0.0092** (0.0009)
Gender	−0.3099** (0.0767)	−0.3157** (0.0762)	−0.3575** (0.1021)	−0.0049 (0.0269)	−0.0065 (0.0265)	−0.0140 (0.0186)
Education	0.3882** (0.0310)	0.3356** (0.0300)	0.4106** (0.0398)	0.1485** (0.0129)	0.1328** (0.0126)	0.0788** (0.0091)
Employer	0.4154** (0.0593)	0.4538** (0.0598)	0.6312** (0.0774)	0.0704** (0.0228)	0.0792** (0.0232)	0.0769** (0.0171)
Spouse	0.6732* (0.2695)	0.5281** (0.1128)	0.5758** (0.1176)	0.2834** (0.0365)	0.2120** (0.0377)	0.0336 (0.0269)
Income	0.0020** (0.0000)	0.0026** (0.0001)	0.0036** (0.0001)	0.0004** (0.0000)	0.0005** (0.0351)	0.0004** (0.0000)
Owner occupied	0.4044** (0.0724)	0.3327** (0.0687)	0.3132** (0.0847)	0.1757** (0.0402)	0.1184** (0.0128)	0.0567** (0.0213)
Parking lots	Na	Na	Na	0.9068** (0.0213)	0.7050** (0.0099)	0.4306** (0.0217)
Household size	0.0717** (0.0226)	0.0376 (0.0236)	0.0395 (0.0332)	0.1773** (0.0097)	0.2113** (0.0212)	0.1600** (0.0103)
Number of elderly members	−0.0986* (0.0722)	−0.0323 (0.0668)	−0.0343 (0.0802)	−0.1917** (0.0223)	−0.2170** (0.1208)	−0.1705** (0.0193)
Number of children	0.0448* (0.0289)	0.0917** (0.0293)	0.1295** (0.0392)	−0.0749** (0.0122)	−0.0864** (0.0011)	−0.0757** (0.0095)
Number of motorcycles	−0.4310** (0.0416)	−0.4068** (0.0413)	−0.4185** (0.5582)	−0.1190** (0.0130)	−0.0875** (0.0224)	−0.0357** (0.0090)
Public transit expenditure	−0.0605** (0.0058)	−0.0620** (0.0061)	−0.0648** (0.0093)	−0.0156** (0.0012)	−0.0135** (0.0242)	−0.0082** (0.0008)
Urban	0.2242** (0.0656)	0.1401* (0.0628)	0.0926 (0.0828)	0.0832** (0.0231)	0.0962** (0.0812)	0.0518** (0.0172)
Variables	2005			2015		
	50th	75th	90th	50th	75th	90th
Intercept	−1.6168** (0.0728)	−1.2434** (0.0779)	−0.7427** (0.0613)	−1.7084** (0.0683)	−1.3191** (0.0758)	−0.7701** (0.0522)
Age	−0.0162** (0.0009)	−0.0176** (0.0010)	−0.0110** (0.0010)	−0.0096** (0.0008)	−0.0109** (0.0009)	−0.0050** (0.0007)
Gender	0.2126** (0.0266)	0.1709** (0.0263)	0.0842** (0.0199)	0.1119** (0.0187)	0.1048** (0.0187)	0.0598** (0.0136)
Education	0.1315** (0.1105)	0.1198** (0.0113)	0.0751** (0.0101)	0.1728** (0.0106)	0.1765** (0.0111)	0.0960** (0.0083)
Employer	0.1329** (0.0182)	0.1784** (0.0185)	0.1478** (0.0179)	0.1729** (0.0167)	0.2058** (0.0174)	0.1306** (0.0151)
Spouse	0.4046** (0.0282)	0.3251** (0.0270)	0.1936** (0.0220)	0.3560** (0.0217)	0.2870** (0.0210)	0.1448** (0.0158)
Income	0.0002** (0.0000)	0.0002** (0.0000)	0.0002** (0.0000)	0.0001** (0.0000)	0.0002** (0.0000)	0.0002** (0.0000)
Owner occupied	0.1908** (0.1354)	0.1585** (0.0309)	0.0974** (0.0220)	0.1730** (0.0340)	0.0700* (0.0301)	0.0036 (0.0199)
Parking lots	0.5788** (0.0126)	0.4782** (0.0123)	0.3467** (0.0112)	0.6036** (0.0120)	0.4725** (0.0112)	0.3204** (0.0081)
Household size	0.1325** (0.0082)	0.1445** (0.0087)	0.1086** (0.0086)	0.1217** (0.0083)	0.1286** (0.0084)	0.1071 (0.0073)
Number of elderly members	−0.2284** (0.0150)	−0.2281** (0.0160)	−0.1296** (0.0151)	−0.1295** (0.0116)	−0.1072** (0.0127)	−0.0571** (0.0091)
Number of children	−0.1023** (0.0105)	−0.1231** (0.0102)	−0.0938** (0.0105)	−0.0999** (0.0112)	−0.1063** (0.0123)	−0.0632** (0.0118)
Number of motorcycles	−0.0028 (0.0089)	0.0063 (0.0091)	0.0048 (0.0086)	0.0115* (0.0077)	0.0246** (0.0079)	0.0146* (0.0071)
Public transit expenditure	−0.0084** (0.0008)	−0.0083** (0.0008)	−0.0065** (0.0007)	−0.0074** (0.0008)	−0.0060** (0.0007)	−0.0036** (0.0006)
Urban	0.0730** (0.0194)	0.0840** (0.2230)	0.0543* (0.2210)	Na	Na	Na

The value in the parenthesis is standard error. *, and ** represent 5% and 1% significance levels, respectively.
Na means that the variable is not available in the dataset. The 1985 database didn't collect the number of parking lots, and the 2015 database didn't collect the urban variable.
The variables not available in the dataset would be excluded in the regression model.

Similar with pervious results of the generalized Poisson models, the variables of household income, house ownership, and the number of parking lots had significantly positive effects in all quantiles of these four datasets. The increase of income levels and parking lots would induce households to have more cars. Owner-occupied households may own more cars than non-owner-occupied households. This study further verifies that the marginal effects of household income and house ownership were larger in 1985 than the effects in other periods, indicating that responses of car demand to the income level or economic ability had declined with time. As the effects among the different quantiles are compared, the results show that the marginal effects of house ownership and parking lots variables were the strongest in the 50th quantile, while the income effects showed small variations across quantiles.

The results of the demographic effects reveal that, in 1985, the effects of household size were only significantly positive in the 50th quantile, while the effects were significantly positive for all of the quantiles in 1995, 2005, and 2015. The positive effects of household size support that an additional family member would generate higher car demand. Moreover, the marginal effects of household size may differ across the quantiles. In 1995, 2005, and 2015, the effects were greater in 75th quantile than theses in other quantiles. Besides, the number of elderly members had negative effects on car ownership, suggesting that households with more elderly members would reduce car ownership. However, the effects of the number of children were positive in 1985 but negative in 1995, 2005, and 2015. The effects of the number of children may be complex. Households may need cars to pick up their children, but they also face greater economic burden that would crowd out the budget for cars if they have children. Thus, for the results of the 1995, 2005 and 2015 datasets, the later effect may dominate the former one.

With respect to the effects of transport attributes, the number of motorcycles had significantly negative effects in 1985 and 1995, but the effects were significantly positive in 2015. These results are similar with our previous findings. During the 1980s and 1990s, the relationship between car and motorcycle ownership was substitutive. Households may own motorcycles for cost-saving but not afford to buy cars. However, as households have higher economic ability, the relationship between motorcycle and car ownership may be complementary. Households may be able to own both cars and motorcycles since motorcycles can satisfy their need for mobility. The variable of public transit expenditure had negative effects on car ownership in all quantiles for all the four datasets, implying that public transit use could bring about the benefit of alleviating the growth of car ownership. As for the spatial effect, the finding shows that the urban variable had positive effects on household car ownership, which means that households living in the urban areas would own more cars than households living in the rural areas. The higher car demand in the urban areas may be related to higher living standards and meeting the demand to commute. The spatial effects are contrary to the typical anticipation that car ownership is generally lower in urban cities. Our result is in line with the findings of Zhao and Bai [37] and Le Vine *et al.* [38]. Their studies evidenced that, in China, car ownership in rural areas was lower than in urban areas. Zhao and Bai [37] suggested that this result is attributed to the income effect and increasing income inequality between urban and rural households has augmented the gap in car ownership, while Le Vine *et al.* [38] suggested that the reasons is inconclusive and further research will be needed. The higher level of car ownership in the urban areas also implies that the public transit network in the urban development may fail to suppress car demand. The fundamental strategy is to improve the quality and convenience of public transport services. More incentives for public transportation should be provided to attract car users.

As the effects across the different quantiles are compared, many explanatory variables, such as the household head characteristics and household income, would have stronger effects in the 90th quantile in 1985. This result may be attributed to the high ratio of carless households. Thus, the effects of possible factors would be greater at the higher tail of the distribution. However, as the level of household car ownership had gradually increased, most households owned at least one car. Thus, in 1995, 2005, and 2015, the effects of possible factors may be greater at the 50^{th} or 75^{th} quantiles of the distribution. Households with one car would be more sensitive to the change of determinants and more likely to buy another car than those households with two cars.

Further analysis for the generation differences in household car ownership

For the past three decades, Taiwan had experienced dramatic changes in the demographic structure, such as population aging, number of births declining, and household size decreasing. Besides, household income level ever exhibited a high annual growth rate of 5.1% during the period 1980-1999. However, during the period 2000-2017, the annual income growth rate decreased to 0.3%, displaying a phenomenon of income stagnation. Therefore, this study further explores how the changes in the demographic structure and income level may bring about generational differences in household car ownership. Taking account that the impacts of explanatory variables may not be linear, the variables of household income, the ages of household heads and demographic structure are respecified. First, all households can be ranked according to household disposable income and divided into five groups. Thus, five dummy variables are used to represent households from the lowest to the highest income levels: Income1, Income2, Income3, Income4, and Income5. In the model, the lowest income group is used as the reference category. Second, households are classified into five groups according to the age of household heads: under 29 (Age1), 30-39 (Age2), 40-49 (Age3), 50-59 (Age4), and above 60 years old (Age5). Thus, the age of household heads can be transformed from a continuous variable to five dummy variables. The group headed by under 29 years old is used as the reference category. Third, the model considers that the effects of household structure may depend on the shares of different age groups. Thus, the model includes the proportion of children aged under 12 (Childrate), and the proportions of family members aged 30-39 (Age30rate), 40-49 (Age40rate), 50-64 (Age50rate), and above 65 (Age65rate). Specifically, the quantile regression model can be estimated after the variables of household income, age of household heads, and household structure are replaced. The definitions of other variables are the same as these in the previous section. Due to the limited space, Table 5 only reports the estimation results of the respecified variables.

Although the age effects were negative in the results of Table 4, the findings in Table 5 showed that the age effects may differ across the age levels. In 1985, the age effects were not significant in all quantiles. In 1995 and 2005, households with heads aged 50-59 would tend to have more cars than the reference group. In 2015, households with heads aged 40-49 would tend to have more cars than the reference group. These findings imply that as household heads were in their middle age, they would have better economic ability to own cars. Besides, in 2005, the results showed that households with heads aged above 60 would have fewer cars than the reference group, implying that the seniority effects would reduce the demand for cars.

As for the income effects, in 1985, only the highest and second highest income groups significantly owned more cars than the reference group in the 75^{th} quantile. In 1995, 2005, and 2015, the income variables were significantly positive for all quantiles, suggesting that households with a higher income level would own more cars than households with a lower income level. Particularly, the income effects would be greater for high-income households than low-income households. In addition, the income effects were stronger at the middle quantile than these at the higher quantile. Thus, the responses of car demand to the income level would be more sensitive for households with one car than those households with two cars.

Table 5. Further analysis of income and demographic variables

Variables	1985			1995		
	50th	75th	90th	50th	75th	90th
Age2	0.1701 (0.1064)	0.1033 (0.1168)	0.0583 (0.1668)	−0.0404 (0.0535)	−0.0953 (0.0561)	−0.0828 (0.0583)
Age3	0.0326 (0.1224)	−0.0471 (0.1281)	−0.1886 (0.1685)	0.0129 (0.0561)	−0.0075 (0.0500)	−0.0041 (0.0426)
Age4	−0.0048 (0.1206)	−0.0944 (0.1275)	−0.1339 (0.1725)	0.1624** (0.0588)	0.1538** (0.0524)	0.1664** (0.0460)
Age5	0.0173 (0.1311)	−0.0145 (0.1367)	0.0313 (0.1802)	0.0519 (0.0622)	0.0294 (0.0565)	0.0847 (0.0472)
Income2	0.6607 (2.0144)	1.0821 (1.1657)	1.3855 (2.2048)	1.1968** (0.0766)	1.1698** (0.0731)	1.1271** (0.1219)
Income3	1.3632 (2.0005)	1.8525 (1.1637)	2.4785 (2.2053)	1.5263** (0.0771)	1.4683** (0.0694)	1.3568** (0.1210)
Income4	1.9069 (2.0004)	2.4844* (1.1635)	3.4271 (2.2042)	1.7355** (0.0769)	1.6468** (0.0680)	1.4613** (0.1213)
Income5	2.5787 (2.0004)	3.2950** (1.1635)	3.3496 (2.2042)	1.9968** (0.0769)	1.8741** (0.0684)	1.6918** (0.1204)
Age30rate	0.0350 (0.1640)	0.0856 (0.1881)	0.0793 (0.2673)	0.1165 (0.0754)	0.1850** (0.0713)	0.2016** (0.0682)
Age40rate	0.0590 (0.2535)	0.2185 (0.2625)	0.2927 (0.3252)	−0.2104 (0.1348)	−0.1960 (0.1233)	−0.1496 (0.0932)
Age50rate	−0.5036* (0.2126)	−0.4933* (0.2152)	−0.6788* (0.2678)	−0.6262** (0.0777)	−0.6066** (0.0819)	−0.5297** (0.0820)
Age65rate	−0.5398** (0.2473)	−0.5610** (0.2793)	−0.9168** (0.3366)	−1.2376** (0.0988)	−1.3113** (0.0957)	−1.4028** (0.1105)
Childrate	0.2787* (0.1252)	0.3731** (0.1391)	0.5845** (0.1879)	−0.0244 (0.0607)	−0.0145 (0.0545)	−0.0589 (0.0509)
Variables	2005			2015		
	50th	75th	90th	50th	75th	90th
Age2	0.0653 (0.0418)	0.0515 (0.0393)	0.0415 (0.0398)	0.1217** (0.0432)	0.0770 (0.0413)	0.0298 (0.0420)
Age3	0.0139 (0.0405)	0.0040 (0.0387)	−0.0084 (0.0386)	0.1774** (0.0433)	0.1630** (0.0427)	0.0883* (0.0416)
Age4	0.0820* (0.0397)	0.0964* (0.0385)	0.0916* (0.0391)	0.0562 (0.0401)	0.0343 (0.0384)	0.0174 (0.0380)
Age5	−0.3352** (0.0535)	−0.3427** (0.0530)	−0.2850** (0.0514)	−0.0097 (0.0461)	−0.0248 (0.0445)	−0.0278 (0.0418)
Income2	0.8812** (0.0648)	0.8788** (0.0590)	0.5416** (0.0630)	0.6623** (0.0511)	0.6580** (0.0497)	0.2921** (0.0290)
Income3	1.1412** (0.0654)	1.0473** (0.0584)	0.6267** (0.0623)	0.8374** (0.0524)	0.8175** (0.0485)	0.3603** (0.0286)
Income4	1.2903** (0.0659)	1.2032** (0.0586)	0.7796** (0.0627)	0.9451** (0.0529)	0.9102** (0.0490)	0.4701** (0.0303)
Income5	1.4162** (0.0665)	1.3349** (0.600)	0.9292** (0.0638)	1.0158** (0.0540)	1.0130** (0.0506)	0.6235** (0.0321)
Age30rate	−0.0420 (0.0586)	−0.0046 (0.0555)	0.0028 (0.0571)	−0.0148 (0.0524)	0.0762 (0.0535)	0.0749 (0.0523)
Age40rate	0.0665 (0.0629)	0.0659 (0.0606)	0.0427 (0.0627)	−0.0294 (0.0583)	−0.0091 (0.0614)	−0.0249 (0.0565)
Age50rate	0.1357* (0.0525)	0.1947** (0.0510)	0.2128** (0.0555)	0.1860** (0.0424)	0.2312** (0.0450)	0.1119** (0.0393)
Age65rate	−0.6773** (0.0624)	−0.6335** (0.0638)	−0.4955** (0.0665)	−0.3787** (0.0462)	−0.3006** (0.0478)	−0.2123** (0.0397)
Childrate	0.0278 (0.0473)	−0.0096 (0.0457)	−0.0554 (0.0480)	0.0791 (0.0491)	0.0870 (0.0527)	0.0886 (0.0530)

The value in the parenthesis is standard error. *, and ** represent 5% and 1% significance levels, respectively.
Na means that the variable is not available in the dataset.

With respect to the effects of household structure, in 1985 and 1995, the results revealed that the proportion of family members aged 50-64 and the proportion of elderly members had significantly negative effects on household car ownership, suggesting that the seniority effects would lead to the decrease of car demand. In 2005 and 2015, the finding that the higher share of the elderly would discourage car ownership can also be verified. However, different from the results in 1985 and 1995, the proportion of family members aged 50-64 had significantly positive effects on household car ownership in 2005 and 2015, which may be due to their better economic ability and postponed retirement. The proportion of children only had significantly positive effects in 1985. One important reason would be attributed to the declining of the proportion of children, which decreased from 0.23 in 1985 to 0.07 in 2015. Hence, these results indicated that the effects of household structure may change along with time.

On the whole, our results verify that the socio-demographic characteristics had significant impacts on household car ownership. The seniority effects would lead to a decrease of household car ownership. Two results can be observed. First, households in the later stages of the life cycle would own fewer cars. Second, households with a higher proportion of elderly members would have a lower level of car ownership. On the other hand, household in the middle stage of the family life cycle may tend to have more cars, which is owing to better economic ability. The findings in 1995 and 2005 showed that as household heads were in their middle age, they would own more cars. Besides, in 2005 and 2015, the increase of the share of family members aged 50-64 would incline to own more cars due to their better economic ability and postponed retirement. The results manifested that car ownership decisions would be associated with the life course, household structure, and economic ability. The important of the life course in car ownership decisions had been found in the study of Guo *et al.* [39]. They indicated that the temporal interdependencies between life course events would be involved in car ownership decisions. Furthermore, it is evident that travel patterns of different age groups would be diversified [40, 41]. Due to different roles in the life stages, travel purposes change during the life course.

Thus, our findings confirm that household car ownership would vary across different generations. The reasons would be related to the life course, household structure, and income effects. The future trend of car ownership may depend on demographic changes and income effects. The policy implication means that the vehicle management policies should pay attention to decoupling the income effects with car ownership. The demographic changes and generational differences in travel preferences should be considered in urban transportation planning. Moreover, considering the increasing life expectancy and aging population, an important concern in transport planning is to enhance the safety and accessibility of transport services for the elderly.

CONCLUSIONS

The stagnation of car demand had been observed in many countries. A similar phenomenon had emerged in Taiwan in recent years. However, the trends of household car ownership may be diverse across generations. Regarding the trends of car ownership for the households headed by different age groups, from 1985 to 2005, the level of household car ownership had increased for all household groups. However, from 2005 to 2015, households headed by persons aged less than 39 had fewer cars than before. This result may reflect the phenomena of income stagnation. The young-headed households decreased car ownership since their economic ability weakened. Another possible reason is the increasing of aged population. Nowadays, more transportation modes are available for people than before. The emerging of shared mobility, such as car sharing and bike sharing, may change people' travel behaviour and influence car ownership. The impacts of shared mobility on car ownership may also vary across different generation groups. Therefore, it is important to analyse the effects of demographic changes on household car ownership. As Taiwan is facing radical demographic changes, such as low fertility rate, aging population, and household size declining, understanding the possible trend of car ownership in the future would be an essential issue.

In this study, this study employs Poisson regression and quantile regression for count data to analyse how household car ownership would be affected by socio-demographic characteristics and investigate generational differences in household car ownership in Taiwan over the period 1985-2015. The empirical results evidence that the socio-demographic characteristics affected household car ownership. First, households in the later stages of the life cycle would own fewer cars. Households with the middle-aged heads would own more cars due to their better economic ability. Household structure is an important determinant for household car ownership. Households with a higher proportion of elderly members would have a lower level of car ownership. Besides, households with a higher proportion of family members aged 50-64 would have a higher level of car ownership in 2005 and 2015. Second, household income significantly affected household car ownership in each period. The marginal effects of income would increase as the level of household income rose. However, for the past decade, the income effects had decreased due to income stagnation.

To sum up, this study verified that household car ownership would vary across different generations, which would be related to the income effects, the life course, and household structure. Generational differences in household car ownership would be displayed in the following ways: first, in terms of income effects, household car ownership would be induced by the increase of income levels. Particularly, the income effects would be greater for high-income households than low-income households. However, the income effects on household car ownership had exhibited a downward trend. Second, from the perspective of the life course, households in the later life-cycle stages would reduce car demand. But, households with the middle-aged heads owned more cars due to their better economic ability. Besides, younger households had reduced car ownership due to income stagnation for the past decade. Third, as for the effects of household structure, households with a higher proportion of elderly members would reduce car demand. Nevertheless, for the increase in the share of family members aged 50-64 would contribute to a higher level of household car ownership for the past two decades.

Therefore, it can be expected that the seniority effects resulted from population aging may lead to the decreasing trend of car demand. On the other side, households with middle-age heads and high-income levels will increase car ownership due to their better economic ability. Thus, the future trend of car ownership will depend on demographic changes and income effects. The policy implication means that the vehicle management policies should pay attention to decoupling the income effects with car ownership. A high priority would be to provide more incentives for middle-age and high-income people to reduce their dependence on cars. Thus, understanding transport preference and travel behaviour of different groups is essential. Transport service alternatives should be developed in accordance with travel purposes of different groups. The fundamental strategy is to improve the quality and convenience of public transport services. More incentives for public transportation should be provided to attract car users. Urban transportation planning should consider the demographic changes and generational differences in travel preferences. Moreover, as Taiwan has entered the stage of an aged society, an important concern in transport planning is to enhance the safety and accessibility of transport services for the elderly. Seamless transportation and senior-friendly facilities would be crucial for transportation demand management.

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