

Life Events, Car Transaction, and Usage by Car Type: Longitudinal Data from Japan

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Abstract: Car transaction (increase/decrease/replacement) is an important determinant of car usage and other travel behavior affecting economic and environmental issues. The aim of this paper is to analyze the impacts of life events, change in attitude, and perceived train frequency on car transactions and usage change by car type using two three-year data (2011-2013 and 2012-2014) obtained from a Japanese household panel survey. We identified the statistically significant factors that affect car ownership in cross-sectional data and verified that their signs are the same when using longitudinal data. Fewer factors are found to affect car replacement than affect car ownership level change. Households that replace Kei-cars with normal cars do not increase mileage.

Key words: Life events, car transaction, usage, car type, longitudinal analysis.

1. Introduction

Car ownership including type selection is an important determinant of car usage, general travel behavior, and energy consumption. Many studies have been done using cross-sectional data. Cross-sectional data are sufficient for establishing evidence of association. However, this approach is inadequate to establish causal relationships [1]. In recent years, life course analysis has become popular [2]. Life events including migration and employment transition affect car ownership and other travel behaviors [3, 4].

Dargay and Hanly [5] focused on changes in car ownership to analyze the impact of events. Based on the British National Household Survey, they showed that various changes in work status as well as the number of license holders within a household affect change in car ownership. Kitamura [6] developed a dynamic system of simultaneous equations to represent household car ownership, the generation of mechanized trips, and the modal split between private car and public transit, using four waves of Dutch

National Mobility Panel survey data. The lagged dependent variables of these models are very significant and, as anticipated, have positive coefficients. The coefficient of the lagged term is the least for the modal split model, suggesting that mode choice is less stable and more responsive to changes in household characteristics and other contributing factors. Scheiner et al. [2] examined changes in travel mode use after residential relocations, using structural equation modelling. They showed that relocations and associated changes in the built environment induce significant changes in car ownership and travel mode use. Changes in levels of satisfaction with attributes of the built environment have a significant impact. The causal direction of the changes fulfils expectations: suburbanization is followed by increases in car use and decreases in public transport use, bicycle use, and walking. The opposite is true for relocations into the city. In addition, they showed that the changes in household structure that tend to accompany relocations had significant effects. However, income and changes in income are not included in the analysis.

Using data from a retrospective survey that records respondents' car ownership status, as well as their

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residential and household situation over the past 20 years, Oakil et al. [3] show that strong and simultaneous relationships exist between car ownership changes and household formation and dissolution processes. Childbirth and residential relocation invoke car ownership changes. Childbirth is associated with increasing car ownership, whereas the effect of employer change goes the opposite way. Job change increases the probability of car ownership change in the following year. Clark et al. [4] reviewed related studies and showed that different life events are associated with different types of car ownership level changes, based on binary logistic regression models using more than 19,000 samples from the UK Household Longitudinal Survey (2009 and 2011). They used a wide range of change variables and baseline variables, but income and change in attitude were not considered in the analysis.

In Japan, Fukuda and Ito developed a dynamic discrete-continuous model for analyzing households' multiple car ownership and vehicle usage, including Kei-cars with restrictions of engine size and size of the car, using panel data from about 2,300 households [7]. They found that income and gender affected car ownership. However, they could not find clear results regarding usage. They concluded that one of the reasons for this was the unreliability of self-reported mileage data.

Regarding car transaction, Mohammadian and Miller [8] applied a mixed (random parameters) logit model to investigate the effects of heterogeneity in the dynamic transaction model and distinguish between heterogeneity and state-dependence-based explanations for the observed persistence in choice behavior. Change in the number of employed persons and household size affect car transaction. Roorda et al. [9] used the concept of activity/travel stress for vehicle transaction. They found an asymmetry in vehicle transactions, as Pendyala et al. [10], Dargay [11] and Rashidi [12] showed that a larger number of children and number of adults per household living in

dense urban areas can reduce the chance of vehicle transaction, while households with larger vehicle fleet sizes are more likely to make vehicle transactions. The household vehicle transaction hazard seems to be positively correlated with the number of household members who leave the household. Having a longer travel time or activity duration can reduce the desire of households for making a vehicle transaction. In addition, increase in gas price increases the probability of vehicle transaction; interestingly, the effect of a one-unit increase in this case is greater than the case where a household member leaves the household. Job relocation is less likely to trigger a household vehicle transaction decision. Change in household residential location has a positive effect on the transaction decision.

To the best of my knowledge, there are no existing studies that investigate the impact of life events on car transaction (increase/replacement/decrease) behavior by car type. Safety and environmental concerns are also important factors when households choose a replacement car type. In addition, migration is usually only considered across two categories (urban and rural); thus, there are limitations in grasping spatial attributes such as changes in service levels of public transport. Furthermore, change in car mileage by transaction type has also not been discussed [13].

In this paper, making use of household panel survey of Japan, we analyze the following two issues:

- (1) impacts of life events on car transactions by car type; and
- (2) relationship between car transaction and mileage change.

The contribution of this paper is as follows: In addition to changes in numbers of children and adults, we discuss the impacts of income, preference for going out, and perceived train frequency. Furthermore, impact of car transaction by car type on mileage change is analyzed. We discuss two car types: Kei-car and normal car. The Kei-car is a unique Japanese car type that requires less use of materials and is cheaper

and more fuel efficient to run, compared with normal cars.

The structure of this paper is as follows: Sections 2 and 3 provide the methodology and data. Section 4 explains the data. Section 5 presents our findings. We discuss conclusions in Section 6.

2. Methodology

2.1 Impacts of Life Events on Car Transactions by Car Type

Like Clark et al. [4], we use binary logistic regression models to estimate the number of cars in households. In these models, the dependent variable takes the value “1” for the outcome of interest (being in a particular car ownership state in wave one or undergoing a particular car transaction), or “0” otherwise. With the logistic model, a binomial distribution is assumed for the dependent variable together with a log-odds link function, which provides the transformation to a linear model. The resulting logistic regression model can be written as:

$$\text{Prob}(\text{event}) = \frac{1}{1 + \exp(-Z)} \quad (1)$$

where, Z is the linear combination:

$$Z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n$$

and $\beta_0, \beta_1, \dots, \beta_n$ are regression coefficients, while X_0, X_1, \dots, X_n are the independent variables.

In addition to changes in household attributes, baseline variables for household characteristics at wave one are included in the model. Life event variables representing changes in household characteristics between waves one and two are also included. These include moving home and gaining/losing an adult, having children, change in income, preference for going out, and perceived train frequency. Variables are selected at the 10% significance level.

2.2 Relationship between Car Transaction and Mileage Change

Life events not only affect car transactions, but also change the mileages travelled. Accordingly, we face

the so-called endogeneity problem when investigating this relationship. Therefore, in this paper, we apply the IV (instrumental variable) method. In the first stage, we estimate the probability of each car transaction type, using life event and baseline variables; using these estimates, we then estimate the impact of car transaction on mileage change. In addition, as probabilities of car transaction types are not independent, multicollinearity, in which two or more predictor variables are highly correlated, is present. These strong correlations will cause computational instability and the OLS (ordinary least squares) approach no longer provides the best linear unbiased estimator. To avoid this problem, we introduce ridge regression [14].

The ridge regression estimate $\hat{\beta}$ is defined as the value of β that minimizes the following formula:

$$\min_{\beta} \sum_{i=1}^p (y_i - x_i \beta)^2 + \lambda \sum_{j=1}^p \beta_j^2 \quad (2)$$

Here, y_i is the explained variable, in this paper, the change rate of mileage in logarithm form; x are the explanatory variables; and λ is the ridge parameter.

The solution to the ridge regression problem is given by:

$$\hat{\beta} = (X^T X + \lambda I)^{-1} X^T Y$$

Note the similarity to the OLS solution, but with the addition of a “ridge” down the diagonal, I . The value of λ is selected to reduce the variance of the estimates. While the parameters are biased, the reduced variance results in a smaller mean square error when compared with least-squares estimates.

3. Data

Households Panel Survey of Japan, 2011, 2012, 2013, 2014.

Respondents: households that registered with Internet survey company.

Survey items:

- Household attributes: age, size, gender of each household member, household income, and attitudes/lifestyle of household head;

- Perceived service level of public transport;
- Number of cars by car type (Kei-car/normal car);
- Self-reported mileage (up to three cars).

We use households that participated in the survey in both 2011~2013 and 2012~2014 with 1~3 cars as the sample. Table 1 shows the sample by number of cars. Car transaction is focused on mid-year (2012 for 2011~2013 and 2013 for 2012~2014). Mileage change is by comparison with first year and third year.

3.1 Car Types and Transactions

In this study, two car types, Kei-cars and normal cars, are considered in the analysis. Therefore, there are 10 categories of car transactions: no transaction; increase in normal car (+N) and Kei-car (+K); replacement from and to normal car and Kei-car (N→N, N→K, K→N, K→K); decrease in normal car

(-N) and Kei-car (-K); and transactions involving more than two cars (others). In this study, transactions of more than two cars are excluded.

3.2 Explanatory Variables

The explanatory variables used in this study are: gain/loss of adults and children; increase/decrease in income; preference for going out; and perceived train frequency. These are all labeled as dummy variables. Baseline variables include income class (low and high), number of adults (2+ or less), gender of household head, age of household head (60+ or not), preference for going out (strong or less), perceived train frequency (high or low). These are selected based on the pooled data analysis and used as dummy variables 8).

Table 2 shows the number of samples by life events

Table 1 Number of samples by number of cars in Year T and T + 2.

T + 2 T	1	2	3	Total
1	1,713	75	5	1,793
2	233	574	39	846
3	24	49	153	226
Total	1,790	698	197	2,865

Table 2 Number of samples by life events and car transaction (total: 2,865).

#		NO	+ N	+ K	N→K	N→N	K→K	K→N	- N	- K
Adult										
	+	81	12	17	5	28	5	2	6	11
	-	103	2	2	10	18	6	10	19	34
Child										
	+	74	5	7	6	19	5	6	15	13
	-	65	1	3	1	10	3	2	4	8
Income										
	+	185	8	11	12	52	13	14	11	15
	-	314	4	16	22	50	8	16	39	45
Preference for going out										
	+	327	3	11	14	58	12	17	25	39
	-	482	9	20	19	69	12	31	39	43
Perceived train frequency										
	+	303	3	9	14	58	10	19	23	39
	-	325	13	13	15	64	15	23	33	36

and car transactions. Needless to say, there are many households with no car transactions.

Basic statistics of other baseline variables are shown in Table 3. Table 4 shows the total car mileage by number of cars in households. As the mean value is larger than the median, the distribution is skewed. We use logarithms for analysis.

4. Results

4.1 Impact of Life Event on Car Transaction by Number of Cars in Households

Results are shown in Tables 5-7. Explanatory power is not high in any of the models.

4.1.1 Increase in Cars

Both normal cars and Kei-cars increase when households gain an adult.

Increases in normal cars occur when train frequency decreases (1→2) and income increases (2→3).

When train frequency is high, Kei-car increase is not likely to happen.

4.1.2 Car Replacement (Same Car Ownership Level)

4.1.2.1 One-Car Households

Replacement to normal car from Kei-car is unlikely to happen, while replacement to and from normal car is likely to happen when the household head is more than 60 years old.

Table 3 Shares of categorical variables at baseline (total: 2,865).

Variable	Categories	Share (%)
Age of household head	60+	44.0
Income	10+(mil. JPY/year)	10.2
Perceived train frequency	6+/hour	29.3

Table 4 Basic statistics of total car mileage (km/year) by number of cars in households.

Number of cars	Min.	1st quantile	Median	Mean	3rd quantile	Max	Std. Dev.
1	1,050	4,000	6,000	7,449	10,000	38,900	4,660
	1,100	4,200	6,800	8,032	10,000	38,900	5,578
2	1,700	10,000	14,000	15,770	19,300	69,000	8,335
	1,100	8,200	13,000	14,500	19,000	58,500	8,495
3	4,500	16,000	22,500	23,260	28,000	57,000	10,066
	1,400	11,000	18,000	19,070	25,000	55,000	10,750
All	1,050	5,000	9,000	10,880	14,500	69,000	8,033
	1,100	5,000	8,500	10,640	14,000	58,500	7,847

Upper: T; Lower: T+2.

Table 5 Estimation results (1-car households).

Upper: coefficient Lower: (z-value)		+N	+K	N→N	N→K	K→N	K→K
Adult	+	1.68 (3.42)	1.73 (4.71)		0.49 (1.83)		
Income	+				0.39 (1.76)		
Going out	—						0.57 (1.74)
Train frequency	—	1.33 (3.13)					
Base-line	Train freq.(H)		−0.79 (−1.87)				
	Aged HH			0.66 (2.29)		−0.96 (−2.02)	
Intercept		−5.01 (−15.91)	−3.81 (−19.04)	−3.56 (−16.48)	−1.85 (−19.14)	−2.36 (−10.35)	−2.26 (−11.58)
Number of samples		1,793	1,793	1,377	1,377	416	416
Residual deviance		227	369	437	1,100	195	286
Null deviance		246	391	443	1,109	200	289

Table 6 Estimation results (2-car households).

Upper: coefficient Lower: (z-value)	+N	+K	N→N	N→K	K→N	K→K	-N	-K	
Adult	+	4.50 (4.11)	1.58 (3.23)	0.99 (1.75)					
	-			-0.96 (-1.82)				1.27 (3.84)	
Child	-						0.55 (1.72)		
Income	+	1.49 (1.78)		0.63 (2.22)	0.95 (2.05)		-0.76 (-1.97)		
Intercept		-7.03 (-6.68)	-3.70 (-15.94)	-3.49 (-15.77)	-2.04 (-15.98)	-3.20 (-13.69)	-2.68 (-15.6)	-1.77 (-15.47)	-1.77 (-14.18)
Number of samples		846	846	765	765	561	561	765	561
Residual deviance		51	217	218	549	207		619	487
Null deviance		81	225	220	558	211		626	501

Table 7 Estimation results (3-car households).

		N→N	N→K	K→N	K→K	-N	-K
Adult	+			3.12 (2,84)			
	-						1.11 (2.23)
Baseline	Train freq.(H)		1.34 (2.62)				
Intercept		-3.98 (-7.88)	-2.39 (-9.14)	-5.13 (-5.11)	-2.44 (-9.06)	-2.29 (-9.45)	-2.44 (-8.09)
Number of samples		217	217	187	187	217	187
Residual deviance			141	25			123
Null deviance		39	147	31	104	133	127

Replacement from normal car to Kei-car is likely to happen with a gain in adults and an increase in income.

Kei-car replacement (to and from Kei-car) is likely to happen when households show less preference for going out. However, as the number of samples is limited, we need further investigation.

4.1.2.2 Two-Car Households

Normal car replacement is likely to happen when a household gains an adult. Replacement from normal car to Kei-car is unlikely to happen when losing an adult.

Interestingly, replacement from normal car to Kei-car is likely to happen when income rises.

Replacement from Kei-car to normal car is likely to happen when income rises.

We could not find any variables that significantly affect Kei-car replacement.

4.1.2.3 Three-Car Households

We could not find variables that significantly affect

Kei-car and normal car replacement. One reason for this is small sample sizes. Replacement from normal car to Kei-car is likely to happen in households that live in perceived high train frequency areas. Replacement from Kei-car to normal car is likely to happen when a household gains an adult.

4.1.3 Decrease in Cars

4.1.3.1 Two-Car Households

Decrease in normal car is likely happen with loss of a child and unlikely to happen with decrease in income.

4.1.3.2 Three-Car Households

Decrease in Kei-car is likely to happen when losing an adult.

4.2 Total Mileage Change Rate by Transaction Categories

Using the predicted value of these car transaction models, we estimated the change in mileage by car

transaction type (Table 8). Losing an adult and decreasing household income affect the mileage as well as the car transaction. Other change and baseline variables are not statistically significant. Car ownership level change affects mileage change. However, car transaction without a change in car ownership level does not affect mileage change. We cannot say that moving from(to) normal car to(from) Kei-car does not affect mileage. In addition, the impact of increase and decrease in cars on mileage are asymmetric. When cars increase, the impact of Kei-car is larger than normal car, but when they decrease, normal car has a greater impact than Kei-car.

5. Discussion

5.1 Life Events

Factors that affect car ownership in cross-sectional data are also statistically significant and the signs are the same as when using longitudinal data. Though the number of samples is limited, some asymmetric results are observed, which is not confirmed when

using cross-sectional data.

Gaining and losing an adult strongly affect car ownership levels. In particular, Kei-car is likely to increase when gaining and decrease when losing an adult, regardless of number of cars.

Change in income also affects various car transactions, especially normal car transactions. Households tend to increase and decrease normal cars together with increases and decreases in income. However, Kei-car ownership levels are not affected by income.

Loss of an adult and a decrease in income also affect mileage.

Losing a child effects a decrease in normal car in two-car households. On the other hand, gaining a child did not affect any car transactions. These results are quite different from previous studies [3, 4]. This might be caused by differing definitions of children. If we distinguish between preschoolers (kindergarteners) and others, these results may change.

Change in preference for going out and perceived train frequency do not affect replacement.

Table 8 Total mileage change rate by transaction categories.

	Estimate	t-value	
— N	-0.26	3.87	***
— K	-0.19	2.62	**
K→N	-0.07	0.93	
N→K	-0.06	0.77	
N→N	-0.05	0.67	
K→K	-0.02	0.35	
+ N	0.07	1.08	
+ K	0.14	2.01	*
adult -	-0.14	2.27	*
income -	-0.15	2.29	*
ridge parameter		0.17	
variance		6.48	
residual		9.94	

Table 9 Summary of car transaction by number of owned cars.

		+N	+K	N→N	N→K	K→N	K→K	-N	-K
Adult	+	+	+	0 +0	(+)0 +				
	-				0 (-)0				+
Child	-							+ 0	
Income	+	0 +			(+) + 0	0 + 0			
	-							+ 0	
Going out	-						+ 0 0		
Train frequency	-	+ 0							
Baseline	Train freq.(H)		- 0		0 0 +				
	Aged HH			+ 0 0		- 0 0			

+: likely happen; -: unlikely happen; 5% significance; (): 10% significance.

5.2 Baseline Conditions

In one-car households and households whose head is more than 60 years old, car replacement from and to normal car is likely to happen, but unlikely to happen from Kei-car to normal car. In addition, households where the perceived train frequency is high, are unlikely to increase in Kei-cars. However, there were no variables that affect car transaction in two-car households.

Income level and preference for going out are not related to car transaction.

6. Conclusions

In this paper, the author analyzed the impacts of life events and change in attitude and perceived train frequency on car transactions and usage change by car type using household panel data. It is shown that the factors that affect car ownership in cross-sectional data are also statistically significant and the signs are the same when using longitudinal data. Fewer factors are found to affect car replacement than affect car ownership level change. Households that replace Kei-car with normal car do not increase mileage (Table 9).

Of course, there are many limitations to this study. One reason for the low explanatory power of the models is small sample sizes. As car transactions and life events are rare in a year, it needs a large number of samples for the analysis. In addition, it is assumed that the impacts of life events occur within a year. In

fact, however, they may take more than a few years. For example, the impact of childbirth on car ownership is felt not in the birth year, but when the child starts to commute to kindergarten/preschool. Time delays may be important for this analysis. In addition, car age should be included in the transaction analysis. Hazard analysis might also be useful [12]. The factors that cause preference and perceived train frequency change (including relocation) can be ignored. Structural equation modeling might be useful to express interactions among behavior and preferences/attitudes/lifestyles.

For policy analysis, exogenous variables such as gas and car price changes should be included [5, 12, 15].

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