**Changes in Car Ownership due to Life Events: Insights from the UK Longitudinal Household Survey**

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## SHORT SUMMARY

The decision of how many vehicles should a household have –if any– is likely to depend on life events that change the transport requirements of the household, such as the birth of a child, the change of employment status, a significant income variation, or a child moving out of the household to start living in another one. In this paper, we model changes in car ownership level as a function of socioeconomic individual and household attributes, as well as significant life events using a large sample of UK households sourced from the Understanding Society survey. We estimate a discrete choice model with specific parameters for increasing or decreasing car ownership levels and considering panel and dynamic effects. Results show that life events play a significant role in predicting car ownership levels, and that households are relatively stable over time in terms of car holdings.

**Keywords:** Car ownership, Discrete choice models, Life events, Longitudinal survey, Panel data

## 1. INTRODUCTION

The decision of how many vehicles should a household have –if any– is likely to depend on socioeconomic, environmental, and accessibility attributes (de Jong *et al.*, 2004 and Anowar *et al.*, 2014), and also on life events that change transport requirements, such as the birth of a child, the change of employment status, a significant income variation, or a child moving out of the household to start living in another one. A large part of the car ownership literature has adopted a cross-sectional approach, analysing the number of vehicles in a household at a specific point in time. Despite its relevance, the key effect of life events has been much less frequently studied, likely because of the lack of suitable longitudinal datasets that allow following household decisions over time.

In this paper, we model changes in car ownership level as a function of socioeconomic individual and household attributes, as well as significant life events, using a large sample of UK households sourced from the Understanding Society survey (University of Essex *et al.*, 2020). This survey has previously been used in the transport context. Whittle *et al.* (2022) use this data analyse transport mode frequency changes triggered by life events, focusing on individual behaviour. They do not study car ownership at the household level. Clark *et al.* (2016), on the other hand, model car ownership changes in UK households, but they only make use of the first two waves of the Understanding Society survey. Additionally, they study the effects of the two possible outcomes (increasing or decreasing car holdings) using independently estimated models, as opposed to a single specification, which allows for a proper representation of the dynamics. This approach has surprisingly been followed in other studies in different contexts (Prillwitz *et al.*, 2006; Oakil *et al.*, 2014).

We take advantage of the richness of our dataset and estimate a single discrete choice model with specific parameters for increasing or decreasing car ownership levels. Furthermore, we estimate additional parameters to analyse potential differences due to the current car ownership level, as it would be expected that, for example, the increased utility drawn from buying an additional vehicle differs from what the household would get from purchasing their first car. To our knowledge, this is the first study to estimate a single discrete choice model that simultaneously accounts for all these effects.

We estimate an error component model with systematic heterogeneity in the preferences, which accounts for the panel effects, i.e., correlations due to the dataset containing repeated observations from the same unit of analysis. In addition, we investigate possible dynamic effects in consecutive choices, incorporating lagged choice variables as explanatory attributes in the utility functions, and correcting for possible endogeneity.

## 2. METHODOLOGY

We rely on data sourced from the Understanding Society survey, a UK-based household longitudinal survey that collects information about social, economic, and behavioural variables, including some transport behaviour questions (University of Essex *et al.*, 2020). The survey follows a large sample of individuals over time, with each observation point defined as a "wave". We define respondents of wave 9 (2018) as the initial household set and work backwards to identify their corresponding household in every previous wave. Our processed dataset contains 10,067 households. The main household attributes remain relatively stable over time, with mean car ownership almost invariant (1.32 cars per HH in the last wave), and the average household size showing a slight 3.3% decrease between waves 1 and 8. Household attributes from wave 1 were used as baseline variables in the discrete choice models.

Inter-wave "life events" were identified by comparing each wave with the previous one. The main household-based inter-wave life events identifiable from the sample are:

- Car ownership changes.
- Household structure changes: Variations in the number of adults and children in the household.
- Residential relocation: Change of address between waves. Some relocations can be further identified as long-distance moves (switching regions), urban to rural moves, and rural to urban moves.
- Income changes between waves.
- Household splits: Household members appear in different households in the next wave.

Similarly, the main personal inter-wave life events are:

- Partner gains and losses.
- New-born child.
- Employment changes: Employment start, Employment exit, Employment switch, Retirement.
- Driving licence acquisition.

On average, 16.2% of households change their level of car ownership between any two waves. The most frequent life events are changes in employment (12.1%) and household composition

(11.3%), while residential relocations (4.3%), childbirths (2.3%) and partner gains and losses (2.1%) are scarcer.

To model the decision of changing the number of vehicles on each household we assumed that, during inter-wave period *t*, each household *h* faces three alternatives *j*:

- Keeping the number of vehicles in the household constant ($j = 0$).
- Increasing the number of vehicles in the household ($j = 1$).
- Decreasing the number of vehicles in the household ($j = 2$).

We defined the systematic utility that household $h$ derives from choosing alternative *j* during period *t* as follows:

$$\begin{aligned} V_{0ht} &= \alpha_0 \\ V_{1ht} &= \alpha_1 + \sum_{k=1}^{K} \beta_{1k} \cdot X_{kht} + \sum_{l=1}^{L} \theta_{1l} \cdot Y_{lh} \\ V_{2ht} &= \alpha_2 + \sum_{k=1}^{K} \beta_{2k} \cdot X_{kht} + \sum_{l=1}^{L} \theta_{2l} \cdot Y_{lh} \end{aligned} \tag{1}$$

Here, $X_{kht}$ is the value of attribute *k* for household *h* during period *t*. These *K* attributes are inter-wave changes. Analogously, $Y_{lh}$ is the value of attribute *l*, one of the *L* baseline attributes that characterise the initial condition of household $h$ in the dataset. Since, for each household and period, these attributes have the same value across all alternatives, we estimate 2 $(K + L)$ alternative-specific parameters $\beta_{jk}$ and $\theta_{jl}$, as well as the alternative-specific constants $\alpha_j$. Sensitivities to the attributes might not be constant across the population and, furthermore, the current car ownership level might influence their relevance. We investigate this effect using systematic taste variations (Ortúzar and Willumsen, 2011) in the inter-wave parameters $\beta_{jk}$. When estimating these effects, we use households with one car as the reference level.

Next, to address the correlation between observations from the same household in different waves, we define the net utility of this model as:

$$U_{jht} = V_{jht} + \lambda_{jh} + \varepsilon_{jht} \tag{2}$$

Here, the error term has two components: $\varepsilon_{jht}$ are i.i.d. extreme value (EV) type 1 error terms and $\lambda_{jh} = \sigma_j \eta_h$, known as the *panel effect*, varies across individuals but not across waves. We assume that the $\eta_h$ terms are Normal (0,1) distributed error components for each household *h*, which capture the correlation between observations from the same household. $\sigma_j$ are alternative-specific parameters to be estimated. The described model (**Model 1**) is an error component model with systematic heterogeneity in the preferences. Following Walker *et al.* (2007), the panel data structure allows estimating the three alternative-specific variances.

In a second specification (**Model 2**) we deal with the time sequence of household choices in a dynamic model. First, we assume that the choice at time $t$ partly depends on choice at $t - 1$ only (dynamic process of order 1), that this dependence is household-specific (i.e., it only depends on previous choice of the same household), and that the weight of this dependence, $\rho$ is the same for every household (Danalet *et al.*, 2016). The net utility of this model becomes:

$$U_{jht} = V_{jht} + \lambda_{jh} + \rho y_{jh,t-1} + \varepsilon_{jht} \tag{3}$$

Here, $y_{jh,t-1}$ is a dummy variable that takes the value 1 when household $h$ chooses alternative $j$ at time $t-1$. As explained by Woolridge (2005), this modelling structure introduces endogeneity due to correlation between the lagged variable $y_{jh,t-1}$ and the unobserved factors $\varepsilon_{jht}$. This phenomenon, called the initial conditions problem, must be corrected to obtain consistent parameters. Following the method proposed by Woolridge (2005) and implemented in Danalet *et al.* (2016), we model the panel effect term as follows:

$$\lambda_{jn} = \lambda_2 + \gamma \cdot y_{jh2} + \tau \cdot {y_{jht}}^{count} + \xi_{jn} \tag{4}$$

Here, $y_{jh2}$ is the choice that household $h$ makes in the first inter-wave period (for most households, $t = 2$, or the period after wave 1), while ${y_{jht}}^{count}$ is the count of previous choices of alternative $j$ up to time $t$ (but not including the choice at time $t$). The inclusion of these terms addresses the endogeneity issue. Finally, $\lambda_2$, $\gamma$ and $\tau_m$ are coefficients to be estimated and $\xi_{jn}$ is the panel effect term.

Since the initial choice is used in the panel effect and this specification considers the trajectory of consecutive choices by the household, we can only model choices from inter-wave period $t = 1$onwards. In our case, this means that the decision of changing car ownership level between waves 1 and 2 is not modelled.

## 3. RESULTS AND DISCUSSION

For clarity, we split the modelling results in two tables. Table 1 presents the main life events coefficients for both estimated models and Table 2 details the goodness-of-fit indicators and the main validation results. For space reasons, we omit the baseline coefficients.

The main life event effects have the expected signs in both specifications. Increasing the number of adults in the household has a positive effect on the probability of acquiring an additional car, although this effect is more relevant for 1-car households than for carless households or those with 2 or more vehicles. Conversely, a higher number of adults tends to reduce the likelihood of discarding a car, with the effect being more significant in households with 2 or more cars. An increase in the number of kids in the household between two waves tends to increase the probability of buying an additional car and reduce the likelihood of discarding one.

As previously found in several studies, the effect of residential relocation in car holdings is mixed. The probability of buying an additional car increases after a house move for carless households and those with just one car and decreases for households with two or more cars. Car dependency has been shown to exist in rural areas where the access of alternatives to the private car is limited (e.g., Zhao and Bai, 2019; Carroll *et al.*, 2021), and our results show that moving from an urban to a rural setting significantly increases the probability of adding a vehicle to the household. Conversely, relocating from an urban to a rural area appears to have the opposite effect, making it more likely that the household discards one of their vehicles. A long-distance move positively influences a reduction in car holdings. As expected, a household split is significantly tied to a reduced car ownership level. This is likely explained by the splitting households sharing the vehicles that originally belonged to the “parent” household, or at least one of them becoming a carless household as a result of the split.

The effects of employment change depend strongly on the current ownership level in the household. Entering employment has a clear and significant positive effect in the likelihood of buying an additional car only for carless households and those with 1 car, but the effect is not significant for households with 2 or more vehicles. Similarly, an employment switch seems to both increase the likelihood of buying an additional car *and* reduce the probability of discarding one; however, the effect is opposite for households with 2 or more cars. On the other hand, as expected, job losses and retirement seem to be positively correlated with car disposals.

### Table 1. Model results I – Life events coefficients

| Attribute | Unit | Model 1: Panel effect, static | | | | Model 2: Panel effect, dynamic | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | 1: Increase | | 2: Decrease | | 1: Increase | | 2: Decrease | |
| | | **Coef.** | **t-test (0)** | **Coef.** | **t-test (0)** | **Coef.** | **t-test (0)** | **Coef.** | **t-test (0)** |
| Alternative specific constant | – | -3.541 | -22.90 | -1.866 | -12.17 | -4.297 | -31.73 | -2.352 | -13.68 |
| *Household size* | | | | | | | | | |
| Adult number increase | *Reference* | 0.992 | 9.88 | -0.691 | -8.02 | 0.983 | 8.45 | -0.626 | -6.38 |
| | *0 car HH* | -0.613 | -3.71 | – | – | -0.521 | -2.93 | – | – |
| | *2+ car HH* | -0.616 | -4.73 | -1.326 | -11.76 | -0.581 | -3.66 | -1.366 | -10.50 |
| Children number increase | *Reference* | 0.447 | 5.05 | -0.540 | -5.78 | 0.563 | 5.77 | -0.489 | -4.51 |
| | *2+ car HH* | -0.310 | -2.65 | – | – | -0.305 | -2.17 | – | – |
| *Residential relocation* | | | | | | | | | |
| Residential relocation | *Reference* | 0.503 | 3.76 | – | – | 0.303 | 1.96 | – | – |
| | *2+ car HH* | -0.973 | -4.14 | – | – | -0.719 | -2.65 | – | – |
| Urban to rural move | – | 0.947 | 4.42 | – | – | 1.321 | 5.41 | – | – |
| Rural to urban move | – | – | – | 1.052 | 4.01 | – | – | 0.851 | 2.67 |
| Long distance move | – | 0.271 | 1.41 | 0.705 | 3.64 | 0.444 | 2.00 | 0.865 | 3.85 |
| Household split | – | – | – | 0.389 | 1.60 | – | – | 0.398 | 1.38 |
| *Personal life* | | | | | | | | | |
| Partner gain | *Reference* | 1.744 | 12.01 | – | – | 1.926 | 11.02 | – | – |
| | *2+ car HH* | -1.720 | -5.55 | – | – | -2.044 | -5.29 | – | – |
| Partner loss | – | – | – | 0.507 | 5.95 | – | | 0.613 | 6.16 |
| *Employment status* | | | | | | | | | |
| Enter employment | *Reference* | 0.643 | 6.71 | – | – | 0.590 | 5.35 | – | – |
| | *2+ car HH* | -0.932 | -5.96 | – | – | -0.721 | -3.96 | – | – |
| Exit employment | – | – | – | 0.392 | 4.05 | – | | 0.334 | 3.01 |
| Retired | – | – | – | 0.330 | 3.20 | – | | 0.371 | 3.25 |
| Switch employment | *Reference* | 0.627 | 7.26 | -1.247 | -5.72 | 0.524 | 5.07 | -1.323 | -5.02 |
| | *2+ car HH* | -0.751 | -6.10 | 1.597 | 6.90 | -0.564 | -3.78 | 1.634 | 5.87 |
| *Transport* | | | | | | | | | |
| Licence acquisition | *Reference* | 1.093 | 6.42 | – | – | 1.284 | 5.46 | – | – |
| | *0 car HH* | 1.316 | 4.80 | – | – | 1.217 | 3.31 | – | – |
| *Income level* | | | | | | | | | |
| Income increase (x £1,000) | – | 0.101 | 8.63 | – | | 0.078 | 8.38 | – | – |
| Income decrease (x £1,000) | – | – | – | 0.046 | 5.12 | – | – | 0.055 | 5.53 |

Acquiring a driving licence has been widely acknowledged as a major transport milestone, and an important predictor of car ownership increase (Clark *et al.*, 2014; Clark *et al.*, 2016; Rau and Manton, 2016). Our models show that this effect is significant for all households, but more than doubled for those without a car. Partner loss is associated with a decrease in car ownership and, conversely, gaining a partner contributes to increase the probability of acquiring an additional car, but only in households with less than 2 vehicles. Finally, family income changes have a significant effect on car ownership variations, but the effect is not symmetric. We found that an increase in income influences the likelihood of buying an additional car, while a reduction in the same amount has a *lower* effect on the probability of discarding a vehicle.

**Table 2. Model results II – Panel/dynamic coefficients, model fit, and validation**

| Attribute | Model 1 | | Model 2 | |
|---|---|---|---|---|
| | **Coef.** | **T-Test** | **Coef.** | **T-Test** |
| *Panel and dynamic coefficients* | | | | |
| Panel effect – Base alternative | 1.062 | 41.69 | 1.576 | 41.04 |
| Panel effect – Increase | -0.012 | -1.82 | -0.028 | -1.03 |
| Panel effect – Decrease | -0.003 | -0.54 | -0.018 | -1.12 |
| Previous choice ($\rho$) | – | – | -0.895 | -13.46 |
| First choice ($\gamma$) | – | – | -0.204 | -3.88 |
| Choice frequency ($\tau$) | – | – | -0.708 | -15.78 |
| *Model fit* | | | | |
| Number of households | 7,080 | – | 7,051 | – |
| Number of observations | 48,930 | – | 41,838 | – |
| Log-likelihood (0) | -50,380 | – | -43,063 | – |
| Log-likelihood (k) | -26,183 | – | -22,044 | – |
| Log-likelihood (*) | -22,001 | – | -18,385 | – |
| Adjusted rho index (0) | 0.562 | – | 0.571 | – |
| Adjusted rho index (k) | 0.157 | – | 0.163 | – |

Table 2 shows that there is a significant correlation between observations by the same household, as shown by the significant variances of the error term for the base alternative in both models. However, only Model 2 considers the trajectory of household choices over time (e.g., the dynamic effect). The three dynamic parameters are significant and have the expected signs as they all point to a stability of car ownership levels. In particular, the probability of purchasing an additional car in wave $t$ is strongly *reduced* if the household already bought an additional vehicle in time $t - 1$. Similarly, the household is much less likely to discard a car if they already did so in the previous wave. Households are also less likely to change their car ownership status if they have done so in the past, which is the main reason why both the choice frequency and the first-choice parameters are negative and statistically significant in explaining choice over time. The dynamic effects appear to reflect the fact that the number of car households tends to be very stable over time, that changes are mostly induced by significant life events, and that they are unlikely to be repeated.

## 4. CONCLUSIONS

Using a highly detailed panel dataset from a nationally representative longitudinal survey, which followed a large sample over a period of 9 years, we estimated choice models to explain changes in car holdings in UK households. The results show that important life events related to household size and structure, employment status, income level changes, transport milestones, and other personal events, can help understanding the decision to increase or decrease vehicle holdings in households.

Our models account for correlation between observations from the same household over time, and our preferred specification (Model 2), also considers dynamic effects. All these are significant in explaining car ownership level changes, and their sign confirms that households are relatively stable over time in terms of car holdings, and they are unlikely to change their car ownership status if they have previously done so. Although both modelling frameworks allow obtaining robust parameters to understand car ownership level change, the dynamic specification shows a slightly improved explanatory power.

It could be argued that life events can also trigger vehicle replacements, which involve substitutions of fuel type, vehicle segment, and even make and model. In addition, a specific life event can also disrupt car use. However, the available dataset is not transport-specific and does not include these variables. In addition, the modelled events are likely not the only causes of changes in car ownership levels. Health-related issues, personal circumstances, and school relocations are examples of variables that cannot be sourced from the sample. Similarly, the decision of buying a car might also be influenced by personal beliefs, attitudes, and social norms, aspects that are absent from the survey.

Our results confirm that plans directed at tackling the increase of the number of cars must not only consider economic measures, but also how to provide access to transport alternatives. The effect of residential location is telling in this respect, as the provision of better transport links might reduce the need of buying a car when moving to a rural setting. Increases in car ownership should not be considered as the only response to changes in the life cycle, or an inevitable consequence of economic growth. The focus should be on offering more sustainable transport opportunities that allow satisfying these needs without relying on additional vehicles, especially considering their adverse environmental and social effects.

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