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Dynamic Models of Car Ownership at the Household Level

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by

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Abstract[1]:

A large number of studies have relied on macro time series or micro cross section data to analyse the demand for car ownership. In this study we analyse a unique micro panel with observations on car ownership and socioeconomic characteristics at household level during a ten year period. The data show very strong persistence in households' car ownership over time. Dynamic logit models with unobserved heterogeneity are estimated using the estimation approach recently suggested by Wooldridge. Results show that the persistence in car ownership should mainly be attributed to state dependence, while unobserved heterogeneity is less important. Small income elasticities with respect to car ownership are found when taking into account the panel nature of the data.

JEL codes: C33, C35, D12 and R41

Key words: Micro panel data, Car ownership, State dependence, Dynamic logit model.

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1. Introduction

Casual observations suggest that there is strong persistence in car ownership – once a car owner always a car owner – though there are rarely data available at the micro level to confirm this intuition, see e.g. Dargay and Vythoulkas (1999). However, in order to make reliable forecast of changes over time in car ownership at household level it is important to obtain estimates of the magnitude of the persistence.

In this paper we analyse panel data on car ownership at the household level to describe the level of persistence over time in car ownership. The analysis confirms that households owning a car in one year are also more likely to have a car in the following year. It has been recognised in the econometric literature (Heckman, 1981) that there may be two different explanations for such a phenomenon. One explanation is that past car ownership has impacts on preferences or economic constraints that influence future car ownership. This is described as "true" state dependence. Another explanation for the persistence in car ownership is that households may differ in certain unobserved characteristics or variables that influence their probability of car ownership. If these unobservables are correlated over time – and not controlled for – past car ownership will be correlated with future car ownership. Examples of such unobserved variables could include the taste of the decision-maker in the household or unobserved factors that influence the need for car ownership e.g. distance to shopping, schools or availability of other transport alternatives etc. Correlation between past and future car ownership derived from unobserved variables (i.e. unobserved heterogeneity) is generally labelled "spurious" state dependence.

The two different sources of persistence have different implications for household responses to policies. For example, say that the persistence in car ownership derives from true state dependence, because households with a car get addicted to the comfort of car ownership, while households without a car get more and more dedicated to the merits of public transport or bicycling (i.e. preferences are changed). In this case a shock that changes level of car ownership (due to say an aggressive policy against or in favour of car ownership) will have long-run impacts on the level of car ownership, but the effect will appear gradually. On the other hand, say that the persistence derives from differences in the taste for car ownership (spurious state dependence). In this case the household will respond immediately to a policy shock.

To distinguish between the different natures of state dependence we estimate dynamic discrete choice models with unobserved heterogeneity following the method proposed by Wooldridge (2002a). Estimation is based on a large representative panel database of Danish households with annual information about car ownership at the household level. The data base is constructed by merging information on car ownership, income and other socioeconomic characteristics from different official Danish registers for the period of 1992 to 2001. Most previous studies on car ownership have either been based on aggregate or micro cross-section data. Pseudo panels have been applied as substitutes to micro panels to study the dynamics of car ownership (e.g. Dargay and Vythoulkas, 1999 and Dargay, 2001).[2] In pseudo panels the mean of the variables of age cohorts is treated as the observations. However, pseudo panels do not reveal the persistence in car ownership at household level and it is therefore impossible to use such data to separate between true and spurious state dependence.

Some previous studies have applied micro panel data to describe the car ownership decision using binary or ordered probit/logit models (e.g. Golob, 1990; Kitamura & Bunch, 1990 and Meurs, 1993), while others have used micro panels to model the duration of car ownership based on hazard functions (e.g. Yamamoto & Kitamura, 2000). However, to our knowledge all previous micro panel studies rely on information collected from surveys or travel diaries. Such survey panels cannot be considered as representative for the whole population due to problems with non-participation (self-selection) and/or attrition over time. In addition, due to the cost of data collection survey panels are often relatively small and available only for a short time period. With a panel collected from official registers the (variable) costs of increasing the sample are very limited, non-response is not present and attrition is limited to "natural" causes like death and emigration.

Different results/assumptions with respect to the nature of state dependence have been obtained in the previous micro panel studies. Kitamura and Bunch (1990) used an ordered probit model with lagged car ownership (true state dependence) and unobserved heterogeneity parameterized by a normal distribution. When estimated in separate models significant effects of both heterogeneity and true state dependence were found, but when estimated simultaneously unobserved heterogeneity was insignificant.[3] In contrast, Meurs (1993) simply assumed that the persistence in car ownership should be explained by unobserved heterogeneity, while a number of early discrete choice transport studies from the 1980s used a lagged endogenous variable (treated as an exogenous variable), but without considering that the persistence in choice could derive from unobserved heterogeneity (see Kitamura & Bunch (1990) for a closer description of these studies).

We estimate separate logit models for car ownership with (true) state dependence and normally

[2] See e.g. Dargay and Vythoulkas (1999) for a discussion for the pros and cons of different data types.

[3] In a specification of unobserved heterogeneity that is similar to the one we apply (time invariant random effect). However, Kitamura and Bunch (1990) examine different specifications of the unobserved heterogeneity. In some specifications the unobserved heterogeneity is significant along with state dependence, but state dependence appears to be the more important of the two when comparing the goodness of fit of the alternative models.

distributed random effects for single males, single females and households with two adults using balanced panels from 1992 to 2001 for a five digit number of different households (in each group). The models are estimated using the approach suggested by Wooldridge (2002a). Results show that both state dependence and unobserved heterogeneity significantly contribute to the observed persistence in car ownership. However, it also appears that the contribution from state dependence is more important than unobserved time invariant heterogeneity. Furthermore, when comparing results from pooled cross section models not taking into account the panel nature of the data with results from panel models, it appears that income elasticities are considerably higher in the cross section models. This suggests that the short-run income elasticity is considerably lower than the long-run income elasticity. The short-run income elasticity is also lower than typically found in studies based on macro data.. Elasticities to car cost could not be identified in the pooled cross section models, but in the panel models elasticities to car cost range from -0.09 to -0.24.

In the next section we describe the models to be estimated. The data are described in section 3. Estimation results are presented in section 4, while estimates of average levels of state dependence and elasticities with respect to income and car cost are discussed in section 5. Section 6 contains a short summary and conclusion.

2. Description of models

Separate car ownership models will be estimated for households with one adult (single males and single females) and households with two adults (couples). This facilitates that the dynamic process and the income responses can be heterogeneous across these household types. For singles the binary choice between 0 or 1 car is the most appropriate because multiple car ownership is only observed in rare cases. Couples may choose between either 0, 1 or 2 cars. In order to ease comparison with the binary models for singles we make the simplifying assumption that the couples make independent decisions with respect to 0 or 1 car and with respect to 1 or 2 cars (conditional on car ownership), so that (separate) binary models can be used to model car ownership also for couples. Similar simplifying assumptions have been used by e.g. Meurs (1993).[4] Although the simplified treatment of multiple car ownership can be questioned it is convenient when we later compare estimates of the magnitude of the state dependence following Wooldridge (2002a).

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[4] Alternative models to describe multiple car ownership are the ordered probit/logit model (used by e.g. Kitumara and Bunch, 1990) or the multinomial logit models, but there are also restrictions imposed by these models. For example, the ordered logit/probit would use a single index function to describe level of car ownership, so that explanatory variables have the same effect (on the index) for 1 and 2 cars.

The binary car ownership model for 1 versus 0 car can be described as follows (and with a slight change in interpretation the model applies to the case of 2 versus 1 car conditional of car ownership). The variable y_{it}^* denotes a continuous latent car ownership variable for household i at time t (from $0\ldots.T$). Note that y_{it} is 1 if $y_{it}^* > 0$ (else we observe $y_{it} = 0$). A standard binary model with a constant term α_0, explanatory variables x_{it} and parameter coefficient β is the *logit model* given below, where the error term ε_{it} is independent extreme value distributed:

$$y_{it}^* = \alpha_0 + \beta x_{it} + \varepsilon_{it} \tag{1}$$

The simple logit model in (1) does not take into account the panel nature of the data. With repeated observations for each household it is possible to model unobserved time invariant heterogeneity in car ownership between households by including a normally distributed random effects term (v_i). This term could be interpreted as differences in households' "taste" or "need" for car ownership derived from unobserved factors. The *random effects (RE) logit* model is given as:

$$\begin{aligned} y_{it}^* &= \alpha_0 + \beta x_{it} + v_i + \varepsilon_{it} \\ v_i &\sim \text{iid Normal}\left(0, \sigma_v^2\right) \end{aligned} \tag{2}$$

One way to include dynamics (state dependence) in the random effects logit model above is to include the observed lagged dependent variable (assuming the dynamics follow an AR(1) process) in the model as regressor with coefficient ρ: ρy_{it-1}. However, this yields the so-called initial conditions problem of how to handle the initial observation y_{i0}. One possibility would be to assume that y_{i0} is a fixed exogenous variable. However, this is an implausible assumption. If $y_{i1\ldots}\ y_{iT}$ is a function of unobserved time invariant heterogeneity then the initial value (y_{i0}) can also be expected to be a function on the unobserved heterogeneity. Wooldridge (2002a) suggests a simple solution to the initial conditions problem. Instead of modelling the joint distribution of all outcomes he instead proposes to model the distribution of $y_{i1\ldots}\ y_{iT}$ conditional on the initial value. In practice this amounts to including y_{i0} as an additional regressor.[5] This yields the following *RE logit model with state dependence* (conditioning on the initial value of y_{i0}).

[5] We use a simplified version of the approach suggested by Wooldridge (2002a). Thus, he also conditioned on the observed history of the exogenous explanatory variables. However, in our case inclusion of variables for the history of some explanatory variables in preliminary regressions indicated that these generally were insignificant and could be excluded

$$y_{it}^{*} = \beta x_{it} + \rho y_{i,t-1} + \alpha_0 + \alpha_1 y_{i0} + v_i + \varepsilon_{it}$$
$$v_i \sim \text{iid Normal}\left(0, \sigma_v^2\right) \tag{3}$$

We estimate model (1), (2) and (3). For comparison we also estimate the following *logit with state dependence* model (conditioning on the initial value of y_{i0}) which is model (3) without unobserved heterogeneity:

$$y_{it}^{*} = \beta x_{it} + \rho y_{i,t-1} + \alpha_0 + \alpha_1 y_{i0} + \varepsilon_{it} \tag{4}$$

Given the estimates of equation 3 the hypothesis $H_{0:}\ \rho = 0$ is a test of no (true) state dependence given that unobserved heterogeneity has been controlled for. As noted by Heckman (1981) true state dependence may be related to past car ownership having impacts on preferences. However, it may also be related to economic constraints in the form of transaction costs related to buying and selling a car. As an example consider a household that has bought a car, but shortly after face a shock that lowers the utility from having a car compared to the point where the car was bought. If there are transaction costs in selling and buying a car it may be optimal for the household to keep the car. Selling the car will give the household lower utility compared to pre-car utility because of the consumption loss deriving from the transaction costs. It may have important policy conclusions whether state dependence derives from change in preferences or transaction cost, but unfortunately we are not able to determine which explanation that is the most important.

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without affecting the remaining parameters. Another simplified version of Wooldridge approach has been applied by Erdem and Sun (2001) to model dynamics in brand choice based on consumer scanner data.

3. Data

3.1. Data sources and selection

The panel database was constructed by linking information from different official registers via the CPR-number that is specific to each person in Denmark. The data was constructed at household level, which seems to be the decision unit relevant in this case. A household is defined as a household unit consisting of 1 or 2 adults and their children. Two adults living in the same flat/house are considered to belong to the same household if they are married, or have common children, or if they are of the opposite sex and the age difference is less than 15 years (taking into account non-married couples living as if they were married). These households with two adults will subsequently be denoted couples.

Information about car ownership was obtained from the Danish Central Register for Motor Vehicles, which contains records of the dates for start and stop of ownership for all owners during the life of a vehicle. The information is considered to be very accurate as it is used to collect annual ownership taxes. Based on this information we calculated the degree of car ownership during the year and subsequently defined discrete car ownership variables (0 if the degree of car ownership during the year was less than 0.5, 1 if the degree was between 0.5 and 1.5 etc.).

Company cars available to private households, but owned by a company cannot be linked with households based on the information from the Danish Central Register for Motor Vehicles. However, information about the presence of a company car in a household was obtained from a tax register (as individuals with a company car in Denmark are to pay income tax on the benefits of having a car at their disposal).

Socioeconomic variables related to the household were extracted from the tax register and other sources. We have information on income (before and after tax), social transfers, demographic information, labour market status and location at municipal level. The municipality of the workplace was also obtained and used to calculate a measure of commuting distance. An index for the cost of car ownership was calculated based on information on the change over time in fuel prices, ownership tax, repair costs, insurance costs, price of new cars and net rate of return (alternative cost). There is only variation in the car cost index across time, but not between households in a given year.[6] Information was available from 1992 to 2001.

[6] There are some differences in the insurance costs for different levels of urbanisation, but these only resulted in minor differences in the development over time in the car cost index. Regional indexes for the change in public transport prices were also collected, but these were insignificant in the models and will not be described further.

In order to compare the impact of socioeconomic variables on different types of households we estimate separate models for single males, single females and couples (0/1 choice and 1/2 choice). We prefer to focus on privately owned cars, as it seems likely that the decision-making process to own a private car is different from the process of obtaining a company car. Furthermore, we also chose to exclude households with self-employed members because self-employed individuals have highly unstable incomes when measured by the tax assessed income (which may not reflect their real consumption possibilities). [7]

For the estimation approach proposed by Wooldridge (2002a) we need balanced panels of households subject to the above criteria. Thus, the sample of couples for the 0 or 1 car models are households with two adults in the whole time period from 1992 to 2001, who have had 0 or 1 car and not in any of these years had a company car or been self-employed. The number of households satisfying these criteria is rather large. To ease computation a random sample of at least 10,000 households in each group was therefore selected.[8]

3.2. Description of data

The development in car ownership over time for the different groups is illustrated in table 1. The table shows the share of households in the respective groups that have had either 0 or 1 car in the whole time period (1 or 2 cars for the sample of couples with at least one car). The table also illustrates the share of households that have become and then remained a car owner in the period (e.g. we observe a car ownership pattern over time like 0111111111, 0011111111 etc.), or have left car ownership (e.g. 1000000000, 1100000000 etc.). Finally, the table also shows the remaining share of respondents with multiple shifts over time in car ownership status (e.g. 1110001111 or 0011100111 etc.).

The distributions in table 1 illustrate the strong persistence over time in car ownership status. Thus, the shares of households that have had either no car or one car over the entire 10-year-period are large for all types of households, while the share of "shifters" is only between 14 to 24% for 0/1 household. For couples with at least one car the share of shifters is somewhat larger at 33%. For the shifters only one shift into or out of car ownership is typically observed, while multiple shifts only occurred for 3-6% of the households (except for multiple car households where 15% change status more than once).

[7] Only 1-2% of the singles have multiple private car ownership, while less than 1% of the couples own 3 cars (calculated for households without self-employed and without company cars).

[8] Corresponding roughly to 10% of all the Danish single male satisfying the criteria, 5% of all the single females, and 3% of all couples with 0 or 1 car and also 3% of all couples with 1 or 2 cars.

Table 1 also illustrates that the level of car ownership is considerably higher for couples as compared with singles, and that single males have higher levels of car ownership than single females.

Table 1 Car ownership status over time from 1992 to 2001

	Single male (0/1)	**Single female (0/1)**	**Couples (0/1)**	**Couples (1/2)**
0 car all years (1 for couples 1/2)	52%	72%	12%	63%
From 0 to 1 car (1 to 2 for couples ½)	9%	4%	13%	10%
From 1 to 0 (2 to 1 for couples 1/2)	8%	7%	5%	8%
Multiple shifts	5%	3%	6%	15%
1 car all years (2 for couples 1/2)	26%	14%	64%	4%
N households	10,113	11,515	11,183	11,351

Note: Panel of households excluding households with self-employed and company cars.

Selection of explanatory variables and choice of transformation of those were based on previous studies and preliminary estimations using simple binary models. As income measure we use log of household income *after* tax measured in 1997 price level (*linc*). This measure includes wage, pensions, net capital income as well as the most important non-taxed public transfers like child support (given in Denmark independently of income), subsidies for housing rents and social benefits. Age is included both in linear and squared forms. A number of dummies indicate labour market status separating between employed (*work*), unemployed (*unemp*), while base case are individuals outside the labour market (as described in section 3.1 households with self-employed are excluded). For couples separate labour market dummies are included for males and females. For respondents employed we calculate a measure of commuting distance based on the mean distance between municipality of living and working. For individuals living and working in the same municipality the expected commuting distance was calculated based on the size of the municipality. The square root of commuting distance was included in the models (denoted *distm_sr* and *distf_sr* for males and females respectively).[9] Dummy variables were included to indicate the presence of children under 18 years of age (*dchild_m*) and adult children living with their parents (*dchild_a*). The variable (*usc*) is the index describing the development in car cost (purchase, ownership and use) relative to consumer prices (normalised to 1 in

[9] Municipality of workplace was not recorded in 2% to 5% of the cases (for persons working). In these missing cases the commuting distance was assumed to be zero.

1997). A *trend* variable normalised at 0 in 1993 is included to account for time effects (annual dummies cannot be included along with *usc*). Indexes for the change in real train and bus prices were included in preliminary regressions, but the prices of these two public transport modes were insignificant. Finally, a range of geographical dummies are included to indicate degree of urbanisation, where *geo11* is Copenhagen (including Frederiksberg and Gentofte), while the base case is rural municipalities. Generally, the level of urbanisation is gradually decreasing compared to geo11, but *geo14* is an exception (rural municipalities relatively close to Copenhagen).

Descriptive statistics for the four samples are given in appendix 1. Net household income is higher for couples as compared with singles. Mean age is also higher for couples as compared with singles, but the standard error of the age distribution of singles is higher as compared with couples, which reflects that there are more young and old singles as compared with the couples. Employment rates are also higher for couples, which is probably related to the differences in age distributions. Finally, the share of households with children is smaller for singles (especially single males) than for couples.

4. Estimation results

Estimation results for single males and females are given in table 2, while estimation results of the 0/1 and 1/2 models for couples are reported in table 3. The tables show results of the simple pooled logit model, the logit with normally distributed random effects, the logit with state dependence and the logit with state dependence and normally distributed random effects. Pseudo R^2 for all models is based on a comparison with the loglikelihood value of the pooled logit with only a constant term as explanatory variable.

Looking first at the results for single males it appears that both the RE logit and the logit with state dependence yield a significant improvement in the loglikelihood values as compared with the simple pooled logit. However, in the model with both RE and state dependence the contribution of the random effects term becomes more modest as the estimate of σ_v is reduced from 4.949 to 1.067 when lagged car ownership is included. The coefficient on lagged car ownership is only reduced from 6.099 to 5.727 when the RE term is included. This suggests that true state dependence is more important than unobserved heterogeneity (though both lagged car ownership and the random effects term are significant). Similar results are obtained in the models based on females and couples.[10] These results

[10] A standard error to σ_v could not be identified in the final 0/1 model for females or the 1/2 model for couples presumably because the parameter was very small and/or correlated with the parameter on lagged car ownership. However, the LR test

correspond with Kitamura and Bunch (1990), who also found that state dependence dominated unobserved heterogeneity.

It appears from the tables that income (in log) has a significant impact on car ownership in all models/households with the expected positive sign. A squared term for log of income was included in preliminary regressions, but this squared income was insignificant for most types of households.[11] The two age variables were also significant in most cases with a positive parameter on age and a negative parameter on age squared. The impact of age on the index function is increasing to the age of 50 for males, 45 for females and 35 for couples (0/1 model). The regional dummies are also generally significant and have the expected relative order. The probability of owning a car decreases with the degree of urbanisation.

Focussing now on the random effects models with state dependence it appears that the presence of minor children does not have any significant impact on car ownership for singles, while presence of young children has a significant negative impact on car ownership for couples. On the one hand, children increase the need for a flexible mode of transportation, but on the other hand, there are also considerable expenses (day-care, clothes, food etc.) associated with children, which makes it difficult to afford a car. Likewise, Meurs (1993) and Kitamura and Bunch (1990) found that increase in household size reduced the probability of car ownership. In the model for 1/2 cars for couples the presence of children above 18 years has a significant positive impact on the probability of having a second car. This result is probably related to speculation in lower insurance premiums. Young people face very high insurance premiums. Living with their parents they can save money if their car is registered as belonging to one of their parents (given that the parents already have a car and have earned discounts in insurance premiums from collusion free years).

Increases in commuting distance have a significantly positive impact on car ownership for singles and for the choice of a second car for couples. In general the labour market status dummies do not appear to have a significant impact on car ownership for couples. For singles unemployment appear to yield lower car ownership as compared with people outside the labour market (base case) though the effect is only significant for females. Single males working have higher levels of car ownership (before taking into account the positive contribution due to commuting). For females a significant negative parameter to the work dummy is obtained, but due to the positive coefficient on

comparing the state dependence model with the RE state dependence model shows that the random effects term (the σ_v parameter) is significant.

[11] Only in the 0/1 model for couples' squared log of income turned up significant (with a negative sign). However, simulation suggested that the impact of the squared term was modest and does not have major impact on the average income elasticities presented in the next section.

commuting distance the combined impact of working/commuting will be positive down to a 5 kilometre commuting distance[12].

Finally, it appears that the index of car cost is significant for couples (both in the 0/1 and 1/2 models) with the expected negative sign. For single males the parameter is negative and "almost" significant (p-value = 0.059). It should be recalled that we only have time variation in the car cost index, so it is not surprising that the precision is low. It should be noted that the size and significance of the parameter to the car cost index are sensitive to the inclusion/omission of the trend variable, so the impact of changes in car cost should be interpreted cautiously.

Finally, it should be noted that the size of the parameters in the different models cannot directly be compared as the variance of the error term plus random effects are different, see e.g. Wooldridge (2002b) or Arulampalam (1999).[13] The impact of changes in income (after tax) and car costs will therefore be described further in the next section. It is, however, worth noting that the standard errors. of the pooled logit models generally are considerably smaller than in the other models even though the pseudo R^2 indicates that the other models are better. This is because the standard errors of the pooled logit are calculated subject to the (incorrect) assumption that the errors of each household are uncorrelated. This is clearly not the case, so the standard errors of the pooled logit are strongly downwards biased.

[12] Labour market participation status is assumed exogenous to car holding. In principle, it is possible that having a car increases the likelihood of obtaining a job. We are, however, not aware of any estimator of dynamic discrete choice panel data models that allows for this.
[13] I.e. in the same way as the size of the parameters of simple logit and probit cannot be compared directly because the parameters are scaled by the different variances of the logit and probit.

Table 2 Estimation results for single males and single females

	MALE LOGIT								FEMALE LOGIT							
	Pooled		RE		State Dep.		RE State Dep.		Pooled		RE		State Dep.		RE State Dep.	
	coef	*s.e.*	*coef*	*s.e.*	*coef*	*s.e.*	*coef*	*s.e.*	*coef*	*s.e.*	*Coef*	*s.e.*	*coef*	*s.e.*	*coef*	*s.e.*
$pcar_{t-1}$	na	na	na	na	6.099 **	0.051	5.727 **	0.072	na	na	Na	na	6.597 **	0.064	6.551 **	0.066
linc	1.797 **	0.028	2.434 **	0.092	0.857 **	0.060	1.034 **	0.073	2.825 **	0.032	4.553 **	0.127	1.570 **	0.079	1.612 **	0.081
age	0.062 **	0.003	0.647 **	0.020	0.032 **	0.008	0.051 **	0.010	0.223 **	0.005	0.848 **	0.022	0.080 **	0.012	0.083 **	0.013
age_sq/100	-0.023 **	0.003	-0.531 **	0.018	-0.033 **	0.007	-0.051 **	0.009	-0.182 **	0.004	-0.768 **	0.019	-0.089 **	0.010	-0.092 **	0.010
work	0.462 **	0.027	0.949 **	0.096	0.418 **	0.066	0.472 **	0.077	-0.294 **	0.033	-0.277 **	0.105	-0.163	0.087	-0.169	0.088
unemp	0.073 *	0.030	0.377 **	0.114	-0.120	0.076	-0.104	0.085	-0.236 **	0.041	-0.428 **	0.115	-0.410 **	0.108	-0.412 **	0.109
dist_sr	0.065 **	0.005	0.035 **	0.012	0.080 **	0.010	0.088 **	0.012	0.073 **	0.007	0.090 **	0.021	0.076 **	0.017	0.076 **	0.017
dchild_m	-0.305 **	0.059	-0.514 **	0.223	-0.163	0.148	-0.227	0.169	-0.054	0.034	-0.214	0.113	-0.006	0.089	-0.015	0.089
dchild_a	-0.079	0.053	0.047	0.162	0.136	0.134	0.114	0.149	-0.392 **	0.037	-0.040	0.102	-0.243 *	0.100	-0.247 *	0.101
usc	0.416	0.435	0.962	0.932	-2.364 **	1.086	-2.140	1.134	0.264	0.499	0.449	1.128	-0.295	1.305	-0.278	1.311
trend	-0.025 **	0.005	-0.037 **	0.010	0.039 **	0.011	0.036 **	0.012	-0.009	0.005	-0.047 **	0.012	0.000	0.014	-0.003	0.014
d_geo11	-1.739 **	0.024	-5.008 **	0.175	-0.806 **	0.059	-0.987 **	0.076	-1.705 **	0.030	-4.744 **	0.158	-0.849 **	0.074	-0.878 **	0.076
d_geo12	-1.335 **	0.026	-2.333 **	0.122	-0.757 **	0.065	-0.928 **	0.083	-1.323 **	0.030	-3.469 **	0.150	-0.801 **	0.078	-0.820 **	0.080
d_geo13	-1.197 **	0.043	-2.928 **	0.179	-0.532 **	0.107	-0.641 **	0.133	-1.110 **	0.044	-2.525 **	0.253	-0.551 **	0.116	-0.567 **	0.119
d_geo14	-0.366 **	0.059	-1.278 **	0.207	-0.491 **	0.142	-0.547 **	0.176	-0.453 **	0.059	-1.968 **	0.462	-0.330 *	0.154	-0.341 *	0.158
d_geo21	-0.907 **	0.027	-2.434 **	0.144	-0.440 **	0.067	-0.543 **	0.084	-0.942 **	0.030	-2.988 **	0.134	-0.541 **	0.078	-0.551 **	0.080
d_geo22	-0.626 **	0.032	-1.383 **	0.140	-0.386 **	0.083	-0.481 **	0.103	-0.811 **	0.038	-3.055 **	0.178	-0.470 **	0.103	-0.483 **	0.105
d_geo2x	-0.428 **	0.023	-1.214 **	0.154	-0.252 **	0.058	-0.319 **	0.073	-0.462 **	0.026	-0.681 **	0.134	-0.188 **	0.070	-0.191 **	0.071
_cons	-23.997 **	0.547	-47.616 **	1.472	-12.006 **	1.288	-15.058 **	1.450	-39.935 **	0.638	-77.445 **	2.016	-23.330 **	1.616	-23.911 **	1.632
pcar_92	na	na	na	na	0.867 **	0.052	1.907 **	0.147	na	na	Na	na	0.822 **	0.064	0.938 **	0.066
σ_v	na	na	4.949 **	0.050	na	na	1.067 **	0.077	na	na	5.280 **	0.059	na	na	0.333	na
RE-share	na	na	0.882 **	0.002	na	na	0.257 **	0.028	na	na	0.894 **	0.002	na	na	0.327	na
p(RE-share=0)	na		0.000		na		0.000		na		0.000		na		0.000	
N obs	91,017		91,017		91,017		91,017		103,635		103,635		103,635		103,635	
N HH	10,113		10,113		10,113		10,113		11,515		11,515		11,515		11,515	
LogL	-51,147.50		-21,828.95		-12,080.51		-12,049.41		-42,578.846		-16,650.318		-8,709.789		-8,702.650	
Pseudo R^2	0.148		*0.636*		0.799		*0.799*		0.185		*0.681*		0.833		*0.833*	

Notes: Significance levels at 5% and 1% are indicated by one and two asterisks, respectively.
RE-share is the proportion of the total variance contributed by the random effect component. p(RE-share)=0 is an LR test comparing with model without random effects.

Table 3 Estimation results for couples

	COUPLE 0/1 LOGIT								COUPLE 1/2 LOGIT							
	Pooled		RE		State Dep.		RE State Dep.		Pooled		RE		State Dep.		RE State Dep.	
	coef	*s.e.*	*coef*	*s.e.*	*coef*	*s.e.*	*coef*	*s.e.*	*coef*	*s.e.*	*coef*	*s.e.*	*coef*	*s.e.*	*coef*	*s.e.*
$pcar_{t-1}$	na	na	na	na	5.823 **	0.046	5.384 **	0.068	na	na	na	na	4.566 **	0.031	4.499 **	0.032
Linc	1.412 **	0.035	1.917 **	0.128	0.656 **	0.066	0.817 **	0.081	1.251 **	0.039	1.552 **	0.099	0.794 **	0.060	0.818 **	0.062
Age	0.113 **	0.004	0.555 **	0.017	0.011	0.008	0.044 **	0.011	0.065 **	0.007	0.326 **	0.019	0.008	0.010	0.011	0.010
age_sq/100	-0.092 **	0.004	-0.502 **	0.016	-0.031 **	0.008	-0.063 **	0.010	-0.075 **	0.007	-0.363 **	0.020	-0.025 *	0.010	-0.029 **	0.010
Workmale	-0.151 **	0.033	-0.568 **	0.100	-0.045	0.069	-0.078	0.081	-0.252 **	0.036	0.091	0.075	-0.127 *	0.057	-0.126 *	0.059
Workfem	0.088 **	0.030	0.159	0.088	0.057	0.062	0.066	0.073	0.091 **	0.033	0.219 **	0.073	0.023	0.051	0.029	0.053
unempmale	-0.410 **	0.039	-0.811 **	0.108	-0.077	0.083	-0.146	0.095	-0.087	0.046	0.239 **	0.087	-0.034	0.071	-0.032	0.073
unempfem	-0.027	0.034	-0.026	0.094	0.010	0.071	-0.021	0.081	0.133 **	0.039	0.263 **	0.077	0.076	0.059	0.083	0.061
distm_sr	-0.005	0.004	0.001	0.010	-0.009	0.008	-0.011	0.010	0.071 **	0.004	0.062 **	0.008	0.056 **	0.006	0.057 **	0.006
distf_sr	0.011	0.006	0.001	0.013	0.019	0.012	0.020	0.013	0.060 **	0.005	0.062 **	0.010	0.052 **	0.008	0.052 **	0.008
dchild_m	-0.023	0.024	0.273 **	0.078	-0.207 **	0.049	-0.216 **	0.058	-0.304 **	0.024	-0.602 **	0.055	-0.205 **	0.039	-0.215 **	0.040
dchild_a	-0.353 **	0.027	-0.192 **	0.070	-0.233 **	0.059	-0.260 **	0.067	0.313 **	0.023	0.398 **	0.044	0.514 **	0.037	0.521 **	0.038
usc	-0.282	0.474	-2.240 *	0.901	-3.882 **	1.011	-5.238 **	1.081	-0.909	0.495	-2.268 **	0.736	-4.242 **	0.785	-4.155 **	0.791
trend	0.042 **	0.005	0.160 **	0.010	0.049 **	0.010	0.102 **	0.012	0.060 **	0.005	0.148 **	0.009	0.078 **	0.008	0.077 **	0.009
d_geo11	-1.883 **	0.029	-4.187 **	0.140	-0.926 **	0.063	-1.189 **	0.083	-0.852 **	0.053	-1.743 **	0.207	-0.314 **	0.077	-0.331 **	0.081
d_geo12	-1.222 **	0.026	-3.076 **	0.132	-0.559 **	0.055	-0.717 **	0.072	-0.618 **	0.030	-1.323 **	0.124	-0.291 **	0.046	-0.306 **	0.048
d_geo13	-1.102 **	0.039	-2.463 **	0.147	-0.523 **	0.082	-0.677 **	0.106	-0.389 **	0.045	-0.900 **	0.173	-0.206 **	0.073	-0.215 **	0.076
d_geo14	-0.661 **	0.054	-1.175 **	0.245	-0.258 *	0.112	-0.394 **	0.141	-0.267 **	0.044	-0.117	0.180	-0.189 **	0.073	-0.196 *	0.076
d_geo21	-0.891 **	0.028	-2.639 **	0.157	-0.335 **	0.060	-0.441 **	0.077	-0.600 **	0.032	-1.443 **	0.168	-0.314 **	0.050	-0.329 **	0.052
d_geo22	-0.583 **	0.037	-1.552 **	0.189	-0.266 **	0.076	-0.360 **	0.097	-0.389 **	0.037	-1.175 **	0.131	-0.176 **	0.058	-0.188 **	0.061
d_geo2x	-0.381 **	0.026	-0.691 **	0.128	-0.186 **	0.054	-0.255 **	0.069	-0.462 **	0.025	-1.005 **	0.096	-0.221 **	0.039	-0.233 **	0.041
_cons	-18.357 **	0.637	-30.285 **	1.842	-5.901 **	1.287	-7.336 **	1.457	-17.793 **	0.705	-27.701 **	1.528	-9.068 **	1.102	-9.539 **	1.126
pcar1992	na	na	na	na	0.566 **	0.046	1.452 **	0.114	na	na	na	na	0.466 **	0.035	0.547 **	0.037
σ_v	na	na	4.298 **	0.043	na	na	1.031 **	0.067	na	na	3.102 **	0.033	na	na	0.333	na
RE-share	na	na	0.849 **	0.003	na	na	0.244 **	0.024	na	na	0.745 **	0.004	na	na	0.032	na
p(RE-share=0)	na		0.000		na		0.000		na		0.000		na		0.000	
N obs	100,647		100,647		100,647		100,647		102,159		102,159		102,159		102,159	
N HH	11,183		11,183		11,183		11,183		11,351		11,351		11,351		11,351	
LogL	-47,314.009		-22,762.718		-13,716.388		-13,673.425		-42,502.707		-27,617.421		-20,136.918		-20,107.658	
Pseudo R^2	0.094		*0.564*		0.737		*0.738*		0.073		*0.398*		0.561		*0.561*	

Notes: See table 2.

5. Size of the state dependence, income and car cost elasticities

To illustrate the impact of state dependence, income and car costs we need to calculate average predicted probabilities over the samples of observed characteristics. Unfortunately, there are no simple estimators for the average probabilities available for the mixed distribution of the logit with normally distributed random effects, see e.g. Wooldridge (2002b).[14] Therefore, we calculate the average probabilities using a simulation approach, where the probability for each household is calculated many times adding draws from the estimated normal distribution to the index function. Let V_{ij} be random draws from the standard normal distribution, where j indexes the draws (1…J). The simulated average probability is then given as follows, where Λ denotes the cumulative logistic distribution:

$$\text{Average probability} = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{J}\sum_{j=1}^{J}\Lambda\left[\hat{\beta}x_{it} + \hat{\rho}y_{i,t-1} + \hat{\alpha}_0 + \hat{\alpha}_1 y_{i,92} + \hat{\sigma}_v V_{ij}\right] \tag{5}$$

The parameter to lagged car ownership is a result of the state dependence. To quantify the size of the state dependence Wooldridge (2002a) suggested to use the difference of the average predicted probabilities for $y_{i,t-1} = 0$ and for $y_{i,t-1} = 1$ as an estimate of the state dependence. These predicted probabilities are calculated for 2001 with 1,000 random draws for each household and presented in table 4 (assuming that *all* households in the sample have first 0 car and next 1 car in 2000, so that there are no differences in the observed characteristics).

Table 4 Estimate of state dependence

Sample	**Estimated probability of car ownership in 2001** Assuming car in 2000	Assuming no car in 2000	**Estimate of state dependence**
Single Males	0.821	0.083	0.738
Single Females	0.786	0.016	0.770
Couple 0/1	0.962	0.315	0.647
Couple 1/2[1]	0.729	0.044	0.685

1) For couples with at least one car the table reports the probability of multiple car ownership.

[14] In contrast, it is easier to calculate average probabilities in the random effects probit, see e.g. Wooldridge (2002a or 2002b). In preliminary estimations we relied on the random effects probit, but it turned out to be difficult to identify the variance parameter of the random effects.

It appears from the table that state dependence is strong for all types of households, though strongest for singles.

In table 5 we present income and car cost elasticities based on the observed characteristics in 2001. The elasticities are calculated by increasing the income and car cost with 1%. The elasticities are given by calculating the difference in average probability (multiplied by 100) before and after the change in income/car cost. Elasticities are calculated based on the simple (pooled) logit, the RE logit and the RE logit with state dependence, but car cost elasticities are not presented for the pooled logit model nor for single females because the parameter on car cost in these cases had the wrong sign or was insignificant.

Table 5 Choice elasticities in 2001

Sample	**Income elasticities**			**Car cost elasticities**	
	Pooled logit	RE logit	RE with state dep.	RE logit	RE with state dep.
Single Males	0.35	0.17	0.04	-	-0.09
Single Females	0.35	0.16	0.03	-	-
Couple 0/1	0.20	0.10	0.03	-0.12	-0.21
Couple 1/2	0.15	0.09	0.04	-0.15	-0.24

It appears that the income elasticities are very small in the model with state dependence and random effects. However, as we condition on observed car ownership in 2000 (and also on initial car ownership in 1992) the income elasticity for the model with state dependence and random effects has a short-run nature. Income elasticities are higher – though still modest – in the pooled logit model, while the income elasticities of the random effects model without state dependence are in between.

The short-run income elasticities in the random effects model with state dependence are considerably smaller than typically found in the other studies, e.g. in studies using cohort data by Dargay (2001) and Dargay and Vythoulkas (1999) short-run income elasticities (based on macro time series methods) ranged between 0.18 to 0.48. In the same studies long-run income elasticities ranging between 0.28 to 0.80 are found. They also survey a number of macro studies with income elasticities around unity. It seems, however, that income elasticities based on micro cross section data are somewhat smaller, e.g. de Jong (1990) and Ramjerdi and Rand (1992) obtained income elasticities at 0.33 and 0.15 respectively. Previous studies based on Danish data (micro cross section) have obtained income elasticities at 0.41 (Bjørner, 1999) and from 0.39 to 0.55 (Fosgerau and Nielsen, 2002). As expected these income elasticities are in the same range as found in the pooled logit model.

The differences in the income elasticities between the model with state dependence and unobserved heterogeneity as compared with short-run income elasticities obtained from studies using more aggregate data suggest that the persistence in car ownership may be underestimated in studies based on macro data (aggregation bias). In any case, it appears that income changes have little impact on car ownership in the short run.

The elasticities with respect to car cost (purchase, ownership and variables costs) range from -0.09 to -0.24. These elasticities appear to be in the same range as found in other studies, e.g. Dargay (2001) finds a car purchase cost elasticity at -0.13, while Dargay and Vythoulkas (1999) find long-run elasticities with respect to purchase and variable costs at -0.33 and -0.51 (for "middle" levels of income and car ownership). However, it should be recalled that the car cost elasticities in this study are based on changes in car cost over time for a relatively short time period and the estimates should therefore be interpreted with some caution due to potential correlation with time varying (unobserved) factors.

6. Summary and conclusion

We analyse a unique panel with information on car ownership at household level covering a period from 1992 to 2001. A descriptive analysis of the change in car ownership status shows strong persistence over time. As an example only 24% of couples with zero or one car changed car ownership status over the ten-year-period. Of these 24% only one change into or out of car ownership was typically observed for each household in the observation period, while multiple shifts in car ownership status were observed only for 6% of the couples.

Different logit models including/excluding, respectively, the lagged dependent variable (state dependence) and the random effects (unobserved time invariant heterogeneity) were estimated using the methodology proposed by Wooldridge (2002a). When estimated separately both the lagged dependent and the random effects term were highly significant. When included jointly the size of the random effects parameter became considerably smaller – though still significant – while the parameter on the lagged dependent variable was only slightly reduced. This suggests that the persistence should mainly be attributed to true state dependence. Estimates of the state dependence show that the difference in probability of car ownership conditional on either no or one car in the previous year is as high as 0.7.

Results suggest that it is important to take into account this persistence in car ownership. Repeated cross section models not taking account of the panel nature yield considerably higher income elasticities as compared with the dynamic panel models suggesting that income elasticities from micro cross section studies may yield upward biased elasticities. As an example, it appears that change in income has very limited impact on car ownership levels in the short run. Furthermore, the strong (true) state dependence also indicates that car ownership only adjusts slowly over time to policy changes and that it is difficult to use policy instruments to reduce car ownership in the short run. However, it is unclear to what extent the state dependence derives from change in preferences over time (habit formation) and/or the transaction cost associated with car ownership.

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Appendix 1 Descriptive statistics for the four samples

	Male				Female				Couple 01				Couple 12			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev	Min	Max	Mean	Std. Dev.	Min	Max	Mean[3]	Std. Dev.	Min[3]	Max[3]
$pcar_t$	0.37	0.48	0.00	1.00	0.20	0.40	0.00	1.00	0.79	0.41	0.00	1.00	1.17	0.37	1.00	2.00
$pcar_{t-1}$	0.37	0.48	0.00	1.00	0.21	0.40	0.00	1.00	0.78	0.42	0.00	1.00	1.16	0.37	1.00	2.00
Linc	11.64	0.41	2.39	14.32	11.52	0.36	5.52	13.99	12.41	0.41	8.22	15.91	12.50	0.38	8.26	14.87
Age	55.14	16.12	19.00	99.00	65.06	16.16	19.00	104.00	52.64	14.79	19.00	100.00	51.83	13.17	19.00	95.00
workmale	0.33	0.47	0.00	1.00	na	na	na	na	0.56	0.50	0.00	1.00	0.63	0.48	0.00	1.00
workfem	na	na	na	na	0.19	0.40	0.00	1.00	0.50	0.50	0.00	1.00	0.57	0.49	0.00	1.00
unempmale	0.12	0.33	0.00	1.00	na	na	na	na	0.07	0.26	0.00	1.00	0.07	0.25	0.00	1.00
unempfem	na	na	na	na	0.07	0.25	0.00	1.00	0.11	0.31	0.00	1.00	0.11	0.31	0.00	1.00
outlabmale	na	na	na	na	na	na	na	na	0.37	0.48	0.00	1.00	0.31	0.46	0.00	1.00
Distm_sr	1.32	2.12	0.00	22.91	na	na	na	na	2.15	2.53	0.00	22.23	2.53	2.62	0.00	22.91
distf_sr	na	na	na	na	0.68	1.50	0.00	21.12	1.53	1.91	0.00	22.67	1.83	2.02	0.00	22.02
Distm_sr[1]	3.14	2.16	0.00	22.38	na	na	na	na	3.44	2.38	0.00	22.23	3.65	2.38	0.00	22.91
distf_sr[1]	na	na	na	na	2.71	1.74	0.00	20.54	2.66	1.75	0.00	22.05	2.82	1.83	0.00	22.02
Dchild_m	0.02	0.13	0.00	1.00	0.09	0.28	0.00	1.00	0.36	0.48	0.00	1.00	0.37	0.48	0.00	1.00
Dchild_a	0.02	0.14	0.00	1.00	0.05	0.22	0.00	1.00	0.11	0.31	0.00	1.00	0.14	0.35	0.00	1.00
Usc	1.02	0.03	0.97	1.09	1.02	0.03	0.97	1.09	1.02	0.03	0.97	1.09	1.02	0.03	0.97	1.09
Trend	4.00	2.58	0.00	8.00	4.00	2.58	0.00	8.00	4.00	2.58	0.00	8.00	4.00	2.58	0.00	8.00
d_geo11	0.22	0.41	0.00	1.00	0.20	0.40	0.00	1.00	0.09	0.28	0.00	1.00	0.04	0.21	0.00	1.00
d_geo12	0.14	0.34	0.00	1.00	0.14	0.35	0.00	1.00	0.16	0.37	0.00	1.00	0.13	0.34	0.00	1.00
d_geo13	0.04	0.19	0.00	1.00	0.05	0.21	0.00	1.00	0.05	0.21	0.00	1.00	0.04	0.19	0.00	1.00
d_geo14	0.02	0.13	0.00	1.00	0.02	0.13	0.00	1.00	0.03	0.16	0.00	1.00	0.04	0.19	0.00	1.00
d_geo21	0.12	0.32	0.00	1.00	0.13	0.34	0.00	1.00	0.12	0.32	0.00	1.00	0.11	0.31	0.00	1.00
d_geo22	0.07	0.25	0.00	1.00	0.06	0.24	0.00	1.00	0.07	0.25	0.00	1.00	0.07	0.25	0.00	1.00
d_geo2x[2]	0.17	0.37	0.00	1.00	0.17	0.37	0.00	1.00	0.20	0.40	0.00	1.00	0.20	0.40	0.00	1.00
pcar92	0.37	0.48	0.00	1.00	0.22	0.41	0.00	1.00	0.73	0.44	0.00	1.00	1.15	0.35	1.00	2.00

Notes:
1) Square root of commuting distance given the person is working (zero when municipality of work is missing from the data).
2) Geo2x corresponds to Geo23 and Geo24.
3) When performing the estimations for couples with multiple car ownership 1 was subtracted from $pcar_t$, $pcar_{t-1}$and pcar92.

Dansk sammenfatning

Panelanalyse af familiers bilejerskab

De fleste tidligere studier af bilejerskab foretaget i Danmark og udlandet har været baseret på enten aggregerede tidsserier eller tværsnitsdata for familier. I denne undersøgelse anvendes en omfattende forløbsanalyse på familieniveau til at analysere bilejerskab, idet der er oplysninger om bilejerskab og andre socioøkonomiske variable for perioden 1992 til 2001. Dette gør det fx muligt at analysere, hvorledes familiernes bilejerskab ændrer sig på kort sigt, hvilket ikke er muligt i analyser baseret på tværsnitsdata for et enkelt år.

Analysen viser, at der er betydelig træghed i bilejerskabet på familieniveau. Eksempelvis har hovedparten af de fulgte familier enten ingen, kun en eller kun to biler i hele den analyserede periode, mens andelen, som får en bil i perioden, er lav. Analysen viser endvidere, at trægheden ikke (hovedsageligt) skyldes forskelle i indkomst eller andre karakteristika som fx alder eller arbejdsmarkedstilknytning. Hvis en familie havde bil året forinden, betyder det, at sandsynligheden for bilejerskab året efter er 0,7 højere, selv efter at der er taget højde for de forskelle, der kan tilskrives forskelle i indkomst, alder, tilknytning til arbejdsmarkedet osv. Denne træghed kan formentlig tilskrives, at man bliver afhængig af bilejerskab, og at der er betydelige transaktionsomkostninger ved køb og salg af biler, som gør, at beslutningen om bilejerskab er en langsigtet beslutning.

Trægheden betyder bl.a., at ændringer i familiernes indkomst har yderst begrænset effekt på bilejerskab på kort sigt. Således estimeres kortsigtede indkomstelasticiteter for bilejerskab på kun +0,03 til +0,04.

Metodisk er analysen foretaget ved at estimere dynamiske diskrete panelmodeller for bilejerskab, hvor lagged bilejerskab indgår som forklarende variabel, og hvor det antages, at uobserveret heterogenitet er normalfordelt. Modellen estimeres ved at bruge den metode, der for nylig er foreslået af Wooldridge.