Aging and transport-related energy use: do generations matter?

Rossella Bardazzi and Maria Grazia Pazienza

University of Florence, Italy

Introduction

Europe is experiencing a fast demographic shift, whose consequences for energy consumption and environment have been studied but generally undervalued by policy makers. The share of elderly people in the total population will significantly increase in the near future as the post-war baby-boom generation reaches retirement. Elderly people, however, are not only a growing proportion of the population but an increasing percentage of "active" householders. Indeed, the economics literature almost universally predicts that an aging population will increase residential energy demand and reduce transport-related energy use: older households spend more on heating and less in transportation, because their members stay at home for a larger proportion of the day. However, this causal link is more complex than expected because of the different pressures exerted by human and non-human factors, as socio-demographic transformations (longer life expectancy and smaller family size), economic transformations (income distribution by age and by income category), changes in lifestyle and environmental attitudes, among which global warming concern. In our view, the latter components can be well represented by the concept of energy culture. According to Stephenson et al. (2015), different social norms, including individual expectations and aspirations, interplay with material culture and energy practices in shaping individual behaviour, subject to the external influences that form the context where energy cultures develop. This is particularly important in the case of transport, where the energy culture of high income countries is indissolubly linked to a preference for car: cars are generally perceived as the means of travel giving status, sense of comfort, control and freedom (Steg, 2003). Additional impacts may come from consumer preference shift (Torgler et al., 2008), different attitude towards environment preservation among generations and from differentiated habits and preferences of the growing immigrant share of the population. In this paper, we pursue this line of research by exploring household heterogeneity in terms of age and generation in Italy. We think that the Italian case is particularly interesting because of at least three concurring factors: an almost complete energy dependency, a very high car and motorcycle ownership rate and a very fast aging transformation, due also to a steady increase in life expectancy. Because of this demographic shift, several generations coexist and a relevant share of the elderly population (aged 80 and over) is still driving a car. After a brief analysis of the relevant literature, we firstly analyse the Italian context and then assess the role of sociodemographic factors by looking at pooled cross section on annual Household Budget Survey (IHBS) published by the Italian Statistical Office (ISTAT) for the period 1997-2013. We then aim at assessing the role of the changing generation preferences by distinguishing between a pure age effect and a cohort effect on transport-related energy demand. Indeed we have built a pseudo panel dataset (Deaton,1985, 1997) by which follow cohorts of people from one survey to another, which allows us to disentangle the generational from the life-cycle components in consumption profiles. In other words, we apply a decomposition into age effects, cohort effects and year effects, in this way analysing how the generational attitude component is interacting with the general transport demand trend.

The paper is organized as follows. After a survey of the literature on the linkages between aging and energy consumption (Section 1), Section 2 briefly discusses the main characteristics of private transport in

Italy and its role on GHG emissions. Section 3 describes the dataset and the results of a pooled regression analysis are discussed. The cohort analysis is introduced in Section 4 and the results of the decomposition of age, period and cohort effects are presented in Section 5. The final section contains our conclusions.

1. The literature review

Is the energy culture linked to generational dynamics and is this link important to forecast energy use and to tailor effective energy saving policies? A growing literature is showing that age-related factors are important drivers of energy demand and then of GHG emissions and they must be considered when designing policies. Several papers highlight the link between age and energy use and the empirical findings proved very robust to cross-countries comparisons: residential energy use generally increases with age, while transport energy use decreases. Both these links are markedly non-linear and the non-linearity can be easily rationalized by considering household transformation (both size and composition matter) during the life cycle. Governments facing aging population are therefore responsible for combining an increasing component of energy use (from the residential sector) and a declining transport fuel use. O'Neill et al. (2012) review the link between CO2 emissions and total population dynamics, ageing, urbanization, and changes in household size in several empirical cross-country estimates based on the IPAT model. By analyzing several studies, they report statistically significant coefficients for population growth and age classes as an evidence of total population significance but also of non-linear effect of age composition of the population. Liddle (2011) finds a positive contribution of young adults in transport decision, whereas for residential electricity consumption, age structure has a U-shaped impact, with the youngest and oldest age groups exhibiting the most intensive consumption. Under a similar line of research of macroeconomic cross-country analysis, Menz and Welsch (2012) consider not only population size and age composition, but also the relevance of year-of-birth effects of demographic change, suggesting that shifts in both age and cohort composition may have contributed to rising carbon emissions in OECD countries. In particular, the authors find evidence at macro level that individuals born in times of peace and affluence seem to have adopted more energy intensive lifestyles than people whose energy use attitude has been shaped by shortage experiences.

When looking at transportation-related energy use, the empirical literature analyses both fuel/emission intensity and car ownership choices. These two variables are profoundly influenced by life-cycle and obviously they decline in old age. As for the emission line of research, Okada (2012) estimates the effect of aging population on CO2 travel emissions under a cross-country perspective. The author finds a sort of Kuznetz curve (an inverted U-shaped relationship) between per capita CO2 emissions from road transportation and the share of elderly in developed countries, therefore forecasting a positive contribution of aging to the reduction of GHG emissions.

All the abovementioned studies give important insights on the role of population and age structure on residential/transport energy use; however, they cannot properly disentangle life-cycle and cohort effects as they use cross- country aggregate data. Another strand of literature goes deeper in considering the demographic factor by considering individual data set and pseudo-panels. Indeed, Yang and Timmermans (2012) use a Dutch pseudo-panel to estimate a dynamic model of transportation energy consumption with the aim of considering fuel price elasticity. In their model, Yang and Timmermans consider also cohort effects and they find significant effects implying that the younger generations consume more energy but at the same time, they are also increasing slow-motion transport mode (walking and cycling). Chancel (2014) also uses individual datasets for France and US to unravel a generational effect on the emission patterns of French and US households, looking at residential and transport energy use. Chancel finds two opposite results: a clear cohort effect for France (with the 1930-1955 cohort consuming more than other cohorts) and a homogenous consumption pattern across US generations. The author presents three drivers as possible explanatory factors of the generational effect in France: an income factor (the 1930-1955 generation experienced better life chances and therefore gains in income differentials), a technological factor (important for residential energy use) and a behavioural factor (younger generations may have higher environmental concern and baby boom generation may have difficulties in altering its behaviour). Significant but separated age and cohort effects have been found for Italy by Bardazzi and Pazienza (2017) in residential energy use. When considering the overall household energy consumption, the usual inverted-U pattern can be found also for Italy (confirming the importance of the household composition and size); however, when different age and cohort components are investigated, younger generations clearly exhibit a higher energy intensity with respect to war generations. A growing number of "new" elderly people in Italy seem to be able to access goods associated with comfort and leisure so a more active lifestyle and therefore a new energy culture call for greater residential energy use demand. Are these elements also relevant for transport-related energy use?

Transport demand forecasts are assuming a growing importance as fuel security, urbanization and climate change are becoming increasing world-wide concerns. An emergent literature is showing that generational factors are important drivers of energy demand and different transport mode choices between baby boomers and millennials are under scrutiny in many countries. Fuels Institute (2014) finds evidence that US elderly people are driving more than in the past and newer generations are driving less, with lower driver-licensing rates. Iacono and Levinson (2015) also find lower car ownership rate among Millennials in Minnesota. This recent reduction in car modal choice is explained by a saturation of transport demand in developed countries and by a preference shift – a declining 'love affair with the car'. In all western countries, cars have been perceived as the means of travel giving status, sense of comfort, control and freedom and the preference for car can be frequently associated with irrationality and cognitive bias. Costs associated with a car are frequently undervalued because they are not paid entirely simultaneously with car use and a specific resistance to reduce it has been proved also by experimental economics (Innocenti et al., 2013). Individual life styles and differences in people's attitudes and personality traits have had such a great impact on these choices to represent a key problem in the implementation of effective transportation policies. The potential shift from car preference towards public transport or slow motion alternatives is therefore particularly interesting and this paper aims at considering whether this kind of shift can be traced in Italy and whether generational factors are playing a role.

Drawing from Stephenson et al. (2014) it is possible to sketch how different social norms, including individual expectations and aspirations, interplay with material culture and energy practices in shaping different transport choices across generations or groups. In Table 1, indeed, we compare the main drivers of energy culture of baby boomers and millennials. The baby boom generations, which grew up with expanding private mobility infrastructures and increasing accessibility to private owned cars, generally perceived cars as a source of prestige. Nowadays, environmental friendly attitude – probably mixed with increasing income inequality among generations– pushes new generations towards different transport modal choices.

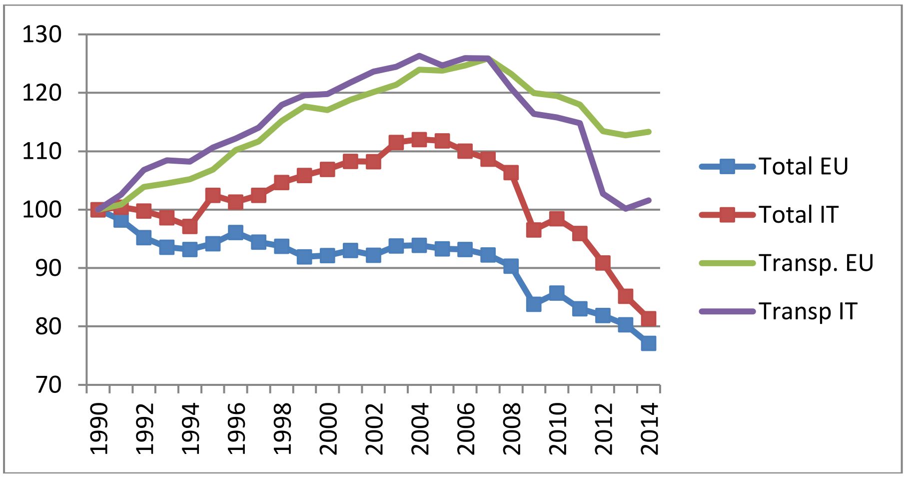
Table 1 - Comparing transport-related energy culture between generations

Baby boom generation	
Material culture/ Public Policies	*Automobile-dominated infrastructure*
Norms	*Car as a status symbol*
Practices	*Big cars, Home purchasing choices and commuting practices*
Millennials	
Material culture/Public Policies	*Public transport infrastructure; Limited Traffic Zones; Emission/Consumption limits*
Norms	*New source of prestige; Environmental concern*
Practices	*IT innovation widely used to improve transport efficiency and share transport costs; IT technology limits learning/work commuting*

2. Travel emissions and car ownership in Italy

These new hints of the international literature appear particularly important for Italy that is struggling to meet the new ambitious emission targets set at EU level and whose share of transport-related emissions on total emissions is approaching 25% in 2014 (24.5% for Italy, 20.1% at EU-28 level). Overall GHG emissions are declining in Italy and the turning point can be observed around 2005, at least three years before the beginning of the economic crisis. Indeed, Figure 1 shows that Italian overall GHG emissions are declining at a slower pace with respect to the EU, whereas transport-related emissions, markedly above the 1990 levels for the whole EU, are again close to the 1990 level in Italy as for 2013-2014.

Figure 1 GHG emissions in Italy and EU-28 (1990=100)



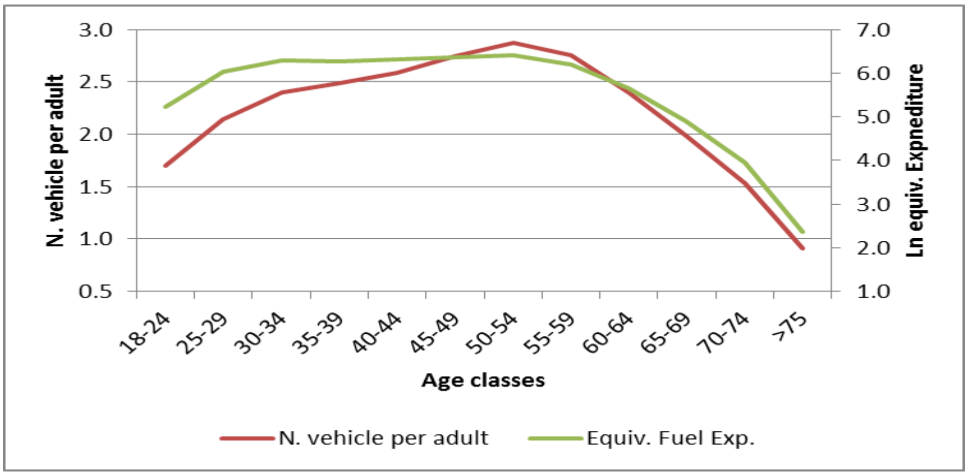
Source: Source: Authors' elaboration on Eurostat database

The turning point of transport-related emissions is the year 2008, so that economic slowdown is deemed to represent an important driver of the recent downward trend of transport-related emissions, being the economic crisis particularly severe for the Italian economy.

Car ownership rate in Italy is among the highest in the world: the number of cars per 1000 inhabitants was 619 in Italy, just after Luxembourg. There are about 1.28 vehicles per driving license for a total of 49 million vehicles circulating in Italy in 2015. More than 12% of active driving licenses belong to elderly drivers (above 70 years old) [1]. The total number of vehicles is still slowly growing – being probably close to a saturation point – and this can also be connected to the trend of smaller household size and increasing number of households that will be discussed in the following paragraphs, so that the average number of family owing a car is stable around 80%.

The use of Household Budget (HBS) published by the Italian Statistical Office (ISTAT) for the period 1997-2013 allows an analysis of transport-related expenditures and socio-demographic drivers. Figure 2 confirms the strict link between number of vehicles e fuel expenditure[2] and the life cycle. However, the fuel expenditure is basically flat from 25 and 65 years old, whereas the household number of vehicle shows a clearer inverted U-shape.

Figure 2 Household number or vehicles and fuel expenditure by householder age classes



Source: Authors' elaboration on IHBS data

What is striking is the remarkable change in behaviour across age classes, as shown by Figure 3[3]. On the one hand, young households reduce the share of car ownership from 90% in the late nineties to 75% in 2013; on the other hand, more than 70% of households with elderly householder (between 70 and 74 years old) currently have at least one car, whereas the share was 50% in 1997[4].

---

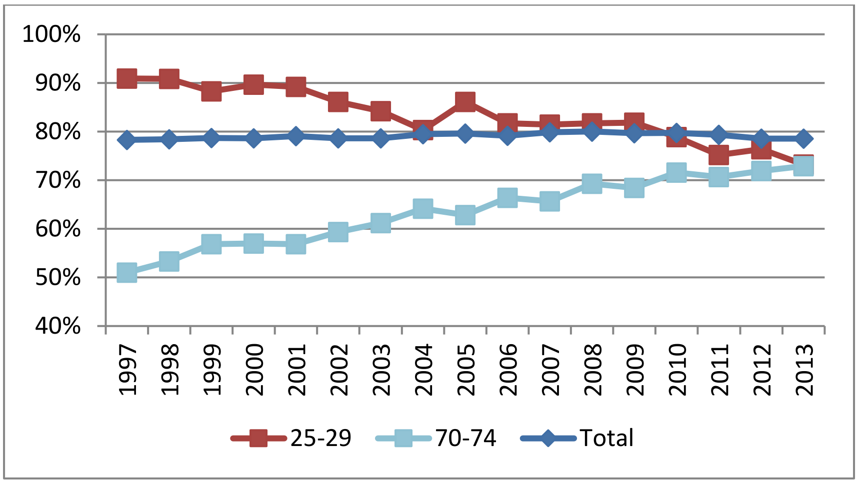
[1] Source: Italian Ministry of Transport. Note that vehicles and cars are not perfect synonym: the vehicle category include cars, trucks, caravan buses ,commercial vehicles and two motor-cycles.

[2] The number of vehicle variable entails non-commercial vehicles (two and four-wheeled) such as cars, motorcycle and camper. The variable is divided by the number of adults in the household. Equivalent fuel expenditure is deflated and taken in logarithm. For the equivalence scale see footnote xx.

[3] Italian Household Budget (IHBS) considers about 22,000 households (sampled throughout the year) to represent the Italian population at the regional level. Beside sociodemographic characteristics, the survey collects information about expenditure on household goods and services. Our analysis uses observations for the period 1997-2013, and therefore includes the years of economic downturn after 2007. The survey is designed as a repeated cross section so it is not possible to look at the behaviour of the same individuals over time, but different ages in different groups of households can be observed. A cross-sectional analysis of energy expenditure is useful to provide an idea of how households with different characteristics compare, but it is difficult to disentangle structural heterogeneity and behavioural differences or changes.

[4] In figures 3 and 4 we decided to include only these two age classes to improve readability of time series. However the behaviour of younger generations is homogenous: all age classes below 50 years old exhibit a clear reduction path; on the contrary, all age classes above 65 old exhibit a clear increasing car ownership rate. We decide not to use the two extreme classes (19-24 and above 75) because smaller frequencies make the analysis unreliable.

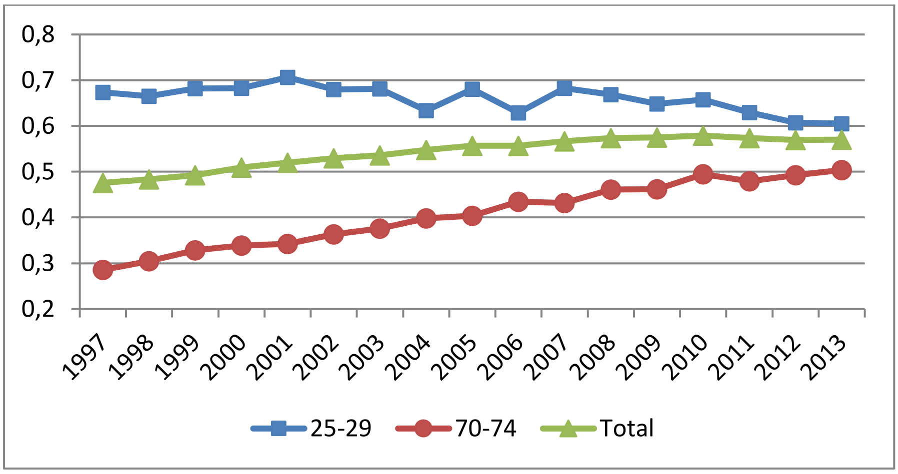
Figure 3 Share of households owing at least one car; young vs old householders (1997-2013, %)



Source: Authors' elaboration on IHBS data

The same time trend is confirmed by the average number of cars by household: the average car number slightly increases between 1997 and 2013; however, in the same period it is evident a positive correlation between car possession and the age of householders, as only younger householders have reduced the average number of cars.

Figure 4 Average number of car per adult; young vs old householders (1997-2013, %)



Source: Authors' elaboration on IHBS data

This trend can be linked to the effect of economic crisis, which hit more severely younger generations and therefore younger householders, but also to a change in environmental preferences and attitude toward transport modal choices.

3. The socio economic drivers: cross sectional results

In order to understand the relative importance of household transport-related behaviour, we use microdata on household consumption considering sociodemographic characteristics, dwelling and vehicles possession and information about total expenditure on household goods and services.[5] Households are grouped according to the head's year of birth[6] using five-year age classes.[7] As we are specifically interested in distinguishing transport-related expenditure and car possession by age, Table 2 reports data on weighted frequencies and on household size by age class at the beginning and end of the period observed. The table highlights how profoundly demographic trends are shaping the population structure in Italy: the share of households with the householder aged 65 or over was 30.7% in 1997 and became 35.5% in 2013 (18.8% for those aged 75 or over). At the same time, we can also observe a sharp increase in household numbers (more than 4 million) and a decrease in the average family size (from 2.7 in 1997 to 2.3 in 2013).

Table 2 - Household demographic characteristics: frequencies and household size

	1997			2013		
Age classes	Freq.	Weighted Freq.	Househ. Size (mean)	Freq.	Weighted Freq.	Househ. Size (mean)
18-24	112	143,888	2.0	52	78,733	1.7
25-29	647	849,854	2.2	324	506,697	1.9
30-34	1,624	1,610,475	2.7	841	1,166,908	2.3
35-39	2,245	2,040,572	3.2	1,491	2,040,740	2.6
40-44	2,329	2,050,547	3.3	1,809	2,459,280	2.9
45-49	2,472	2,166,883	3.4	2,151	2,835,754	2.9
50-54	2,236	1,972,227	3.3	2,110	2,743,916	2.9
55-59	2,290	2,069,242	2.9	1,913	2,468,415	2.7
60-64	2,044	1,958,594	2.5	1,876	2,153,662	2.3
65-69	1,980	1,959,762	2.1	1,910	2,169,403	2.1
70-74	1,838	1,923,905	1.8	1,850	2,084,170	1.8
>75	2,390	2,628,425	1.7	4,109	4,788,616	1.6
Total	22,207	21,374,373	2.7	20,436	25,496,294	2.3

Source: Authors' elaboration on IHBS data

The decrease in family size is important because, although much more difficult to estimate than in the case of residential ownership and energy use, there are economies of scale also related to car possession. Economies of scale arise directly from sharing car use, that is the time of distance that members of the same family ride together; however, it is also possible that relatives in two different households share the same vehicle.

In order to describe the key determinants influencing the decision and the level of possession of cars, we consider the effect of age and other sociodemographic characteristics among which size of the family, householder's education and employment status and proxy of family income and wealth.
Briefly, the basic equation to be estimated is

$$Ln\ (Eeq_{it}) = \alpha_0 + \beta X_{it} + u_{it}\ , \qquad (1)$$

5 The categories included are: food and beverages, household appliances and durables, household maintenance and operation, clothing, health expenditure, transport and communication, culture and education, and other services.
6 The household head is the reference person as indicated in the civil registry. Householders under 18 have been excluded from our dataset.
7 The microdata released only report the age of household members as a continuous variable for the years 1997-2001. Since 2002, ISTAT has adopted a new methodology to protect the privacy of the individuals surveyed. Therefore, for the years 2002-2013 the age variable is aggregated into 15 classes (0-5; 6-14; 15-17, 18-24; 25-29; 30-34; 35-39; 40-44; 45-49; 50-54; 55-59; 60-64; 65-69; 70-74; and 75 and over).

where the dependent variable is the logarithm of the household's deflated equivalent fuel expenditure[8] or the number of cars or vehicle per adult in the household, Xit is the set of socio-demographic characteristics. The three dependent variables are obviously highly correlated, nevertheless there are several reasons for considering them separately. Due to the middle-aged origin of several Italian towns, limited traffic and parking zones are frequent and traveling by motorcycle is an important substitute for car modal choices. Therefore, considering vehicle as an alternative to cars can be important. On the other hand, households with elderly householders may have the financial possibility to enjoy more than one vehicle but at the same time may have lower fuel demand.

Due to the characteristic of the data set, designed as a repeated cross section, we cannot look at the behaviour of the same individuals over time and therefore we analyse transport related choices by looking at pooled cross section. When considering the number of cars or motor-vehicles in the family other estimation techniques can be employed. In particular, it is possible to consider the (absolute) number of car as ordered alternatives, so that the ordered logit model can be a sound option. Being OLS pooled regression results very similar to the order logit ones (see the appendix), we prefer to discuss the pooled regression results also because of the higher simplicity in interpreting it.

Table 3 describes the variables employed in the equation. The dependent variables are grouped at the top of the list.

Table 3 - Regression variables

Variable Name	Type	Notes
Number of cars per adult in the household	continuous	
Number of vehicles per adult in the household	continuous	
Equivalent fuel expenditure	monetary	log, deflated values
Bike possession	binary	1= yes
Boat possession	binary	1= yes
Children in the household (0-18)	binary	1= yes
Education level	binary	University degree=1
Employment status	binary	Employed=1
Equivalent household consumption for public transport	monetary	log, deflated values
Gender	binary	male=1
Home Property and size	Integer	Integer
Household size	Integer	Integer
Householder Age classes	15 classes	1= youngest
Motorbike possession	binary	1= yes
Self Employment	binary	1= yes
Total equivalent household consumption	monetary	log, deflated values
Urban Sprawl	binary	1= yes

[8] Nominal variables have been converted to real values using commodity-specific price indexes (base year 2010). Moreover, in order to make household expenditure comparable with different demographic compositions we use an equivalence scale which divides household income by the square root of household size. The square root scale, adopted in recent OECD works (OECD, 2013), implies that a household of four persons has needs twice as large as one composed of a single person. We use an age-neutral equivalence scale because we want to highlight the age effect in the regression.

Table 4 presents the regression results[9] for the whole period (1997-2013). The first two columns of the table present the regression results when the number of car per adult or the number of vehicle per adult are the dependent variable. Regarding socio-demographic drivers, a positive link between income, wealth and the number of vehicle is confirmed, as is the fact that women householders are associated with lower number of vehicle in the household. The effect of the different age classes on regression has been shown through age dummies, so highlighting that the effect is nonlinear[10]. This effect is negative for the younger and older householders, thus confirming the findings of a life-cycle pattern in vehicle possession, previously shown in figure 2. The total household consumption level – as a proxy for household income level – has a clear and positive link with vehicles availability, as is the role of wealth, here approximated by the room size of the home residence, if the householder is the owner. The regression results also confirm that high education levels and employment status are associated with higher vehicles belonging to the family, whereas the self-employment status appears to be slightly negatively related. Car and vehicles per adult are lower the higher the household size, thus confirming the importance of economies of scale, whereas the presence of dependent children pushes the need to have more vehicles. The number of vehicles obviously depend on the availability of alternatives: equivalent public transport expenditure exhibits a negative coefficient, whereas the fact that family residence is not close to a municipality increases the demand for more vehicles. Finally, motorcycles clearly show a substitution process in car ownership, whereas boat and bikes exhibit complementarities.

The general framework is confirmed by the third column, where results for equivalent fuel expenditure are shown. In this case, the role of age classes appears constantly increasing with age, notwithstanding a difference in age classes' coefficient magnitude. A change of coefficient sign is evident also for education level. This negative link between education level and equivalent fuel consumption seems to confirm that higher education levels are associated to a higher propensity toward an energy-saving behaviour, as widely confirmed by the literature[11]. A change of coefficient sign is evident also for household size and presence of dependent children, because economies of scale are less important with regards to fuel expenditure. Finally, the motorbike presence is confirmed as a complementary vehicle as fuel expenditure increase in this case.

This pooled regression analysis confirms the key role of the socio-demographic drivers in transport-related choices[12]. However, it cannot allow disentangling the role of generational change of behaviour, which we think has an important role and will be analysed in the next section.

[9] In the OLS pooled estimations shown in Table 3, errors are clustered by year.
[10] Householders belonging to age class "40-44" have been chosen as reference group so this class has been excluded from estimation.
[11] A positive influence of education level on energy saving behaviour has been widely found in the literature both in case of residential and transport energy use. However, Mills and Schleich (2012) find that this impact varies greatly among countries.
[12] Similar results on drivers of vehicle ownership can be found in Eakins (2013) on Irish Household Budget Survey.

Table 4
Pooled OLS regression results (1997-2013). Dependent variables in column headings

	N. Car	N. Vehicles	Eq. Fuel exp.
Age classes			
18-24	-0.090***	-0.145***	-0.066
	(0.014)	*(0.033)*	*(0.071)*
25-29	-0.023**	-0.045**	0.316***
	(0.009)	*(0.017)*	*(0.043)*
30-34	0.007	0.001	0.260***
	(0.005)	*(0.011)*	*(0.034)*
35-39	0.020***	0.033***	0.114***
	(0.003)	*(0.006)*	*(0.030)*
45-49	-0.044***	-0.094***	-0.110***
	(0.004)	*(0.007)*	*(0.021)*
50-54	-0.057***	-0.156***	-0.250***
	(0.002)	*(0.006)*	*(0.025)*
55-59	-0.068***	-0.211***	-0.414***
	(0.004)	*(0.007)*	*(0.027)*
60-64	-0.101***	-0.285***	-0.662***
	(0.007)	*(0.011)*	*(0.032)*
65-69	-0.170***	-0.412***	-1.089***
	(0.007)	*(0.012)*	*(0.043)*
70-74	-0.259***	-0.583***	-1.686***
	(0.006)	*(0.012)*	*(0.051)*
75 and over	-0.393***	-0.858***	-2.746***
	(0.004)	*(0.007)*	*(0.026)*
Gender	-0.110***	-0.251***	-1.110***
	(0.002)	*(0.004)*	*(0.020)*
Education level	0.064***	0.101***	-0.171***
	(0.003)	*(0.004)*	*(0.031)*
Employment status	0.075***	0.151***	0.354***
	(0.003)	*(0.005)*	*(0.018)*
Total equivalent consumpt. (ln)	0.187***	0.361***	1.831***
	(0.002)	*(0.004)*	*(0.028)*
Home property size	0.014***	0.022***	0.016***
	(0.001)	*(0.001)*	*(0.004)*
Houlsehold size	-0.067***	-0.186***	0.612***
	(0.002)	*(0.006)*	*(0.011)*
Eq. Public Transp. exp. (ln)	-0.021***	-0.036***	-0.131***
	(0.000)	*(0.001)*	*(0.003)*
Self-employer	-0.003*	-0.003	-0.196***
	(0.002)	*(0.004)*	*(0.022)*
Children (dummy)	0.094***	0.187***	-0.724***
	(0.005)	*(0.010)*	*(0.014)*
Urban sprawl (dummy)	0.034***	0.058***	0.309***
	(0.008)	*(0.012)*	*(0.037)*
Boat	0.036***	0.146***	
	(0.005)	*(0.011)*	
Motorbike	-0.033***		0.129***
	(0.001)		*(0.016)*
Bike	0.059***		0.023
	(0.002)		*(0.022)*
Constant	-0.989***	-1.590***	-11.936***
	(0.022)	*(0.028)*	*(0.273)*
R^2	0.34	0.36	0.35
N	390,328	390,328	390,328

* p<0.1; ** p<0.05; *** p<0.01

Source: Authors' elaboration on IHBS data

4. Energy consumption profiles: the life cycle and generations

The empirical analysis presented in the previous section has the aim of investigating consumer choices at specific ages for different groups of households. Consumption behaviour at different ages for the same cohort cannot be analysed because in repeated cross-sections families are not followed over time as in panel data. To identify whether "transport culture" changes over time we need to distinguish between age (life-cycle) and cohort (generational) effects in fuel consumption profiles. Two research strategies can be employed. One the one hand, we could include age and cohort effects within a model based upon pooled cross section data. In this case, the problem of zero observations arises and must be appropriately treated using a double-hurdle model such as the model proposed by Cragg (1971). On the other, we can rely upon repeated cross-sections and build a pseudo panel to apply a cohort analysis and estimate age, period and cohort (APC) effects. In the present paper, we follow the latter approach where zero observations are not an issue and APC effects can be estimated.

To obtain this research perspective, birth cohorts must become the unit of analysis: generations encounter different historical and social conditions as they age and therefore it is reasonable for them to have diverse behavioural attitudes. Cohort analysis is crucial for inference about age-period-cohort effects. *Age effects* represent aging-related changes in behaviour and are common to many issues, including consumption choices. *Cohort effects* reflect similarities in experiences and social influences across a generation that affect its members' choices. Finally, all cohorts may be affected by macro shocks so *period effects* represent events that synchronously but temporarily move all cohorts away from their profiles.

To estimate the decomposition of effects, we can regress the cohort consumption averages against dummy variables for all three sets of effects. Obviously, other restrictions could be used such as polynomials, but with plentiful data we can use dummy variables and thus allow the data to choose any pattern. The model can be written as

$$y = \beta + A\alpha + C\gamma + Y\psi + u \,, \tag{2}$$

where y is the stacked vector of observations, A is a matrix of age dummies, C a matrix of cohort dummies, and Y a matrix of year dummies.[13]

We must drop one column from each of the three matrices of dummies to avoid singularity. However, it is still impossible to estimate this regression because of an additional linear relationship across age, cohort and year. That is, if we decide to label cohorts *c* as the age of the household head in year t = 0 and *t* refers to the date, we can infer the cohort's age a as

$$a = c + t \tag{3}$$

Therefore, it is necessary to impose another restriction to obtain the normalisation effects. There are several possible alternatives and each of them implies different results. This identification problem is well-known in the literature and several alternative normalization methods have been proposed (among others, by McKenzie (2006); Schulhofer-Wohl (2013) and Yang et al. (2008)). All these approaches have their shortcomings and their increased generality comes at the cost of increased technical complexity.

One of the most common normalisations imposes the constraint that year dummy coefficients are orthogonal to a time-trend and sum to zero (Deaton and Paxson, 1994). To understand this approach, we can consider an example of a variable, say consumption, growing at 5 per cent for each year for each cohort. This growth can be represented by a time trend of 5% a year in the year effects, without either cohort or age effects, or by age effects that rise linearly with age added to cohort effects that fall linearly with age. Note that these two effects are equal (5 per cent) but of opposite sign, because the cohorts are labelled by age at a fixed date, so that the older cohorts (larger c) are poorer, not richer. In our case, where energy consumption is the variable to be decomposed, it seems reasonable to attribute all the trends

[13] In our case, all the matrices have *m* rows, which is the number of cohort-year pairs for each commodity. The number of columns is 57 (the number of ages) for matrix *A*, 73 (the number of cohorts) for *C*, and 17 (the number of years) for *Y*.

observable in the data to age and cohort effects, not time, and to use the year effects to capture cyclical fluctuations that average to zero over the long run.

5. Cohort empirical analysis: data and results

We investigate the heterogeneity of Italian households with respect to the use of private transport by applying the decomposition method described in the previous section to distinguish between behavioural effects due to population ageing and effects that can be ascribed to changing energy culture between generations. To perform this empirical analysis, we build a pseudo-panel , from the dataset described above, according to the approach designed by Deaton (1985) and implemented in a previous work (Bardazzi and Pazienza, 2017). The key variables of interest are household equivalent real expenditure on transport fuels and total energy expenditure for residential uses. Extreme and unreliable values are cleaned from the dataset through a trimming procedure that excludes observations falling outside the first and last percentiles. Furthermore, we only keep households in which the head is 25-81 years old to avoid a selectivity problem. For each survey, we average the expenditure by the age of the head and then track the sample from the same cohort one year older in the next survey. We build and use cohorts at each age and therefore we end up with 73 cohorts: the youngest of these is 25 years old in 2013; the oldest is 65 years old in 1997.

We estimate the model of equation (2) on this pseudo-panel. To avoid singularity and to implement the normalisation designed by Deaton and Paxson (1994), the first age group and the seventeenth cohort are omitted, so that the reference group is that of a household headed by a 25-year-old in 1997. The year dummies are constrained to be orthogonal to a time trend and to add up to zero.[14] The model allows to estimate age and cohort effects for the energy expenditure of the households related to fuels for private transport. Then we compare the empirical results with the effects estimated for the total energy expenditure, including electricity, heating fuels and transport fuels. The results of the decomposition of age and cohort effects are presented in Figures 5 and 6; the estimated parameters cited below and their statistics are shown in a Table included in the Appendix.

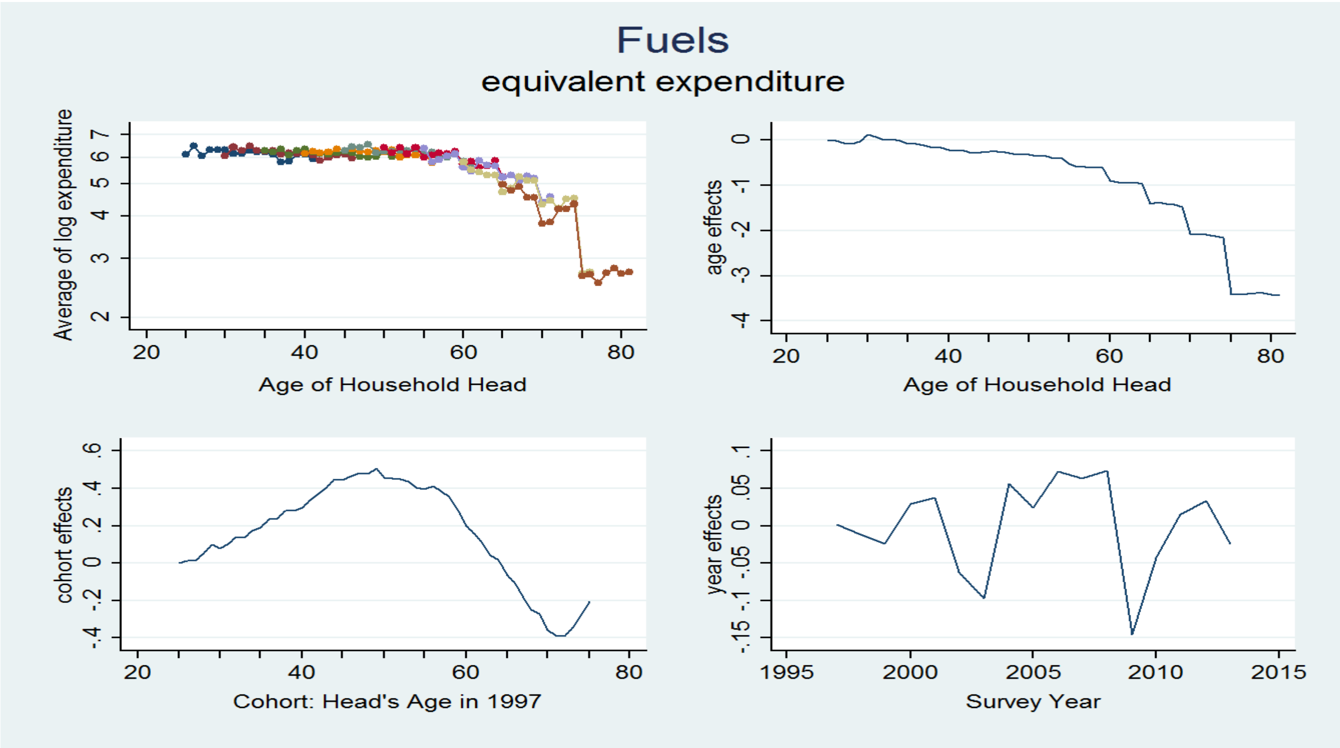
We present graphs with four panels with the original cohort data and the estimated effects. The first plot shows the average of logged consumption for every fifth cohort for the sake of simplicity. The three other panels show the age effects, the cohort effects (plotted as a function of the age of the householder in 1997, so the younger generations are on the left and the older on the right of the panel), and the year effects respectively. In the first plot of Figure 5, equivalent transport fuel expenditure is stable across time up to the age of 60 and then decreases at older ages. This life-cycle pattern is confirmed by the age effect, where the parameter goes from -0.025 and +0.025 between ages 25 and 33 and then decreases to -3.4 at age 80. The cohort effects (bottom left-hand panel) are of smaller magnitude than the age effects, and they are nonlinear. Indeed, transport fuel expenditure increases with a peak for the cohort born in 1940 (householders aged 57 in 1997) with an estimated parameter of 0.5. Then the cohort effect decreases for older generations (with a trough for those born in 1925 (aged 72 in 1997) and fluctuating for oldest cohorts where the number of householders is reduced for mortality and, therefore, variability of expenditure is

[14] Consider d_t as the usual zero-one dummy. To enforce this restriction, we use a set of T-2 year dummies, d_t *, defined as follows, from t = 3, ... T

dt *= dt - [(t-1) d2 - (t-2) d_1]

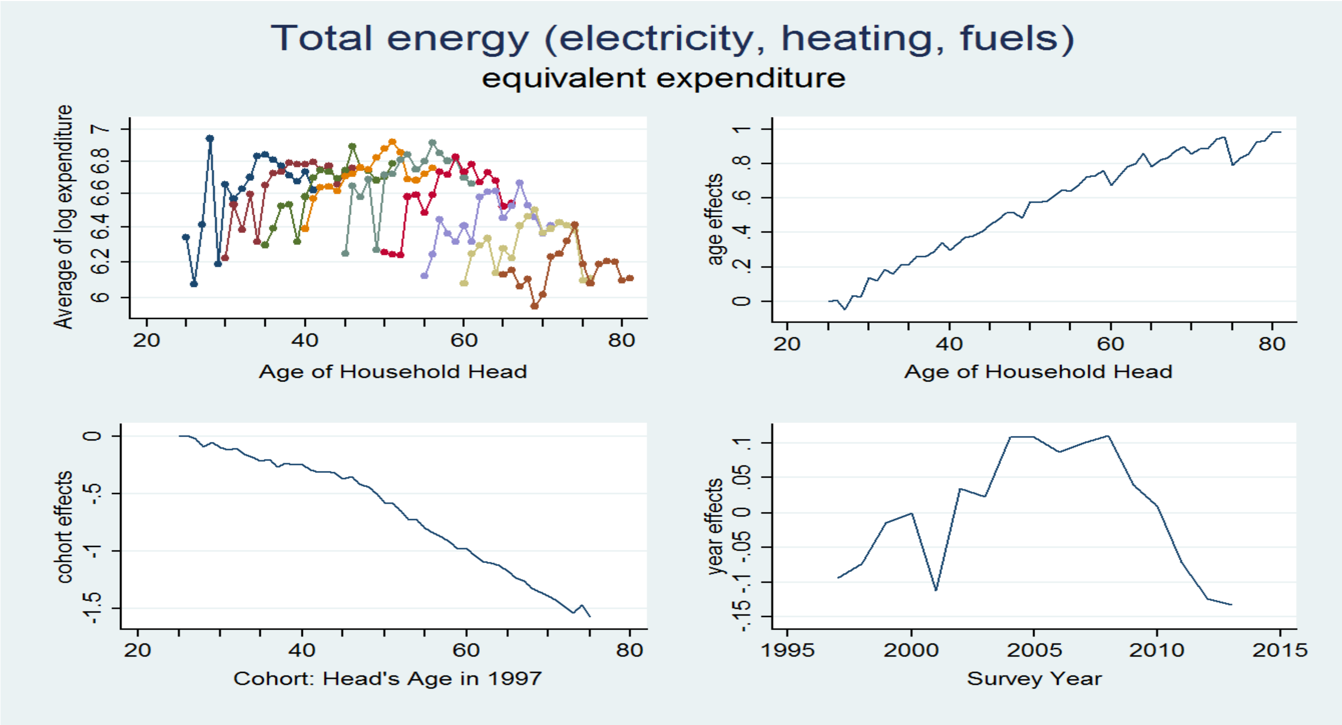
very high. With respect to the reference cohort (numbered 17, headed by those born in 1972), cohort effects are not statistically different for neighbouring previous generations and begin to differ significantly for baby boomers and older generations. Therefore, for example, the expenditure at age 50 of someone born in 1947 is on average 27 per cent higher than the expenditure at the same age of someone born in 1963. However, the baby boomers show a significant positive cohort effect when compared with the younger reference group of those born in 1972 (+17 per cent). The year effects (bottom right-hand panel) appear multi-peaked and seem to reproduce the economic cycle. To determine if cohort and age effects are statistically significant, Wald tests are performed and results are presented in Table 5. As shown, for both expenditure categories these effects are statistically significant.

Figure 5 – Cohort and age effects for equivalent transport fuel expenditure



Source: Authors' elaboration on IHBS data

Figure 6– Cohort and age effects for total household energy expenditure



Source: Authors' elaboration on IHBS data

Table 5- F-tests of significance of cohort and age effects

Equation	Cohort effects	Age effects
Transport fuels	F(72, 825) = 14.40 Prob > F = 0.0000	F(56, 825) = 130.21 Prob > F = 0.0000
Total household energy expenditure	F(72, 825) = 38.08 Prob > F = 0.0000	F(56, 825) = 16.87 Prob > F = 0.0000

Source: Authors' elaboration on IHBS data

Cohort and age effects for total household energy expenditure – the sum of residential and transport related energy demand - reveal a different pattern. Equivalent energy expenditure shows a steadily increasing age effect with an average increase of 1.8 per cent per year. As regards cohort effects, younger generations clearly have increased total energy expenditure and this is particularly true for the cohort of those born in the 1970s. This overall effect is due to the predominance of cohort and age effects related to electricity and heating fuels as shown in Bardazzi and Pazienza (2017). Indeed, for these energy expenditures we could roughly divide the 73 cohorts into two groups: the younger cohort – born between 1947 and 1988 – that grew up in the post-war period, a time of relative peace and economic growth and thus showing a preference for more heating comfort and leisure. The older generations (born before 1947) spend less for energy as most of these cohorts lived through the war and their spending attitudes were influenced by the experience.

6. Conclusions

The economics literature almost universally predicts that an aging population will increase residential energy consumption and reduce transport-related energy use: older households spend more on heating energy and less for private transport, because their members are at home for a larger proportion of the day. However, this causal link is more complex than expected because of the different pressures exerted by socio-demographic transformations (longer life expectancy and smaller family size), economic transformations (welfare state retrenchment, changes in job market, income distribution) and changes in lifestyle. Furthermore, the role of an evolving energy culture, as social norms, appears non-negligible.

In this paper, we have found evidence of a life-cycle pattern in vehicle possession and fuel expenditure, beside confirming the importance of other socio-demographic determinants on household transport-related energy use. This pattern is consistent also with the estimated age effects on the pseudo panel with a decreasing equivalent transport fuel expenditure after the age of 55. Age has the opposite effect on household total energy expenditure as older householders steadily increase their demand. However, by building cohort data for Italian households, we have decomposed and estimated also significant nonlinear cohort effects on transport fuel expenditure which interplay with the age effects to decrease transport fuel consumption in newer generations. According to our estimates, baby boomers and older generations have a positive cohort effect, so that their transport fuel expenditure is significantly higher compared with the younger generations. This evidence supports the argument of Stephenson et al. (2015) that different social norms, including individual expectations and aspirations, interplay with material culture and energy practices in shaping individual behaviour, subject to the external influences, which form the context where energy cultures develop. The changing age structure of population is interplaying with differentiate transport cultures: for baby boomers cars still give status and individuals of this generation drive more and more. On the other hand, Millennials show a higher environmental attitude and use new technologies to share and mix transport means. This transport transition can be appreciated by looking at age and cohort effects in Italy. Fuel consumption steadily declines with age, whereas cohorts born after the War (between 1949 and 1959) exhibit the highest fuel consumption intensity. In other words, beyond population aging, new generations may contribute to a reduction of transport fuel use and GHG emissions.

References

Bardazzi R. and M.G. Pazienza (2017), “Switch off the light please! Energy consumption, aging population and consumption habits”, *Energy Economics*, 65, 161-171.

Chancel L. (2014), “Are younger generations higher carbon emitters than their elders? Inequalities, generations and CO2 emissions in France and in the USA”, *Ecological Economics* 100 (2014) 195–207.

Deaton, A. (1985), “Panel data from time series of cross-sections”, *Journal of econometrics*, 30(1), 109-126.

Deaton, A. (1997), *The analysis of household surveys: a microeconometric approach to development policy*, World Bank Publications.

Deaton and Paxson (1994), “Intertemporal Choice and Inequality”, *Journal of Political Economy*, Vol. 102, No. 3 (June), 437-467.

Eakins, J. (2013), “The Determinants of Household Car Ownership: Empirical Evidence from the Irish Household Budget Survey”, *Surrey Energy Economics Centre (SEEC) 144*, School of Economics, University of Surrey.

Fuels Institute (2014), *Driver Demographics. The American Population's Effect on Vehicle Travel and Fuel Demand*, Fuels Intitute

Iacono, M., and Levinson, D. (2015), "Cohort Effects and Their Influence on Car Ownership", presented at the Transportation Research Board Annual Meeting 2016.

Innocenti A., Lattarulo P. and Pazienza M.G. (2013), "Car stickiness: Heuristics and biases in travel choice", *Transport Policy*, 25, 158-168

Liddle B. (2011) , "Consumption-driven environmental impact and age structure change in OECD countries: A cointegration-STIRPAT analysis", *Demographic Research*, Volume 24, Article 30.

McKenzie, D.J, (2006), "Disentangling Age, Cohort, and Time Effect in the additive Model", *Oxford Bulletin of Economics and Statistics*, 68, 473-495.

Menz T. and Welsch H., (2012), "Population aging and carbon emissions in OECD countries: Accounting for life-cycle and cohort effects", *Energy Economics,* 34 (2012) 842–849.

Mills, B. and Schleich, J., (2012), "Residential energy-efficient technology adoption, energy conservation, knowledge, and attitudes: An analysis of European countries", *Energy Policy*, 49, 616–628.

O'Neill B., Liddle B., Jiang B, Smith K., Pachauri S, Dalton M., Fuchs R. (2012), "Demographic change and carbon dioxide emissions", *Lancet* 2012; 380: 157–64

Okada A. (2012), "Is an increased elderly population related to decreased CO2 emissions from road transportation?", *Energy Policy* 45 (2012) 286–292.

OECD (2013), *Framework for Statistics on the Distribution of Household Income, Consumption and Wealth*, OECD, Paris.

Schulhofer-Wohl, S. (2013), "The Age-Time-Cohort Problem and the Identification of Structural Parameters in Life-Cycle Models", Federal Reserve of Minneapolis, Working Paper 707.

Steg, L., (2003), "Can public transport compete with private cars?", *IATSS Research* 27, 27–35.

Stephenson, J., Hopkins, D., & Doering, A. (2014), "Conceptualizing transport transitions: Energy Cultures as an organizing framework", *Wiley Interdisciplinary Reviews: Energy and Environment*, *4*(4), 354-364.

Stephenson, J., Barton, B., Carrington, G., Doering, A., Ford,R., Hopkins, D., Lawson, R., McCarthy,A., Rees, D., Scott,M., Thorsnes,P., Walton, S., Williams, J., Wooliscroft, B., (2015), "The energy cultures framework: Exploring the role of norms, practices and material culture in shaping energy behaviour in New Zealand", *Energy Research & Social Science*, Volume 7, 117-123.

Torgler, B., Garcia-Valiñas, M.A. and A. Macintyre, (2008), "Differences in Preferences Towards the Environment: The Impact of a Gender, Age and Parental Effect", FEEM Working Paper No. 18.2008. SSRN: http://ssrn.com/abstract=1105320

Yang, Y., Schulhofer-Wohl, S., Fu, W. J., and Land, K. C. (2008), "The Intrinsic Estimator for Age-Period-Cohort Analysis: What It Is and How to Use It", *American Journal of Sociology*, 113 (6), 1697-1736.

Yang D. and Timmermans H. (2012), "Effects of Fuel Price Fluctuation on Individual CO2 Traffic Emissions: Empirical Findings from Pseudo Panel Data", *Social and Behavioral Sciences* 54, 493 – 502.

Appendix

Table A1. Ordered Logit Regression. Dependent variable household car number(*)

Age classes	*18-24*	-0.233***
		(0.077)
	25-29	0.170***
		(0.054)
	30-34	0.294***
		(0.030)
	35-39	0.144***
		(0.014)
	45-49	0.004
		(0.023)
	50-54	0.128***
		(0.015)
	55-59	0.158***
		(0.032)
	60-64	-0.074*
		(0.042)
	65-69	-0.527***
		(0.051)
	70-74	-1.065***
		(0.057)
	75 and over	-1.903***
		(0.037)
	Gender	-0.687***
		(0.014)
	Education level	0.230***
		(0.024)
	Employment status	0.470***
		(0.017)
	Total equivalent consumpt. (ln)	1.306***
		(0.035)
	Home property size	0.126***
		(0.006)
	Houlsehold size	1.117***
		(0.029)
	Eq. Public Transp. exp. (ln)	-0.123***
		(0.002)
	Self-employer	-0.023*
		(0.013)
	Children (dummy)	-1.123***
		(0.032)
	Urban sprawl (dummy)	0.248***
		(0.063)
	Boat	0.320***
		(0.028)
	Motorbike	-0.018
		(0.011)
	Bike	0.536***
		(0.022)
	cut1	12.669***
		(0.328)
	cut2	16.452***
		(0.360)
	cut3	19.540***
		(0.370)
	N	390,328

* $p<0.1$; ** $p<0.05$; *** $p<0.01$

(*) The household car number has been classified in four categories:0,1,2,3 and above

Table A2 – Estimated parameters of age, period, cohort decomposition

		Fuels	Total Energy
age	26 years	-0.025	0.008
		(0.054)	*(0.032)*
age	27 years	-0.065	-0.049
		(0.054)	*(0.033)*
age	28 years	-0.080	0.037
		(0.055)	*(0.033)*
age	29 years	-0.038	0.026
		(0.055)	*(0.033)*
age	30 years	0.124**	0.137***
		(0.056)	*(0.033)*
age	31 years	0.069	0.123***
		(0.056)	*(0.034)*
age	32 years	0.009	0.188***
		(0.056)	*(0.034)*
age	33 years	0.025	0.160***
		(0.057)	*(0.034)*
age	34 years	-0.010	0.212***
		(0.057)	*(0.034)*
age	35 years	-0.075	0.218***
		(0.058)	*(0.034)*
age	36 years	-0.089	0.263***
		(0.058)	*(0.035)*
age	37 years	-0.123**	0.261***
		(0.058)	*(0.035)*
age	38 years	-0.166***	0.289***
		(0.059)	*(0.035)*
age	39 years	-0.179***	0.340***
		(0.059)	*(0.036)*
age	40 years	-0.218***	0.298***
		(0.060)	*(0.036)*
age	41 years	-0.228***	0.337***
		(0.060)	*(0.036)*
age	42 years	-0.227***	0.372***
		(0.061)	*(0.037)*
age	43 years	-0.289***	0.379***
		(0.061)	*(0.037)*
age	44 years	-0.269***	0.409***
		(0.062)	*(0.037)*
age	45 years	-0.255***	0.447***
		(0.062)	*(0.037)*
age	46 years	-0.256***	0.477***
		(0.063)	*(0.038)*
age	47 years	-0.274***	0.519***
		(0.063)	*(0.038)*
age	48 years	-0.299***	0.513***
		(0.064)	*(0.038)*
age	49 years	-0.328***	0.484***
		(0.064)	*(0.038)*
age	50 years	-0.324***	0.580***
		(0.065)	*(0.039)*
age	51 years	-0.358***	0.575***
		(0.065)	*(0.039)*
age	52 years	-0.355***	0.585***
		(0.066)	*(0.039)*
age	53 years	-0.407***	0.619***
		(0.066)	*(0.040)*
age	54 years	-0.398***	0.651***
		(0.066)	*(0.040)*
age	55 years	-0.516***	0.640***
		(0.067)	*(0.040)*
age	56 years	-0.589***	0.676***
		(0.067)	*(0.040)*
age	57 years	-0.580***	0.725***
		(0.068)	*(0.041)*
age	58 years	-0.600***	0.732***
		(0.068)	*(0.041)*
age	59 years	-0.592***	0.762***
		(0.069)	*(0.041)*
age	60 years	-0.889***	0.675***
		(0.069)	*(0.041)*
age	61 years	-0.926***	0.731***
		(0.069)	*(0.042)*
age	62 years	-0.944***	0.782***
		(0.070)	*(0.042)*
age	63 years	-0.938***	0.802***
		(0.070)	*(0.042)*
age	64 years	-0.958***	0.862***
		(0.071)	*(0.042)*
age	65 years	-1.419***	0.785***
		(0.071)	*(0.043)*
age	66 years	-1.375***	0.822***
		(0.072)	*(0.043)*
age	67 years	-1.418***	0.836***
		(0.072)	*(0.043)*
age	68 years	-1.431***	0.876***

		(0.072)	*(0.043)*
age	69 years	-1.465***	0.898***
		(0.073)	*(0.044)*
age	70 years	-2.076***	0.859***
		(0.073)	*(0.044)*
age	71 years	-2.086***	0.885***
		(0.074)	*(0.044)*
age	72 years	-2.095***	0.887***
		(0.074)	*(0.044)*
age	73 years	-2.114***	0.943***
		(0.074)	*(0.045)*
age	74 years	-2.144***	0.956***
		(0.075)	*(0.045)*
age	75 years	-3.418***	0.789***
		(0.075)	*(0.045)*
age	76 years	-3.410***	0.832***
		(0.076)	*(0.045)*
age	77 years	-3.396***	0.858***
		(0.076)	*(0.046)*
age	78 years	-3.381***	0.928***
		(0.076)	*(0.046)*
age	79 years	-3.374***	0.933***
		(0.077)	*(0.046)*
age	80 years	-3.419***	0.987***
		(0.078)	*(0.046)*
age	81 years	-3.423***	0.986***
		(0.078)	*(0.047)*
cohort	9	-0.393**	0.274***
		(0.165)	*(0.099)*
cohort	10	-0.400***	0.197***
		(0.120)	*(0.072)*
cohort	11	-0.489***	0.256***
		(0.100)	*(0.060)*
cohort	12	-0.455***	0.264***
		(0.088)	*(0.053)*
cohort	13	-0.446***	0.209***
		(0.081)	*(0.048)*
cohort	14	-0.469***	0.185***
		(0.075)	*(0.045)*
cohort	15	-0.446***	0.192***
		(0.071)	*(0.042)*
cohort	16	-0.348***	0.140***
		(0.067)	*(0.040)*
cohort	17	-0.336***	0.131***
		(0.065)	*(0.039)*
cohort	18	-0.309***	0.153***
		(0.062)	*(0.037)*
cohort	19	-0.255***	0.138***
		(0.060)	*(0.036)*
cohort	20	-0.224***	0.115***
		(0.059)	*(0.035)*
cohort	21	-0.190***	0.119***
		(0.057)	*(0.034)*
cohort	22	-0.110*	0.129***
		(0.056)	*(0.034)*
cohort	23	-0.117**	0.056*
		(0.055)	*(0.033)*
cohort	24	-0.098*	-0.021
		(0.054)	*(0.032)*
cohort	26	0.012	0.004
		(0.053)	*(0.032)*
cohort	27	0.012	-0.021
		(0.053)	*(0.032)*
cohort	28	0.049	-0.092***
		(0.053)	*(0.032)*
cohort	29	0.098*	-0.047
		(0.054)	*(0.032)*
cohort	30	0.079	-0.094***
		(0.054)	*(0.032)*
cohort	31	0.101*	-0.117***
		(0.054)	*(0.033)*
cohort	32	0.141**	-0.104***
		(0.055)	*(0.033)*
cohort	33	0.134**	-0.153***
		(0.055)	*(0.033)*
cohort	34	0.172***	-0.178***
		(0.055)	*(0.033)*
cohort	35	0.187***	-0.211***
		(0.056)	*(0.034)*
cohort	36	0.235***	-0.201***
		(0.056)	*(0.034)*
cohort	37	0.240***	-0.266***
		(0.057)	*(0.034)*
cohort	38	0.283***	-0.230***
		(0.057)	*(0.034)*
cohort	39	0.284***	-0.250***
		(0.058)	*(0.035)*
cohort	40	0.301***	-0.241***
		(0.058)	*(0.035)*
cohort	41	0.341***	-0.291***

		(0.059)	*(0.035)*
cohort	42	0.368***	-0.313***
		(0.060)	*(0.036)*
cohort	43	0.403***	-0.307***
		(0.060)	*(0.036)*
cohort	44	0.450***	-0.319***
		(0.061)	*(0.036)*
cohort	45	0.445***	-0.368***
		(0.061)	*(0.037)*
cohort	46	0.468***	-0.348***
		(0.061)	*(0.037)*
cohort	47	0.483***	-0.411***
		(0.062)	*(0.037)*
cohort	48	0.477***	-0.445***
		(0.062)	*(0.037)*
cohort	49	0.505***	-0.503***
		(0.063)	*(0.038)*
cohort	50	0.460***	-0.573***
		(0.063)	*(0.038)*
cohort	51	0.454***	-0.581***
		(0.064)	*(0.038)*
cohort	52	0.450***	-0.649***
		(0.064)	*(0.038)*
cohort	53	0.435***	-0.728***
		(0.065)	*(0.039)*
cohort	54	0.403***	-0.723***
		(0.065)	*(0.039)*
cohort	55	0.395***	-0.798***
		(0.066)	*(0.039)*
cohort	56	0.413***	-0.843***
		(0.066)	*(0.040)*
cohort	57	0.383***	-0.876***
		(0.066)	*(0.040)*
cohort	58	0.355***	-0.916***
		(0.067)	*(0.040)*
cohort	59	0.288***	-0.977***
		(0.067)	*(0.040)*
cohort	60	0.198***	-0.983***
		(0.068)	*(0.041)*
cohort	61	0.160**	-1.039***
		(0.068)	*(0.041)*
cohort	62	0.109	-1.087***
		(0.069)	*(0.041)*
cohort	63	0.041	-1.102***
		(0.069)	*(0.041)*
cohort	64	0.018	-1.123***
		(0.069)	*(0.042)*
cohort	65	-0.065	-1.177***
		(0.070)	*(0.042)*
cohort	66	-0.114	-1.237***
		(0.071)	*(0.042)*
cohort	67	-0.181**	-1.262***
		(0.072)	*(0.043)*
cohort	68	-0.250***	-1.324***
		(0.073)	*(0.044)*
cohort	69	-0.270***	-1.355***
		(0.074)	*(0.044)*
cohort	70	-0.358***	-1.390***
		(0.075)	*(0.045)*
cohort	71	-0.386***	-1.429***
		(0.077)	*(0.046)*
cohort	72	-0.389***	-1.490***
		(0.079)	*(0.047)*
cohort	73	-0.345***	-1.543***
		(0.081)	*(0.048)*
cohort	74	-0.276***	-1.469***
		(0.083)	*(0.050)*
cohort	75	-0.204**	-1.573***
		(0.086)	*(0.052)*
cohort	76	-0.385***	-1.582***
		(0.090)	*(0.054)*
cohort	77	-0.410***	-1.536***
		(0.095)	*(0.057)*
cohort	78	-0.778***	-1.789***
		(0.101)	*(0.061)*
cohort	79	-0.256**	-1.622***
		(0.112)	*(0.067)*
cohort	80	-0.473***	-1.553***
		(0.130)	*(0.078)*
cohort	81	-1.241***	-1.964***
		(0.172)	*(0.103)*
year	1999	-0.024	-0.015
		(0.019)	*(0.011)*
year	2000	0.030	0.000
		(0.019)	*(0.012)*
year	2001	0.038*	-0.111***
		(0.019)	*(0.012)*
year	2002	-0.062***	0.035***
		(0.020)	*(0.012)*
year	2003	-0.098***	0.023*

		(0.020)	*(0.012)*
year	2004	0.056***	0.109***
		(0.020)	*(0.012)*
year	2005	0.025	0.108***
		(0.020)	*(0.012)*
year	2006	0.073***	0.088***
		(0.020)	*(0.012)*
year	2007	0.063***	0.100***
		(0.020)	*(0.012)*
year	2008	0.073***	0.110***
		(0.020)	*(0.012)*
year	2009	-0.146***	0.040***
		(0.019)	*(0.012)*
year	2010	-0.042**	0.008
		(0.019)	*(0.012)*
year	2011	0.015	-0.072***
		(0.019)	*(0.011)*
year	2012	0.034*	-0.124***
		(0.019)	*(0.011)*
year	2013	-0.024	-0.133***
		(0.018)	*(0.011)*
Constant		6.201***	6.449***
		(0.055)	*(0.033)*
R^2		0.99	0.92
N		969	969

* p<0.1; ** p<0.05; *** p<0.01