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Are younger generations higher carbon emitters than their elders?

Inequalities, generations and CO_2 emissions in France and the USA

Lucas Chancel (IDDRI)

GENERATIONAL CHANGE AS A DRIVER OF CO2 EMISSIONS PATTERNS

The need for sustainable and fair energy policies calls for a precise understanding of the determinants of household energy consumption—or CO2 emissions. In this context, based on empirical material, this article is the first attempt to explore the interactions between date of birth, income and CO2 emissions over time in France and the USA. Groups of individuals born in a given year may indeed have similar consumption patterns, and date of birth can actually drive social and behavioral change.

BABY BOOMERS ARE HIGHER EMITTERS THAN THEIR ELDERS AND FOLLOWERS

Certain generations, like French 1935-1955 baby boomers cohorts, stand out as higher carbon emitters than others, once age and period have been controlled for. This trend, clearly observed in France and less pronounced in the USA, is the translation of significant inter-generational income inequalities. Since direct CO2 emissions do not exhibit an environmental Kuznets curve relationship—as households become richer, direct CO2 emissions do not decrease—richer generations emit more CO2.

EXPLAINING THE GENERATIONAL EFFECT BEYOND INCOME

Beyond income, other factors explain these generational trends. Different rates of technology penetration among cohorts, a modification in the composition of the consumption basket and a progressive modification of value systems also play a role. In terms of public policy design, this stresses the importance of education of the young in order to curb and durably alter the consumption behavior of future cohorts, beyond energy taxation and regulatory measures.

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Are younger generations higher carbon emitters than their elders? Inequalities, generations and CO_2 emissions in France and the USA

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ABSTRACT

A proper understanding of the determinants of household CO_2 emissions is essential for achieving a shift to sustainable lifestyles. This paper explores the impacts of date of birth and income on household CO_2 emissions in France and the USA.

Direct CO_2 emissions of French and American households are calculated from consumer budget surveys, over the 1980-2000 time period. The intrinsic estimator derived by Yang *et al.* (2004) is used to isolate the generational effect on CO_2 emissions—*i.e.* the specific effect of date of birth, independent of the age, year and other control variables. The paper shows that the French 1935-55 birth cohorts have a stronger tendency to emit CO_2 than both their predecessors and descendants. In the USA, the effect of date of birth is less significant. The generational effect is explained by the fact that over their lifespan, baby boomers are better off than other generations. Persistence of the generational effect once income is controlled for can be explained by cheaper access to housing for pre-1960 generations, enabling higher expenditure on energy intensive activities. Another explanation may be the difficulty for 1935-55 cohorts to adapt to energy efficient consumption patterns.

1. INTRODUCTION

The unsustainable nature of consumption patterns in industrialized countries is one of the greatest policy challenges of the 21st century (IPCC, 2007). The need for sustainable and fair policy calls for a precise understanding of the determinants of household consumption and, in particular, energy consumption—or CO_2 emissions. However, until recently, most national statistical tools were not equipped to address the distributional dimension of environmental footprints (Stiglitz *et al.*, 2009). While the recent failure of the carbon tax project in France revealed a high level of concern for the distributional impacts of resource taxation and policymakers' inability to address it convincingly.

While research on the links between national household inequalities and resource consumption is flourishing and gradually overcoming the research gap (see Druckman *et al.*, 2008, Weber *et al.*, 2008, Pasquier *et al.*, 2010), in this paper I argue that one important dimension is being overlooked: generations. Cohorts (*i.e.* groups of individuals born in the same year) may have a strong role in the determination of consumption patterns in general and for energy in particular. Through the influence of early life conditioning and of the historical or economic trends that have shaped their life cycles, cohorts may actually drive social and behavioral change (Ryder, 1965).

This paper represents the first attempt to explore the interactions between generational and income-expenditure effects on household CO_2 emissions. The precise objective is to provide historical empirical material on the interactions between income inequalities and inequalities in resource use, in France and the USA.

Firstly, I show that direct CO_2 emissions of French and American households have been relatively stable over the time period—while bottom decile emissions have increased. Results also reveal that direct CO_2 emissions do not exhibit an environmental Kuznets curve[1] relationship: as households become richer, direct CO_2 emissions do not decrease. Secondly, the paper shows that certain generations emit more CO_2 than others, once age and period have been controlled for. The consequential impact of this, which can be clearly observed in France, is the translation of important inter-generational inequalities. The cheaper access to housing enjoyed by post-1960 cohorts, along with, potentially, their higher ability to monitor energy consumption, explains the persistence of the effect after correcting for income.

The article then provides a literature review on household environmental footprints and on the generational determinants of consumption (II), a description of the methodology followed (III), a presentation of the results (IV), a discussion of their relevance (V) and a conclusion (VI).

2. INEQUALITIES, GENERATIONS AND HOUSEHOLD CO_2 EMISSIONS

2.1. The Kuznets curve

Grossman and Krueger (1995) posited an inverted U-shape relationship between income and environmental footprint—the so-called Environmental Kuznets Curve[2] (EKC). The theory being that as income grows, the willingness to pay for environmental protection increases, eventually leading to reduced environmental impact. The EKC hypothesis has been subjected to several empirical tests and validated for certain types of pollutants (e.g. SO_2, see Roca *et al.*, 2001) but

1. *i.e.* an inverted U curve associated to environmental pressure.
2. After Kuznets (1955) who showed that an inverted U-shape relationship existed between income and inequalities in the first half of the 20th century in the US.

not for others (e.g. greenhouse gases [GHG], see Stern *et al.*, 1996). A serious limitation of the EKC debate is that it focuses on mean income and mean CO_2 emissions of a given country and omits the national distributional dimension of resource consumption. Some authors, such as Pacala *et al.* (2009) have thus called for a focus on CO_2 distributions within countries, and on their relationship with national income distribution.

2.2. Household level CO_2 emissions and the Input-Output approach

Recent studies on household CO_2 emissions tend to invalidate the EKC at the household level. Using an Input-Output (I-O) approach, most authors show that the expenditure elasticity of energy or carbon emissions lies between 0.5 and 1 (Lenzen *et al.*, 2006). The I-O approach uses Leontief type (Leontief, 1986) matrices applied to energy fluxes to calculate the CO_2 content of production, taking into account carbon emissions associated to the carbon content of intermediary consumption, imports and exports. Each row of the matrix corresponds to an equation accounting for the flow of a good to each sector of the economy. Monetary flows can be converted into energy or carbon flows, which are then matched with household budgets, using household consumption categories (see Pasquier *et al.*, 2010 or Jackson *et al.*, 2009).

Using the I-O methodology, Pasquier *et al.* (2010) looked at direct and indirect CO_2 emissions of five different categories of emitters in France (*i.e.* income quintiles). They show that direct and indirect CO_2 emissions increase with income but that the income elasticity of CO_2 emissions is less than one. Top quintile households emit 2.7 times more CO_2 than the bottom ones, while they are 3.4 times richer. Poorest quintile households emit 8.3t per year per household while the richest emits 22t per year per household. In the US, with a similar approach, Weber *et al.* (2009) show that the poorest quintile emits 23t per year per household while the richest emits 73t CO_2 per annum.[3] The top quintile emits 3.3 times more CO_2 per household than the bottom quintile while it earns 4.7 times more. Weber *et al.* find an expenditure elasticity of CO_2 emissions ranging from 0.6 to 0.8—again invalidating the EKC hypothesis.

3. Estimates from Weber are calculated using 2003 US national income distribution, 1st quintile earning less than $19,000 per household per annum and top quintile earning more than $90,000 per household per annum.

Table 1. Energy consumption of top and bottom quintiles in France and the USA

	France Pasquier *et al.*, 2010	USA Weber *et al.*, 2009
Bottom quintile	8.3t	23t
Top quintile	22t	73t

These studies show that income is an important driver of CO_2 emissions in France and the USA but also reveal the importance of national fixed-effects (*i.e.* carbon intensity of the electricity mix, urbanization patterns, cultural determinants, etc.) which stand out as crucial factors. These effects are responsible for the fact that the richest households in France emit as much as the poorest households in the USA.

Most household level studies focus on a single time-period, due to the lack of reliable historical energy consumption data to fit I-O tables. Focusing on France, Pasquier (2012) calculated the evolution of total CO_2 emissions over a long time period (showing a 5% increase in direct and indirect per capita CO_2 footprint over the period, while emissions from the territory decreased by 15%). However, due to the limitations of the statistical database, the author could not distinguish between the emission levels of different income fractiles. Jackson and Papathanasopoulou (2008) are among the few authors who have looked at the emissions patterns of different population categories over a long time frame. Their study focused on the UK and shows that over the 1968-2000 time period, the energy consumption Gini coefficient[4] grew faster than the income Gini. In other words, income inequalities increased but inequalities in the use of resources increased at a higher rate. According to the authors this larger concentration of resource use by the richest households is mainly due to the development of air travel and car transportation for leisure purposes. The study also shows that energy consumption of all income groups increases over time, suggesting a Veblen effect for energy consumption as posited by Wilkinson & Pickett (2009): lifestyles of the top deciles seem to drive the consumption of other deciles upwards via mimetic effects.

2.3. Non-monetary drivers of CO_2 emissions

Several factors other than income drive energy consumption and related CO_2 emissions. It is

4. To calculate the resource Gini, the authors replaced total population income with resource use on the y-axis of the Lorenz curve.

helpful to distinguish between "environmental" factors (urban density, type of dwelling, technology type) and "lifestyle" (age, size of household, education level). Some authors have also looked at the role of cultural determinants in energy consumption (see Lutzenhiser, 1992).

Among the energy consumption drivers explored, age has been the subject of extensive analysis. Studies have looked at household carbon lifecycle for instance (see Pasquier, 2010). The generational factor, however, has been given little attention. Focusing on the fixed effects of date of birth is challenging because it requires historical data and a statistical estimator capable of isolating the effect of date of birth from the age and the year of observation. Pasquier *et al.* show that CO_2 emissions vary with age but their analysis did not allow them to distinguish between age, period or proper generational effects: *"In this study we compare consumption habits of different generations at the same date and we are not able to differentiate specific effects of date of birth and age. For instance, low levels of transport related-CO_2 emissions of the elders may be due to lesser demand and need for mobility after a certain age, as well as a low travel habits of generations born up to the 1930s."* (Pasquier *et al.*, 2010).

There are convincing theoretical and empirical arguments for a focus on energy consumption and generational dynamics. Literature from the fields of epidemiology, economics, geography and sociology shows that generational factors can be important determinants of observed differences between individuals and households (see Chauvel [2010] for France or Krugman [1977] for the USA). By shaping life chances (level of income, access to education, employment, housing), date of birth can also impact consumer behavior and ultimately environmental footprint.

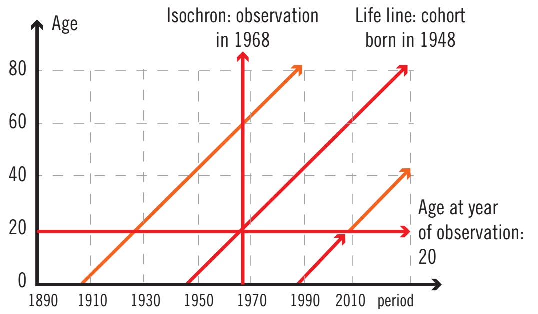
According to Ryder (1965), early life exposure to a certain socio-economic context can shape behaviour throughout ones' life trajectory. Date of birth can also affect values and consumption norms. This calls for the study of *scarring effects* associated to energy consumption. For instance, cohorts which lacked resources in general, and energy in particular, during young age, may have maintained low consumption habits over time (e.g. generations raised during wartime). Cohorts raised during economic booms may prolong their energy consumption habits over time, and have more difficulties adapting to reduced energy consumption behavior.

Inglehart (1977) posited that new values are not disseminated homogeneously among the population; instead, generations are the vectors through which values emerge and these are formulated in the context of family and public education. The author states that post-1950 cohorts are characterized by strong "post-materialistic" values, supposedly higher concern for environmental protection, more community interactions and altruism. "Post-materialism" has been criticized for its lack of empirical basis or weak conceptualization (Flanagan, 1980; Van Deth, 1983). But the idea that younger generations may have stronger environmental concerns and hence different consumption behavior clearly deserves attention.

Measuring generational impacts on consumption

Conceptually, the Lexis diagram presented below maps the interactions between three dimensions: age (on the x-axis), periods (on the y-axis) and cohorts. Diagonals correspond to the lifelines of cohorts: for example, the "68 generation" was born in 1948 and was twenty in 1968.

Figure 1. The Lexis diagram



Source: Chauvel (2010).

The major issue with Age-Period-Cohort (APC) analysis is the statistical identification problem associated with perfect linearity between age, period and cohort regressors.[5] The colinearity issue implies that regressors of the model produce multiple estimators of the three effects (*i.e.* there is an infinite number of possible solutions for the Ordinary Least Square estimators), making it impossible to interpret the results in a meaningful way. Constrained Generalized Linear Models (CGLIM) for APC analysis have been criticized for their inability to give convincing answers to the identification problem associated with linear dependency (see Yang *et al.*, 2004).

Recent studies in biostatistics and quantitative sociology can prove helpful for sustainable consumption researchers. Fu (2000) derived a statistical estimator which bypasses multicolinearity

5. In fact, *cohort=period-age*: there is perfect colinearity between the three regressors. See the appendix for a short mathematical description.

problems associated with linear dependency. According to Yang *et al.* (2008) the intrinsic estimator derived by Fu solves the issue by identifying an estimable function able to determine unique parameter estimates. The intrinsic estimator removes the impacts induced by the design matrix on coefficient estimates, making it possible to extract unique age, period and cohort coefficients—this is briefly detailed in the Appendix. The intrinsic estimator makes it possible to explore the dynamics between cohorts, income and time and see whether date of birth plays a role in energy consumption and lifestyle.

3. METHODOLOGY

3.1. Construction of household carbon footprints

The database constructed for this study uses information from the US Consumer Expenditure (CE) and the French Budget de Famille (BDF) surveys. The CE survey is performed by the Census Bureau for the Bureau of Labor Statistics in the US on an annual basis and distinguishes between 109 income, expenditure and wealth categories. The sample is obtained from a uniform randomization of Census surveys and consists of about 1,700 dwelling units.[6] The datasets chosen for this study correspond to the first quarter waves of the surveys for 1980, 1985, 1990, 1995 and 2000.

The French BDF survey is performed every five years by the National Institute for Statistics (INSEE). The survey sample is obtained from uniform randomization and consists of about 10,000 dwelling units.[7] The datasets chosen for this study correspond to the years 1979, 1985, 1989, 1995 and 2000. Since 1995, expenses have been examined through the Classification of Individual Consumption according to Purpose (COICOP). Evolution of the nomenclature over the time period studied required a significant amount of harmonization. A description of categorical variables used for the study can be found in the Appendix.

In both countries, expenditure per consumer unit is used as a proxy for living standard. Expenditure can be considered as a better marker for standard of living as it is smoothed over time while income can vary in the short run. Expenditure is further weighted according to the consumer unit[8] to account for family size and to more effectively bring into line the perceived and measured changes in welfare (see Ruiz, 2009).

3.2. Direct carbon footprints

Given the difficulty in obtaining historical data on energy to fit I-O tables, this study focuses solely on direct energy carbon footprints which can be calculated from household budget surveys, under a set of assumptions regarding fuel mix, fuel price and the carbon content of fuels. I have calculated CO_2 emissions equivalents associated with energy bills reported for electricity, gas, liquid domestic fuel, gasoline, personal and air transport. Estimates do not take into account CO_2 emissions arising from indirect energy consumption nor from fuels such as coal, wood or peat which are excluded from the analysis as they do not appear in the CE survey. Omission of such fuels may distort results, but presumably such a distortion would be minor as, in 1990, coal represented only 2.5% of total household energy consumption in France (French Environment and Energy Management Agency (ADEME), 2011).

Emissions were calculated from fuel expenditure, through the application of mean year fuel prices (obtained from 2010 data - from the French Ministry of Ecology, Sustainable Development and Energy (MEDDAT) for France and from the United States Department of Energy (DOE) for the USA) for all households. This study used IPCC emission factors and historical carbon content of electricity, which were provided by national energy agencies (DOE and ADEME). Emission factors include CO_2, CH_4 and N_2O.[9] A significant assumption made was the use of a single price per fuel for all households in one country - such an approach is standard in other household carbon footprint studies that use consumer budget surveys, but may result in an overestimation of the consumption of higher income groups as they generally pay less per unit. Air travel emissions were calculated from household expenditure on air travel, while the carbon content of flights was calculated from the average distance travelled per unit expenditure, derived from air transport databases (US Bureau of Travel Statistics (BTS), 2011). Databases were not available for France, so the US carbon per unit expenditure values were used,

6. Given a certain amount of attrition in the data, the Congressional Budget Office recommends the use of a weighting factor provided in the dataset (see Haris & Sabelhaus, 2000).
7. I have also applied a weighting factor, provided in the dataset, as recommended by INSEE.
8. For simplification purposes, consumer unit is defined as the square root of the number of inhabitants.
9. I thus use "CO_2" or "CO_2-e" without distinction.

correcting for exchange rate and average flight price differences in 2010.

The direct carbon footprint can be written as follows:

$$(1)\quad CO_{2it} = \sum_{k=1}^{N} \frac{exp_{ikt}}{price_{kt}} \times content_{kt}$$

Where CO_{2it} is the total household direct emissions for household *i* at time *t*, exp_{kt} the expenditure on fuel *k* at time t, $price_{kt}$ is the price of fuel *k* at time *t* and $content_{kt}$ the carbon content of fuel *k* at time *t*.

3.3. Age Period Cohort estimations

As discussed above, Yang *et al.* (2008) provide strong arguments for the use of the intrinsic estimator derived by Fu (2000). The Stata package "apc_ie" developed by Yang and Schulhofer-Wohl was used to compute it. As a first step, the intrinsic estimator of an APC model of log-CO_2 emissions without controls was calculated:

$$(2)\quad \log(CO_{2ij}) = \mu_0 + \alpha_i + \beta_j + \gamma_k + \varepsilon_{ij}$$

Where μ_0 is the intercept or adjusted mean logged-CO_2 emissions, α_i the i-th row age effect or coefficient for the i-th age group, β_j the j-th column period effect or the coefficient for the j-th time period, γ_k is the k-th diagonal cohort effect or the coefficient for the k-th cohort, with k=a-i+j. ε_{ij} is a random error with $E(\varepsilon_{ij}) = 0$.

As a second step, socio-economic, geographical and technical controls were introduced into the model:

$$(3)\quad \log(CO_{2ij}) = \mu_0 + \alpha_i + \beta_j + \gamma_k + \sum_m \mu_m \times \log(k_{mij}) + \sum_n \mu_n \times D_{nij} + \varepsilon_{ij}$$

Where μ_m is the coefficient for the continuous control variable k_m (*i.e.* total expenditure), and μ_n the coefficient for the categorical variable D_n (*i.e.* geographical location, building type). Several categorical variables were recoded (*i.e.* in order to reduce the number of categories) to increase statistical significance. The apc_ie package derived by Yang *et al.* on Stata was used to compute the estimate of Y_k for each cohort.

4. RESULTS AND ANALYSIS

Descriptive statistics

This section gives a very brief overview of the descriptive statistics derived from the two datasets.

Table 2. Descriptive statistics for the CE dataset (USA)

	1980	1985	1990	1995	2000
N	1,747	1,739	1,678	1,652	2,478
Age	46.6 (.91)	46.4 (.77)	47.5 (.76)	47.9 (.77)	48.5 (.68)
Person/hh	2.9 (.07)	2.7 (.06)	2.6 (.06)	2.6 (.06)	2.5 (.05)
tCO2cap	6.8 (.22)	8.1 (.18)	8.1 (.20)	8.3 (.20)	8.4 (.17)
Total Exp /cu	7,359 (249)	10,919 (258)	11,454 (304)	12,225 (342)	12,560 (296)
Gini	0.42	0.44	0.43	0.44	0.47

Note: Standard errors in parentheses. Total expenditure per consumer unit in 1980 US dollars

Table 2 shows that there is a sharp rise in per capita direct CO_2 emissions between 1980 and 1985 in the USA. This is presumably due to a reduction in oil consumption during the second oil crisis and the subsequent increase in usage once this period had ended. Interestingly, the top decile is not affected by oil price movements as their consumption is stable over time - reflecting the inelastic nature of energy for high income households.[10] Over the time period, the mean US household gets richer, older and smaller. The expenditure Gini coefficient significantly increases, showing strong variations behind mean variations. In fact, the income of bottom deciles stagnates while it increases for top fractiles (Piketty and Saez, 2003).

Table 3. Descriptive statistics of the BDF dataset (France)

	1980	1985	1990	1995	2000
N	10,080	11,074	9,022	9,634	10,211
Age	47.7 (.21)	48.6 (.18)	49.5 (.20)	49.3 (.19)	50.9 (.22)
Person/hh	2.84 (0.01)	2.73 (0.01)	2.7 (0.02)	2.5 (0.01)	2.5 (0.02)
tCO2cap	1.9 (.02)	2.4 (.02)	2.5 (.03)	2.6 (.04)	2.6 (.06)
Total Exp /cu	46,182 (302)	46,234 (325)	49,159 (384)	52,408 (491)	54,409 (588)
Gini	0.32	0.31	0.32	0.32	0.33

Note: Standard errors in parentheses. Weighting factor ponder is used. Total expenditure per consumer unit in 1980 FRF.

10. The consequences of this must be more carefully addressed in the drafting of environmental taxes: the wealthy do not modify their consumption as prices increase. If, as Veblen (1898) posited, society is driven by the social norm set by top deciles, consumption may be inelastic. Lower deciles may thus reduce consumption on other goods, reduce savings or increase demand for credit to maintain a certain consumption level.

The direct CO_2 emissions trend is similar in France (Table 3), with a sharp increase in per capita CO_2 emissions from 1980 to 1985 and relative stability afterwards. Over the time period average total expenditure increases, the expenditure Gini is relatively stable and households get smaller and older.

Figure 2 presents the evolution of direct CO_2 emissions of the top and bottom deciles in the USA. Breakdown of these emissions and emissions levels for other expenditure categories are presented in the Appendix. Figure 3 shows a factor three gap between top and bottom decile per capita direct CO_2 emissions. The difference in CO_2 emissions between rich and poor is due to three main factors: first to an intense use of personal transport by top decile households (and possibly less efficient vehicles); second, to the use of air travel by top decile households;[11] and third to a much greater use of electricity by top decile households, largely due to their possession of a greater amount of electrical appliances. In 2000 in the USA, 83% of top quintile households had a dishwasher against 19% of bottom quintile households; 92% of top quintile households had a washing machine and clothes dryer, against only 45% of the bottom quintile (RECS, 2000). The rich have more energy intensive durable goods (consumer durables) than the poor and use them more. In a context of the high carbon content of electricity, this translates into high electricity related CO_2 emissions for the top decile. Figure 3 uses data from another survey, the Residential Energy Consumption Survey (RECS, 2000), to break down household electrical energy consumption in further detail.

The gap between the top and bottom deciles is shown to reduce over time due to an increase in the direct energy consumption of poor households.[12] This increase is characterized by a higher use of private transport by poor households[13] and a higher use of electric devices. In 1980, only 35% of US homes had a dishwasher, compared to 60% in 2000; while the share of households with air conditioning increased from less than a quarter in 1980 to more than half in 2000 (RECS, 2000).

Figure 4 shows the evolution of CO_2 emissions for French households. There is a factor 3.2 gap between mean US and French household CO_2 emissions. The top US decile household emits three times more per capita than the top French decile household, while the bottom US decile household emits as much as the top French one—in line with the studies presented above. Two factors explain this result:

First, the average top French decile household emits very low levels of electricity related emissions compared to American standards. This is due to the specific nature of the French electricity mix: 690g CO2e/kWh in the USA against 150g CO2e/kWh in France in 1990[14] and to a higher equipment rate in electric devices in the USA. For instance, in 2000, 92% of top quartile American families had an electric clothes dryer compared to only 36% of French top quartile households (RECS, 2000 and BDF, 2000).

Second, Americans in the poorest decile emit one ton CO_2 per year per capita through private transportation, a much greater amount than their French counterparts that emit 0.3 ton. Urban planning and sprawl (see Karlenzig, 2009) are important drivers of this Franco-American divergence.

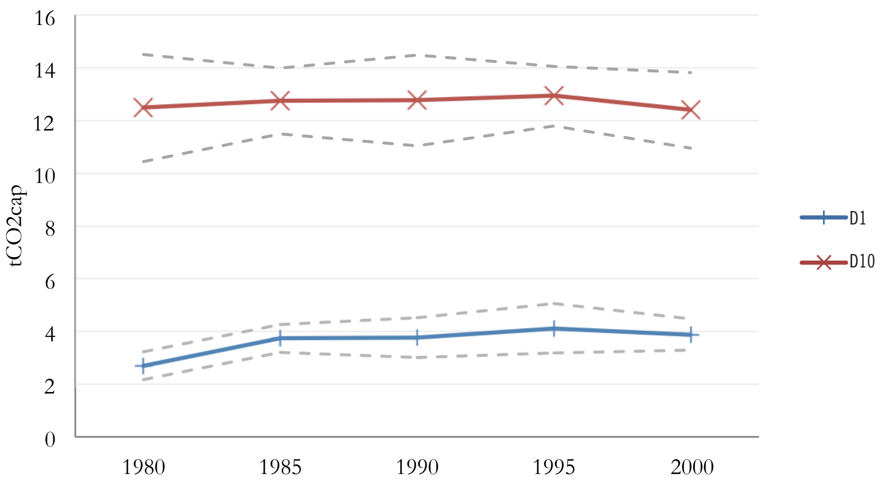
The gap between the direct CO_2 emissions of the rich and poor also reduces in France over the time period and is characterized by an increase in gas and domestic fuel energy by bottom decile households.

Comparison with other studies

The results were compared with other studies: Pasquier *et al.* (2010) for France, RECS (2000) and Weber *et al.* (2008) for the US. The RECS estimates for bottom decile households match the results obtained in this study. However, top decile households estimates are lower in the RECS than the CE survey (potentially due to the inclusion of secondary household expenses in CE estimates and not in the RECS). In France, Pasquier and others find higher values for top and bottom decile direct CO_2 emissions, but the top-bottom quintile gap is very close to the result obtained in this study: 2.3 for Lenglart compared to 2.6.[15] Comparisons with these studies show that estimates are meaningful enough to be used for further analysis. The aim of this paper is not the presentation of precise CO_2 per capita estimates (data sets from surveys precisely targeting energy consumption would be more pertinent for this) but rather to examine the long-term dynamics and to extract generational determinants.

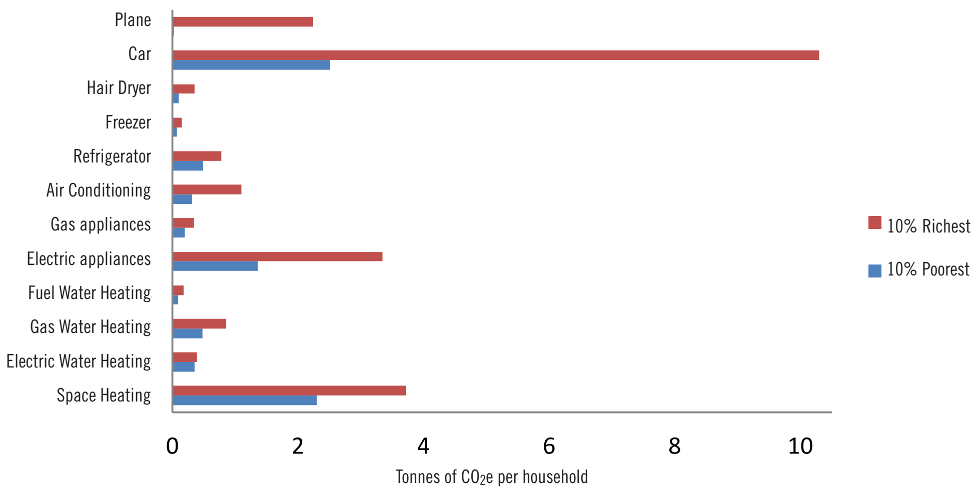
11. Caution: air travel emissions may be underestimated (see Methodology section).
12. Note: inclusion of indirect CO_2 emissions are likely to invert this trend—see Jackson and Papathanasopoulou (2008) for the UK.
13. From 1970 to 2000, the distance driven per month by average households increased by 50% (Ramey and Vine, 2010). The increase may also be due to a return to normality after the second oil shock.
14. This value is due to a high share of nuclear electricity, a relatively low carbon technology yet with its own types of pollutants which are not the subject of this study.
15. Note: Lenglart and others do not present results for income deciles.

Figure 2. Evolution of CO_2 emissions of the richest and poorest 10% in the USA



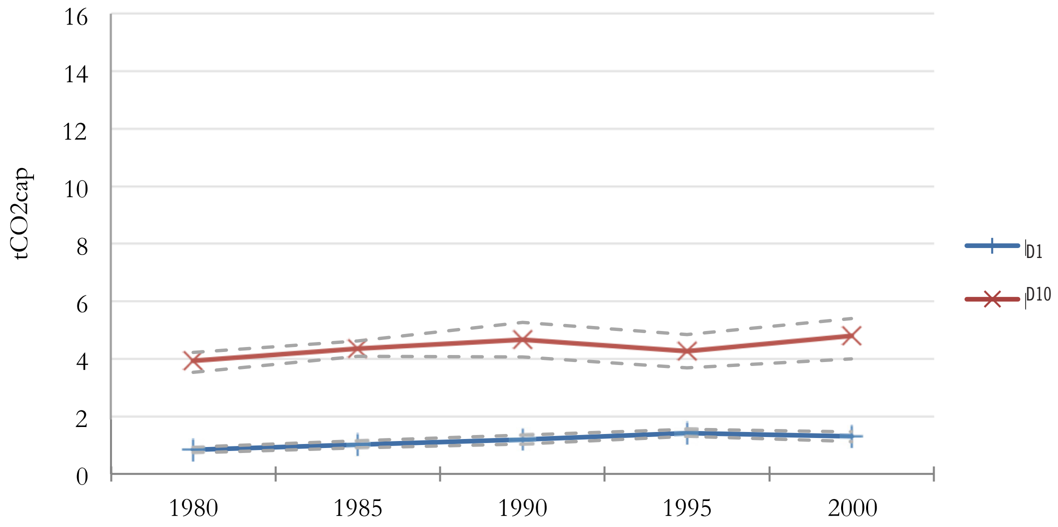
Note: Per capita direct CO2 emissions in top and bottom decile households. The dotted lines represent 95% confidence intervals

Figure 3. Detailed sources of CO_2 emissions for top and bottom deciles of US households in 2000.



Note: Estimates from US RECS 2000 (NB: car and plane data obtained from the US CE survey).

Figure 4. Evolution of CO_2 emissions of the richest and poorest 10% in France



Source: BDF. The dotted lines represent 95% confidence intervals

Table 4. Comparison between the estimates in RECS and this study (CE)

		RECS	CE
10% Poorest	1990	6.3	6.2
		(.16)	(.45)
	2000	5.7	6.1
		(.13)	(.46)
10% Richest	1990	10.8	14.2
		(.29)	(.79)
	2000	9.4	15.7
		(.25)	(.73)

Note: Figures shown are from the 1990 RECS survey estimates of direct CO_2 emissions (without transport) of the first American decile at 6.3 tCO_2 per year. Standard errors are in parentheses

Table 5. Comparison of estimates in Lenglart (2010) and this study

	BDF	Lenglart
20% Poorest	3.3	4.8
	(0.09)	
20% Richest	8.9	11.1
	(0.28)	

Capturing the specific effect of date of birth

Equation (2) was then applied to compute γ, the coefficient specific to date of birth, *i.e.* the impact of date of birth on direct CO_2 emissions once age and year fixed effects have been controlled for. Then, equation (3) was used to control for socio-economic, geographic and technical variables.

Figure 5 shows that in the USA, cohorts born from 1920 to 1940 emit more than average over the 1980-2000 time period, *i.e.* independently of their age and the year of observation. No significant cohort effect can be observed for cohorts born before 1920 and after 1940.

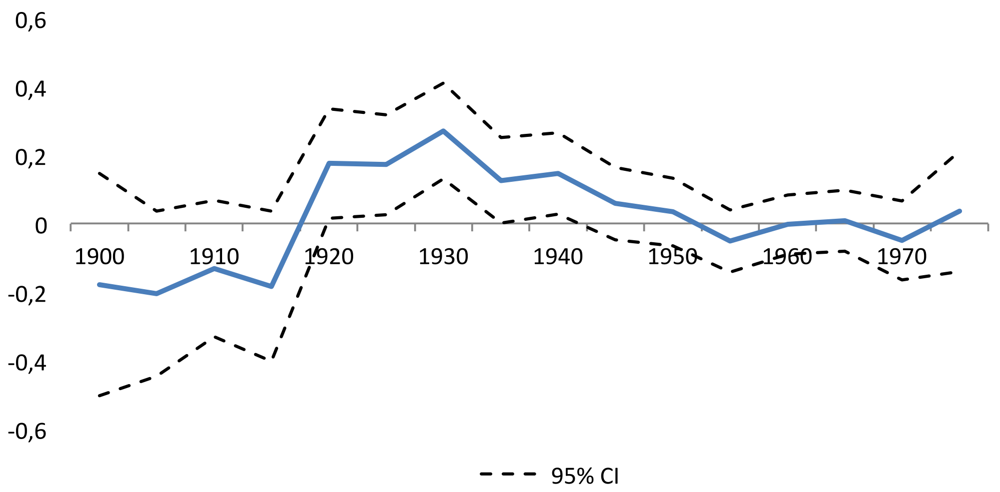
When socio-economic, geographic and housing-type controls (see Appendix) are included in the model, the cohort effect is reduced and becomes no longer statistically significant - apart from 1950 cohorts, below the average (Fig. 6). Cohorts born between 1920 and 1940 emit more than average because they are richer and more educated on average. When these effects are controlled for, no difference between cohorts can be found.

In France, the cohort coefficient, *i.e.* the effect of date of birth once age and period effects have been controlled for, is more apparent than in the US. Over the time period, cohorts born from 1920 to 1960 emit more direct CO_2 than average (Fig. 7). In particular, cohorts born from 1930 to 1955 stand at the top of the CO_2 emissions curve. Independently of their age and the year of measurement, they emit 30% more than the average household. This effect is presented in the 3D plot below (Fig. 8), which maps percentage difference between actual and predicted CO_2 emissions by a model with age and period regressors only.[16] This clearly shows that beyond age and year-average differences, some cohorts are stronger emitters than others.

Figure 8 shows a relative decrease in emissions from younger people in comparison to the

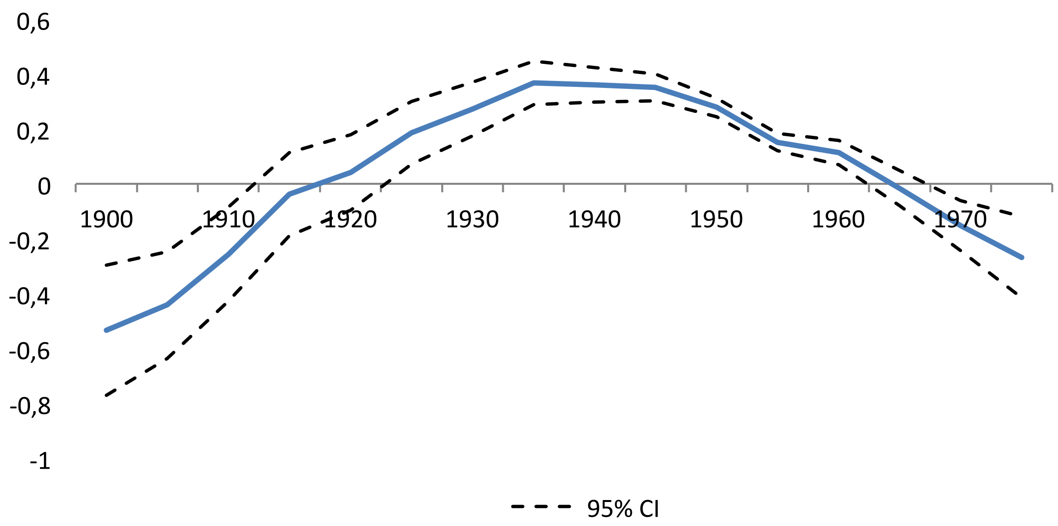
16. I plot residuals ε_{ij} of a regression model of the form: $\log(CO_{2ij}) = \mu o + \alpha i + \beta j + \varepsilon_{ij}$

Figure 5. Cohort effects on direct CO_2 emissions in the USA



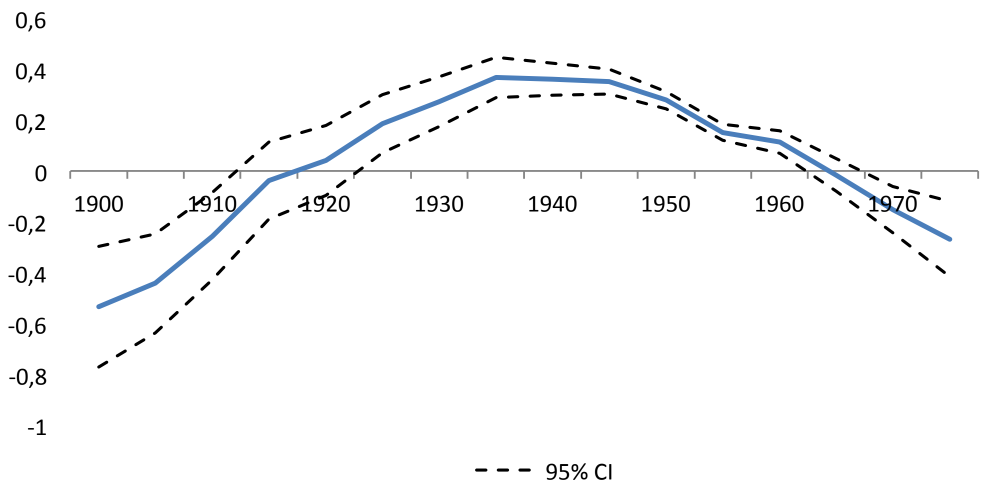
Note: The y-axis plots the γk coefficient of model 2. Households where the head is born in 1930 emit 29% more CO2 emissions than average, over the 1980-2000 time period. The exact effect can be computed using exp(α). When α is small, exp(α) $\approx$ α+1.

Figure 6. Cohort effects on direct CO_2 emissions in the USA— γk coefficients of model (3)



Note: The y-axis plots the γk coefficient of model 3. Households where the head is born in 1930 emit 29% more CO_2 emissions than average, over the 1980-2000 time period. The exact effect can be computed using exp(α). When α is small, exp(α)-1 $\approx$ α.

Figure 7. Cohort effects on direct CO_2 emissions in France



Note: The y-axis plots the γk coefficient of model 2. Households where the head is born in 1945 emit 35% more CO2 emissions than average, over the 1980-2000 time period. The exact effect can be computed using $\exp(\alpha)$. When α is small, $\exp(\alpha) \approx \alpha + 1$.

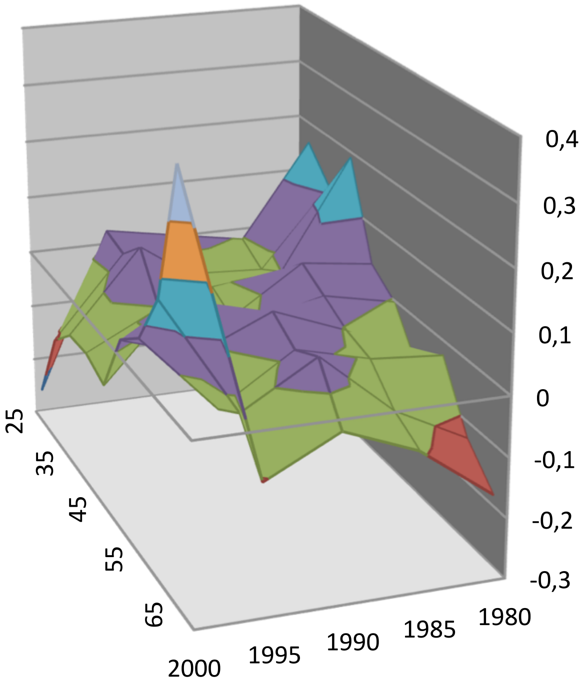
emissions of the elderly. In 2000, the young emitted 20% less than predicted, while they emitted 15% more in 1980. Second, elders emitted relatively more in 2000 than they did in 1980. Third, the back right corner—front left corner diagonal on the graph corresponds to the 1930-1955 cohorts who emitted more than predicted throughout the entire time period.

Interestingly, unlike in the US example, the effect remains strong and statistically significant after the introduction of socio-economic, geographic and housing-type controls (Fig. 9). Independently of their age, expenditure level, housing type, the number of people per household, their region, the urbanization pattern of their locality and their education level, 1930-1955 cohorts emit more than the others, over the 1980-2000 period. Further analysis of the cohort effects on the five CO_2 emissions sources in France[17] (Fig. 10) reveals the following trends:

- i) Electricity: Electricity consumption and related carbon emissions decline sharply for cohorts born after 1950. This may be due to several factors: possession of inefficient electric devices by cohorts born before 1950, or ownership of more electric devices and a tendency to use them more;
- ii) Gas: 1920 to 1950 cohorts are responsible for higher than average CO_2 emissions resulting from gas consumption (though only the coefficients for 1940-50 cohorts are statistically significant). This may be due to the higher share of households of these cohorts possessing gas devices and/or a higher tendency to heat;
- iii) Private transport: There is a sharp increase in the emissions from private transport for cohorts born after 1920 and a small decrease for post-1960 cohorts: one possible explanation is differential rates of unemployment among cohorts leading to reduced use of private transport;
- iv) Domestic fuel: post-1945 cohorts are below average in terms of domestic fuel emissions. This may reflect a progressive technology shift, from domestic fuel to gas and/or electricity. Younger cohorts are likely to enter new houses equipped with recent technology, inducing this generational trend, or they may tend to heat their homes less.
- v) Air transport: cohorts from 1920 to 1950 have higher emissions from air transport than average, presumably due to higher relative purchasing power than subsequent generations, as discussed below.

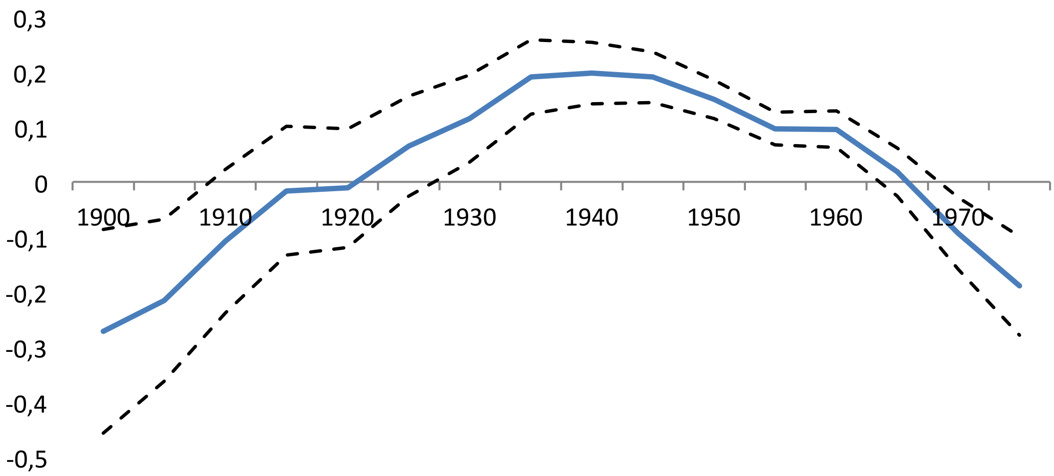
17. The same analysis in the USA yields insignificant results.

Figure 8. Percentage variation from mean CO_2 emissions of different age groups in France



Note: In 2000, 65-year olds emit 30% more than in the model that includes time and period controls. In 1980, the same age group emitted 20% less. The purple spine of the surface (back right corner to the front left corner) corresponds to the generation born in 1935-55.

Figure 9. Cohort effects on direct CO_2 emissions in France– γk coefficients of model 3



Note: The y-axis plots the γk coefficient of model 3. Households where the head is born in 1945 emit 35% more CO2 emissions than average, over the 1980-2000 time period. The exact effect can be computed using exp(α). When α is small, exp(α)-1≈α.

5. DISCUSSION

What are the drivers behind the cohort effect on CO_2 emissions and why is it stronger in France than in the USA? There are three lines of explanation to answer these questions: first, the trend may be due to long term social dynamics (a "generational rift"); the differences may also be due to different rates of technology penetration among cohorts; and thirdly the divergence between young and older cohorts may be due to a progressive modification of value systems and behavior.

5.1. Generational rift

The generational rift hypothesis stems from a growing body of literature on intergenerational inequalities in France and in the USA. The fact that 1930-55 cohorts in France have throughout their lives enjoyed better life chances (*i.e.* access to employment, housing, public services, etc.) than any other generation has been the subject of several empirical analyses that have supported each others findings (see Baudelot and Establet, 2000; Chauvel, 2006). During the *Trente Glorieuses* (1940s-1970s), young people began careers that paid the same income as their parents received at the end of their careers: they did better than their elders thanks to economic acceleration. With the post-1970 economic slowdown, new generations became more economically and socially fragile. The 1974 unemployment rate of school leavers, within 24 months of leaving school, was 5%; a figure that rose to 35% in 2000. Marginalized access to labor markets contributed to an increased earning gap between generations. In 1977, the earnings gap between the age groups 30-35 and 50-55 was 15%, rising to about 40% in 2009 (Chauvel, 2010). Post-1960 generations are thus, on average, economically worse-off than their elders.[18]

It is thus not surprising that 1930-55 cohorts stand at the top of the CO_2 emissions curve (Fig. 10) as they enjoyed higher expenditure levels than those that followed after them (and their predecessors), they could also spend more on energy intensive activities, inducing higher carbon footprints. This is in line with section IV: income elasticity of direct CO_2 emissions is less than one but positive. In other words, CO_2 emissions levels are driven by expenditure level, which varies among cohorts. In France, the 1930-55 generations are richer than subsequent generations and hence emit more.

However when expenditure level is controlled for in France, as shown in equation (3), the cohort coefficient remains strong. This suggests that expenditure level is not the only explanation for the generational gap in CO_2 emissions in France. Even when age, expenditure level, education level, household size, location and building type are the same, households whose head is born before 1960 emit more than households whose head is born after 1960. How can we explain the persistence of the generational effect beyond controls?

In the view of the author, housing expenses play a role in explaining the cohort CO_2 emissions gap. The share of the total expenditure on rent and loan reimbursement is presented in Figure 12. Households whose head was aged 40 in 1980 (born in 1940) spent 6% of their budget on rent/mortgage. In 2000, the corresponding figure for the same age group (born in 1960) was 17%. . In fact, the "generational rift" impacts not only on the level of income (or expenditure) but also on the composition of the expenditure basket. It is clear that post-1960 cohorts spend more on rent than their elders, meaning that at the same level of expenditure, the latter must reduce expenses on other categories: such as entertainment (and private transportation), travel (air transport) or household energy.[19]

5.2. Technology and values change

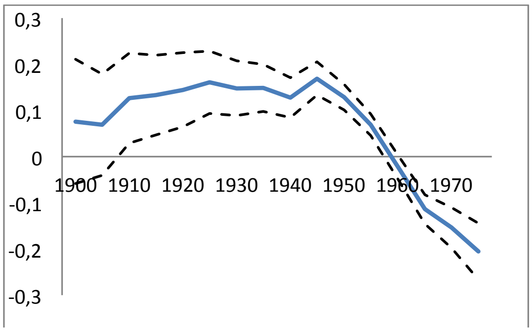
The preceding sections highlight the role of economic factors in influencing the expenditure patterns of certain French generations more so than others. Budget constraints may not explain the entire generational gap. Younger generations may also be more likely to adopt more efficient technologies, simply because such technologies are available when they enter into adult life and they begin to equip their homes, or because of a willingness to be more energy efficient. The French Research Centre for Studies and Observations into Living Conditions (CREDOC) (2009) showed that in 2009 in France, the 1970-75 cohorts had more class A appliances than pre-1970 cohorts. However, such a technological shift does not necessarily translate into a reduction in energy use. Much literature on the subject of the rebound effect shows that more efficient technology can actually lead to increased energy consumption.

This implies that younger French generations may progressively become less energy intensive

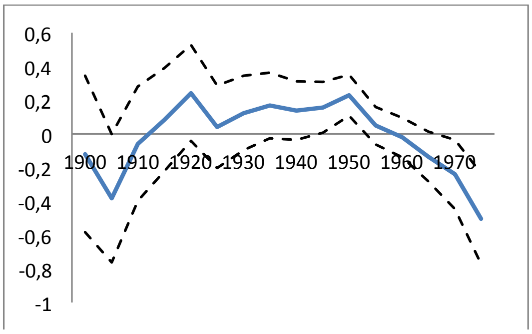
18. Indeed, there are strong variations beyond the mean and higher intergenerational inequalities, which by no means imply a leveling of intra-generational inequalities.

19. This is apparent in the data: at the age of 30, the 1955 generation spent a higher share of its budget on transport than average (2.5 percentage points more). At the same age, the 1970 generation does not spend more than average.

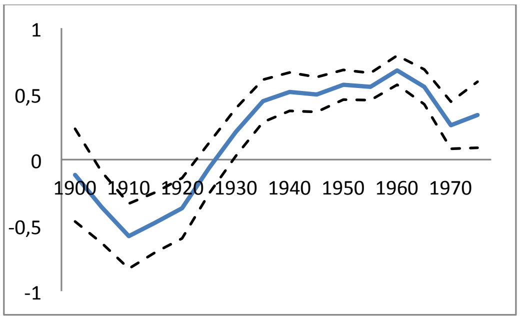
Figure 10. Cohort effect on different emissions sources in France



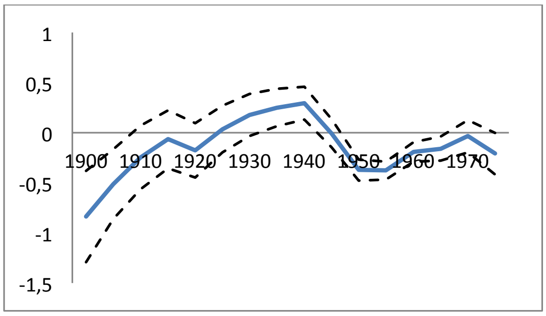
Electricity



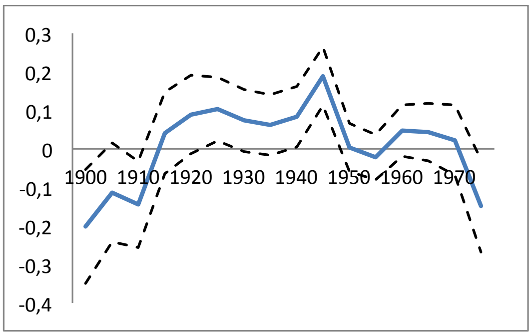
Gas



Private transport



Domestic fuel



Air transport

Note: The y-axis plots the γk coefficient of model 3. Households where the head is born in 1945 emit 20% more CO_2 emissions than average, over the 1980-2000 time period. The exact effect can be computed using exp(α). When α is small, exp(α)-1≈α.

than their elders (beyond socio-economic constraints and technical change dynamics). This argument is supported by the fact that once the share of rent in total expenditure is included (model 3), it only accounts for a fraction of the CO_2 emissions differential among cohorts. The dataset in the study cannot distinguish between technology change and reduced consumption to explain the emission gap beyond budget constraint, but it is likely that both play a role.

In the USA, the cohort effect is less striking than in France. As Chauvel (2006) shows, there are generational inequalities in the USA, translating into poverty rates above 20% for post-1955 cohorts and below 12% for pre-1955 cohorts.[20] The 1920-40 cohorts emit more than average because they are socio-economically better off. But when expenditure level and education level are controlled for, the effect disappears. This reflects different dynamics in the inequalities between cohorts in the USA and in France. In the US, these dynamics tend to be more complex and more equivocal than in France, with a stronger class/ethnic dimension in the US, reducing the impact of date of birth versus that of social background. In addition, it is not possible to identify any significant modification of behavior among younger cohorts in the USA.

Scope and limits of the study

The paper highlights interesting generational drivers on energy consumption. There are however limits to the results, some are inherent to historical data mining exercises and others are associated with the statistical tool used. Several assumptions were made to compute direct carbon footprints over a long time frame and they limit the precision of the results. For instance, I assumed that households at a given period all paid the same price per unit fuel purchased, while price generally decreases with quantity. This tends to underestimate energy consumption of the richest households. Estimates of air travel emissions required several major assumptions: estimates were only calculated from non-business flights, using expenditure on air transport reported in consumer budget surveys. In addition, any travel not accounted for in the household consumer budget surveys would have been omitted from the carbon contents.

It was also assumed that the generational effect is a "head of the household" generational effect. In other words, I assumed that the date of birth of the head actually influences the energy consumption behavior of the rest of the dwelling unit.

The intrinsic estimator used in the study must also be interpreted with caution (see O'Brien, 2011, for a detailed discussion). On the one hand, the intrinsic estimator distorts values for cohorts at both ends of the time spectrum, potentially increasing the gap between cohorts. At the time of writing, a corrected version of the estimator has been developed and is currently being finalized. It is intended to provide a detrended version of Fu's estimator, reducing the end of time frame distortions. On the other hand, estimator precision depends on the length of the time period studied. The larger the time period, the more accurate is the cohort effect—and the less it captures age effects. In this analysis, I look at cohorts over the 1980-2000 horizon, which means that some cohorts enter the dataset having already retired. This influences their cohort fixed effects. In this light, it is better to focus on cohorts who are working at the time of their entry into the dataset, and also at their exit from it. These correspond to households aged between 30 and 60 over the time period, *i.e.* 1940-70 cohorts. And it is precisely over this cohort time frame that the emission gap is apparent in France. The main insight of the analysis thus holds when we focus solely on working-age households.

Finally, I only focus on direct CO_2 emissions. Incorporating indirect emissions would yield different results. Jackson (2009) showed that the total direct footprint of the top income group increases faster than other groups—which is not what is observed for direct carbon footprints in this dataset.

Implications of the generational carbon gap

"There is a generational impact on CO_2 emissions. So what?" In terms of sustainable consumption research, the cohort effect highlighted in the study shows that there is clear pertinence in the application of APC models for the analysis of (unsustainable) resource consumption. It will be particularly interesting to look at direct and indirect CO_2 emissions, *i.e.* coupling the APC approach with the I-O methodology in the future. Beyond CO_2 emissions, other types of resources should also be looked at, such as water and land use. As the emissions gap has different characteristics in France and the USA, further cross country comparisons are required. In particular, APC analysis on resource use in emerging countries will be interesting.

Regarding policy design, results must be split into two categories: intra-generational income inequalities and carbon emissions; and inter-generational issues. The distributional impacts of carbon taxation are the subject of a growing body of literature (see Hourcade *et al.*, 2010, for a discussion in France). The failure of the carbon tax proposal in France stressed the need for a better identification of who will be the losers of carbon tax reforms

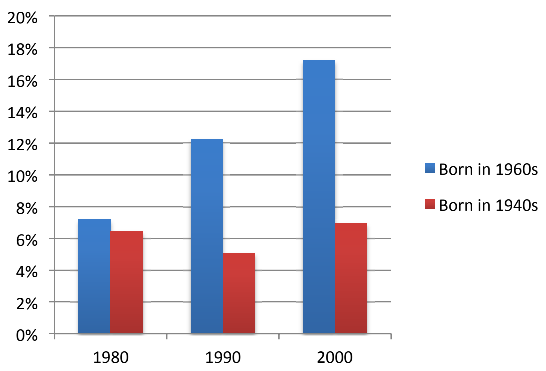
20. See also Krugman (1992)

(Senit, 2012). This is apparent in the dataset: in both countries the poorest decile emits three times less direct emissions than the top decile, but there is a significant number of bottom decile high emitters. In fact, a tenth of bottom decile households emit as much as the top decile in France in 2000. This calls for smart compensation mechanisms on top of a carbon tax—or its integration into a wider fiscal reform for greater progressivity.

In terms of inter-generational issues, this paper reveals that budget constraints induce behavioral change among bottom and medium deciles: due to higher socio-economic constraints, post-1960 generations enjoyed relatively lower expenditure levels than their elders (and hence the level of energy intensive activities). This is a rather undesirable picture of social change—the lower direct CO_2 emissions of the young are largely due to their increased marginalization, high unemployment rate and higher share of expenses on housing.

The persistence of the generational effect in France, once standard of living has been controlled for, also shows the role of social change and long-term dynamics in determining CO_2 emissions trends. Beyond their higher budget constraints, the French post-1960 cohorts emit less than their elders. The results suggest that once consumption trends were adopted by 1930-55 cohorts, they persisted throughout their lives. Persistence of this effect stresses how difficult it is for individuals to alter the energy consumption behaviors that they adopted in their younger years, despite technological change and the potential diffusion of new values. This highlights the importance of policy to alter these trends. It also stresses the importance of education of the young in order to curb the consumption behavior of future cohorts, beyond energy taxation and regulatory measures.

Figure 11. Share of budget spent on housing in France among age groups in 1980 and 2000



Note: In 1980, households where the head was aged between 20 to 30 spent 13% of income on rent or housing Source: BDF survey

6. CONCLUSION

This paper uses consumer household budget data to calculate direct carbon footprints of different categories of households over time in France and the USA.

The analysis first looks at the expenditure/emissions gap between households. It shows that: i) the richest 10% of the population emits around three times more direct CO_2 than the poorest 10% in both countries; ii) there is a small but statistically significant reduction in the gap between rich and poor emissions over time; iii) there is a substantial difference in terms of mean CO_2 emissions in both countries, which translates into the richest French emitting as much direct CO_2 as the poorest Americans.

Secondly, I explore the role of date of birth on CO_2 emissions. Principal component regression is used to compute the intrinsic estimator of an APC model. The analysis shows that: i) there is no cohort effect on CO_2 emissions in the USA once expenditure and educational controls are included in the model; ii) there are clear cohort effects on CO_2 emissions in France, before and after controlling for socio-demographic and technical variables, the 1930-1955 cohorts stand out as the highest emitters, holding other factors constant; iii) the generational effect is the reflection of a progressive marginalization of later cohorts as well as the more consumerist living standards of the French “baby boomers” compared to subsequent generations.

The historical household level carbon database created for this study can be enlarged for other countries (*i.e.* emerging countries). It can be coupled with the I-O methodology to include indirect CO_2 emissions, *i.e.* carbon which is not emitted at the point of use but during the production processes of goods. There is further work to be done on bridging the gap between 2000 and the present to observe whether the latest cohorts have inverted the observed “generational carbon trend”. In terms of public policy design, the study reveals that focusing on education of the young is an efficient way to durably alter consumption patterns.

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APPENDIX

The intrinsic estimator

The APC model of logged CO_2 emissions can be written as follows:

$$(4) \quad \log(CO_{2ij}) = \mu_0 + \alpha_i + \beta_j + \gamma_k + \varepsilon_{ij}$$

Where μ is the intercept or adjusted mean logged-CO_2 emissions, α_i the i-th row age effect or coefficient for the i-th age group, β_j the j-th column period effect or the coefficient for the j-th time period; γ_k is the k-th diagonal cohort effect or the coefficient for the k-th cohort, with k=a-i+j. ε_{ij} is a random error with $E(\varepsilon_{ij}) = 0$.

The model is reparameterized to centre its parameters and hence can be treated as a fixed effects generalized linear model:

$$(5) \quad \sum_i \alpha_i = \sum_j \beta_j = \sum_k \gamma_k = 0$$

In conventional matrix form it can be written as:

$$(6) \quad Y = Xb + \varepsilon$$

Where Y is a vector of log-transformed CO_2 emission rates, X is the regression design matrix, which consists of column vectors for the vector of model parameters b, with

$$(7) \quad b = \left(\mu_0, \alpha_1, \dots, \alpha_{a-1}, \beta_1, \dots, \beta_{p-1}, \gamma_1, \dots, \gamma_{a+p-2}\right)^T$$

With α i $\beta j \gamma$ k the coefficients on each age/period cohort category.

As stated above, there is no uniquely defined vector of coefficient estimates because of the colinearity problem. The OLS estimator, $(X^TX)^{-1} X^TY$, does not exist: the structural identification problem of APC models. The Intrinsic Estimator approach tries to solve this issue by rewriting each of the model's infinite number of solutions as:

$$(8) \quad b_{est} = B + kB_0$$

Where k is a scalar and B_0 is a unique eingenvector which does not depend on observed CO_2 emissions, only on the design matrix X—which is determined by the number of age, period and cohorts categories. In the CGLIM approach, k is not constrained to 0 which implies that B_0 can play a role in the estimation of effect coefficients, although it should not.

In fact, the linear dependence between age, period and cohort can be restated as:

$$(9) \quad XB_0 = 0$$

With B_0, the normalized vector of B_1:

$$(10) \quad B_0 = \frac{B_1}{|B_1|}$$

$$(11) \quad B_1 = (0, A, P,$$

$$\text{with } (12) \quad A = \left(1 - \frac{a+1}{2}, \dots, (a-1) - \frac{a+1}{2}\right), P = \left(\frac{a+1}{2} - 1, \dots, \frac{p+1}{2} - (p-1)\right),$$

$$(13) \quad C = \left(1 - \frac{a+p}{2}, \dots, (a+p-2) - \frac{a+p}{2}\right)$$

where a, p and c are the number of age, period and cohort categories. B_0 is a function of the dimension of the design Matrix X (*i.e.* the number of age and period groups) and independent of the explained variable Y. It should not enter into the computation of effect coefficients (*i.e.* k must be set to 0).

B from equation (8) is thus the *intrinsic estimator* of the model, which corresponds to the impact of age, period, and cohort on CO_2 emissions. It lies in the parameter subspace orthogonal to the nullspace.

The model can be rewritten with controls:

$$(14)\quad b = b_0 + tB_0$$

With μ_m the coefficient for m-th logged regressors (*i.e.* total expenditure), μ_n the coefficient for the n-th dummy (*i.e.* urban/rural). The vector of parameters rewrites:

$$(15)\quad b_0 = (\mathrm{I} - B_0\, B_0^T)b$$

With α i $^{\beta i\gamma}$ i the coefficients on each age/period cohort category an dμ_i the coefficients on controls.

The package *apc_ie* developed by Yang Yang and Sam Schulhofer-Wohl computes the intrinsic estimator. Its algorithm is based on a principal component regression which calculates the eigenvalues and eigenvectors (*i.e.* the principal components) of the matrix X^TX. The principal components are then normalized to have unit length and B_0 is identified. A principal component regression model is then estimated and an orthonormal matrix of all eigenvectors is used to transform the coefficients of the principal component regression model to the regression coefficients of the intrinsic estimator.

As Yang *et al.* (2008) remind, the intrinsic estimator is not a "complete solution" to the structural identification problem of APC models.

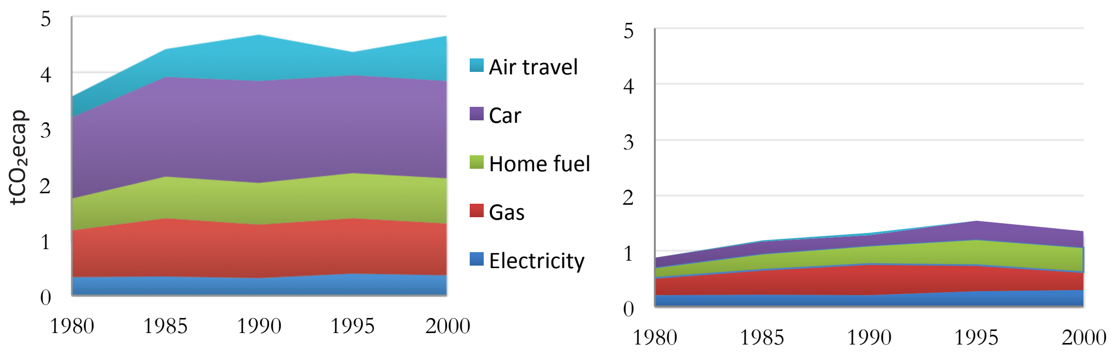
Table 6. Detailed CO_2 emissions per decile in France and in the USA

Age period cohort regression in France

	Robust	Std. Err.	Z	P>z	[95% Conf.	Interval]
logCO2totuc	.					
logdeptotuc	0.736909	0.0122332	60.24	0	0.7129324	0.7608856
nbpers	0.1568772	0.0063346	24.77	0	0.1444617	0.1692927
rooms	0.0615402	0.0127141	4.84	0	0.0366211	0.0864593
_Irg_2	0.0616671	0.0149926	4.11	0	0.0322821	0.091052
_Irg_3	0.0344324	0.0126649	2.72	0.007	0.0096097	0.0592551
_Irg_4	0.0637556	0.0183893	3.47	0.001	0.0277133	0.0997979
_Icommune_1	0.0008598	0.0144471	0.06	0.953	-0.027456	0.0291756
_Icommune_2	0.0691605	0.01306	5.3	0	0.0435633	0.0947576
_Icommune_3	-0.0030984	0.0203042	-0.15	0.879	-0.042894	0.0366972
_Idate_2	0.1966521	0.0125508	15.67	0	0.1720529	0.2212512
_Idate_3	0.0543094	0.0124154	4.37	0	0.0299756	0.0786431
_Idate_4	-0.1179384	0.0149567	-7.89	0	-0.1472529	-0.0886238
_Idiplome_1	0.1107123	0.0187064	5.92	0	0.0740483	0.1473762
_Idiplome_2	0.0786222	0.0247991	3.17	0.002	0.0300168	0.1272276
_Idiplome_3	-0.0481405	0.0245799	-1.96	0.05	-0.0963162	0.0000351
_Itypelog_2	-0.0969228	0.0284825	-3.4	0.001	-0.1527475	-0.041098
_Itypelog_3	-0.3130406	0.0163894	-19.1	0	-0.3451632	-0.2809179
age_20	0.1495564	0.0444651	3.36	0.001	0.0624063	0.2367065
age_25	0.1744035	0.0326534	5.34	0	0.110404	0.238403
age_30	0.0611055	0.0265254	2.3	0.021	0.0091167	0.1130943
age_35	-0.0478906	0.0228997	-2.09	0.036	-0.0927733	-0.003008
age_40	-0.0737332	0.0206084	-3.58	0	-0.114125	-0.0333414
age_45	-0.0967935	0.0205676	-4.71	0	-0.1371053	-0.0564817
age_50	-0.0688543	0.0230388	-2.99	0.003	-0.1140094	-0.0236991
age_55	-0.0617891	0.0270565	-2.28	0.022	-0.1148188	-0.0087593
age_60	-0.063288	0.032028	-1.98	0.048	-0.1260618	-0.0005143
age_65	-0.0586034	0.037596	-1.56	0.119	-0.1322902	0.0150834
age_70	-0.0842999	0.0433371	-1.95	0.052	-0.1692392	0.0006393
age_75	-0.1013399	0.0494773	-2.05	0.041	-0.1983135	-0.0043662
age_80	-0.0384656	0.0578722	-0.66	0.506	-0.1518929	0.0749618
age_85	-0.0434892	0.0690335	-0.63	0.529	-0.1787923	0.091814
age_90	0.3097241	0.109883	2.82	0.005	0.0943573	0.5250909
age_95	0.0437571	0.2571068	0.17	0.865	-0.4601629	0.5476771
period_1980	-0.0162542	0.0177305	-0.92	0.359	-0.0510054	0.018497
period_1985	-0.1400845	0.0150806	-9.29	0.000	-0.1696419	-0.1105271
period_1990	-0.2619299	0.0151036	-17.34	0.000	-0.2915323	-0.2323274
period_1995	-0.5199259	0.0149009	-34.89	0.000	-0.5491311	-0.4907207

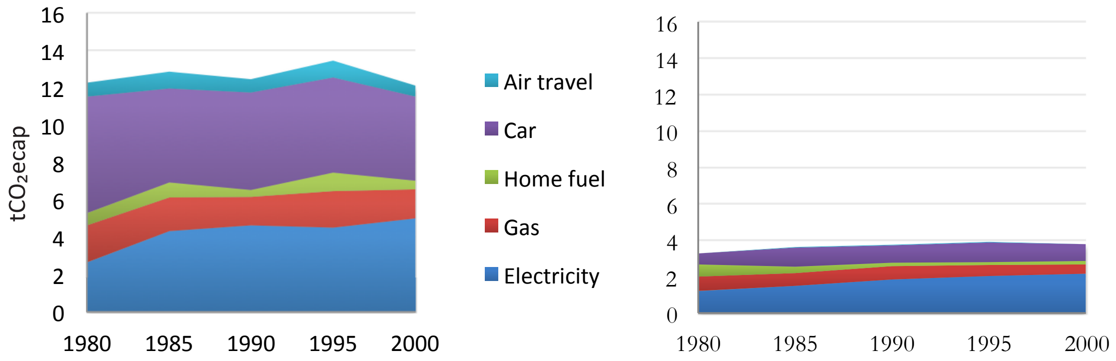
period_2000	0.9381945	0.025718	36.48	0.000	0.8877881	0.988601
cohort_1885	1.045354	0.253535	4.12	0.000	0.5484345	1.542273
cohort_1890	-0.5226934	0.348202	-1.5	0.133	-1.205157	0.1597699
cohort_1895	-0.3294907	0.1291461	-2.55	0.011	-0.5826125	-0.0763689
cohort_1900	-0.2701322	0.0943903	-2.86	0.004	-0.4551338	-0.0851305
cohort_1905	-0.2173763	0.074985	-2.9	0.004	-0.3643442	-0.0704084
cohort_1910	-0.1065129	0.066836	-1.59	0.111	-0.237509	0.0244832
cohort_1915	-0.0140304	0.0596308	-0.24	0.814	-0.1309045	0.1028438
cohort_1920	-0.0062294	0.0551419	-0.11	0.910	-0.1143056	0.1018468
cohort_1925	0.0677502	0.0462666	1.46	0.143	-0.0229307	0.158431
cohort_1930	0.1183632	0.0405033	2.92	0.003	0.0389782	0.1977482
cohort_1935	0.1936731	0.0342531	5.65	0.000	0.1265382	0.260808
cohort_1940	0.1970769	0.0286278	6.88	0.000	0.1409674	0.2531864
cohort_1945	0.1874889	0.023546	7.96	0.000	0.1413397	0.2336382
cohort_1950	0.149501	0.0180119	8.3	0.000	0.1141984	0.1848036
cohort_1955	0.0968998	0.0152491	6.35	0.000	0.0670121	0.1267875
cohort_1960	0.0968204	0.0170461	5.68	0.000	0.0634106	0.1302303
cohort_1965	0.0185576	0.0223577	0.83	0.407	-0.0252626	0.0623778
cohort_1970	-0.0934538	0.0330066	-2.83	0.005	-0.1581456	-0.0287621
cohort_1975	-0.1896653	0.0458589	-4.14	0.000	-0.279547	-0.0997835
cohort_1980	-0.4219007	0.0870541	-4.85	0.000	-0.5925236	-0.2512777
_cons	-0.4900384	0.115126	-4.26	0.000	-0.7156812	-0.2643955

Figure 12. Breakdown of CO_2 emissions per capita for top (left) and bottom deciles of French households



Source: Data from BDF.

Figure 13. Breakdown of CO_2 emissions per capita for top (left) and bottom deciles of US households



Source: Data from CES.

Table 7. APC regression in France Age period cohort regression in France

Categorical variables for France

0.educatio	School drop out
1.educatio	Baccalauréat
2.educatio	Bachelor
3. education	Master and Doctorate
1.urban	Urban
2.urban	Rural
1.region	North, North east and Bassin Parisien
2.region	Center, Rhones Alpes, Bourgogne
3.region	West coast
4.region	South coast
1.date	Built before 1948
2. date	Built from 1948 to 1970
3. date	Built from 1970 to 1980
4.date	Built from 1980 to 2000
1.typelog	Single household
2.typelog	Small flat (2 to 9 dwellings)
3.typelog	Large flat (+9 dwellings)

Are younger generations higher carbon emitters than their elders? Inequalities, generations and CO_2 emissions in France and the USA

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