# *Are older generations also to be blamed for climate change ?*

Inequalities, generations and $CO_2$ emissions in France and in the USA.

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## Abstract.

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

Direct $CO_2$ emissions of French and American households are computed 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, the year and other control variables. The paper shows that French 1935-55 cohorts have a stronger tendency to emit $CO_2$ than their predecessors and followers. In the USA, the effect of date of birth is less significant. The generational effect in France is explained by the fact that over their lifespan, French babyboomers 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.

# I. 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 design calls for a precise understanding of the determinants of household consumption and, in particular, energy consumption – or $CO_2$ emissions. However, up to recently, most national statistical apparels were not equipped to address the distributional dimension of environmental footprints (Stiglitz et al, 2009). 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 within country household inequalities and resource consumption is flourishing, gradually overcoming the research gap (see Druckman et al, 2008, Weber et al. 2008, Pasquier et al, 2010), I argue in this paper that it omits an important dimension: generations. Cohorts (i.e. groups of individual born at the same date) may have a strong role to play in determining consumption patterns in general and energy in particular. By integrating early life conditioning and historical or economic trends which shape their life trajectories, cohorts may actually drive social and behavioral change (Ryder, 1965).

The scope of this paper is to explore the interactions between generational and income-expenditure effects on household $CO_2$ emissions. Precisely, the present study has two objectives i) provide historical empirical material on the interactions between income inequalities and inequalities in resource use in France and in the USA and ii) suggest a new area for sustainable consumption research: the study of the role of generational determinants in consumption trends and, ultimately, environmental footprints.

Firstly, I show that direct $CO_2$ emissions of French and American households are relatively stable over the time period – while bottom decile emissions increase. Results also reveal that it is not possible to talk about any environmental Kuznet's curve[1] associated to direct $CO_2$ emissions: as households get richer, direct $CO_2$ emissions do not decrease. Secondly, the paper reveals how certain generations emit more $CO_2$ than others once age and period are controlled for. The effect is very clear in France and is the translation of important inter-generational inequalities. Cheaper access to housing and, potentially, higher ability to monitor energy consumption by post 1960-cohorts can explain persistence of the effect once income is controlled for.

The rest of this paper consists of a literature review on household environmental footprints and on 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).

[1] I.e. inversed U curve associated to environmental pressure.

# II. Inequalities, generations and household $CO_2$ emissions

*The Kuznets curve*

Grossman and Kruger (1995) posited an inverse-U shape relationship between income and environmental footprint - the so called Environmental Kuznets Curve[2] (EKC). As income grows, willingness to pay for environmental protection would increase, eventually leading to reduced environmental impact. This hypothesis has been the subject several empirical tests, which validated the EKC for certain types of pollutants (e.g. SO2, see Roca et al., 2001) but not for others (e.g. 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, like Pacala et al. (2009), have thus called for a focus on within country $CO_2$ distributions and on their relationship with national income distribution.

*Household level $CO_2$ emissions and the Input-Output approach*

Recent studies on household $CO_2$ emissions tend to invalidate the Environmental Kuznets curve at the household level. Using an Input-Ouput (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 (1986) matrices applied to energy fluxes to compute the $CO_2$ content of production, taking into account carbon emissions associated to the carbon content of intermediary consumption, imports and exports of the production process. 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 is 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 income elasticity of $CO_2$ emissions is smaller 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

[2] After Kuznets (1955) who showed an inversed U shape relationship between income and inequalities in the first half of the XXth century in the US.

[3] Estimates from Weber are computed 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.

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.

| | France<br>Pasquier et al., 2010 | USA<br>Weber et al. 2009 |
|---|---|---|
| **Bottom quintile** | 8.3t | 23t |
| **Top quintile** | 22t | 73t |

Fig 1 – Energy consumption of top and bottom quintile in France and the USA

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. As a result, richest households in France emit as much as 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 Input-Output tables. Focusing on France, Pasquier (2012) computed 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 on the territory decreased by 15% ). But given limitations of the statistical database, the author could not distinguish between emission levels of different income fractiles. Jackson and Papathanasopoulou (2008) are among the few authors who were able to look at emissions patterns of different categories of the population over a long time frame. Their study focuses on the UK and shows that over the 1968-2000 time period, the energy consumption-gini[4] grew faster that 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 resources use by richest households is mainly due to the development of air travel and car transportation for entertainment purposes. The study also shows that energy consumption of all income groups increases over time, suggesting a Veblen effect on energy consumption as posited by Wilkinson & Pickett (2009): lifestyle of top deciles seems to drive the consumption of other deciles upwards via mimetic effects.

*Non-monetary drivers of $CO_2$ emisions*

Several factors other than income drive energy consumption and related $CO_2$ emissions. It is helpful to distinguish between "environmental" factors (urban density, type of dwelling, technology type) and lifestyle (age, size of the household, education level). Some authors have also looked at the role cultural determinants in energy consumption (see Lutzenhiser, 1992). Traditionally, sociological literature

[4] In order to compute the resource-gini, authors replace total income of the population on the y-axis of the Lorenz curve by resource use.

distinguished between exogenous constraints and individual choices. But recent research is increasingly looking at the interaction of technology, value systems and learning process in the determination of consumption behavior (see Reckwitz, 2000 and Shove, 2003).

Among energy consumption drivers explored, age has been extensively studied- studies look household carbon lifecycle for instance (see CREDOC, 2009). But the generational factor is given little attention. Focus on date of birth fixed effects 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 does 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. The epidemics, economics, geography or sociology literature showed that generational factors can be important determinants of life trajectories (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 on consumer behavior and hence on environmental footprint.

According to Ryder (1965), early life exposure a certain socio-economic context can shape behaviour throughout ones' life trajectory. Beyond exposure to economic constraints, date of birth can also impact on the creation of 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 in their young age may have kept low consumption habits over time (e.g. generations raised during war times). Cohorts raised during high growth periods may prolong their energy consumption habits over time, and have more difficulties to adapt to reduced energy consumption habits.

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 interactions between three dimensions of "social time": age (on the x-axis), periods (on the y-axis) and cohorts. Diagonals correspond to lifelines of cohorts: born in 1948, the "68 generation" was twenty in 1968.

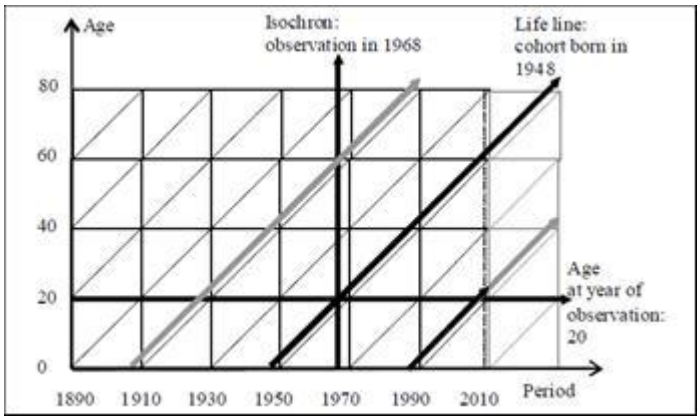



Fig 2 - The Lexis diagram

Source: Chauvel (2010)

The major issue with Age Period Cohort 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. APC Constrained Generalized Linear Models (CGLIM) used for APC analysis in the past have been criticized because of their inability to give convincing answers to the identification problem associated with linear dependency (see Yang et al, 2004).

However, recent studies in biostatistics and quantitative sociology can prove very helpful for sustainable consumption researchers. Fu (2000) derived a statistical estimator which bypasses multicolinearity problems associated to 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 extract unique age, period and cohort coefficients – this is further detailed 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 on energy consumption and lifestyle.

# III. Methodology

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

*Construction of household carbon footprints*

The database constructed for the study uses US Consumer Expenditure (CE) and the French Budget de Familles (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 from Census surveys and consists of about 1,700 dwelling units[6]. The datasets chosen for this study correspond to the first quarter waves of survey of 1980, 1985, 1990, 1995 and 2000.

The French Budget des Familles (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 years 1979, 1985, 1989, 1995 and 2000. Since 1995, expenses are ventilated using the Classification of Individual Consumption according to Purpose (COICOP). Evolution of the nomenclature over the time period studied required 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 by consumer unit[8] in order to account for family size and to bring perceived and measured changes in welfare better in line (see Ruiz, 2009).

*Direct carbon footprints*

Given the difficulty to obtain historical data on energy to fit I-O tables, this study focuses solely on direct energy carbon footprints which can be computed directly from household budget surveys, under a set of assumption regarding fuel mix, fuel price and carbon content of fuels. I compute $CO_2$ emissions equivalent associated with energy bills reported for electricity, gas, liquid home fuel, gasoline, personal and

[6] Given a certain amount of attrition in the data, Congressional Budget Office recommends to use a weighting factor (see Haris & Sabelhaus, 2000).
[7] I also use of a weigthing 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.

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 seemingly in a minor way as coal represents 2.2% of household energy budget in 2000 (INSEE, 2011).

Emissions are computed from expenditure on fuels, applying mean year fuel prices obtained from (MEDDAT, 2010 for France and DoE, 2010 for the USA) to all households. I use IPCC emission factors and historical carbon content of electricity provided by national energy agencies (DoE and ADEME). Emission factors include $CO_2$, $CH_4$ and $N_2O$ [9]. A strong assumption is the use of a single price per fuel for all households of the country - this is standard in other household carbon footprint studies using consumer budget surveys. Air travel emissions are computed from household expenses on air travel and the carbon content of flights is computed from the average distance travelled per unit expenditure, derived from air transport databases (BTS, 2011). Databases were not available for France so the US carbon per unit expenditure values were used, correcting for exchange rate and average flight price differences.

The direct carbon footprint can be written as follows:

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

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

*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 is used to compute it - a brief presentation of the estimator is presented in the Appendix. As a first step, I estimate the intrinsic estimator of an APC model of log-$CO_2$ emissions without controls:

[9] I thus use "$CO_2$" or "$CO_2$-e" without distinction.

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

Where $\mu_0$ is the intercept or adjusted mean logged-$CO_2$ emissions, $\alpha_i$ the i-th row age effect or coefficient for the i-th age group, $\beta_j$ the j-th column period effect or the coefficient for the j-th time period; $\gamma_k$ is the k-th diagonal cohort effect or the coefficient for the k-th cohort, with k=a-i+j. $\varepsilon_{ij}$ is a random error with $E(\varepsilon_{ij}) = 0$ .

As a second step, I introduce socio-economic, geographical and technical controls in the model:

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

With $\mu_m$ coefficient for continuous control variable $k_m$ (i.e. total expenditure), and $\mu_n$ coefficient for categorical variable $D_n$ (i.e. geographical location, building type). Several categorical variables were recoded (i.e. number of categories reduced) to increase statistical significance. I use the apc_ie package derived by Yang et al on Stata to compute estimate of $\gamma_k$ for each cohort.

# IV. Results and analysis

*Descriptive statistics*

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

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

| | | | | | |
|---|---|---|---|---|---|
| | (249) | (258) | (304) | (342) | (296) |
| Gini | 0.42 | 0.44 | 0.43 | 0.44 | 0.47 |

Table 1 - Descriptive statistics for the CE dataset (USA)
Standard errors in parentheses. Total expenditure per consumer unit in 1980 US dollars.

Table 1 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 oil consumption reduction following the second oil shock and increase afterwards. 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 significantly increases, showing strong variations behind mean variations. In fact, the income of bottom deciles stagnates while it increases for top deciles (Piketty and Saez, 2003).

| | **1980** | **1985** | **1990** | **1995** | **2000** |
|---|---|---|---|---|---|
| N | 10,080 | 11,074 | 8,709 | 9,354 | 7,462 |
| Age | 50.7 | 49.1 | 50.6 | 50.4 | 51.4 |
| | (.21) | (.18) | (.20) | (.19) | (.22) |
| Person/hh | 2.84 | 2.73 | 2.6 | 2.5 | 2.4 |
| | (0.01) | (0.01) | (0.02) | (0.01) | (0.02) |
| tCO2cap | 1.8 | 2.4 | 2.5 | 2.6 | 2.6 |
| | (.02) | (.02) | (.03) | (.04) | (.06) |
| Total Exp /cu | 46,182 | 47,179 | 49,083 | 52,789 | 54,409 |
| | (302) | (325) | (384) | (491) | (588) |
| Gini | 0.32 | 0.31 | 0.32 | 0.31 | 0.33 |

Table 2 - Descriptive statistics of the BDF dataset (France)
Standard errors in parentheses. Weighting factor ponder is used.
Total expenditure per consumer unit in 1980 FRF

[10] 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, taxes may lead to increased demand for credit rather than reduction in consumption.

The direct $CO_2$ emissions trend is similar in France (Table 2), 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.

Evolution of direct $CO_2$ emissions of top and bottom decile households

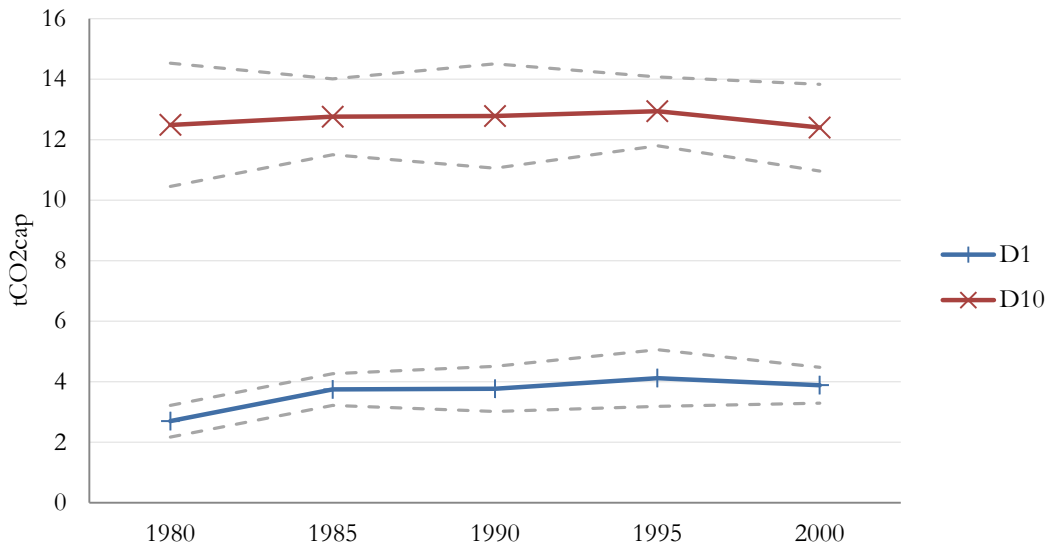



Figure 3 - Evolution of $CO_2$ emissions of the richest and poorest 10% in the USA.

Per capita direct $CO_2$ emissions in top and bottom decile households. The dotted lines represent 95% confidence intervals

Figure 3 presents the evolution of direct $CO_2$ emissions of American top and bottom deciles. 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 the 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 more important use of electricity by top decile households, largely due to the possession of a large set 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 a clothes dryer against only 45% of the bottom quintile (RECS, 2000). The rich have more energy intensive durables than the poor and use

[11]Caution: air travel emissions may be underestimated (see Methodology section).

them more. In a context of high carbon content of electricity, this translates into high electricity related $CO_2$ emissions for the top decile. Fig. 4 uses data from another survey, the Residential Energy Consumption Survey (RECS, 2000), to break down household electrical energy consumption in further detail.

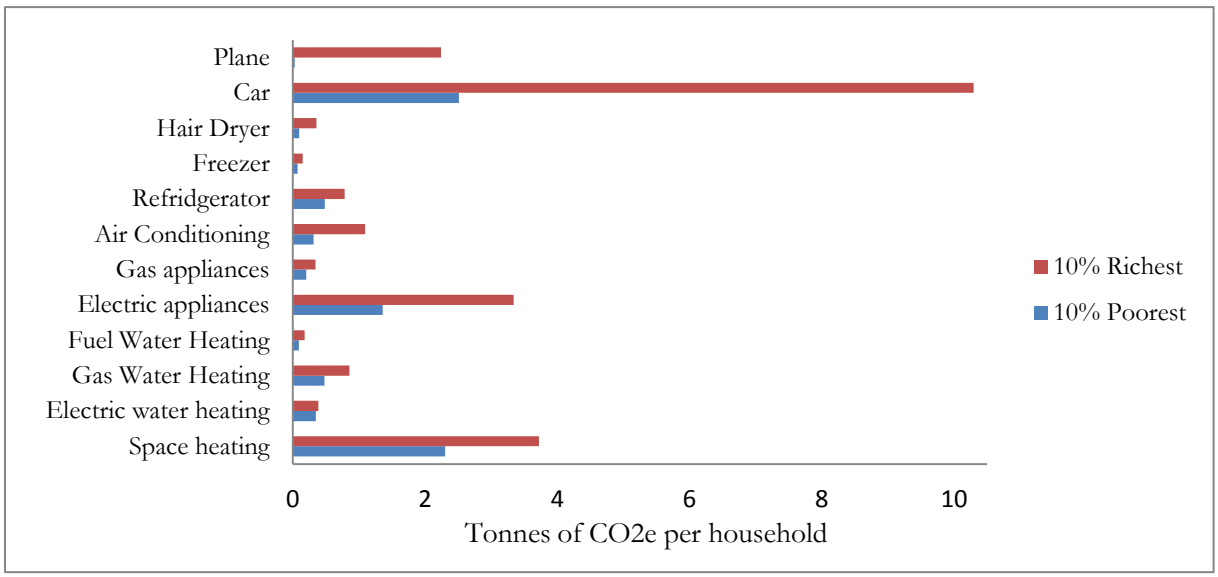



Figure 4 - Detailed sources $CO_2$ emissions for top and bottom deciles of US household in 2000
Estimates from US RECS 2000 and (car an plane computed from US CE survey)

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

Figure 5 shows the evolution of $CO_2$ emissions of 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 emit as much as the top French one – in line with the studies surveyed above. Two factors explain this

[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, distance driven per month by average households increased 50% (Ramey and Vine, 2010). The increase can also be due return to normarlcy after the second oil shock

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 French electricity mix: 690gCO2e/kWh in the USA against 150gCO2e/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 against only 36% of French top quartile households (RECS, 2000 and BDF, 2000).

Second, Americans of the poorest decile emit one ton $CO_2$ per year per capita due to private transportation travels, much more than their French counterparts, emitting 0.3 ton. Urban planning and sprawl (see Karlenzig, 2009) are important drivers of the Franco-American divergence.

The gap between rich and poor direct $CO_2$ emissions is also reduced in France over the time period and is characterized by an increase in gas and homefuel energy by bottom decile households.

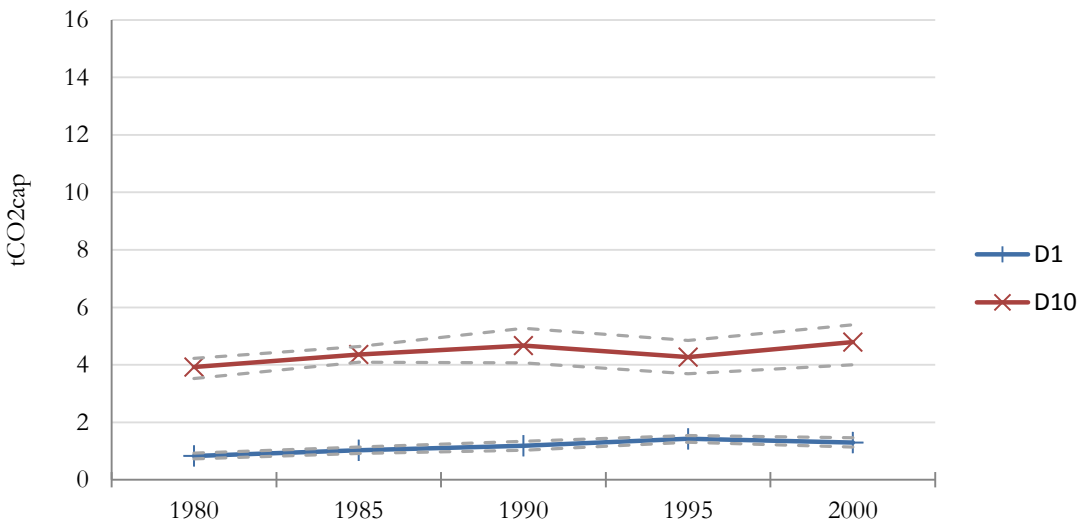



Figure 5 - Evolution of $CO_2$ emissions of the richest and poorest 10% in France

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

Comparison with other studies

Results are compared with other studies: Pasquier et al. (2010) for France, RECS,2000 and Weber et al. 2008 for the US. RECS estimates for bottom decile households match with the results. However, top

[14] This value is due to a high share of nuclear electricity, relatively low carbon technology yet with its own types of pollutants which are not the subject of this study.

decile households estimates are lower in the RECS than the CE survey (potentially due to 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 $CO_2$ emission, but the top-bottom quintile gap is very close to this study: 2.3 for Lenglart vs. 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 (studies precisely targeting energy consumption would be more pertinent for this) but rather to inform on the long term dynamics and to extract generational determinants.

| | | 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) |

Table 3 - Comparison of estimates in RECS and this study (CE)

Key: in 1990, the RECS survey estimates direct $CO_2$ emissions (without transport) of the first American decile at 6.3tCO2 per year. Standard errors in parentheses

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

Table 4 - Comparison of estimates in Lenglart (2010) and this study

Capturing the specific effect of date of birth

[15] Note Lenglart and others do not present results for income deciles.

I then use equation (2) to compute $\gamma$, 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 are controlled for. Next, I use equation (3), to control for socio-economic, geographic and technical variables.

Cohort effect in the USA

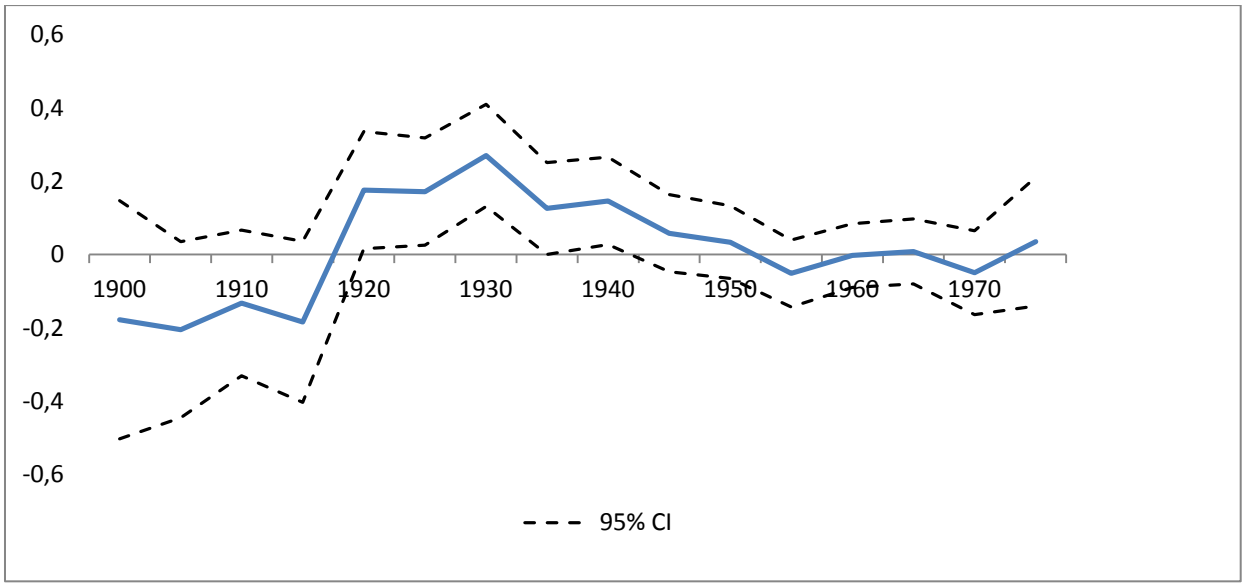



Figure 6 - Cohort effects on direct $CO_2$ emissions in the USA

The y-axis plots $\gamma_k$ coefficient of model 2. Key: Households whose head is born in 1930 emit 29% more $CO_2$ emissions than average, over the 1980-2000 time period. To compute the exact effect, compute exp($\alpha$). When $\alpha$ is small, exp($\alpha$)≈$\alpha$+1.

Fig. 6 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.

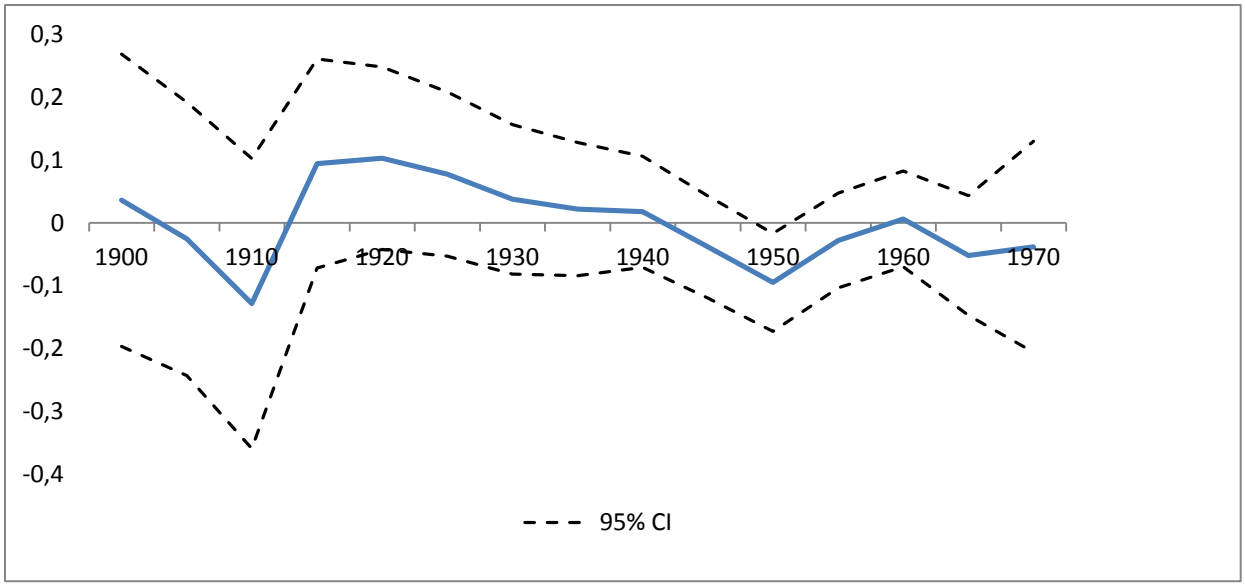



Figure 7 - Cohort effects on direct $CO_2$ emissions in the USA – $\gamma_k$ coefficients of model (3)

The y-axis plots $\gamma_k$ coefficient of model xx. Key: Households whose head is born in 1930 emit 29% more $CO_2$ emissions than average, over the 1980-2000 time period. To compute the exact effect, take exp(α). When α is small, exp(α)-1≈α.

When socio-economic, geographic and housing-type controls (see Appendix) are included in the model, the cohort effect is reduced and does not turn out to be statistically significant anymore- apart from 1950 cohorts, which are below the average (Fig. 7). Cohorts 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.

Cohort effect in France

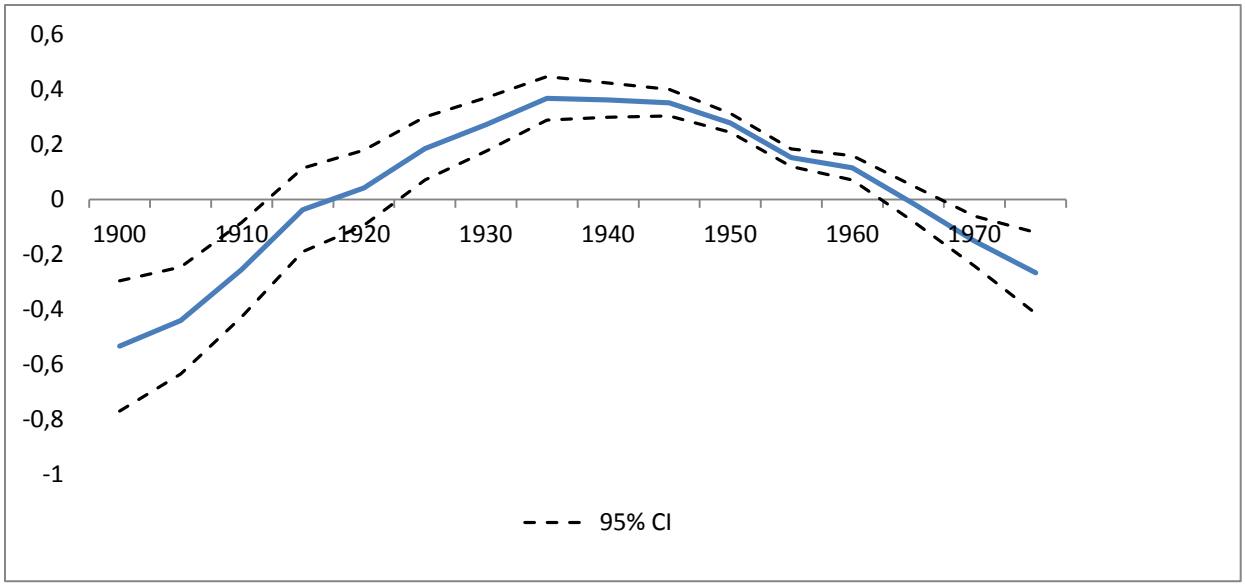



Figure 8 - Cohort effects on direct $CO_2$ emissions in France

The y-axis plots $\gamma_k$ coefficient of model (2). Key: Households whose head is born in 1945 emit 35% more $CO_2$ emissions than average, over the 1980-2000 time period. To compute the exact effect, take exp(α). When α is small, exp(α)≈α+1.

In France, the cohort coefficient, i.e. effect of date of birth once age and period effects are controlled for, is more apparent than in the US. Over the time period, cohorts born from 1920 to 1960 emit more direct $CO_2$ more than average (Fig. 8). 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 the measure, they emit 30% more than the average household. This effect is presented on a 3D plot below (fig. 9), 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.

[16] I plot residuals $\varepsilon_{ij}$ of a regression model of the form: $\log(CO_{2ij}) = \mu_0 + \alpha_i + \beta_j + \varepsilon_{ij}$

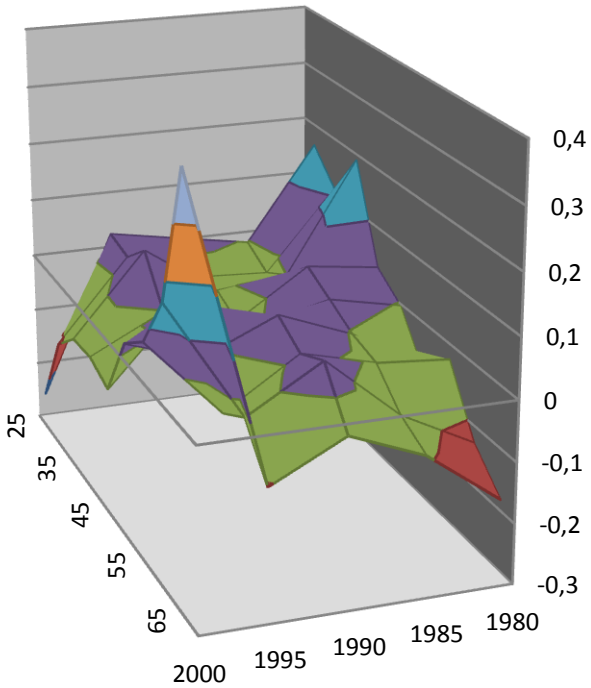



Figure 9 - Percentage variation from mean $CO_2$ emissions of different age groups in France

Key: in 2000 the 65-year old emit 30% more than in a model including time and period controls[17]. 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.

Fig 9. shows a relative decrease in emissions from the young with respect to the emissions of the elderly. The young emit 20% less than predicted in 2000 while they emit 15% more in 1980. Second, elders emit relatively more in 2000 than in 1980. Third, the back right corner – front left corner diagonal on the graph corresponds to the 1930-1955 cohorts who emit more than predicted throughout the entire time period.

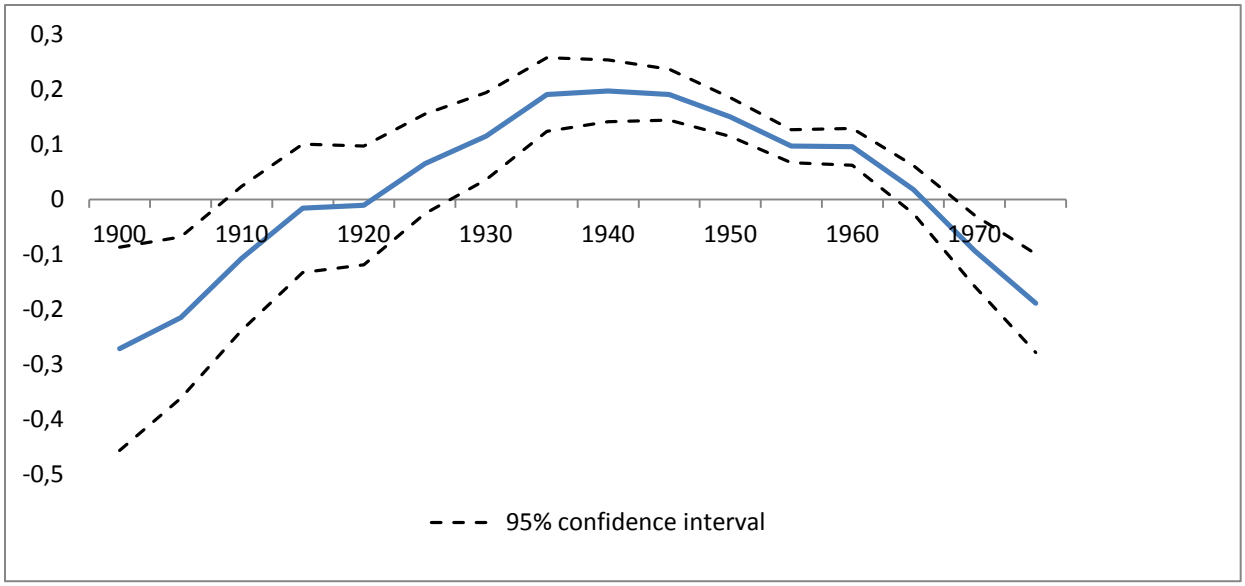



Figure 10 - Cohort effects on direct $CO_2$ emissions in France– $\gamma_k$ coefficients of model (3)

The y-axis plots $\gamma_k$ coefficient of model xx. Key: Households whose head is born in 1945 emit 35% more $CO_2$ emissions than average, over the 1980-2000 time period. To compute the exact effect, take exp(α). When α is small, exp(α)-1≈α.

Interestingly, the effect remains strong and statistically significant after the introduction of socio-economic, geographic and housing-type control (fig 10) – in opposition with the US. Independently of their age, their expenditure level, the type of housing they have, the number of people in the 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. Looking into further details at cohort effects on the five $CO_2$ emissions sources in France[18], we observe (fig. 11) the following trends:

i) Electricity: Electricity consumption and related carbon emissions decline sharply for cohorts born after 1950. This can be due to several factors: possession of inefficient electric devices by cohorts born before 1950, or ownership of more electric devices and tendency to use them more;

ii) Gas: 1920 to 1950 cohorts emit more than average (though only the coefficients for 1940-50 cohorts are statistically significant). This can be due to higher share of households of these cohorts possessing gas devices and/or higher tendency to heat;

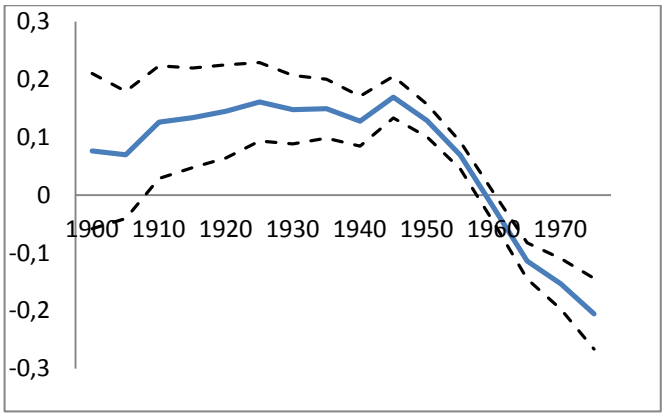
iii) Private transport: There is a sharp increase in the emissions from private transport for cohorts born after 1920 and a little decrease for post 1960 cohorts: one possible

[18] The same ventilation in the USA yields insignificant results.

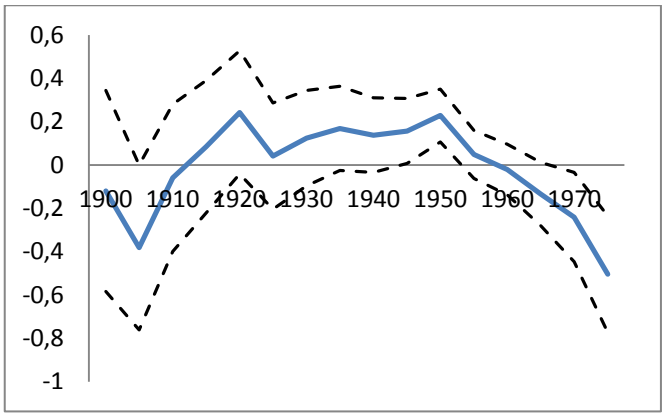
explanation is differential rates of unemployment among cohorts leading to reduced use of private transport;

iv) Homefuel : post 1945 cohorts are below average in terms of homefuel emissions. This may reflect a progressive technology shift, from homefuel 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.

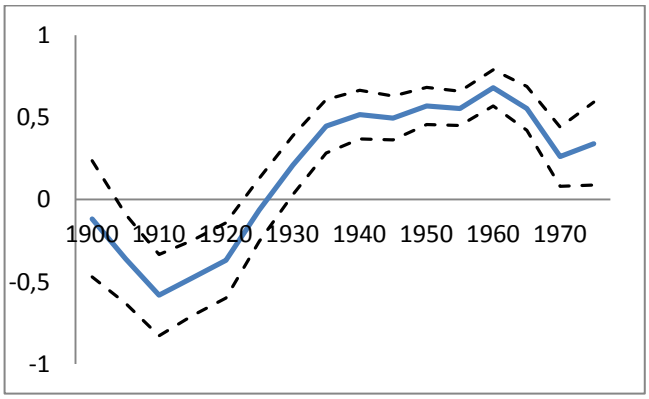
v) Air transport: cohorts from 1920 to 1950 have higher emissions from air transport than average, presumably due to higher relative purchasing power than their followers as I discuss below.



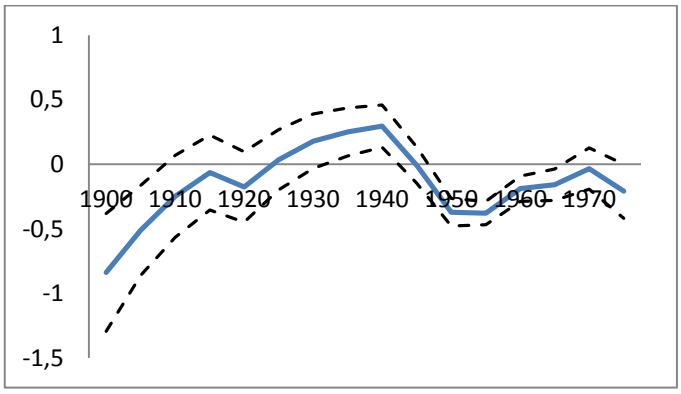

Electricity



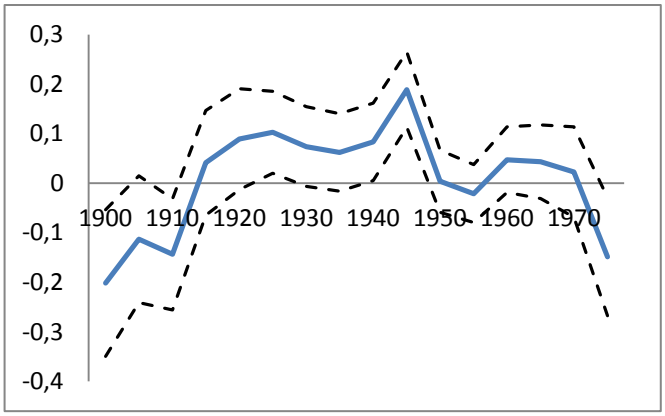

Gas




Private transport




Homefuel




Air transport

Figure 11 - Cohort effect on different emissions sources in France

The y-axis plots $\gamma_k$ coefficient of model xx. Key: (Air transport) Households whose head is born in 1945 emit 20% more $CO_2$ emissions than average, over the 1980-2000 time period. To compute the exact effect, take exp(α). When α is small, exp(α)-1≈α.

# V. 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 can be due to long term social dynamics (a "generational rift"), the differences can also be due to different rates of technology penetration among cohorts and third, divergence between young and older cohorts can be due to a progressive modification of value systems and behavior.

Generational rift

The generational rift hypothesis stems from an growing body of literature on intergenerational inequalities in France and in the USA. The fact 1930-55 cohorts in France enjoyed throughout their life trajectories better life chances (i.e. access to employment, housing, public services etc.) than any other generations has been the subject of several empirical analyses confirming one another (see Baudelot and Establet, 2000; Chauvel, 2006). During the Trente Glorieuses (1940s-1970s), the young started their career with the same pay as their parents at the end of their career: 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 unemployment rate of those who left school within 24 months was

5% in 1974 and rose to 35% in 2000. Marginalized access to labor markets contributed to an increased earning gap between generations. In 1977, earnings gap between age group 30-35 and 50-55 was 15% and rose to about 40% in 2009 (Chauvel, 2010). Post 1960 generations are thus, on average, economically worse-off than their elders[19].

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 their followers (and 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 smaller than one but positive. In other words, $CO_2$ emissions levels are driven by expenditure level, which varies among cohorts. 1930-55 french generations are richer than their followers and hence emit more.

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

I argue that housing expenses play a role in explaining the cohort $CO_2$ emissions gap. The share of total expenditure on rent and loan reimbursement is presented in fig. 12. Households whose head was 25 in 1980 spend 14% of their budget on rent/housing loan. In 2000, the same age group spends 42% of its income. The generation born in 1940 spends 19% of its revenue on housing at age 40, while at the same age, the generation born in 1960 spends 30% of its revenue. In fact, the "generational rift" does not only impact on the level of income (or expenditure) but 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

[19] Indeed, there are strong variations beyond the mean and higher intergenerational inequalities by no means imply leveling of intra-generational inequalities.

expenditure, the latter must reduce expenses on other categories: like entertainment (and private transportation), travels (air transport) or household energy[20].

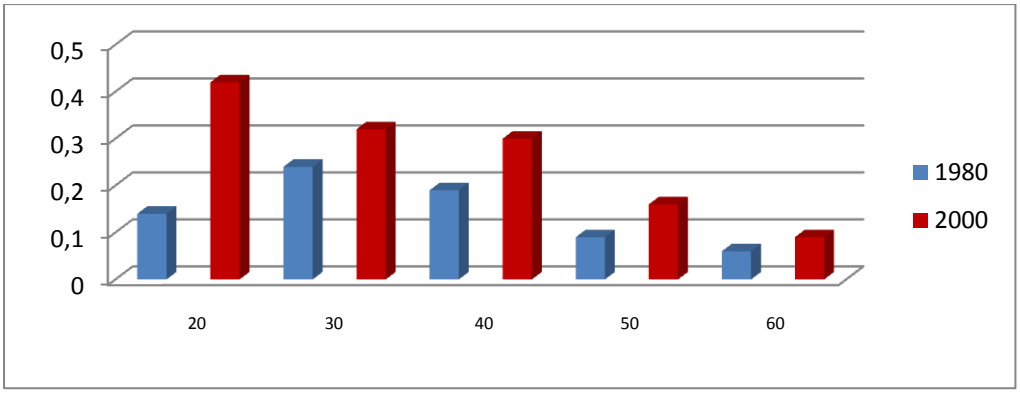



Fig. 11 - Share of budget spent on housing in France among age groups in 1980 and 2000

Key: in 1980, households whose head was 20 to 30 spent 13% of their income on rent or housing

Source : BDF survey

Technology and values change

Above sections highlight the role of economic factors which impacted expenditure patterns of certain French generations more 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 they are available to them when they enter adult life and need to furnish their homes, or because of a willingness to be more energy efficient. CREDOC (2009) shows that in 2009 in France, 1970-75 cohorts had more class A apparels than pre-1970 cohorts. However, such a technological shift does not necessarily translate into the reduction in energy use. The rebound effect literature showed how more efficient technology could actually lead to increased energy consumption.

This implies that younger French generations may progressively become less energy intensive than their elders (beyond socio-economic constraints and technical change dynamics). This argument is supported by the fact that once included in model (3), the share of rent in total expenditure only explains a

[20] This is apparent in the data: at age 30, 1955 generation spent a higher share of their budget on transport than average (2.5p.p more). At the same age, 1970 generation does not spend more than average.

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 stringent than in France. As Chauvel (2006) shows, there are generational inequalities in the USA, translating into above 20% poverty rates for post-1955 cohorts and below 12% poverty rates for pre 1955 cohorts[21]. 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, they 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 vs. that of social background in the explanation of life trajectories. 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 inherent to historical datamining exercices and other associated with the statistical tool used. Several assumptions were made in order 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 richest households. Air emission estimates required several strong assumptions: I only compute estimates from non-professional flights, using expenditure on air transport reported in Consumer budget surveys. In addition, any travel not appearing in household consumer budget survey are not included in carbon contents.

It is also assumed that the generational effect is a "head of the household" generational effect. In other words, I assume that date of birth of the head can actually influence energy consumption behavior of the rest of the family.

[21] See also Krugman (1992)

The intrinsic estimator used in the study must also be interpreted with precaution (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. A corrected version of the estimator has been developed and is being finalized as I am writing these lines. It aims at producing a detrended version of Fu's estimator, reducing the end of time frame distortions. On the other hand, precision of the estimator 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 while 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 entry in and exit from the dataset. 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 shows 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 a clear pertinence in applying Age Period Cohort models to (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 in two categories: intra-generational income inequalities and carbon emissions and inter-generational issues. Distributional impacts of carbon taxation is 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 better identification of losers of carbon tax reforms (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 in a wider fiscal reform for more progressivity.

In terms of inter-generational issues, the paper revealed that budget constraints induce behavioral change among bottom and medium deciles: as they faced 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 – 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.

But persistence of the generational effect once standard of living is controlled for in France 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 life trajectories. Persistence of this effect stresses the difficulty by individuals to alter energy consumption behavior adopted in young age, despite technological change and 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 consumption behavior of future cohorts in the right direction, beyond energy taxation and regulatory measures.

# VI. Conclusion

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

The analysis first looks at 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 in order to compute the intrinsic estimator of an Age Period Cohort 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 effect on $CO_2$ emissions in France, before and after control 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 more consumerist living standards of the French "babyboomers" compared to their followers.

The historical household level carbon database created for this study can be enlarged for other countries (i.e. emerging countries). It be coupled with the IO methodology to include indirect $CO_2$ emissions, i.e. carbon which is not rejected at the point of use but during production process of goods. Further work also involves bridging the gap between 2000 and the present in order to observe if latest cohorts invert the "generational carbon trend" observed. 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 Age Period Cohort 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 $\mu$ is the intercept or adjusted mean logged-$CO_2$ emissions, $\alpha_i$ the i-th row age effect or coefficient for the i-th age group, $\beta_j$ the j-th column period effect or the coefficient for the j-th time period; $\gamma_k$ is the k-th diagonal cohort effect or the coefficient for the k-th cohort, with k=a-i+j. $\varepsilon_{ij}$ is a random error with $E(\varepsilon_{ij}) = 0$ .

The model is reparameterized in order to centre its parameters and hence treat it 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 $\alpha i$ $\beta j$ $\gamma_k$ the coefficients on each age/period cohort category.

As it was 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 it by rewriting each of the infinite number of solution of the model 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 the observed $CO_2$ emissions, only on the design matrix X – it 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 while 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 $B_1$:

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

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

With

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

and

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

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 in 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:

$$(14) \quad \log(CO_{2ij}) = \mu_0 + \sum_m \mu_m \times log\,(k_{mij}) + \sum_n \mu_n \times D_{nij} + \alpha_i + \beta_j + \gamma_k + \varepsilon_{ij}$$

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

$$(15) \quad b = \left(\mu_0, \dots, \mu_n, \alpha_1, \dots, \alpha_{a-1}, \beta_1, \dots, \beta_{p-1}, \gamma_1, \dots, \gamma_{a+p-2}\right)^T$$

With $\alpha$i $\beta i$ $\gamma$i the coefficients on each age/period cohort category an d $\mu_i$ 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 computes 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.

*Detailed $CO_2$ emissions per decile in France and in the USA*

| | **1980** | | | **1985** | | | **1990** | | | **1995** | | | **2000** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | mean | 95% CI | | mean | 95% CI | | mean | 95% CI | | mean | 95% CI | | mean | 95% CI | |
| **10% poorest** | **2.92** | 2.39 | 3.45 | **3.83** | 3.30 | 4.36 | **3.98** | 3.22 | 4.74 | **4.24** | 3.29 | 5.20 | **4.27** | 3.68 | 4.86 |
| **D2** | **4.42** | 3.55 | 5.30 | **6.08** | 5.16 | 6.99 | **5.62** | 5.04 | 6.20 | **5.55** | 4.65 | 6.45 | **6.27** | 5.60 | 6.93 |
| **D3** | **4.45** | 3.50 | 5.40 | **7.23** | 6.33 | 8.13 | **7.71** | 6.63 | 8.80 | **6.52** | 5.66 | 7.38 | **7.07** | 6.22 | 7.92 |
| **D4** | **6.03** | 4.61 | 7.45 | **7.44** | 6.18 | 8.69 | **6.95** | 5.81 | 8.10 | **8.52** | 7.30 | 9.74 | **7.67** | 6.87 | 8.46 |
| **D5** | **6.01** | 5.22 | 6.81 | **7.58** | 6.72 | 8.45 | **8.12** | 7.01 | 9.23 | **8.10** | 6.79 | 9.42 | **8.34** | 7.45 | 9.22 |
| **D6** | **7.59** | 6.67 | 8.50 | **8.55** | 7.64 | 9.45 | **10.08** | 8.82 | 11.35 | **9.16** | 8.06 | 10.26 | **9.06** | 7.97 | 10.15 |
| **D7** | **7.78** | 6.75 | 8.81 | **9.06** | 8.21 | 9.92 | **9.55** | 8.55 | 10.56 | **9.54** | 8.31 | 10.76 | **9.76** | 8.48 | 11.03 |
| **D8** | **7.88** | 6.90 | 8.86 | **9.92** | 8.90 | 10.93 | **9.75** | 8.60 | 10.89 | **9.97** | 9.02 | 10.92 | **10.20** | 9.20 | 11.20 |
| **D9** | **9.87** | 8.79 | 10.95 | **10.85** | 9.70 | 12.01 | **9.12** | 8.16 | 10.08 | **10.44** | 9.29 | 11.60 | **10.49** | 9.47 | 11.51 |
| **10% richest** | **12.49** | 10.45 | 14.52 | **12.75** | 11.51 | 14.00 | **12.78** | 11.06 | 14.50 | **12.94** | 11.80 | 14.07 | **12.40** | 10.96 | 13.83 |

**Annual tCO2 per capita of American expenditure groups**
**Mean and 95% CI**

| | 1980 | | | 1985 | | | 1990 | | | 1995 | | | 2000 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **mean** | 95% CI | | **mean** | 95% CI | | **mean** | 95% CI | | **mean** | 95% CI | | **mean** | 95% CI | |
| **D1** | **0.80** | 0.74 | 0.86 | **1.10** | 1.01 | 1.18 | **1.24** | 1.13 | 1.35 | **1.61** | 1.49 | 1.72 | **1.45** | 1.34 | 1.57 |
| | **1.24** | 1.18 | 1.31 | **1.51** | 1.41 | 1.60 | **1.80** | 1.68 | 1.92 | **1.90** | 1.79 | 2.01 | **1.98** | 1.84 | 2.11 |
| | **1.40** | 1.33 | 1.47 | **1.80** | 1.70 | 1.90 | **1.91** | 1.79 | 2.03 | **2.03** | 1.91 | 2.14 | **2.05** | 1.92 | 2.18 |
| | **1.54** | 1.47 | 1.63 | **2.08** | 1.94 | 2.23 | **1.95** | 1.84 | 2.06 | **2.19** | 2.06 | 2.31 | **2.23** | 2.10 | 2.35 |
| | **1.67** | 1.70 | 1.86 | **2.22** | 2.09 | 2.34 | **2.19** | 2.07 | 2.31 | **2.33** | 2.19 | 2.47 | **2.40** | 2.24 | 2.55 |
| | **1.92** | 1.83 | 2.02 | **2.31** | 2.20 | 2.42 | **2.42** | 2.27 | 2.57 | **2.45** | 2.31 | 2.58 | **2.75** | 2.57 | 2.93 |
| | **2.07** | 1.98 | 2.17 | **2.63** | 2.50 | 2.75 | **2.61** | 2.47 | 2.75 | **2.56** | 2.40 | 2.71 | **2.87** | 2.67 | 3.06 |
| | **2.29** | 2.19 | 2.40 | **2.79** | 2.67 | 2.91 | **2.75** | 2.61 | 2.90 | **2.82** | 2.61 | 3.04 | **2.96** | 2.77 | 3.16 |
| | **2.62** | 2.50 | 2.74 | **3.20** | 3.06 | 3.34 | **3.23** | 3.03 | 3.43 | **3.47** | 2.92 | 4.02 | **3.36** | 3.08 | 3.64 |
| **D10** | **3.33** | 3.16 | 3.50 | **4.37** | 4.13 | 4.61 | **4.45** | 4.05 | 4.86 | **4.32** | 3.77 | 4.87 | **4.41** | 3.87 | 4.94 |

**Annual tCO2 per capita of French expenditure groups**
**Mean and 95% CI**

*Breakdown of $CO_2$ emissions in France and in the USA*

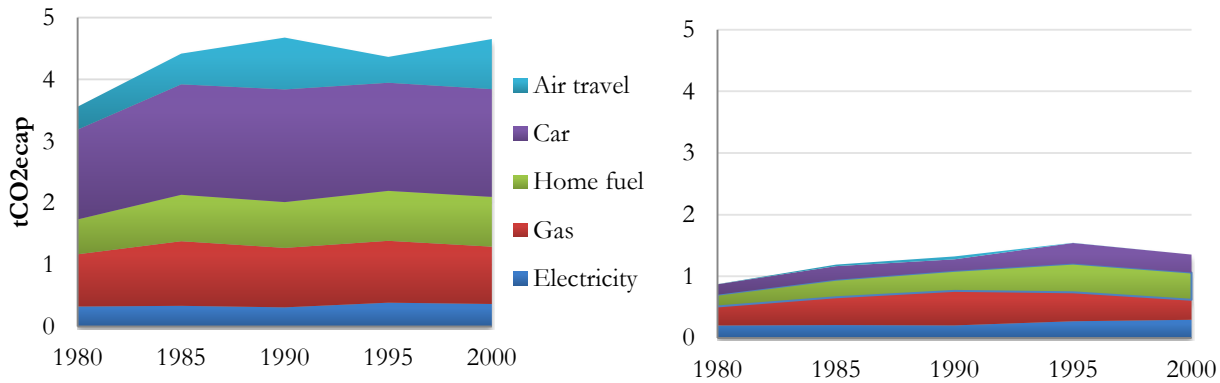


Fig. 12 - Breakdown of $CO_2$ emissions per capita for top (left) and bottom deciles of French households

Source: BDF

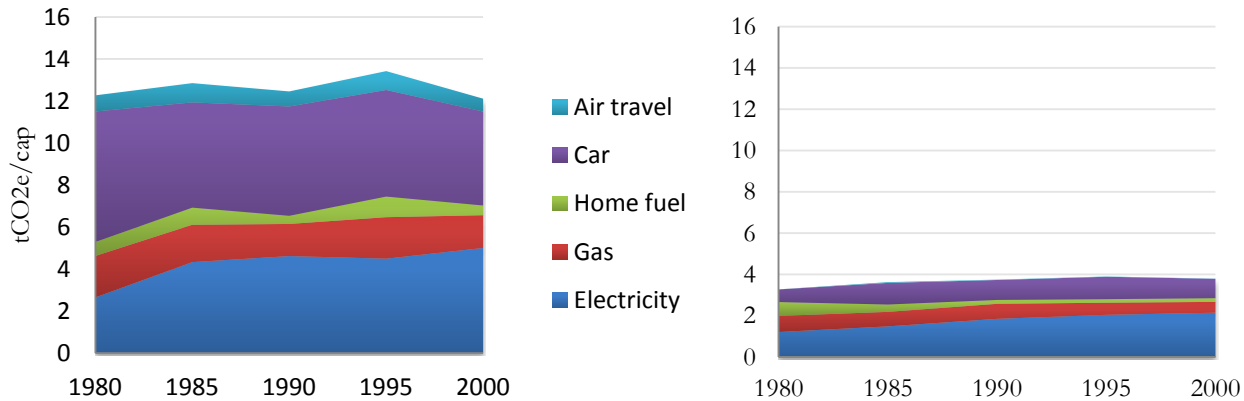


Fig. 13 Breakdown of $CO_2$ emissions per capita for top (left) and bottom deciles of US households

*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 |

**Table 5 - APC 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 48 to 70 |
| 3. date | Built from 70 to 80 |
| 4.date | Built from 80 to 2000 |
| 1.typelog | Single household |
| 2.typelog | Small flat (2 to 9 dwellings) |
| 3.typelog | Large flat (+9 dwellings) |