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Income and Consumption Risk: Evidence from France

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In this paper, we draw life cycle inequality profiles for cohorts born between 1921 and 1975 and observed from 1974 to 2005 from a pseudo-panel of French households. While cross-sectional inequality has not changed much over the period, the within cohort inequality has increased substantially with age. Using the interplay between income and consumption, we decompose the change in inequality into a permanent and a transitory component. The former, called *income risk*, measures shocks affecting income which are transmitted to consumption levels, while the latter affects income but can be smoothed and thus does not have an impact on the consumption distribution. We find that income risk increases with age while transitory shocks remain broadly constant over a lifetime. The decomposition sheds light on the diverging trends over time between income and consumption inequality. Consumption inequality has increased since the middle of the nineties because the population has aged and permanent shocks increase with age, while income inequality has not changed much because of negative transitory shocks that have compensated the permanents shocks.*

Introduction

Since the beginning of the eighties income inequality has risen to the top of the social agenda in many OECD economies. Economists have devoted a large strand of empirical research to measuring the extent of the change in inequality (GOTTSCHALK and T. SMEEDING [1997]) and to revealing the social welfare implications of these sharp transformations of income distributions. While the literature has not reached any consensus regarding the causes of the phenomenon (see L. F. KATZ and AUTOR [1999]) for a review of potential explanations) it emerges that the observed changes differ among the developed economies and a thorough examination on a country-by-country basis is needed.

The literature measuring changes in income inequality using cross-section micro-data has been criticized on several grounds. Some authors (CUTLER and L. KATZ [1992]; KRUEGER and PERRI [2006]) point out that assessing changes in individual welfare considering only the evolution of the income distribution might provide a biased picture. They suggest that using consumption data would complement the information provided by income data, based on results from economic theory (FRIEDMAN [1957]) distinguishing transitory and permanent components in income fluctuations. Life cycle-permanent income theory predicts that rational consumers having access to financial markets can smooth out transitory shocks in their consumption, and thus consumption dispersion mirrors only permanent differences in well-being. Therefore, comparing income and consumption dispersion provides a decomposition which is better suited to inferring inter-individual welfare changes.

*JEL: D31, D12. / KEY WORDS: Inequality, Consumption Distribution, Income Risk.

Secondly, empirical research on the change in inequality is criticized along a different dimension for not being representative of what a given individual would experience over time (DEATON and PAXSON [1994]). Changes in the cross-sectional dispersion are not invariant to the modification in the structure of the population: with new generations of individuals replacing older ones over time, the population composition also changes. Moreover, if the size of cohorts differs, *e.g.* younger cohorts being smaller than older ones, the aggregate change might mainly be due to the composition effect. As HEATHCOTE, STORESLETTEN, and VIOLANTE [2005] have pointed out, the change in inequality indicators computed on different cross-sections mixes within and between cohort changes and may not be representative of the life cycle differences between individuals born at the same time. Properly assessing changes in well-being requires adopting a *within cohort* perspective.

In this paper, we run an empirical study measuring inequality changes in France from 1974 to 2005 and pay particular attention to the previous caveats. Firstly, to assess welfare changes we compare the change in income and consumption dispersions and decompose them into permanent and transitory components. Permanent income shocks, called income risk, are transmitted to consumption levels and generate permanent differences in incomes, while transitory shocks only impact the income distribution and are smoothed by rational consumers. Secondly, to control for the changing structure of the population, we study individuals born at the same point in time and we consider the change in dispersion between the particular group using a within-cohort perspective. As long panel data for France do not exist, we use a pseudo-panel approach and track groups of individuals defined by the same age and the same education. We build life-cycle inequality profiles that display a different pattern from changes in cross-sectional inequality indicators.

Our results are the following: First, contrary to countries like the U.S., Canada and the U.K., there is no evidence that France has experienced any large change in inequality since the mid-seventies. Second, the mild aggregate change in inequality over the period is not representative of life cycle evolution. On average, inequality between individuals belonging to the same generation has increased by almost 1 percentage point a year over thirty-five years. Such a very large increase conflicts deeply with the evolution of cross-sectional inequality indicators. The inequality profile is linear for income but increases at an increasing rate for consumption. Decomposing the change in total inequality into permanent and transitory components, we find that the former increases with age, while the latter does not display any clear age pattern. Finally, we link these conclusions to the cross-sectional changes and consider how the two can be related.

Our paper departs from the literature studying the evolution of life cycle consumption inequality. The initial contribution from DEATON and PAXSON [1994] documented a large increase in within cohort inequality with age in the U.S., the U.K. and Taiwan. They discussed the possible theoretical implications for a consumption life cycle model fitting these results. They do not decompose the life cycle profiles though. In an influential paper, BLUNDELL and PRESTON [1998] built life cycle changes in income and consumption inequality using a pseudo-panel from the U.S. and derived the theoretical conditions under which transitory and permanent components can be distinguished with such data. Our econometric model is directly related to the methodology they developed. More recent contributions have generalized their approach. GUVENEN [2007] introduced heterogeneity in the income profile, while PRIMICERI and VAN RENS [2009] added idiosyncratic shocks to income. Both studies conclude that it is important to take account of the non-concave consumption inequality profile.

For France, only a few papers establish life cycle inequality profiles from micro-data. ARRONDEL and MASSON [1990] tested the life cycle hypothesis on asset holdings in France. They found a strong life cycle effect on individual investment behavior using cross-sectional data. LOLLIVIER and VERGER [1999] proposed a method to estimate permanent income from cross-sectional data, using retrospective individual information and imputing future values. They compared the permanent income dispersion with the current income one. Interestingly, they concluded that strong cohort effects explain the change in income dispersion. Using the same data, LOLLIVIER [1999] adopted a pseudo panel approach estimating the elasticity of consumption relative to income in cross-sectional data and over time. Finally, BONHOMME and ROBIN [2009] decomposed earnings data into permanent and transitory components, relating mobility on the earnings distribution to employment risk using a structural approach. Our approach is a more reduced-form approach, and we follow a different strategy using information from consumption data.

SECTION I describes the data, and SECTION II contrasts the life cycle and the cross section inequality profiles. SECTION III presents our decomposition into permanent and transitory factors, and finally SECTION IV concludes the paper.

I. Data

In SECTIONS I.1 and I.2 we present the data and the sample selection. In SECTION I.3 we discuss how we built the life cycle inequality profiles from pooled cross-sectional data.

I.1. *BdF Surveys*

Budget de familles (BdF) data is a time series of cross-sectional household surveys released by INSEE, the French statistical office. Starting in 1972, nine waves are available: 1972, 1973, 1974, 1980, 1985, 1990, 1995, 2000 and 2005. In this study we concentrate on waves from 1974 to 2005.[1] The BdF is representative of the French population and is carried out on around 10,000 households in each wave. Households are not re-interviewed over time, *i.e.*, a given household only appears in one wave. The main purpose of the survey is to collect detailed information about consumption behavior. It includes detailed income and socio-demographic characteristics. Household members complete a single questionnaire concerning expenditures on durables over the year. They also fill in a questionnaire on expenditures on non-durables over two weeks. These expenditure data include more than 900 items, including taxes, insurance premiums, intergenerational transfers, second-hand durables and loan repayments. They gather consumption items that do not necessarily give place to monetary transfers such as home-grown food or in-kind benefits provided by the employer. Annual consumption of non-durables is then extrapolated from the two weeks' booklet.

1. Early waves released in 1972 and 1973 have not been used. They are poorly comparable and according to INSEE their reliability would appear to be questionable.

Additionally, BdF data contain many socio-demographic characteristics on household members including their age, nationality, gender, educational background, occupation, employment status, hours worked, marital status and geographic region. Household heads provide income sources, including earnings, investment income, transfers received and taxes paid. Finally, BdF is the single micro data source representative of the French population where income and consumption data are homogeneous over a sufficiently long period to measure life-cycle inequality profiles.

I.2. *Samples*

We restrict the analysis to male individuals who are heads of households aged 25 to 60, and observed in one of the waves between 1974 and 2005. As consumption and some income sources are measured at the household level, we define income and consumption accordingly, and our samples are representative of those French households headed by a man in that particular age range. We drop observations in the bottom first percentile of the income distribution for each survey wave to minimize the impact of measurement error on the results. As the first percentile of observations have very low income levels, it is highly likely that they represent outliers and income non-respondents. When these observations are kept in the samples, the overall change in income inequality is consistent with that described in this paper, but much more volatile; we thus decided to drop them. As explained below, individual observations are studied at the group level, defined by year of birth and educational level.

Consumption is measured as annual expenditures on non-durables in the household. Our principal definition of consumption is based on expenditures on goods and services. It includes rents, cash contributions to organizations, interest payments on mortgages and insurance premiums but excludes durables. In the sensitivity analysis we implement a second less restrictive definition including durables, and a third more restrictive definition using food consumption only. Income is measured by total family income net of taxes, including labor income, transfer income and investment income. We exclude windfall income such a lottery gains. In the sensitivity analysis we explore other more restrictive definitions, such as labor income and find that this does not change our main conclusions. Each annual measure is translated into 2002 euros using the French consumption price index. We use the OECD equivalence scale, *i.e.*, we divide income and consumption by the square root of the household size.

Descriptive statistics of the sample are provided in TABLE I. Each column describes a cohort observed at different points in time, while each row represents a survey wave containing data over several cohorts. Pooling the survey waves over time gives us 37,500 individual observations. As Table I indicates, the different cohorts are observed at very different points in their life cycle. Older cohorts born between 1921 and 1925 are observed in 1974 and 1980 only. The youngest cohort, born between 1971 and 1975, is observed thirty years later in 2000 and 2005 when they are between 25 and 34. The nine intermediate cohorts are observed from three to seven times. The composition of each cohort by educational levels varies markedly, with younger cohorts being much better educated than older ones. Two thirds of the younger cohorts have at least a high-school diploma while 64% of the older cohorts have only primary education. Therefore, in the following analysis we concentrate on groups defined by year of birth and education. Overall, at a given point in time, the population is composed of individuals at very different points in their life-cycle. Considering the change in inequality over time on the full population might not be representative of what a given group of individuals can experience. In the rest of the analysis, we will pay particular attention to this issue.

Regarding these data, two caveats should be considered. First, as we concentrate on non-durable consumption; annual household consumption is measured from a two-week survey only. It may be wondered whether this does not entail too many measurement errors, and whether periodic expenditures may not be excluded from the data because they may not occur within this two-week period. This can be true for a given household, but, once averaged over several households, non-durable consumption should be representative from the two-week questionnaire. Many household surveys use the same approach; for instance the British Family Expenditure Survey consumption data are collected identically. In addition, it has been much used to study changes in inequality within and between cohorts (see for example DEATON and PAXSON [1994] or BLUNDELL and PRESTON [1998]). Secondly, the five year time span across two survey waves implies that when following cohorts over time, we will have a quite imprecise profile, with a maximum seven data points for a given cohort, which is admittedly restrictive. Annual survey waves would make it possible to estimate the changes in inequality over time more precisely. However, annual consumption data over thirty years are not available for France. On the other hand, the very long time span between survey waves makes it possible to benefit from homogeneous data over a very long period, which is an obvious advantage when studying long term inequality changes. Overall, data requirements for such an exercise are very demanding, and BdF data limitations should clearly be kept in mind when analyzing the results. In the following section we explain how the pseudo-panel structure of our data.

I.3. *A Pseudo Panel Approach*

Most studies investigating the changes in inequality consider the evolution of different cross-sectional distributions over time. However, this approach is valid only under very restrictive stationarity assumptions on the structure of the population. If the population gets older and more educated over time, and inequality is larger within these groups, then overall inequality increases as a consequence of the change in the structure. While the change in the cross-sectional distributions remains interesting, it is very different from the perspective of a given cohort of individuals. In this study we consider the recent literature proposing such a perspective to be better suited to representing changes in welfare levels. This argument has been made by DEATON and PAXSON [1994], BLUNDELL and PRESTON [1998], HEATHCOTE, STORESLETTEN, and VIOLANTE [2005], PRIMICERI and VAN RENS [2009], JAPPELLI and PISTAFERRI [2010], and AGUIAR and HURST [2010] among others.

Empirically, it is necessary to use panel or pseudo-panel data to track cohorts over time. To that purpose, we construct a synthetic panel for 5-year cohorts born between 1921 and 1975 and observed from 1974 to 2005. TABLE I presents the pseudo-panel structure of our data. The cohort of individuals aged between 25 and 29 in 1980 is followed through those aged 30-34 in 1985 and those aged 35-39 in 1990 and so on. The cohorts are observed from two to seven times from 1974 to 2005.

Each cohort is divided into three groups depending on the individual educational levels. Educational levels are defined in order to meet two conflicting criteria: reflecting a relevant

TABLE I. – Descriptive Statistics by Cohort

Cohort	1	2	3	4	5	6	7	8	9	10	11
Year of birth	1921-25	1926-30	1931-35	1936-40	1941-45	1946-50	1951-55	1956-60	1961-65	1966-70	1971-75
Sample size by year											
1974	644	691	689	600	597	799	0	0	0	0	0
1980	779	820	954	882	876	1,121	1,026	0	0	0	0
1985	0	496	746	750	771	1,134	1,182	1,050	0	0	0
1990	0	0	489	562	558	807	895	833	709	0	0
1995	0	0	0	521	509	877	922	888	900	754	0
2000	0	0	0	0	622	848	913	966	863	788	744
2005	0	0	0	0	0	746	775	811	902	870	821
Education (%)											
Lower	0.64	0.60	0.55	0.44	0.37	0.34	0.31	0.31	0.30	0.33	0.24
Intermediate	0.22	0.25	0.32	0.37	0.39	0.41	0.43	0.43	0.43	0.37	0.33
Higher	0.15	0.15	0.14	0.20	0.24	0.25	0.26	0.26	0.27	0.30	0.42

NOTE: The second panel shows the proportion of individuals with primary school attainment (lower education), the proportion with high-school attainment (intermediate education) and the proportion with higher education (higher education) for each cohort.
Source: BdF Survey. The first panel of the table provides the number of observations by survey wave.

TABLE II. – Summary of the Data

Cohorts	11
Educational levels	3
Nb of groups	33
Time periods	from 2 to 7
Total nb of cells	141

NOTE: Cohorts are defined as sets of individuals born in the same five-year birth interval. Groups are defined by cohort and educational level. Cells are defined by group at one particular point in time. Groups (and cohorts) are observed from 2 to 7 times. Overall, the pseudo-panel is defined by 141 observations at the group level. Source: BdF Survey.

partitioning of the population, and sample size homogeneity. The lower educational level is defined as primary school attainment or less. The intermediate educational level groups individuals with (professional or general) high school attainment. The higher educational level represents individuals with higher educational attainment. We define groups of individuals by age and educational levels for two reasons. First, it provides a more detailed description of the life cycle inequality profile with more homogeneous sets of individuals over time. Second, as demonstrated by ATTANASIO *et al.* [1999], education influences impatience and affects life cycle consumption trajectories. One caveat to this approach is that the initial data wave, 1974, does not provide information on educational levels. We therefore had to impute it from individual observable characteristics. The estimating equation is provided in the appendix (see TABLE A.1). We do not give a causal interpretation to these estimates but use them simply to impute the missing education variable for the 1974 survey. The fit is quite good, in spite of the small number of individual characteristics measured (adjusted R^2 of 0.48). Of course, using imputed data is a highly restrictive assumption. To check the robustness of our results to these imputed values, we ran the same empirical study excluding observations from 1974 and the results remained close. We favor including these data since, except for education, the survey questionnaire is very comparable across survey waves. Moreover, as explained below, the major changes in inequality take place at the end of the period. Most of the cohorts involved in theses changes were too young to be part of the 1974 sample. Only one cohort in 1974 is still present in the final years of the panel when most of the changes in inequality took place.

TABLE II summarizes the structure of the pseudo-panel. We were able to study 33 groups[2] made up of individuals with the same age and educational level. We define a cell by a group of individuals at one point in time. On average, each cell is composed of 268 observations. Each group is observed from two to seven times over the period 1974 to 2005. Overall, we obtained 141 cells. This represents our number of observations at the aggregate level. This figure is very comparable to the rest of the literature using pseudo panel data. For each cell, we computed the variance of log income and consumption. In SECTION III we use regressions at the group level, and the group observations are weighted by the inverse of their relative size. Admittedly, the group definition is quite imprecise but a tighter definition would increase measurement error in the variance of logs and would drastically decrease the sample size.

2. ie: 11 cohorts times 3 education levels.

In the next section, we compare the change in inequality over time across the different survey waves over the full population with the within-cohort approach of the pseudo-panel.

II. Life Cycle *vs* Cross-Sectional Time Changes in Income and Consumption Inequality

FIGURE 1 depicts the change in inequality over time. It is represented here using four different indexes: the variance of logs, the P90/P10 ratio, the Theil and the Gini indexes. OK and FOSTER [1999] proved that the variance of logs might in some situations not respect the principle of transfers and therefore provide conclusions which are inconsistent with most other inequality indexes. We admit this potential weakness but keep the variance of logs for the following reasons. First, as shown in this section, the results are very close using the different inequality indicators. Second, we are in line with the literature that uses that particular index for obvious comparability reasons. Third and more importantly, only the variance can be decomposed, as we do in SECTION III.

On each panel of FIGURE 1 the dotted points with dashed lines represent income inequality, while the circles with full lines stand for consumption dispersion. These graphs lead to the following comments. First, the cross-sectional income dispersion is larger than the cross sectional consumption inequality by one third on average for most of the time periods in our data. This mirrors the usual assumption that income dispersion includes permanent and transitory factors, while consumption is only affected by permanent shocks. A more careful analysis is needed to disentangle the respective share of these two components. Second, for all inequality indicators the change from 1974 to 2005 in cross-sectional income and consumption inequality is not very large: using standard errors estimated by bootstrap most of the confidence intervals overlap. Considering the point estimates, income inequality increases slightly till 1995, and decreases slightly thereafter. Third, the only major change is caused by the consumption dispersion that increases considerably after 1995. As a consequence, the gap between income and consumption inequality dropped dramatically in 2000 and 2005. For three of the four inequality indicators, income and consumption inequality are not statistically different in 2000 and 2005.

The pattern of income inequality shown in these graphs is similar to that found in HOURRIEZ and ROUX [2001] covering the period 1975-2000. It is equally comparable with the trend and level in an INSEE study 1996 (see in particular FIGURE 1 page 36), from 1975 to 1994 with the same data. For consumption inequality we are not aware of any longitudinal study on French data. The results depicted in FIGURE 1 are interesting mainly for two reasons. Firstly, compared to the large changes observed in countries such as the U.S. and Canada, the French income and consumption distributions display a different trend with no major increase in dispersion. The slight increase in the French consumption dispersion (+8% on the Gini index) should be compared to that of US (+18% see L. F. KATZ and AUTOR [1999], p. 1475, table 1). This conclusion is well known in the literature. The French income distribution did not display major changes during the eighties and the nineties (see GUILLEMIN and ROUX [2003], GOTTSCHALK and T. SMEEDING [1997] or BRANDOLINI and T. M. SMEEDING [2007]). Secondly, as will be explained below, the stable pattern of the cross-sectional distribution is in stark contrast with that of a within-cohort perspective.

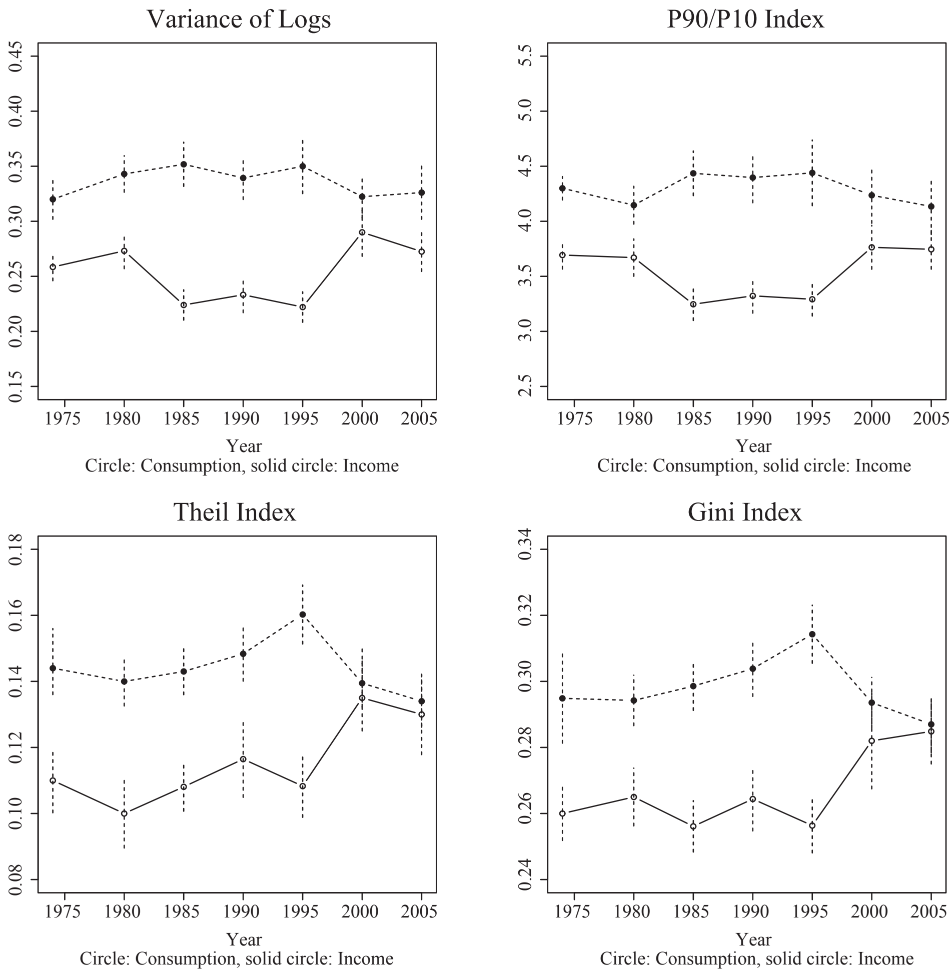

FIGURE 1. – Changes in Income and Consumption Inequality 1974-2005

FIGURE 2 represents the same data, but instead of considering time changes we look at age profiles for different cohorts. The left panel displays income inequality by age, while the right panel displays consumption inequality. Each line represents a different cohort. Clearly, income inequality increases with age for any cohort, while the increase in consumption dispersion is milder.

In order to obtain a finer perspective, we sort each cohort into three educational levels. FIGURE 3 shows this. The upper panel represents the variance of log income, while the bottom panel represents the variance of log consumption. Strikingly, for any group the spread of income and consumption increases with age. Moreover, the initial level of inequality between individuals in the same group is very similar across cohorts, except for the youngest one. On average, life cycle inequality increases by 77% between 25 and 60 (from 0.23 to 0.36). The results are in accordance with observed patterns in DEATON and PAXSON [1994] on U.S.,

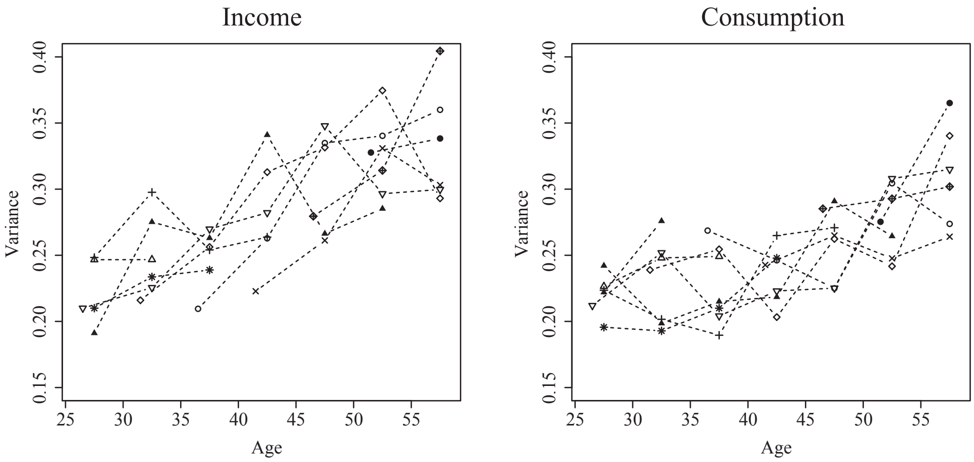

FIGURE 2. – Variance of Income and Consumption Relative to Age by Cohort

NOTES: The figure displays the variance of log income (resp. log consumption) for different cohorts by age.
Source: BdF Survey.

U.K. and Taiwanese data, BLUNDELL and PRESTON [1998] or AGUIAR and HURST [2010] on U.S. data. On these raw graphs, the change in inequality with age is mixed with cohort and time effects. In order to estimate how income and consumption inequality change with age, controlling for cohort and time, we run the following regression:

$$\ln(I_{kt}) = \alpha_0 + g(a_{kt}) + \beta X_k + \gamma_k + \delta_t + \varepsilon_{kt} \tag{1}$$

where $\ln(I_{kt})$ denotes the log of an inequality indicator, k and t are indices for cohort and time. α_0 is an intercept, g is a polynomial function of age, X_k is education, γ_k are cohort dummies and δ_t are time dummies. TABLE III presents the estimated age effects of these regressions using the variance of logs as an inequality indicator. As we cannot simultaneously control for age, cohort and time, since these three variables are collinear, we present alternative specifications. Columns 1 and 2 control for age and time effects only. Columns 3 and 4 control for age and cohort effects only, restricting time effects to zero. In columns 5 and 6 we control for age, time and cohort effects simultaneously but we constrain time dummy coefficients to be orthogonal to a linear time trend. Empirically, this is implemented by estimating equation (1) under the following constraint[3]:

$$\sum_t t\,\delta_t = 0. \tag{2}$$

In TABLE III the upper panel shows that income inequality is a linear function of age, since in columns 2, 4, and 6 the quadratic term for age is never significant. Income inequality increases by 0.9% to 1.4% per year between 25 and 60. This represents a large rate of growth over such a

3. Another possibility would be to constrain the cohort coefficients to sum up to zero, and to leave the time effect unrestricted. This does not change the results and seems less natural (see HEATHCOTE, STORESLETTEN, and VIOLANTE [2005] for a discussion of these two approaches).

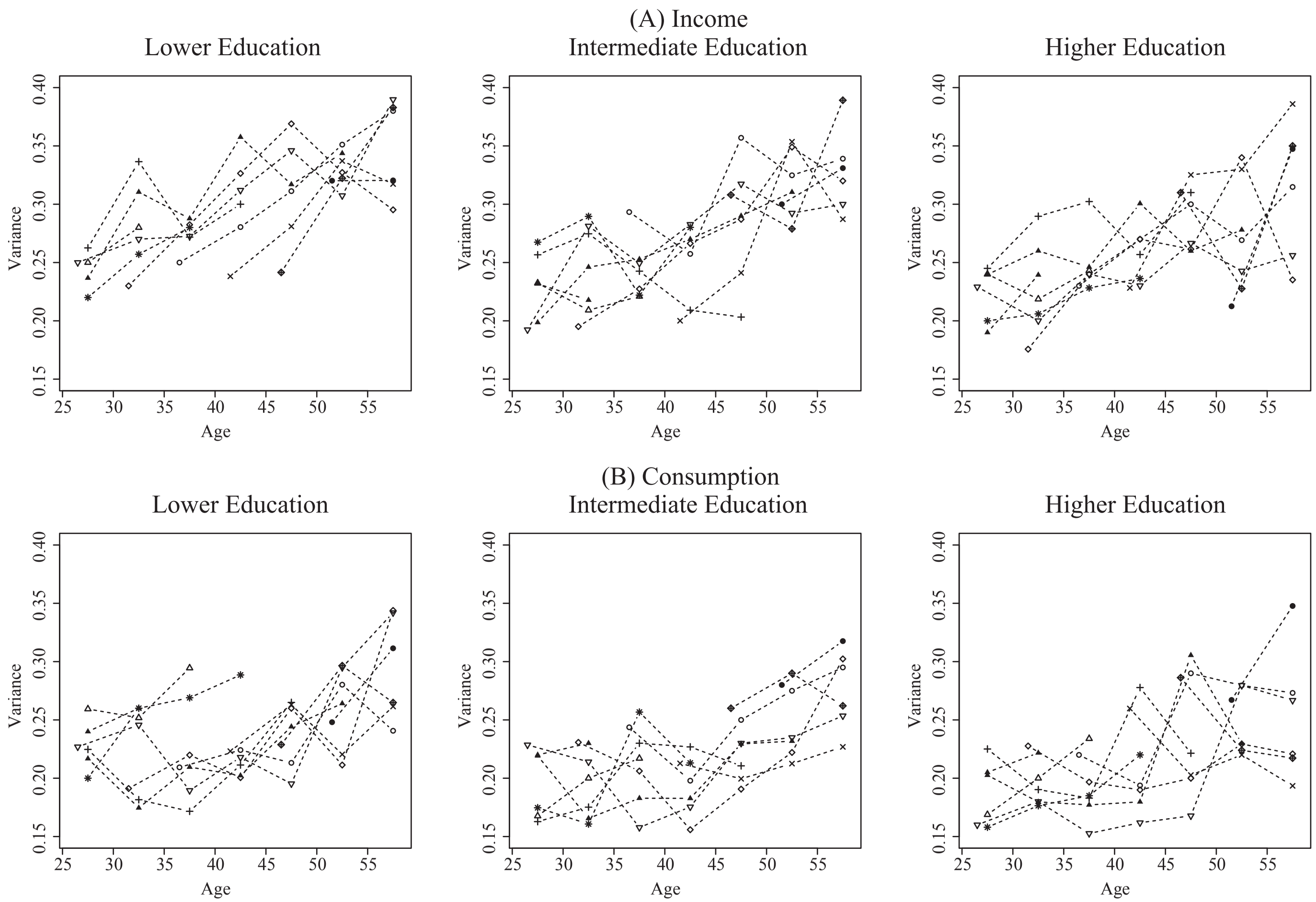

FIGURE 3. – Variance of Income and Consumption Relative to Age by Cohort and Educational Level

NOTES: Each panel presents the change in the variance of logs income (top panel) or log assumtion (bottom panel) with age for different

TABLE III. – Regressions of Within Cohort Inequality on Age

	1	2	3	4	5	6
	Income					
Age	0.009	−0.012	0.014	−0.006	0.014	0.006
	(5.9)	(−0.8)	(6.4)	(−0.4)	(7.3)	(0.4)
Age^2		0.024		0.024		0.009
		(1.4)		(1.2)		(0.5)
Intermediate Educ.	−0.121	−0.121	−0.121	−0.121	−0.121	−0.121
	(−3.4)	(−3.4)	(−3.1)	(−3.1)	(−3.5)	(−3.5)
Higher Educ.	−0.148	−0.148	−0.148	−0.148	−0.148	−0.148
	(−4.1)	(−4.1)	(−3.7)	(−3.7)	(−4.3)	(−4.3)
Cst	−1.760	−1.344	−1.823	−1.430	−1.738	−1.598
	(−23.5)	(−4.4)	(−12.6)	(−4.1)	(−13.9)	(−5.2)
Year Effect	Yes	Yes	No	No	Yes	Yes
Cohort Effect	No	No	Yes	Yes	Yes	Yes
R^2	0.457	0.465	0.359	0.367		
Observations	141	141	141	141	141	141
	Consumption					
Age	0.007	−0.045	0.009	−0.019	0.009	−0.035
	(5.1)	(−3.7)	(4.1)	(−1.1)	(5.5)	(−2.8)
Age^2		0.060		0.033		0.053
		(4.3)		(1.7)		(3.6)
Intermediate Educ.	−0.121	−0.121	−0.121	−0.121	−0.121	−0.121
	(−3.9)	(−4.1)	(−3.1)	(−3.1)	(−3.9)	(−4.1)
Higher Educ.	−0.088	−0.088	−0.088	−0.088	−0.088	−0.088
	(−2.8)	(−3.0)	(−2.2)	(−2.2)	(−2.9)	(−3.0)
Cst	−1.615	−0.579	−1.672	−1.132	−1.778	−0.921
	(−24.7)	(−2.3)	(−11.6)	(−3.2)	(−15.7)	(−3.5)
Year Effect	Yes	Yes	No	No	Yes	Yes
Cohort Effect	No	No	Yes	Yes	Yes	Yes
R^2	0.539	0.597	0.288	0.304		
Observations	141	141	141	141	141	141

NOTE: OLS regression of the (log) within cohort variance of income and of consumption on age, education (reference level Basic Education), cohort dummies and year dummies. In parenthesis t-stats. Observations are weighted by the standard error of the estimated cell means. We do not provide R^2 for regressions 5 and 6 since they are constrained linear regressions.
Source: BdF Survey.

long period. Symmetrically, on the bottom panel, consumption inequality is an increasing and convex function of age. Both are decreasing functions of educational attainment, since income inequality between high-school graduates is 12% smaller than inequality between individuals with low education. Among educated individuals, income and consumption inequality are smaller by 14.8% and 8.8%, respectively. However, the age inequality profile does not seem to depend on education, since the interaction between education and age is never significant. In TABLE A.2 in the appendix we provide evidence for other inequality indicators. The main conclusion remains that inequality in income and consumption increases with age.

These results are in stark contrast with the changes in the cross-sectional distributions from FIGURE 1 that did not display a lot of change over time. They are more appropriate for assessing welfare changes, since they represent the spread in income and consumption levels that would be experienced by a set of individuals of the same cohort and education level. In the rest of the paper we shall seek to decompose this particular representation of the change in inequality over time into permanent and transitory factors.

In the appendix, FIGURE A.1 represents these estimated age effects net of cohort and time effects. On the same graph we display non-parametric estimates of these age effects using dummy variables. Both non-parametric profiles remain in the 95 % confidence intervals of the parametric (linear for income and convex for consumption) estimates. From the results of the regressions and these graphs, it is clear that there is a very large increase in within-cohort inequality in France for individuals between 25 and 60 years. This result has strong consequences for the evolution of inequality. The convex profile for consumption implies that the rise in consumption inequality does not slow down as a cohort gets older (see DEATON and PAXSON [1994], AGUIAR and HURST [2010] for similar results on U.S. data). While the non-concave profile for consumption inequality might seem counter-intuitive, it is possible to obtain the same profile from a version of the permanent income model with quadratic utility and consumers learning their income profile in a Bayesian way (see GUVENEN [2007] for such a model leading to a convex inequality consumption profile).

In the rest of the paper we decompose these life cycle inequality profiles for income and consumption into permanent and transitory components. SECTION III details the model and the empirical results.

III. Decomposing Life Cycle Inequality Into Permanent and Transitory Components

In this section we first set out how we can measure income and consumption risk from a simple decomposition of the change in the variance of log income and consumption over time. Secondly, SECTION III.2 discusses identification and SECTION III.3 presents the econometric methods. Finally, III.4 sets out the results.

III.1. *Measuring Income Risk*

Following FRIEDMAN's [1957] classical decomposition of income changes into permanent and transitory components, income risk is defined by permanent shocks affecting the income and consumption distributions simultaneously and symmetrically. The model was applied to micro-data by BLUNDELL and PRESTON [1998] and extended by PRIMICERI and VAN RENS [2009].

In order to implement the decomposition between permanent and transitory shocks empirically, we characterize the reduced form stochastic process for (log) individual income for individual i in cohort k in period t as the sum of two components, a permanent and an transitory one:

$$y_{it} = y_{it}^{p} + u_{it}, \qquad \text{for i} \in \text{k}, \tag{3}$$

with y_{it}^{p} denoting permanent component of income, and u_{it} a transitory one. The permanent component is represented by a random walk process

$$y_{it}^{p} = y_{it-1}^{p} + \upsilon_{it}, \tag{4}$$

where υ_{it} is a permanent shock orthogonal to u_{it}. In this approach, υ_{it} represents income risk since it cannot be predicted by the agent. We assume that the variance of shocks is the same for any individual in any period but can change over time: $V_t(u) = \sigma^2_{ut}$ and $V_t(\upsilon) = \sigma^2_{\upsilon t}$. Moreover, the cross sectional covariance of shocks with previous-period income is assumed to be zero. Let us use as an inequality indicator the variance of logs for cohort k at time t denoted by $V_{kt}(y)$ for income and $V_{kt}(c)$ for consumption. These variances are measured conditional on cohort and time periods.[4] Finally, we measure the changes in inequality for cohort k by $\Delta_{kt}V(y) = V_{kt}(y) - V_{kt-1}(y)$.

Proposition 1. Under the previous assumptions, the change over time in income inequality for cohort k has two sources: either a new permanent shock or the change in a transitory shock; that is:

$$\Delta_{kt}V(y) = V_{kt}(\upsilon) + \Delta_{kt}V(u). \tag{5}$$

Proof. Substituting (4) into (3) we get $y_{it} = y_{it-1} + \Delta_t u_i + \upsilon_{it}$ for $i \in k$. Computing the variance on the right and left hand sides, we get:

$$V_{kt}(y) = V_{kt-1}(y) + V(\Delta_{kt}u) + V_{kt}(\upsilon) - 2cov_{kt-1}(y,u).$$

As $V(\Delta_{kt}u) = V_t(u) + V_{t-1}(u)$, since u_{it} is independently distributed. Moreover, $cov_{kt-1}(y,u) = cov_{kt-1}(u,u) = V_{kt-1}(u)$. Thus the previous equation yields condition (5), since we can now write

$$V_{kt}(y) = V_{kt-1}(y) + V_{kt}(\upsilon) + V_{kt}(u) - V_{kt-1}(u).$$

□

The connection between income and consumption inequality is given by the following proposition.

Proposition 2. Under the previous assumptions and assuming CRRA preferences, and no stochastic asset return, the within-cohort change in consumption inequality can be decomposed as

$$\Delta_{kt}V(c) = V_{kt}(\upsilon). \tag{6}$$

Proof. From the permanent income hypothesis BLUNDELL and PRESTON [1998] have demonstrated that consumption follows a random walk[5] with innovations represented by the permanent shocks to income, *i.e.*:

$$c_{it} = c_{it-1} + \upsilon_{it}, \qquad \text{for i} \in \text{k}.$$

From this equation, using the variance to measure consumption inequality, condition (6) follows immediately.[6] □

4. Symmetrically, covariances between income and consumption for cohort k at time t, denoted $cov_{kt}(y,c)$ and variances in log consumption, denoted $V_{kt}(c)$ should always be considered as conditional on time t and cohort group k.
5. This represents a generalization of HALL's [1978] landmark result that assumed quadratic preferences.
6. See BLUNDELL and PRESTON [1998], proposition 3, p. 612, for details of the random walk of the consumption variable.

Interestingly, only permanent shocks affect the consumption dispersion, which is appealing since it has the immediate interpretation that perfectly informed agents cannot predict permanent shocks, while they can insure against transitory ones using consumption smoothing over time. Moreover, from the econometrician's point of view, simultaneously considering the change in consumption and income dispersion, it is possible to decompose the sources of the change in inequality over time into permanent and transitory components.

Finally, more information is available to implement this decomposition. One can consider the change in the within-cohort covariance between income and consumption.

Proposition 3. From the previous assumptions, the change over time in the covariance of income and consumption can be decomposed as:

$$\Delta_{kt} cov(y,c) = V_{kt}(\upsilon) = \Delta_{kt} V(c). \tag{7}$$

Proof. Considering the covariance of income and consumption, it is possible to write:

$$\begin{aligned} cov_{kt}(y,c) &= cov(y_{t-1} + \Delta_{kt} u + \upsilon_{kt}, c_{kt-1} + \upsilon_{kt}). \\ &= cov_{kt-1}(y,c) + cov_{kt}(\upsilon,\upsilon). \end{aligned}$$

Condition (7) follows immediately. □

The result from Proposition 3 represents an additional source of information that will be used to enhance the precision of the estimation.

Of course the previous model is somewhat restrictive and could be extended in several ways. Firstly, defining permanent shocks as affecting both income and consumption, with transitory shocks impacting only income, implicitly implies that individuals can hedge against the latter but not against the former. Therefore, with this framework permanent shocks have to be unexpected, unlike transitory ones. While it is difficult to believe that some major events having long-lasting effects, such as lay-offs or chronic diseases, cannot be expected by an agent under rational expectations, we argue that such events should be considered as transitory shocks as long as their impact decays over time.

Additionally, the distinction between permanent and transitory shocks implies that the latter can be insured against, unlike the former. However this does not take into account that some shocks are partially insured against through social insurance such as unemployment benefits and health insurance. BLUNDELL, PISTAFERRI, and PRESTON [2008] proposed a more general decomposition dealing with partial insurance mechanisms. Their approach requires panel data to identify the partial insurance parameters. With only repeated cross-sections, it is impossible to estimate partially insurable shocks in our model. As a consequence, they will be associated to permanent shocks as long as their effect is constant over time, and with transitory ones if they decrease over time. Without any information about the relative importance of these two different partially insurable shocks, it is difficult to assess *a priori* if our representation overestimates permanent or transitory shocks. In a different perspective, the literature on incomplete markets (CARROLL [1997]) has underlined that individuals may hold buffer savings to self-insure against future shocks. Savings decisions could be used to infer individuals' knowledge about future income risks. Using savings data could represent an important step for a more precise definition

TABLE IV. – Moments and Parameters

Moments		Parameters	
$\Delta_{kt}V(y)$	108	$V_{kt}(\upsilon)$	108
$\Delta_{kt}V(c)$	108	$\Delta_{kt}V(u)$	108
$\Delta_{kt}cov(y,c)$	108		
Nb of moments	324	Nb of parameters	216

$\Delta_{kt}V(y)$ (resp. $\Delta_{kt}V(c)$) represents the change in the variance of income (resp. consumption) as defined by equation (5) (resp. 6), and $\Delta_{kt}cov(y,c)$ represents the change in the covariance of income and consumption as defined by equation (7). $V_{kt}(\upsilon)$ is permanent variance and $V_{kt}(u)$ transitory variance.

of permanent and transitory shocks. Our approach can be considered as a first step, and we retain a more general analysis proposing a more elaborate decomposition of the determinants of income shocks for future work.

Finally, the unit root hypothesis of the permanent income component is a strong assumption. However, it is commonly derived from the permanent income hypothesis. Using a stationary process with an autoregressive coefficient smaller than one in absolute value is rejected by the data, since, as we will see below, in our data the variance of y^p increases linearly over time. Secondly, to model transitory shocks we use a white noise process. In the literature it is sometimes modeled with a longer ARMA structure. Hence, for example MACURDY [1982] and MOFFITT and GOTTSCHALK [2008] used an ARMA(1,2). More recently, MEGHIR and PISTAFERRI [2004] used ARCH processes. While it would be interesting to generalize the model in this direction, the lack of panel data precludes these more advanced modelings. Here we develop a first approach that is in accordance with the rest of the literature (see the survey by MEGHIR and PISTAFERRI [2010]).

III.2. *Identification*

In this setting, in order to identify the relative importance of these two components, two empirical strategies are possible. A first possibility is to use panel data on income and introduce a decomposition of the residual with a simple ARMA structure as in the earnings dynamics literature (LILLARD and WILLIS [1978]). Unfortunately, we do not dispose of panel data on households for France for a sufficiently long period. A second possibility is to use consumption data and the additional moment conditions that the model imposes on the change of consumption inequality to identify the variance in the permanent and transitory shocks. This is the road we will follow in the rest of the paper.

To summarize, for a cohort observed over T periods, T ranging from 2 to 7, we need to identify $T-1$ permanent variances $V_{kt}(\upsilon)$, $T-1$ changes in transitory variances $\Delta_{kt}V(u)$ and we get $3(T-1)$ conditions with (5) and (6), and (7) providing $(T-1)$ over-identifying restrictions. From the 141 data cells, we can build 108 cells in differences, each cell providing three moments; hence we obtain 324 observed moments in the data. Overall, we have 324 observed moments and 216 parameters to estimate. TABLE IV summarizes these figures. The next section sets out our estimation framework.

III.3. *Econometric Framework*

To recover the covariance structure of the change in inequality we have $3(T-1)$ moment conditions and $2(T-1)$ parameters to estimate for each cohort. Therefore we implement a GMM estimator. Let $\theta = (\sigma^2_{ut}, \sigma^2_{vt})$ be the vector of structural parameters of dimension $(2q, 1)$, with q ranging from 1 to 5 depending on the number of times each cohort is observed. Let $\hat{\pi}$ be the vector of moments of dimension $(r, 1)$ with $r > 2q$ whose true value is denoted $\pi_{\mathbf{0}}$. It is assumed that $\sqrt{N}(\hat{\pi} - \pi_0) \sim N(0, \Sigma_\pi)$ with N the sample size. The theoretical counterpart of π can be obtained from θ through the mapping $h(\cdot)$. The Minimum Distance (MD) estimator $\hat{\theta}_{MD}$ of θ is defined by (see CAMERON and TRIVEDI [2005], chapter 6):

$$\hat{\theta}_{MD} = \underset{\theta \in \Theta}{\arg\min} (\hat{\pi} - h(\theta))' \mathbf{W}_N (\hat{\pi} - h(\theta)). \tag{8}$$

Here $\mathbf{W}_N$ is a (r, r) positive definite weighting matrix and Θ the set of admissible values for the parameters θ. For inferences purposes CHAMBERLIN [1984] shows that the covariance matrix of the MD estimator is given by

$$\Sigma_\theta = \left(\frac{\partial h'}{\partial \theta} \mathbf{W}_N \frac{\partial h}{\partial \theta'} \right)^{-1} \frac{\partial h'}{\partial \theta} \mathbf{W}_N \Sigma_\pi \mathbf{W}_N \frac{\partial h}{\partial \theta'} \left(\frac{\partial h'}{\partial \theta} \mathbf{W}_N \frac{\partial h}{\partial \theta'} \right)^{-1}.$$

The term $\frac{\partial h'}{\partial \theta}$ representing the gradient of the moment conditions evaluated at $\hat{\theta}$, and Σ_π the covariance matrix of the moment conditions.

As with any GMM estimator, the choice of the weighting matrix is important. Two major possibilities have been explored in the literature. Firstly, some authors have implemented the equally-weighted minimum-distance estimator setting $\mathbf{W}_n = \mathbf{I}$. Secondly, an asymptotically more efficient estimator defined by $\mathbf{W}_n = V(\hat{\pi})^{-1}$ can be used (GOURIEROUX and MONFORT [1995]). As ALTONJI and SEGAL [1996] demonstrated, the optimal estimator has a finite-sample bias that can be important in small samples. Therefore, we try both approaches. As the results are very close – but more precise with the two-step estimator – we only present estimation results with the optimal estimator. Results with the one-step GMM estimator are available upon request.

In SECTION III.4 we compute the three moment conditions (5), (6) and (7), namely the change in the variance of income, the change in the variance of consumption and the change in the covariance between the two. Then, we estimate the permanent and transitory components in the variance of income by minimum distance. Finally, we set out how these two components change over the life cycle.

III.4. *Estimation Results*

As explained in SECTION III.2 we estimate 216 parameters. With such a large number of parameters, it is difficult to interpret all the different values and we favor a graphical representation. FIGURE 4 displays the estimated permanent and transitory variances. The upper panel indicates the change in the former, while the lower panel provides the latter for each cohort and educational group. Once again, dotted lines link the different estimated variances for a given group. Three observations can be made. First, the changes in permanent and transitory variances are not smooth and the graphs display large changes over time for a given group. This results from the small number of observations per cell. One must be careful and keep in mind this caveat when interpreting the results. Second, as FIGURE 4 demonstrates, the permanent component increases with age for the three educational levels and for most cohorts. Concerning the transitory variances in the lower panel, after visual inspection of the graph it is difficult to detect any age pattern in the change in the transitory variances. Third, there are no marked differences, either by educational group (between the graphs) nor between groups (within each graph) in both permanent and transitory variances.

The previous results should be confirmed by proper statistical analyses using the standard errors of the estimated parameters. These are presented with their standard errors in TABLES V and VI. The former provides changes in the permanent variances by age per group defined by cohort and educational level, while the latter displays the change in transitory variances. The three previous comments from FIGURE 4 are confirmed by this table, namely; the age profile is not very smooth, and permanent inequality increases with age, while transitory variance does not. Moreover, most of the coefficients are significant. For permanent variances, 90% (97 out of 108) are statistically different from 0, while for transitory variances a smaller share of 62% (67 out of 108) are significant. This should be kept in mind in order not to over-interpret the results. To explain this difference one should remember that permanent variances are in levels, while transitory variances are in differences. We conclude that permanent inequality increases with age, while there is no statistically significant change in transitory inequality over the life cycle.

Is it possible to test our modeling assumptions using these results? The linear increase in the permanent component of the variance is in line with the unit root assumption of the permanent component, since with such a process the variance should at least be non-stationary. Similarly, we have assumed that the transitory component can be modeled as a process of independent shocks. This is not contradicted by the unchanging variance in differences. Of course, many other time series processes could have these properties, but we interpret these results as a *weak* test of our assumptions. With a small time dimension ($T \leq 7$) it is difficult to go further.

In TABLE VII we provide the distribution of these permanent and transitory shocks by education, cohort and age groups. There are 108 of each that have been estimated. Permanent shocks increase with age: the median permanent shock for individuals between 32 and 37 years of age is equal to .05, while the median for individuals between 52 and 57 is .09, so nearly 80% larger, which represents a considerable difference. A potential explanation of this result might be that older individuals might be subjected to larger health shocks. This could affect individuals because of market imperfections on health insurance markets, since long term disabilities might not be insurable. However, it is not possible to test this assumption with our consumption data since only out-of-pocket health spending is recorded in the survey. On the contrary, in the right hand side panel, there is no change in age for transitory shocks, as already observed in FIGURE 4. Younger cohorts experience smaller permanent shocks but they are observed at a younger age too. There is no major change in permanent shocks in more recent years (from .057 between 1974 and 1980 to .058 between 2000 and 2005). While for transitory shocks no time pattern exists, there are slightly more positive transitory shocks

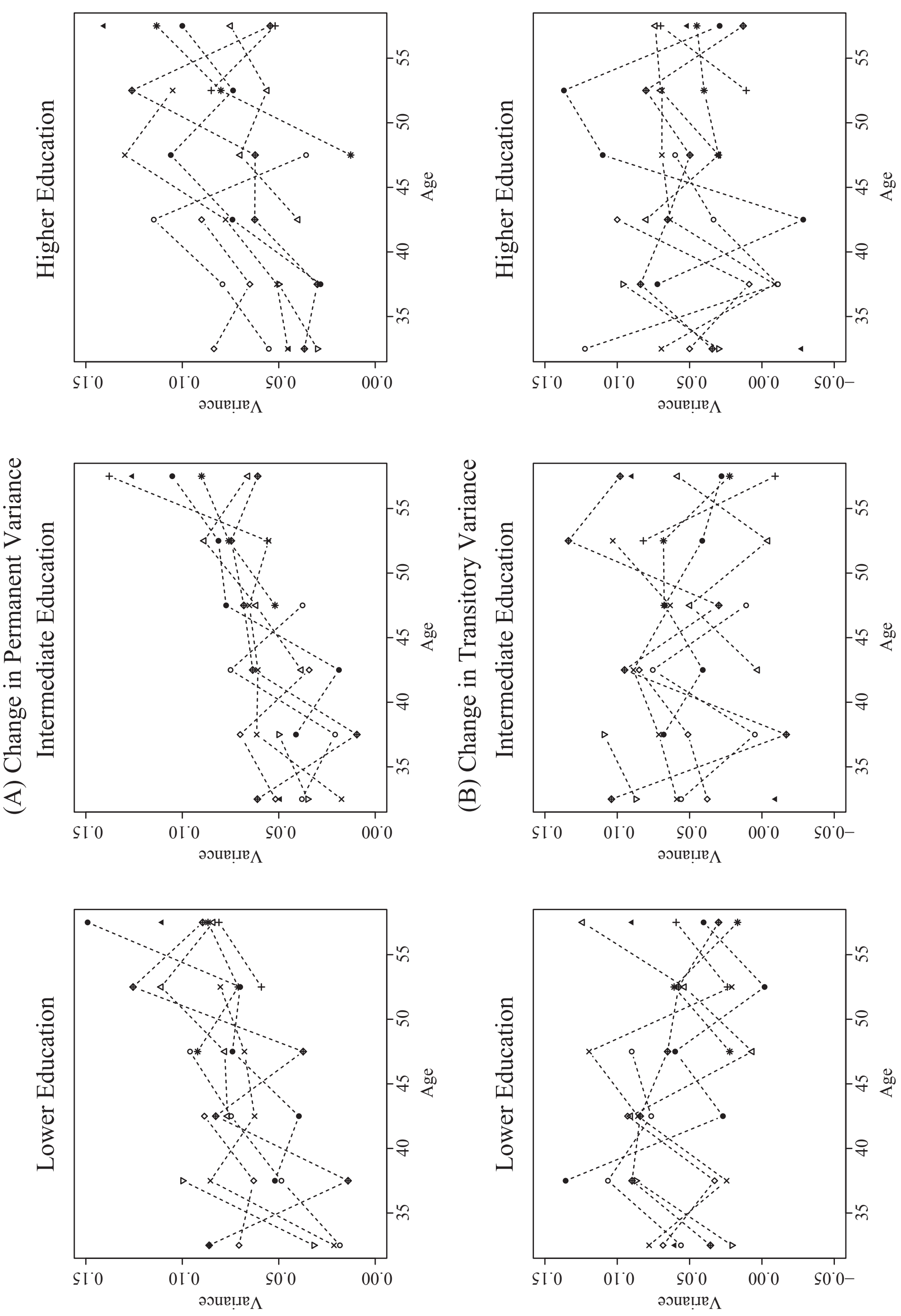

FIGURE 4. – Variance of Permanent and Transitory Shocks Relative to Age by Cohort and Educational Level

Table V. – Estimates of the Variances of Permanent Shocks to Income by Cohort and Education

Cohort	1	2	3	4	5	6	7	8	9	10	11
						Lower Education					
Age											
30						0.086 (0.013)	0.021 (0.013)	0.018 (0.014)	0.070 (0.016)	0.031 (0.019)	0.086 (0.024)
35					0.052 (0.014)	0.014 (0.012)	0.085 (0.016)	0.048 (0.016)	0.063 (0.016)	0.099 (0.021)	
40				0.076 (0.014)	0.039 (0.015)	0.082 (0.014)	0.062 (0.016)	0.074 (0.015)	0.088 (0.020)		
45			0.092 (0.013)	0.078 (0.015)	0.074 (0.020)	0.037 (0.017)	0.067 (0.016)	0.096 (0.020)			
50		0.059 (0.013)	0.071 (0.013)	0.111 (0.016)	0.07 (0.021)	0.126 (0.018)	0.080 (0.017)				
55	0.111 (0.014)	0.081 (0.016)	0.086 (0.015)	0.084 (0.019)	0.149 (0.021)	0.089 (0.020)					
						Intermediate Education					
30						0.061 (0.010)	0.017 (0.010)	0.038 (0.010)	0.051 (0.012)	0.035 (0.015)	0.049 (0.015)
35					0.041 (0.012)	0.009 (0.011)	0.061 (0.010)	0.020 (0.010)	0.07 (0.013)	0.05 (0.014)	
40				0.038 (0.013)	0.018 (0.011)	0.063 (0.011)	0.060 (0.012)	0.075 (0.011)	0.034 (0.014)		
45			0.052 (0.014)	0.061 (0.013)	0.077 (0.014)	0.068 (0.012)	0.065 (0.013)	0.037 (0.012)			
50		0.056 (0.021)	0.075 (0.015)	0.088 (0.017)	0.081 (0.020)	0.074 (0.014)	0.055 (0.014)				
55	0.126 (0.029)	0.138 (0.031)	0.09 (0.021)	0.066 (0.019)	0.105 (0.025)	0.060 (0.017)					
						Higher Education					
30						0.036 (0.017)	0.045 (0.013)	0.055 (0.019)	0.083 (0.015)	0.03 (0.020)	0.044 (0.013)
35					0.028 (0.016)	0.03 (0.013)	0.051 (0.014)	0.079 (0.019)	0.065 (0.016)	0.05 (0.018)	
40				0.04 (0.017)	0.074 (0.013)	0.062 (0.014)	0.077 (0.018)	0.115 (0.017)	0.09 (0.017)		
45			0.012 (0.022)	0.07 (0.015)	0.106 (0.022)	0.062 (0.014)	0.130 (0.021)	0.035 (0.018)			
50		0.085 (0.022)	0.08 (0.018)	0.056 (0.022)	0.073 (0.026)	0.126 (0.016)	0.105 (0.021)				
55	0.141 (0.033)	0.051 (0.032)	0.113 (0.031)	0.075 (0.028)	0.1 (0.023)	0.054 (0.021)					

The table indicates the estimated values of the variance of permanent shocks, $V_{kt(\upsilon)}$, for each group of individuals by age. Eg 0.086 represents the variance of permanent shocks estimated for group 7 estimated when they were aged 30. They were estimated using the moment conditions (5), (6), and (7) as explained in the main text. Standard errors are in parentheses.

TABLE VI. – Estimates in the Change of the Variances of Transitory Shocks to Income by Cohort and Education

Cohort	1	2	3	4	5	6	7	8	9	10	11
						Lower Education					
Age											
30						0.035 (0.014)	0.078 (0.019)	0.056 (0.022)	0.068 (0.026)	0.020 (0.026)	0.060 (0.027)
35					0.136 (0.016)	0.089 (0.015)	0.024 (0.022)	0.106 (0.024)	0.032 (0.019)	0.087 (0.022)	
40				0.090 (0.022)	0.027 (0.021)	0.084 (0.017)	0.085 (0.019)	0.076 (0.021)	0.092 (0.028)		
45			0.022 (0.027)	0.006 (0.018)	0.06 (0.025)	0.065 (0.02)	0.119 (0.023)	0.09 (0.022)			
50		0.023 (0.023)	0.060 (0.018)	0.053 (0.022)	−.001 (0.029)	0.057 (0.022)	0.020 (0.024)				
55	0.09 (0.029)	0.059 (0.021)	0.016 (0.021)	0.124 (0.026)	0.040 (0.028)	0.030 (0.023)					
						Intermediate Education					
30						0.104 (0.015)	0.058 (0.012)	0.055 (0.016)	0.037 (0.019)	0.087 (0.025)	−.009 (0.022)
35					0.067 (0.014)	−.016 (0.014)	0.071 (0.014)	0.004 (0.019)	0.051 (0.022)	0.109 (0.017)	
40				0.003 (0.028)	0.040 (0.017)	0.095 (0.017)	0.088 (0.018)	0.075 (0.019)	0.084 (0.021)		
45			0.067 (0.019)	0.049 (0.027)	0.067 (0.025)	0.029 (0.022)	0.063 (0.018)	0.010 (0.016)			
50		0.082 (0.034)	0.068 (0.025)	−.004 (0.034)	0.041 (0.029)	0.134 (0.026)	0.103 (0.031)				
55	0.09 (0.050)	−.009 (0.047)	0.022 (0.035)	0.058 (0.041)	0.027 (0.025)	0.098 (0.025)					
						Higher Education					
30						0.034 (0.018)	0.069 (0.029)	0.122 (0.025)	0.05 (0.022)	0.03 (0.030)	−.027 (0.020)
35					0.072 (0.013)	0.083 (0.02)	−.008 (0.028)	−.011 (0.020)	0.008 (0.022)	0.096 (0.022)	
40				0.080 (0.018)	−.028 (0.019)	0.065 (0.025)	0.063 (0.025)	0.033 (0.025)	0.100 (0.026)		
45			0.030 (0.034)	0.030 (0.063)	0.110 (0.031)	0.049 (0.025)	0.069 (0.029)	0.060 (0.035)			
50		0.010 (0.042)	0.040 (0.045)	0.070 (0.067)	0.137 (0.052)	0.080 (0.027)	0.069 (0.029)				
55	0.051 (0.066)	0.070 (0.077)	0.045 (0.056)	0.073 (0.042)	0.029 (0.049)	0.013 (0.029)					

The table indicates the estimated values of the change in variance of the transitory shocks by age, $\Delta V_{kt(u)}$, for each group defined by cohort and education. Eg: 0.035 represents the estimated change in transitory shocks for group 7 estimated at age 30. They were estimated using the moment conditions (5), (6), and (7) as explained in the main text. Standard errors are in parentheses.

TABLE VII. – Distributions of Permanent and Transitory Shocks by Age, Cohort, Year and Education

	Permanent Shocks				Transitory Shocks			
	Median	Min.	Max.	Std	Median	Min.	Max.	Std
Age								
32.5-37.5	0.050	0.009	0.100	0.023	.057	−.027	0.136	0.041
37.5-42.5	0.069	0.019	0.115	0.024	.078	−.029	0.100	0.035
42.5-47.5	0.068	0.013	0.130	0.028	.060	0.007	0.119	0.031
47.5-52.5	0.078	0.055	0.126	0.022	.059	−.004	0.137	0.041
52.5-57.5	0.090	0.052	0.149	0.030	.048	−.009	0.124	0.034
Cohort								
1921-30	0.085	0.052	0.141	0.036	.059	−.009	0.090	0.036
1931-35	0.080	0.013	0.113	0.029	.040	0.017	0.068	0.020
1936-40	0.073	0.038	0.111	0.020	.056	−.004	0.124	0.039
1941-45	0.074	0.019	0.149	0.034	.041	−.029	0.137	0.046
1946-50	0.062	0.009	0.126	0.032	.065	−.017	0.134	0.037
1951-55	0.063	0.017	0.130	0.029	.069	−.009	0.119	0.032
1956-60	0.052	0.018	0.115	0.030	.058	−.011	0.122	0.041
1961-65	0.057	0.030	0.100	0.022	.056	−.027	0.109	0.040
1965-75	0.049	0.030	0.100	0.024	.060	−.027	0.109	0.049
Year								
1974-1980	0.057	0.013	0.141	0.035	.068	0.003	0.136	0.036
1980-1985	0.057	0.009	0.138	0.033	.054	−.029	0.090	0.035
1985-1990	0.076	0.018	0.113	0.025	.058	−.009	0.122	0.036
1990-1995	0.069	0.021	0.084	0.017	.061	−.011	0.137	0.040
1995-2000	0.075	0.030	0.149	0.035	.054	0.009	0.134	0.034
2000-2005	0.058	0.034	0.105	0.024	.077	−.027	0.109	0.043
Education								
Lower edu.	0.077	0.014	0.149	0.029	.060	−.002	0.136	0.035
Interm. edu.	0.061	0.009	0.138	0.02	0.061	−.017	0.134	0.038
Higher edu.	0.068	0.013	0.141	0.031	.056	−.029	0.137	0.039
	0.068	0.009	0.149	0.030	0.060	−.029	0.137	0.037

The table provides summary statistics for the distribution of permanent and transitory shocks for each age, cohort, year and educational level. Hence, the overall median permanent shocks is .068, while the overall median of transitory shocks is .060.

than negative ones (76 *vs* 32).[7] Finally, the median transitory shock is slightly smaller than the median permanent one (.068 *vs* .060). This indicates that both components could have played a role in the change in the cross-sectional income distributions. This would need to be confirmed by a more precise analysis. SECTION III.5 investigates the connection between the permanent-transitory decomposition and the change in the cross-sectional distributions.

III.5. *Can We Explain the Changes in the Cross-Sectional Distributions?*

Can we link these decomposition results with the observed evolution of the cross-section distributions from FIGURE 1? As noted above, the income and consumption distributions do not display major changes in the first part of the period from 1974 to 1995, but after 1995 they follow diverging trends. The consumption dispersion increases markedly from 1995

7. A strong imbalance between the two would plead for some specification error of the model. One should remember however that only 62% of the transitory shocks are statistically different from 0.

onwards and remains at high levels in 2000 and 2005 compared to the eighties, while income inequality remains constant or decreases slightly. Now that the two possible conflicting sources of inequality – permanent and transitory shocks – have been disentangled, it is possible to come back to these opposite patterns between income and consumption distributions.

Regarding consumption inequality, from our decomposition, the change over time can only be explained by changes due to permanent shocks (see equation 6). The following three reasons could explain these changes. Firstly, the variance of permanent shocks could be larger in more recent periods thereby increasing the spread in the consumption distribution. We call this the time-effect hypothesis. Secondly, younger cohorts could have larger permanent shocks at a given age than older cohorts. This is the cohort-effect hypothesis. Finally, the structure of shocks could have stayed the same over time but the share of older individuals could have increased. This would increase the consumption dispersion, since, as demonstrated above, the permanent variance is an increasing function of age. This is the aging-effect hypothesis.

To disentangle the three possibilities, we regress the log of the permanent shocks on age, cohort and time effects:[8]

$$\ln \hat{\upsilon}_{kt} = \alpha_0 + \alpha_a + \gamma_k + \delta_t + \varepsilon_{kt}, \tag{9}$$

where $\hat{\upsilon}_{kt}$ represents the estimated permanent variance for cohort k at time t. α_0 is an intercept, α_a are age dummies, γ_k are cohort dummies and δ_t time dummies. The first three columns in TABLE VIII display the results for different specifications of this regression. Column 1 estimates mean differences of permanent shocks by cohort. It restricts the age coefficients, α_a, and time effects, δ_t, to be zero. Column 2 adds controls for age, and column 3 introduces time dummy variables. As in SECTION II, without additional assumptions it is not possible to identify the model. In column 3 we therefore estimate equation (9) under the same restrictions (see equation 2), which implies that time coefficients are constrained to be orthogonal to any linear trends.

These regressions are presented in TABLE VIII. The reference cohort is the older one, with individuals born in 1921-1925. In specification 1 there is no significant difference between the younger and the older cohorts. In specification 2 we add controls for age, and find that the younger cohorts do not have larger permanent shocks than the older since the coefficients are not significant. Finally, in specification 3, when time and age are controlled for, once again we reject the cohort effect hypothesis that younger cohorts have larger permanent shocks than older ones. We conclude that this potential explanation is rejected by the data. At the same age, younger cohorts were not affected by larger permanent shocks. Regarding the time-effect hypothesis, TABLE VII shows no significant increase in the permanent variance over time unconditional on age or cohort. Finally, in TABLE IX we simultaneously test whether the different coefficients are significant for cohorts and year variables. The null hypothesis of no difference between cohorts and between time periods is never rejected. Therefore, there is no evidence that the cohort-effect hypothesis or the time-effect hypothesis explain the observed changes in the consumption distribution.

In our model, the increase in consumption inequality can only be due to a change in the structure of the population. TABLE X indicates that the share of younger individuals (below 32.5) decreases by five percentage points between 1974 and 2005 (from 31% (18 + 13) to 26%

8. We used the log in order to interpret estimated coefficients as percentage changes.

TABLE VIII. – Regression of Permanent and Transitory Variances on Cohort, Age and Time

	Permanent Shocks			Transitory Shocks		
	1	2	3	4	5	6
Cohorts						
1926-30	0.047 (0.02)	0.041 (0.01)	0.047 (0.01)			0.11 (0.04)
1931-35	−0.003 (0.01)	0.002 (0.01)	0.096 (0.01)			0.07 (0.04)
1936-40	−0.008 (0.01)	0.003 (0.01)	0.033 (0.01)			0.11 (0.04)
1941-45	−0.005 (0.01)	0.012 (0.01)	0.023 (0.01)			0.02 (0.04)
1946-50	−0.015 (0.01)	0.009 (0.01)	0.017 (0.01)			0.11 (0.04)
1951-55	−0.013 (0.01)	0.017 (0.01)	0.003 (0.01)			0.04 (0.04)
1956-60	−0.021 (0.01)	0.015 (0.01)	−0.016 (0.01)			0.01 (0.04)
1961-65	−0.009 (0.01)	0.032 (0.01)	−0.008 (0.01)			0.06 (0.04)
1966-70	−0.029 (0.01)	0.019 (0.01)	−0.035 (0.01)			0.04 (0.05)
1971-75	−0.018 (0.02)	0.035 (0.01)	−0.02 (0.01)			0.06 (0.05)
Years						
1980-85			−0.033 (0.01)	0.053 (0.02)	0.053 (0.02)	0.032 (0.02)
1985-90			−0.029 (0.01)	−0.054 (0.02)	−0.054 (0.02)	−0.075 (0.02)
1990-95			−0.001 (0.01)	0.005 (0.01)	0.005 (0.01)	−0.014 (0.02)
1995-00			0.027 (0.01)	−0.17 (0.02)	−0.17 (0.02)	−0.19 (0.02)
2000-05			0.016 (0.01)	0.021 (0.02)	0.021 (0.02)	0.01 (0.02)
Cst	0.078 (0.01)	−0.053 (0.02)	0.063 (0.01)	0.03 (0.01)	0.044 (0.03)	−0.063 (0.03)
Age	No	Yes	Yes	No	Yes	Yes
R^2	0.07	0.33		0.55	0.55	
N Obs	108	108	108	108	108	108

Regression of permanent shocks in columns 1 to 3, and transitory shocks in columns 4 to 6 on cohort, age and time dummies. In columns 3 and 6 we define time effects to be orthogonal to any linear trend. The reference cohort is 1921-1925, the reference year is 1974-1980. Standard errors in parentheses. In columns 3 and 6 we do not provide R^2 since these are constrained linear regressions.

(11 + 15)), while the share of older people, above 52.5, increases by 3.1 percentage points.[9] As a consequence, the mean age in the sample increases from 40.4 in 1974 to 42.6 in 2005. As explained in SECTION III.4: as the variance of permanent shocks increases with age, and the population gets older, these two phenomena translate mechanically into a larger consumption dispersion. This conclusion is more general than in our application on French data. For a given structure of shocks, any economy with a population that becomes older witnesses a larger consumption inequality as long as the variance of permanent shocks increases with age.

While aging of the population could be part of the story, our analysis does not take into account the impact of mortality on life cycle inequality. Mortality risk could impact the results through two different channels. First, if educational groups face different mortality risks, there might be some endogenous selection among older individuals that should be taken into account.

9. However, the change is not monotonous.

TABLE IX. – Tests of Cohort and Year Effects in the Variance of Shocks

	Permanent Shocks		Transitory Shocks	
	Stat.	p-value	Stat.	p-value
Test A: $H_0 : \gamma_k = 0$	F(10,92) = 1.27	0.256	F(10,92) = 1.41	0.180
Test B: $H_0 : \delta_t = 0$	F(5,92) = 1.71	0.138	F(6,92) = 1.90	0.101

Reading: Test A: We test the null hypothesis that the coefficients for the cohort dummy variables are jointly equal to 0. Test B: We test the null hypothesis that the coefficients for the year variables are jointly equal to 0. Permanent shocks refer to regression 3 in TABLE 8, and transitory shocks refer to regression 6 in TABLE 8. All tests conclude that we cannot reject the null hypothesis.

Second, mortality risk could induce some agents to alter their consumption smoothing pattern, depending on their preferences, while this model does not assume any heterogeneity related to inter-temporal consumption behavior. Finally, differences in mortality risk play a key role and should be considered in future analyses.

Income cross-sectional inequality displays a different pattern from that of consumption inequality. It remains constant or drops slightly with the four inequality indexes after 1995 in FIGURE 1. However, the mechanism at stake in the consumption dispersion should work identically to the income distribution, since the variance of permanent shocks is larger when the population is older. The only reason why the change in income inequality might be different from the change in consumption dispersion is the transitory component (see formula 5). Income inequality decreases only if the transitory shocks, in later years, or for younger cohorts at a given age, are smaller. In the right hand side panel of TABLE VIII we regress transitory variances on age, cohort and time effects to test this hypothesis. In columns 4, 5 and 6, we observe a strong significant negative correlation between the more recent years (1995-00) and the transitory variance. In columns 4 to 6 there is a strong negative coefficient ranging from -19% to -17% for the change in transitory shocks between 1995 and 2000, which is, for example, ten times larger than the change in transitory inequality between 2000 to 2005. From these results, we conclude that overall income inequality would have increased if only the change in the structure of the population had taken place. Simultaneously, though, smaller transitory shocks more than compensated this increase, leading to a stable income dispersion. Admittedly, our reduced form approach does not specify where these transitory shocks come from, a more structural methodology would be necessary for this.

These results shed light on the mechanisms at play in the aggregate changes in income and consumption inequality. The decomposition is useful to understand the observed evolutions in the cross-sectional distributions. The permanent and transitory components can change in opposite directions, leading to diverging trends in dispersions. Of course, an important direction for further research would be to understand the sources of these permanent and transitory shocks. The single contribution that we are aware of trying to assess the source of such shocks is provided by JAPPELLI and PISTAFERRI [2011]. They tested whether the integration to the euro system increased the access to financial markets and consumption opportunities in Italy. They were unable to statistically confirm this hypothesis however. With our data, understanding where the large negative transitory shocks come from represents a necessary extension to this work.

TABLE X. – Age Structure of the Population

	1974	1980	1985	1990	1995	2000	2005
Age %							
27.5	0.18	0.16	0.17	0.15	0.14	0.13	0.11
32.5	0.13	0.17	0.19	0.17	0.17	0.14	0.15
37.5	0.13	0.14	0.19	0.18	0.17	0.15	0.16
42.5	0.15	0.14	0.13	0.17	0.17	0.17	0.16
47.5	0.16	0.15	0.12	0.11	0.16	0.16	0.15
52.5	0.14	0.13	0.12	0.12	0.09	0.15	0.14
57.5	0.10	0.12	0.08	0.10	0.10	0.11	0.13
Mean	40.47	41.52	40.12	40.91	41.11	42.33	42.67

IV. Conclusion

The objective of this paper was twofold. First, we compared the changes in income and consumption inequality over time using repeated cross-sections with a life cycle perspective constructed using a pseudo-panel of micro data from the French household BdF survey between 1974 and 2005. We showed that the two perspectives provide very different pictures. While the cross-sectional distributions do not display important changes over the period, the within-cohort inequality profiles have a clear increasing pattern that is linear for income dispersion, and convex for consumption dispersion. An explanation for these discrepancies is the changing structure of the French population. Over the last thirty years it has become better educated and older. Secondly, we used consumption data to disentangle permanent from transitory factors in the variance of income. The two components play an important and sometimes conflicting role. Permanent inequality increases with age, while transitory inequality has no clear age pattern. Finally, the sharp increase in consumption dispersion is at least partly due to the aging population, while the rather stable income inequality is due to negative transitory shocks that mitigated against the increase due to the permanent component. As a consequence, these results imply that in the next few years it is likely that income and consumption inequality will continue to increase due to the aging of the population. The *composition effect* as presented by LEMIEUX [2006] for the U.S. seems to be at work in France as well. Needless to say, in our analysis this effect might be underestimated due to the limited age range we have chosen. An interesting extension would be to investigate inequality among older individuals, but this would require another research project.

It should be kept in mind that our results rely on restrictive assumptions; it would therefore be interesting to extend this analysis to a more general framework. Hence, some authors have used richer settings introducing borrowing constraints to the model, as well as different risk-sharing arrangements that allow consumption smoothing (BLUNDELL, PISTAFERRI, and PRESTON [2008]). However, this approach requiers individual panel data which are not available in the BdF data set.

In this paper, we have restricted the analysis to a particular definition of life cycle inequality, defining it as inequality in different parts of the life cycle. Yet, the expression could be given a more elaborate meaning. Life cycle inequality could be associated with a measure of inter-temporal inequality measuring differences in income and at the same time differences of mobility prospects across the income distribution. In this setup, BOWLUS and ROBIN [2004]) built present value life cycle measures to assess what they call lifetime inequality. This second perspective presents the advantage of explicitly modeling the dynamic dimension of the changes in inequality over time, unlike our approach, that remains mostly static. It could be interesting to try to mix the two frameworks in future works. In this respect, BONHOMME and ROBIN [2009] studied lifetime earnings inequality using French data. These approaches considerably enrich the analysis compared to cross-sectional income inequality.

Starting from this analysis, an important research agenda would be to investigate more deeply the increasing convex consumption life cycle inequality profile documented here. It is an important fact that the spread in consumption levels increases at an increasing rate, due to the consequences for individuals' well-being. A more disaggregated approach would be necessary to understand the mechanism at work, and to suggest which kind of public policy might correct this. In a recent contribution AGUIAR and HURST [2010] built these life cycle profiles from U.S. data using a more disaggregated consumption definition by sub-components. They showed that the profile is very different for various consumption categories. This represents an interesting direction for future research on French data.

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Appendix

Additional Results

TABLE A.1. – Regression of Education on Individual Characteristics

Age	−1.211 (0.35)	Nationality - Africa	−0.586 (0.05)
Age^2	4.299 (1.29)	Nationality - Other	−0.401 (0.05)
Age^3	−6.922 (2.06)	Civil servant	0.476 (0.02)
Age^4	4.095 (1.21)	Rural	−0.688 (0.09)
Year	0.024 (0.00)	City	−0.609 (0.09)
Male	−0.097 (0.03)	Paris area	−0.514 (0.09)
p1- Farmer	0.045 (0.06)	Paris	0.194 (0.04)
p2- Self-Empl.	0.516 (0.06)	Family size	−0.090 (0.01)
p3- Top Exec.	3.101 (0.05)	Nb children- 2	0.135 (0.04)
p4- Interm. Exec.	1.597 (0.05)	Nb Children- 4	−0.060 (0.03)
p5- Clerks	0.201 (0.05)	Nb children-16	−0.007 (0.02)
p6- Workers	−0.647 (0.05)	Cons.	−29.649 (4.11)
p7- Unempl.	0.531	R^2	0.486
	(0.07)	N	43,575

Regression of the number of years of education on individual characteristics. Robusts standard errors in parentheses. Age: Age of the individual. Year: linear time trend. Male: sex of the individual. Occupational class (reference: out of the labor force) p1: Farmers, p2: Self-employed, p3: Top executives, p4: Intermediate Executives, p5: Clerks, p6: Workers, p7: Unemployed. Nationality: (reference: French). Place of residence: (Reference: lives in the suburbs excluding the Paris area), rural: lives in the countryside, City: lives in a city, Paris area: Lives in the Paris suburbs, Paris: Lives in Paris. Family structure: Family size: number of family members. Nb children: Number of children of age below 2, 4 and 16 (reference: No children).

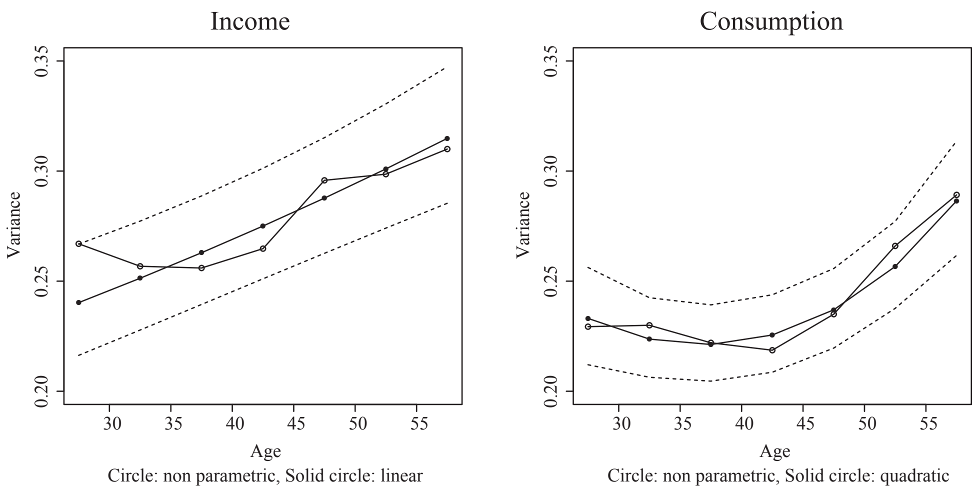

FIGURE A.1. – Changes in Income and Consumption Inequality with Age

Source: BdF Survey. Estimated age effect from regressions 5 (for income) and 6 (for consumption) in TABLE III on the variance of income and consumption. Left panel: linear and non parametric (dummy variables) specifications in age. Right panel: quadratic and non-parametric (dummy variables) specifications in age.

TABLE A.2. – Regressions of Within-Cohort Inequality on Age

	Theil Index					
	Income			Consumption		
	(1)	(2)	(3)	(4)	(5)	(6)
Age	0.007 (4.2)	0.005 (2.1)	0.005 (2.2)	−0.046 (−3.3)	−0.018 (−0.8)	−0.040 (−2.7)
Age^2				0.059 (3.6)	0.030 (1.1)	0.057 (3.3)
Intermediate Educ.	−0.176 (-4.3)	−0.176 (-4.3)	−0.176 (-4.4)	−0.121 (-3.5)	−0.121 (-2.3)	−0.121 (-3.5)
Higher Educ.	−0.308 (-7.5)	−0.308 (-7.5)	−0.308 (-7.7)	−0.094 (-2.7)	−0.094 (-1.8)	−0.094 (-2.7)
Cst	−2.210 (-25.8)	−1.984 (-13.3)	−1.971 (-13.4)	−1.115 (-3.8)	−1.840 (-3.9)	−1.555 (-5.1)
Year Effect	Yes	No	Yes	Yes	No	Yes
Cohort Effect	No	Yes	Yes	No	Yes	Yes
R^2	0.389	0.411		0.648	0.185	
Observations	141	141	141	141	141	141

	Gini Coefficient					
	Income			Consumption		
	(1)	(2)	(3)	(4)	(5)	(6)
Age	0.003 (4.3)	0.003 (3.3)	0.003 (3.4)	−0.022 (-3.7)	−0.009 (-1.0)	−0.019 (-3.1)
Age^2				0.029 (4.1)	0.015 (1.3)	0.027 (3.7)
Intermediate Educ.	−0.084 (-4.9)	−0.084 (-4.9)	−0.084 (-5.1)	−0.053 (-3.7)	−0.053 (-2.4)	−0.053 (-3.7)
higher Educ.	−0.144 (-8.4)	−0.144 (-8.3)	−0.144 (-8.6)	−0.044 (-3.1)	−0.044 (-2.0)	−0.044 (-3.1)
Cst	−1.393 (-38.9)	−1.344 (-21.2)	−1.329 (-21.7)	−0.845 (-6.9)	−1.161 (-5.9)	−1.027 (-7.9)
Year Effect	Yes	No	Yes	Yes	No	Yes
Cohort Effect	No	Yes	Yes	No	Yes	Yes
R^2	0.438	0.442		0.647	0.209	
Observations	141	141	141	141	141	141

Source: BdF Survey. OLS regression of the (log) within cohort variance of income in (1) to (3) and of consumption in (4) to (6) on age, education (reference level Basic Education), cohort dummies and year dummies. In parentheses t-stats. Observations are weighted by the standard error of the estimated cell means.

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