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Abstract

This paper computes lifetime earnings (LTE) in France for the 1967 to 1987 entry cohorts and compares our results with the US. Median LTE in France increased moderately for both genders, in contrast to the US where men's LTE declined and women's rose sharply. We also examine some of the factors driving the dynamics of LTE in France. We find that education plays a key role in shaping LTE across cohorts, place of birth has a large influence on lifetime earnings, and differences in working time explain a *larger* share of the gender gap for younger than for older cohorts.

JEL Classification: *J16, J31, J62*

Key words*:* Lifetime earnings, inequality, gender earnings gaps.

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1 Introduction

Cross-sectional measures of earnings inequality have been widely used to assess the dynamics of inequality over time and for cross-country comparisons. However such point-in-time measures of inequality present limitations. In particular, they do not reflect income mobility over the life cycle and are affected by transitory income shocks. Therefore, a broader perspective based on lifetime earnings, i.e. looking at the earnings of a cohort over its life cycle, can significantly enrich the analysis. The analysis of the dynamics and distribution of lifetime earnings has however been limited by data availability, and the bulk of recent contributions focuses on the US (Kopczuk et al. (2010), Guvenen et al. (2022a) or Ozkan et al. (2023)). Existing work for the US has found striking patterns, with male lifetime earnings exhibiting a decline in their median across cohorts and a sharp increase in inequality. Based on cross-sectional data, a vast literature has found that both trends in average earnings and their dispersion have followed different paths in the Western European economies when compared to the US, notably with the latter exhibiting much higher levels of earnings inequality than the former. This raises the question of to what extent these differences still hold when one considers lifetime rather than point-in-time earnings.

We address this question by providing estimates of lifetime earnings for a large European country, France, and compare our results with those of Guvenen et al. (2022a) for the US. This comparison is particularly interesting as France is, relative to the US, a country characterized both by a low level of cross-sectional inequality (e.g. Atkinson (2003), Alvaredo et al. (2018) or Garbinti et al. (2018)) and by limited intra-generational mobility (see Kramarz et al. (2022) and Aghion et al. (2023)). Our paper hence seeks to understand how these two features translate into lifetime earnings, examining how they have evolved at different points of the distribution and what have been the factors shaping the observed trends.

Our contribution to the literature is threefold. First, we conduct the first analysis of lifetime earnings distributions for a large number of cohorts in France and provide a direct comparison with the results for the US obtained by Guvenen et al. (2022a). We document crucial differences between France and the US regarding trends in median and average lifetime earnings and in lifetime inequality. In particular, we show that earnings dynamics by gender dramatically diverge across countries. Second, we add to the literature by providing new results about the determinants of the dynamics of lifetime earnings. We observe a decline in the returns to all educational qualifications other than master's degrees (or above), which implies that the modest increase in lifetime earnings across cohorts can be attributed to the rise in educational attainment over the period. Our data also allows us to establish how the place of birth shapes lifetime earnings. Third, regarding the evolution of the gender gap over cohorts, we document the increasing contribution of differences in working time between men and women.

Our analysis relies on a long administrative data panel encompassing firm-level and census information.[1] This allows us to build the first series of lifetime earnings at the individual level for France. For comparison purposes, we follow closely Guvenen et al. (2022a) in terms of sample selection and lifetime earnings computation. As they do, our lifetime earnings measure is based on 31 potential working years between ages 25 and 55. Our core sample consists of the cohorts born between 1942 and 1962, who turned 25 years old between 1967 and 1987. Throughout this paper, we refer to cohorts by the year in which they turned 25.

We derive three types of results. First, in section 3, we analyze the trends in median and mean lifetime earnings in France and compare their dynamics and age profiles with those in the US. Although the overall pattern for the entire population is similar in France to that observed in the US (i.e. a flat curve since the late 1960s/early 1970s), we unveil major differences between the two countries. For the US, Guvenen et al. (2022a) show that it is the result of large losses for men and large gains for women, while in France we find that it results from moderate increases of both male and female lifetime earnings combined with an increase in female labor force participation. More precisely, the median lifetime earnings of French men initially increased, rising up to the cohort entering in 1973, and subsequently stagnated. For women, median lifetime earnings increased moderately throughout. The age profiles across cohorts also differ from those observed in the US. Our results for France indicate that the stability of male median lifetime earnings across cohorts hides a significant change in the pattern of their yearly earnings over their life cycle. Starting with the late 1970's cohorts, there is a decrease in entry wages, which has been nevertheless compensated by faster earnings growth between ages 35 and 55. We find a similar pattern for women.

Second, in section 4 we assess how lifetime inequality has evolved over time. We find that inequality in lifetime earnings is much lower in France than in the US over the whole period we study. While Guvenen et al. (2022a) report a steady increase in the US across cohorts, France exhibits moderate changes, displaying a U-shaped pattern with inequality first falling and then increasing from the 1979 or 1981 cohorts onwards for women and men, respectively. For the most recent cohorts, only the top of the distribution experienced earning gains, which raises the question of whether France is on a path

[1] The Permanent Demographic Sample or *Échantillon Démographique Permanent*

of growing inequality too, albeit with a lag with respect to the US. Regarding the comparison between lifetime and cross-sectional measures, we find that inequality is lower for lifetime earnings than in the cross-section, yet in both instances, the data display a comparable U-shaped broad pattern. In cross-sectional data, we observe a sharp increase in inequality at the top of the distribution, but this does not translate into a large increase in lifetime earnings inequality, in contrast with findings for the US. Gender-specific lifetime inequality exhibits a roughly similar pattern to overall inequality, leading to a decreasing gender lifetime earnings gap, although to a lesser extent than the one observed in the US. Interestingly, we show however that when looking at inequality dynamics by gender, the dynamics of the cross-section is not able to provide a good approximation for lifetime inequality patterns, highlighting the interest of lifetime measures to assess inequality developments.

Third, in section 5 we analyze how the roles of education, geography and working time in shaping lifetime earnings and the gender gap have evolved across cohorts, estimating the impact of these variables on lifetime earnings. Our results imply that there was a sharp drop in the return to all education qualifications other than a master's degree (and above) across cohorts, for both men and women. We also find a significant role for working hours (number of years working part-time or full-time) and place of birth. In particular, we find that being born in the Paris region confers an advantage that is due both to it leading to higher educational attainment and to the fact that those individuals born in the Paris region (which pays the highest earnings) tend to spend more years working here. To better assess the magnitude of all these different channels in explaining the lifetime earnings dynamics, we perform reduced-form counterfactual exercises. We find that the fall in returns to education plays a key role: had the returns to education remained at their 1967 level, the growth in earnings experienced by men between the 1967 and the 1987 cohorts would have been twice as fast as the growth of men earnings we actually observe. The change in education attainment has also played a major role: given the fall in the return to all educational qualifications other than a master's degree, had the distribution of education observed for the 1967 cohort of men remained the same over time, lifetime earnings would have declined over the period instead of growing mildly. In contrast, although we find a significant effect of place of birth on lifetime earnings within a given cohort, this factor does not play a role in understanding the dynamics across cohorts.

Comparing results for men and women allows us to assess the key aspects driving the evolution of the gender gap in lifetime earnings. Both in the US and in France, the lifetime gender gap has narrowed across cohorts. Women's lifetime earnings as a percentage of men's are however far larger in France, where this percentage increased from about 61% to 70% (compared to about 41% to 60% in the US). Based on a Oaxaca-Blinder decomposition, we show that much of the change in the gender gap over time in France is explained by differential developments in working time and in educational attainment and its returns. More precisely, the contribution of working time to explaining the gender gap has increased from 30% to 60% across cohorts. The reason for this is that although younger women work more years than their predecessors, they have tended to mainly increase their years in part-time employment, which has contributed to deepening the gender gap. At the same time, education played a major role in reducing the gender gap due to both a fast increase in female educational attainment and a reduction in the gap in the returns to education.

Related literature - The closest paper to ours is Guvenen et al. (2022a). We build on their empirical approach in terms of sample selection and definitions to provide new results about trends and inequality in lifetime earnings for a large European country (France) and compare it with the US. To the best of our knowledge, few other papers perform similar analyses. Focusing on Norway, Aaberge and Mogstad (2015) compare lifetime inequality and cross-sectional inequality for the cohorts born between 1942 and 1944. For Germany, Bönke et al. (2015) show increasing lifetime earnings inequality for cohorts born between 1935 and 1968. Corneo (2015) also finds increasing lifetime earnings inequality in Germany for cohorts born between 1935 and 1972. Besides providing a comparison between France and the US both for lifetime earnings trends and inequality, we add to this literature by assessing the role of various channels in explaining lifetime earnings developments across cohorts. In particular, the combination of firm and census data allows for rich information both on individuals' work and personal characteristics. We are hence able to examine the effect of declining education returns, of the increase in women's part-time work, and of the influence of place of birth on lifetime earnings.

There has been a long-standing interest in lifetime earnings, in particular, because they play a central role in human capital theory. In order to circumvent the data limitation, one literature estimates parametric econometric models for earnings dynamics from panel data to simulate the distribution of lifetime earnings (Bowlus and Robin (2004)). Using such an approach, Bowlus and Robin (2012) shows, for five countries including France and the US, how cross-country differences are narrowed when considering lifetime inequality measures instead of cross-sectional ones. Using the same data as this paper, Magnac and Roux (2021) deals with another issue. They focus on a single cohort of male wage earners observed over 30 years, and estimate individual-specific parameters of a human capital investment model allowing for heterogeneity so as to describe the distribution of earnings. They find that wage profiles stabilize over the life-cycle and heterogeneity becomes less and less transitory.

A recent literature examines annual earnings dynamics based on administrative data (see Guvenen et al. (2022b) as well as Bowlus et al. (2022) for Canada, Drechsel-Grau et al. (2022) for Germany, Hoffmann et al. (2022) for Italy, and Kramarz et al. (2022) for France). These papers focus on cross-sectional information. We differ from this literature by focusing on lifetime earnings to provide new insights on inequality developments across cohorts.[2] There is also an extensive literature focusing on earnings volatility, following the pioneering work by Gottschalk and Moffitt (1994). In a recent paper using US data covering cohorts from the 1920s to the 1990s, Blundell et al. (2023) find a strong U-shape pattern of volatility over the working life, which comes from large permanent shocks early and later in the life-cycle. This U-shape shifted downward and leftward for more recent cohorts due to lower transitory variances among younger cohorts.

2 Data

2.1 Data Sources

The Permanent Demographic Sample (*Échantillon démographique permanent* or EDP) is a large panel designed to study fertility, mortality, family backgrounds, and salaries. We use the 2019 EDP which combines several data sources. The main one consists of an administrative data set obtained from firms that gives information on employees' salaries and firm characteristics, the *Déclaration annuelle des données sociales* or DADS, and which covers the period 1967-2017. These data are combined with registry data indicating dates of birth, marriage, and death, and with census data.[3] We use a sample of the EDP that corresponds to 0.5% of the population.[4] The observations for 1981, 1983, and 1990 are missing as data were not collected in those years.[5] Due to its large sample size, the EDP allows for a detailed analysis that can take into account heterogeneity across generations and qualifications. A further advantage of these data is that there is no top-coding of earnings.[6]

Earnings include all wage and salary income supplied by employers. Earnings are

[2] Income mobility has recently been studied in France and found to be limited (Aghion et al. (2023)) and stable over a recent period (1991-2016, see Kramarz et al. (2022)).

[3] For 1968, 1975, 1982, 1990, 1999, and 2004, and annual from then onwards up to 2015.

[4] More precisely, initially the data set covered only those individuals born in the four first days of October of even years, and for consistency reasons across cohorts, we select for all cohorts individuals born on those dates.

[5] In what follows we will simply ignore those years when computing average lifetime earnings and divide by the number of years for which we have data. A consequence of that is that the number of years in which we have data for an individual ranges between 28 and 31.

[6] In contrast, for the US the origin of the data implies that until 1978 earnings above the threshold for being subject to social-security contributions are not recorded and need to be imputed by researchers making assumptions on the upper tail of the distribution for much of the period under study.

reported net of all social security contributions but not of income taxes. Since our data are provided by firms, we only have information on labor earnings and not full incomes including capital income and public or private transfers. Our dataset allows us to compute a number of additional variables that will be used in our analysis: the number of years that the individual worked, whether they worked full- or part-time, as well as the region where the individual worked at each point in time. Census sources allow us to collect information on the highest educational degree obtained by the individual, as well as whether they were ever married (or in a legally established couple) and whether they ever had children.

2.2 Sample selection

The sample is selected across several dimensions in order both to ensure the reliability of our results and to be able to compare our conclusions with Guvenen et al. (2022a). First, we restrict it to individuals employed by private companies, individual entrepreneurs, and public companies subject to private law. This restriction comes from the fact that individuals employed by the public sector or by natural persons are only included in the database from 1988 and 2009, respectively.[7] Also, following standard practice in the literature as well as Guvenen et al. (2022a), we consider only prime-age workers, i.e. those aged 25 to 55 years. Given our focus on lifetime earnings, we restrict the sample to those still alive at 55.[8]

Hence, following Guvenen et al. (2022a), we define lifetime earnings as

$$\bar{y}_i = \frac{1}{n}\sum_{t=25}^{55} y_{it} \qquad n \in \{28, 29, 30\} \tag{1}$$

The sample includes individuals born between 1942 (i.e. 25 in 1967) and 1962 (i.e. 55 in 2017). This restriction is due to the need to observe individuals over their entire lifetime, i.e. for the 28- to 30-year period between ages 25 and 55 (depending on the number of years of data collection missing). We hence have data on 11 cohorts spanning over 21 years.

One concern is that earnings may not be observed in certain years, as individuals leave the DADS data set for various reasons: they became unemployed, are on sick or maternity leave, change type of employer, or leave the labor force. From 1988, we have data on civil servants and from 2009 on those working for individual employers (rather than for firms); hence after those dates we can see if the individual disappears from the sample because it

[7] We do not find major differences in our results when including these two groups in our sample. Results are available from the authors upon request.

[8] This selection criterion could be a concern if the probability of early death were correlated with earnings potential. Again, we make this assumption in order to follow Guvenen et al. (2022a) as closely as possible,

switches jobs into those categories. Unfortunately, we cannot distinguish between being non-employed or self-employed. As a result, we cannot know whether missing earnings are due to having switched to self-employment. We hence consider individuals for whom we have 'sufficient' data, following procedures common in the literature that impose restrictions on wages to mitigate sample bias. We follow Guvenen et al. (2022a) and restrict wages to include only individuals earning at least a sixteenth of the minimum wage in at least half of the period we can observe them.[9] This ensures that the individual displays sufficient attachment to the labor market. The final sample has about 1.06 million individual-year observations, consisting of 11 cohorts comprising between 2,668 and 5,058 individuals each.

2.3 Adjusting for inflation

To obtain real earnings, nominal earnings are deflated by an appropriate price index. The choice of deflator is important given the length of the period we consider. Two deflators are used. Our analysis employs the Personal Consumption Expenditure (PCE) deflator, using the time series provided by the French statistical institute, Insee. As an alternative, we also construct earnings time series using the consumer price index, CPI.[10] Our choice of deflator has been made following that in Guvenen et al. (2022a), which allows us to keep our analysis comparable to theirs, although a comparison between patterns using the two deflators is provided in the appendix (Figure A.1).

3 Trends in lifetime earnings

In this section, we first analyse how median lifetime earnings have evolved over cohorts and then explore how life-cycle profiles have changed over time, documenting sharp differences between France and the US. We then ask how similar are the dynamics of lifetime earnings compared to those obtained on the cross-section of individuals.

[9] We use the restrictions, 507*0.25*the minimum hourly wage or 455*0.25*the minimum hourly wage. The Figure 507 corresponds to a quarter of the legal annual working hours in France, which were 2028 until 1999, corresponding to a 39-hour working week. For subsequent years this number is adjusted to 455 as weekly hours were reduced to 35. Guvenen et al. (2022a) consider a threshold of 520*0.5 because the legal working time in the US is 40 hours per week. We divide the yearly hours threshold by 4 to account for the fact that the labor market adjusts more slowly in France than in the US so that individuals can experience longer periods of unemployment spaced in-between short contracts. Further, although in France the minimum wage is mandatory, receiving a lower hourly wage is possible with certain types of contracts, notably for young workers and trainees.

[10] Over the period, the CPI and the personal consumption expenditure (PCE) deflator have evolved similarly. The PCE is generally considered as taking into account a broader view of consumption. For instance, it includes spending on behalf of consumers by employers and government health agencies (see for instance Appendix, section A.6 in Piketty and Zucman (2014)).

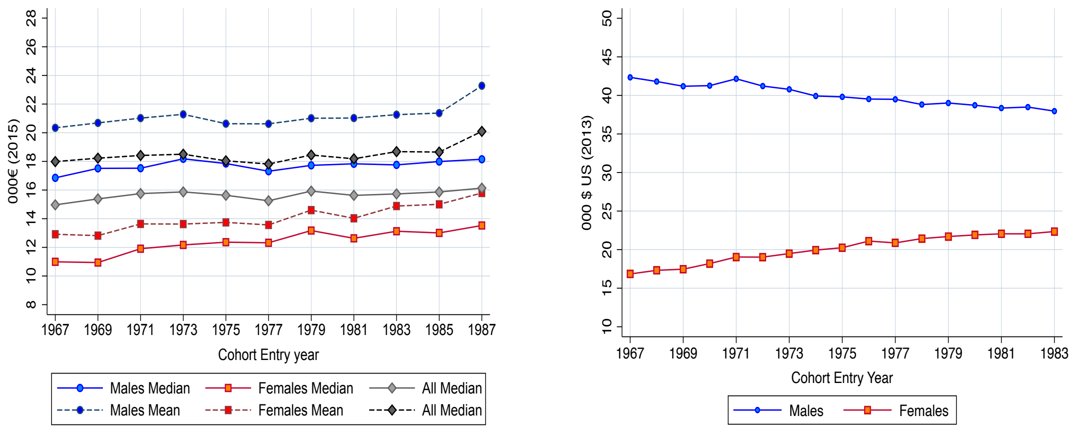
3.1 Trends in median lifetime earnings

We start by considering the trends in median lifetime earnings. The left panel of Figure 1 reports our results for France, displaying the evolution of median and mean lifetime earnings. The data are reported by gender as well as for the entire population, with the year in the horizontal axis indicating the year of presumed entry into the labor market (age 25). For ease of comparison, the right-hand panel reports the results obtained by Guvenen et al. (2022a) for the median lifetime earnings of men and women in the US.

Figure 1: Median and mean lifetime earnings by cohort and gender

(a) France

(b) US



Notes: The left-hand graph depicts our own computations, while the right-hand side one reproduces the results in Guvenen et al. (2022a). Both figures report individual lifetime earnings. For France, we compute both median and mean earnings, for men, for women, and for the entire population (All). For the US we report median lifetime earnings for men and for women.

Consider first median earnings. In France, annualized lifetime earnings for men rose from 16,850 € for the oldest cohort –those entering the labor market in 1967- to 18,150 € for those in the 1987 cohort, an increase of 7.7% for cohorts that are 20 years apart. Note, however, that all of the gains accrued to the first cohorts, and that from 1973 we only observe small fluctuations around a flat trend (in fact, between the 1973 and 1987 cohorts median earnings fell slightly, by 0.18%). Women exhibit faster growth, with annualized lifetime earnings increasing from 11,000 € to 13,530 €, i.e. by 23%. Again, most of the increase occurs early on, with the cohorts from 1979 onwards exhibiting moderate growth (earnings grew by 19.85% between the 1967 and 1979 cohorts, and by 2.68% between the 1979 and the 1987 ones). The dynamics for the entire population follow closely those of men's earnings, with a small increase between the 1967 and 1979 cohorts and no earnings growth between the 1979 and the 1987 cohorts.[11] The overall increase in lifetime earnings

[11] Figure A.1 in the Appendix reports median lifetime earnings with the two possible deflators and shows that the dynamics are not affected by the choice of deflator. Median earnings are slightly higher when we

across cohorts for both men and women is partly explained by the extensive margin: the number of years worked by individuals has increased, conditional on having worked 15 years out of the 31 years we consider. This is clearly observed in our data, as shown in Figure A.2 in the Appendix. This increase in participation is well documented (see Kramarz et al. (2022)) and, starting in the 1980s, is partly driven by women.[12]

France and the US exhibit different patterns regarding the evolution of median lifetime earnings across cohorts. Our data start later than those used by Guvenen et al. (2022a), hence we are not able to document their earlier period where they find an increase in male lifetime earnings for their initial cohort (1957) to that of 1967 (i.e. those born between 1932 and 1942). However, the French data do display rising male earnings early on in the sample, increasing by 5% between our initial cohort (1967) and that of 1973 (birth years 1942 to 1948). The median American man experienced a considerable decline after 1967, losing 10% of their earnings between 1967 and 1983 (and 7% in the 10 years after 1973); in contrast, the median French man experienced a reduction of 2% between the 1973 and 1979 cohorts, but recovered the loss so that lifetime earnings were virtually identical for those entering the labor market in 1973 and in 1987, as can be clearly seen in Figure 1. Table 1 reports lifetime earnings growth across cohorts when we consider the cohorts available for both countries and indicate that between the 1967 and the 1983 cohorts they grew by 5.36% for the median French man and fell by 10.34% for the median American man.

A second difference is that the US data indicate much greater differences across gender dynamics than those we find. In France, these differences are moderate, with the median lifetime earnings of women growing more than that of men but exhibiting a flattening out for the youngest cohorts, as is the case for men. The increase is milder than in the US, 19.41% versus 32.67% for the 1967-1983 cohorts. The overall pattern for the entire population in the US, a flat curve, is the result of large losses for men and very large gains for women; in France, moderate average growth results from moderate increases in both male and female lifetime earnings.[13]

Figure 1 also displays mean lifetime earnings in France. As expected, mean earnings are higher than median earnings, with the gap being larger for men than for women. Overall, the dynamics are similar between the mean and the median, with the data also displaying moderate growth of mean earnings for men, women, and the overall popu-

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use the CPI rather than the PCE deflator, and growth is slightly faster with the latter. In all further analysis, we will focus on data deflated using the PCE deflator, partly because this is the measure chosen by Guvenen et al. (2022a) with which we will systematically compare our results.

[12]The increase in the overall participation rate identified in existing work is also driven by those aged above 55 years of age who are not included in our sample.

[13]Over the 1967-1983 cohorts average lifetime earnings growth was 0.12% in the US (see Guvenen et al. (2022a), Table 2) and 3.88% in France.

Table 1: Growth of lifetime median and mean earnings between the 1967 and the 1983 cohorts

	France		US	
	Men	Women	Men	Women
Median	5.36	19.41	-10.34	32.67
Mean	4.51	15.25	1.46	44.76

Notes: This table reports the growth rates (in %) in median and mean lifetime earnings between the 1967 cohort and the 1983 one, for both France and the US. The figures from the US come from Guvenen et al. (2022a).

lation. In France, median earnings rose faster than mean earnings but the gap is small (especially for men), while in the US the opposite holds and the gap is large, with mean earnings growth being about 11 percentage points higher than for the median for both sexes (see Table 1). This is consistent with the sharp increases in inequality observed in the US. However, for the last cohort in France, those entering the labor market in 1987, we find a much sharper increase in male mean than median earnings, which drives a similar pattern for the population as a whole.

3.2 Age profiles

As a first step to understanding the dynamics of lifetime earnings, we explore how life-cycle profiles of earnings have changed across cohorts. In Figure 2 we plot median earnings at each age for each of the 11 cohorts we observe, separately for males and females. The dashed lines guide us through a cohort's lifetime. The coloured marks (circles, squares, etc.) connect earnings at common ages across cohorts, thus showing how the median earnings of particular age groups have evolved over time.[14]

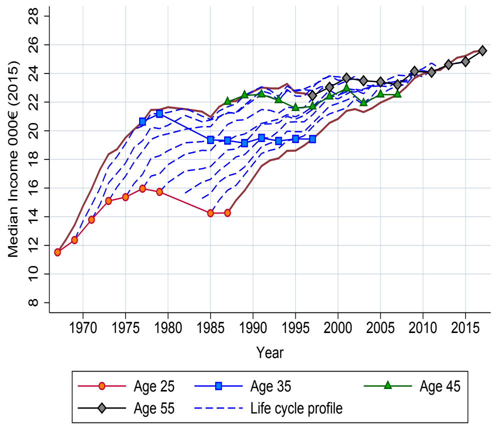
Consider first the patterns for men. Both France and the US exhibit low initial earnings that rise sharply between ages 25 and 45 and then stabilize. Guvenen et al. (2022a) find that in the US the decline in median earnings across cohorts is apparent at all ages. It is particularly pronounced at age 35 (blue squares), while there are considerable fluctuations for those aged 25 (red circles). In France, we observe a rather different pattern. At age 25 (red circles) we find that earnings first increase and then decline. The downward trend is present but less marked at age 35 (blue squares). At age 45 (green triangles) we observe a rather flat curve, and at age 55 median earnings increase for most cohorts, especially for the youngest ones, in contrast to the downward trend observed by Guvenen et al. (2022a). This implies that the stability in male median earnings that we observe in France from the 1973 cohort onwards is the result of considerable changes over the lifetime. From

[14]Note that missing data points are due to data not being collected in 1981, 1983, and 1990.

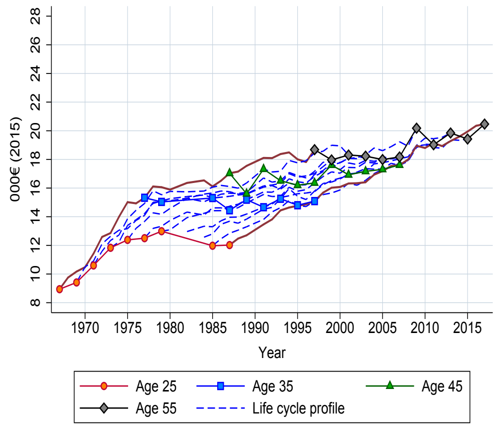
the late 70's entry cohorts, lower initial earnings have been accompanied by faster growth between ages 35 and 45 as well as between ages 45 and 55 (though of lesser magnitude), so this late-career growth has compensated for the lower entry remuneration and led to stable lifetime earnings.

Figure 2: Age profiles of median earnings by cohort

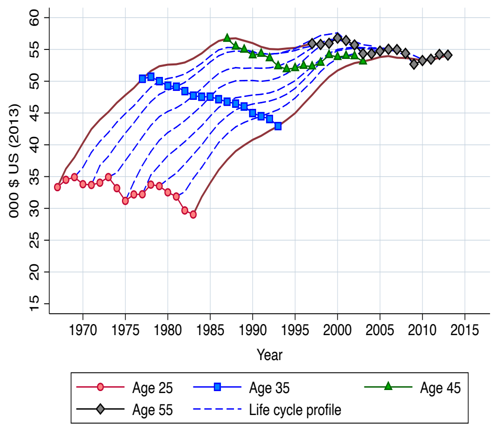
(a) Men France



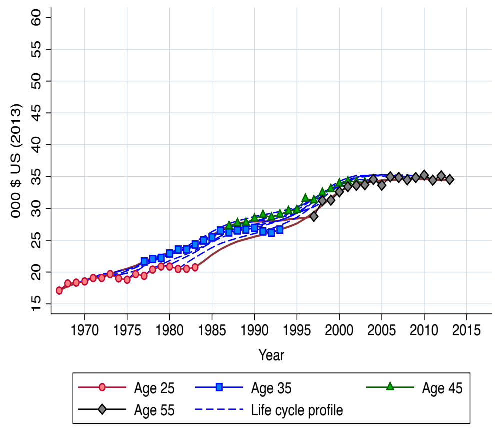
(b) Women France



(c) Men US



(d) Women US



Sources: Our own computations for France, Guvenen et al. (2022a) for the US.
Notes: Panels (a) and (c) display the age profiles of male cohorts in France and the US, respectively; Panels (b) and (d) display the age profiles of female cohorts in France and the US, respectively. Each dot represents the median earnings of men or women of a particular age in a particular year. For example, the 1967 cohort is represented by an age 25 dot in 1967, an age 35 dot in 1977, an age 45 dot in 1987, and an age 55 dot in 1997. The dotted lines (solid for the first and last cohort) connect all age-year dots for each cohort. Values for France are displayed in thousands of 2015 euros and deflated using the PCE.

Table 2 reports growth rates over each decade of the individual's lifetime for selected cohorts. It indicates that men in the 1967 cohort experienced an increase in wages of 88% between ages 25 and 35 and of only 21% between ages 35 and 55. For the 1987 cohort, these figures were respectively 40% and 35%. This implies that although earnings roughly doubled for both cohorts between age 25 and age 55, for the oldest one most of the growth happened in the first 10 years, while for the youngest about half of the growth occurred in the first decade and a half in the two subsequent ones.[15] This pattern contrasts with that observed for the US where earnings growth rates between ages 25 and 35 are roughly equal across all cohorts and amount to the bulk of earnings growth experienced during each cohort's lifetime.

Table 2: Annual median earnings growth by cohort, France & the U.S.

Cohort		Men			Women		
		Median earnings growth between					
		25 and 35 yo	35 and 45 yo	45 and 55 yo	25 and 35 yo	35 and 45 yo	45 and 55 yo
France	1967	0.792	0.067	0.020	0.714	0.112	0.097
	1977	0.210	0.123	0.070	0.156	0.132	0.111
	1983	0.262	0.137	0.123	0.213	0.126	0.156
	1987	0.361	0.160	0.136	0.255	0.167	0.162
US	1967	0.511	0.125	-0.013	0.267	0.256	0.056
	1977	0.451	0.119	0.051	0.352	0.191	0.115
	1983	0.479	0.237	0.019	0.286	0.279	0.013

Notes: This table reports the cumulative growth rates in median earnings between ages 25-35, 35-45, and 45-55 for selected cohorts. Note that because the 1983 data are missing, for the 1983 cohort we compute the growth rate for 26-35 year olds. The figures from the US are from Guvenen et al. (2022a).

For French women, the data display a pattern relatively similar to that of men. Initial earnings first increased, with the magnitude of the increase in earnings for 25-year-olds being rather similar for women and men (between the 1967 and the 1977 cohorts, they rose by about 60% for both). Starting in the late 1970s initial earnings fell, though less sharply than for men. We find a flat profile at age 35 and increasing median earnings at older ages. This indicates that the source of the gains achieved by women differs across cohorts; the oldest ones experienced particularly rapid growth between ages 25 and 35, while for younger women growth has been fastest in the last two decades of their careers. This can be seen in the right-hand panel of Table 2. A notable difference with the US is

[15] In order to be able to compare our results with those for the US, we have computed the growth rate per decade of the median earnings. Table A.1 in the Appendix computes the growth rate over each decade for each individual and then takes the median of the growth rates across individuals. We find the same pattern of growth rates as in Table 2.

that while American women experienced earnings growth in the decade 25-35 that was systematically lower than that experienced by American men, in France these growth rates are much more similar across the sexes.

The observed earnings growth rates for French women are somewhat surprising. Women of older cohorts were often working in jobs with moderate wage growth (e.g. clerical jobs) and have over time gained access to traditionally male-dominated careers with faster wage growth (such as lawyers and doctors),[16] hence we would have expected to see faster wage growth for younger cohorts. At the same time, a large literature has shown that, even within occupations, the returns to potential experience remain lower for women because of career interruptions.[17] Our results indicate that occupational upgrading has not resulted in younger cohorts experiencing faster earnings growth during the life cycle than older ones, at least at the median.

To highlight the importance of changes over the life-cycle, we compute a discounted value of lifetime earnings, which are reported in Figure A.3 and Table A.2.[18] We use a discount rate of 2% per year, as is standard in the literature. The data for France indicate that during the period of fast growth–that is, the 1967 to 1973 cohorts– growth across cohorts is faster for discounted than for non-discounted earnings, capturing the fact that earnings growth happened in the early career years. This is the case for both men and women, with the gap being particularly large for the latter (1.5 pp higher growth, compared to 0.76 higher for men). Over the 1973 to 1987 cohorts, growth was slower when we discount earnings, capturing the shift in earnings from early to late career. The differences between discounted and undiscounted earnings growth across cohorts are considerably smaller for the US. This reflects the fact that there were less marked changes in the age profiles than in France.

3.3 Cross-sectional versus lifetime earnings

How similar are the dynamics of lifetime earnings to those obtained when we look at a cross-section of individuals? Figure 3 compares lifetime earnings with cross-sectional earnings computed for various age groups for both men and women. We consider three groups, 25 to 35 year-olds, 35 to 45 year-olds, and 45 to 55 year-olds, and compute for each group median and mean earnings in a particular year.[19] We report cross-sectional

[16]See, for example, Hakim (1993).

[17]See, for example, Altonji and Blank (1999) and Meurs and Ponthieux (2006).

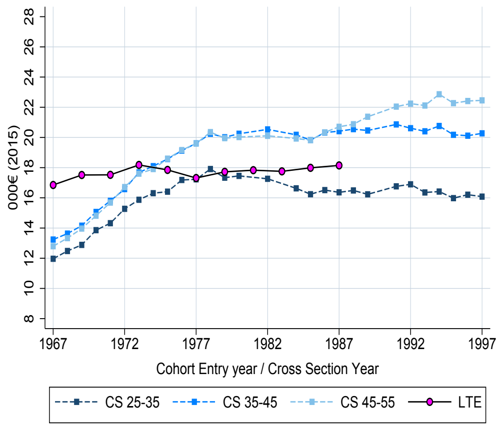
[18]Because for the US we do not have access to individual data, only to the median for each year at each age, these figures are "hypothetical" median lifetime earnings computed by attributing to a hypothetical individual in each cohort the median lifetime earning observed at each age and then computing their lifetime earnings. That is, we use the data displayed in Figure 2 for both France and the US.

[19]For the cross-sections, we use the same sample restrictions as for the computations of our lifetime earnings. Note also that some of the data used for these calculations is not in our core sample. For example,

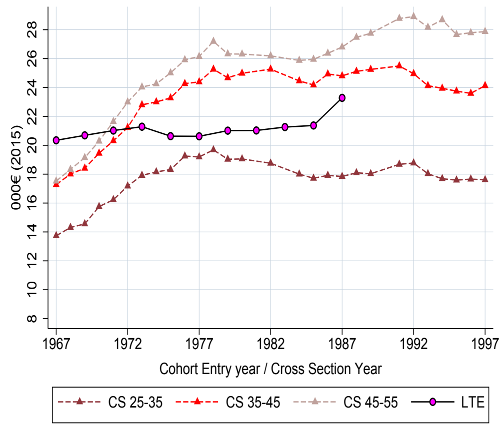
earnings from 1967 to 1997.

Figure 3: Approximations of Lifetime Earnings by Earnings at Selected Age Periods

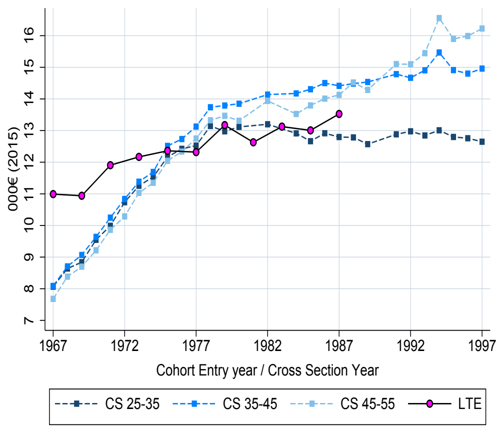
(a) Median - Men



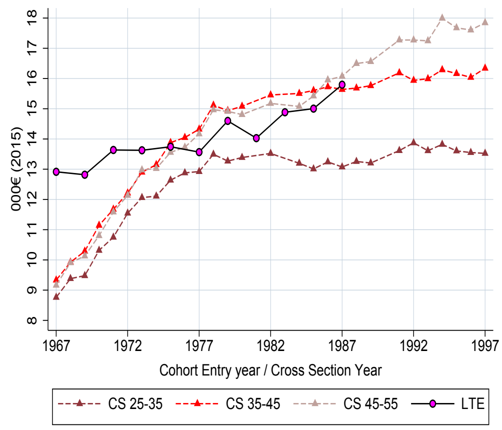
(b) Mean - Men



(c) Median - Women



(d) Mean - Women



Notes: The graphs display, for each cohort over time, median and mean lifetime earnings (LTE) for men (women), against a series of male (female) average earnings computed over a cross-section (CS) of individuals of different ages: 25 to 35, 35 to 45, and 45 to 55.

The four graphs show a considerable discrepancy between the dynamics of median/mean lifetime earnings and those observed in the cross-section. For men, we observe rapid growth of median cross-sectional earnings at all ages in the early years (up to 1977). After this date, median earnings remained roughly constant for those aged 35 to 45, fell for younger workers, and increased for older ones. A similar pattern appears for the mean earnings of men. The graphs hence highlight the difficulty of inferring the dynamics of lifetime earnings from cross-sectional trends. The patterns observed are also consistent with our result on age profiles, as they indicate that young individuals have experienced

the cross-section for the 25 to 35 year-olds in 1967 computes earnings over all individuals in that age group available in the data for 1967, but only those aged 25 are in our core sample used to compute lifetime earnings.

earning losses compared to earlier cohorts since the 1970s, while those aged 45 to 55 have seen consistent earnings gains. Panels (c) and (d) of Figure 3 perform the same analysis for women. Growth is faster than for men, but otherwise the graphs display similar dynamics. It is particularly striking that initially median earnings in the cross-section are virtually identical for all age groups. They then grow together up to the late 1970s and diverge afterwards, with the earnings of young workers declining (though less than for men) and those of the other age groups increasing.

Overall, our analysis of the median and mean lifetime earnings across cohorts points out two key insights. First, there are no marked gender differences in the dynamics of median lifetime earnings in France, in contrast to the US. However, in both countries, the overall pattern for the entire population is similar, i.e. a flat curve since the late 60s/early 70s, we find that in France it results from moderate increases of both male and female lifetime earnings. In contrast, in the US Guvenen et al. (2022a) show that it is the result of large losses for men and very large gains for women. Second, in France, the stagnation observed from the mid-1970s hides a change in lifetime earning profiles whereby younger cohorts have lower earnings when young but faster growth later in their careers than older ones. In the next section, we delve into the distributional consequences of these dynamics.

4 Patterns of lifetime inequality

The second aspect we explore are trends in inequality in lifetime earnings and how they differ between France and the U.S. Additionally, we also assess whether the existing patterns of earnings inequality found on cross-sectional data also appear when we consider the distribution of lifetime earnings.

4.1 Earnings at different percentiles

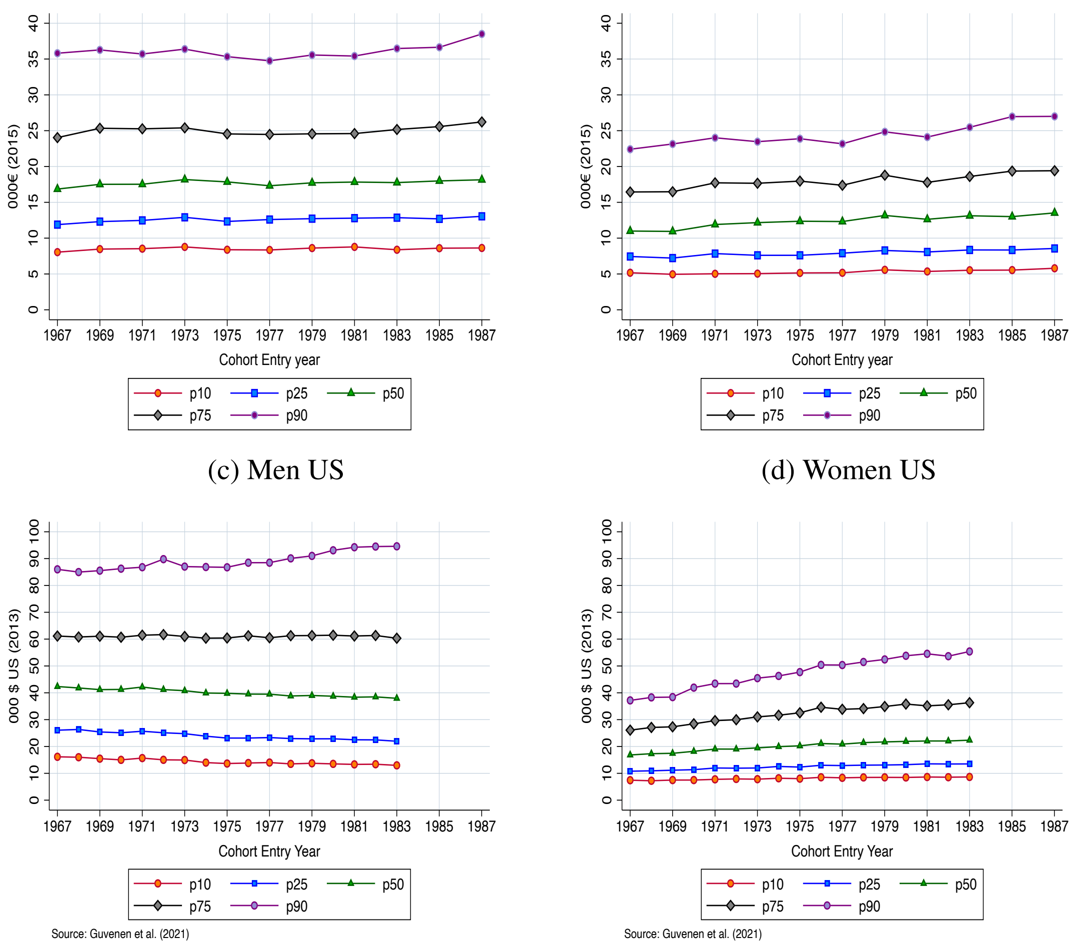
We first compute the lifetime earnings of selected percentiles. Figure 4 reports those for the 10th, 25th, 50th, 75th, and 90th percentile of the distribution of lifetime earnings, where the position in the distribution of an individual is computed within the distribution of her/his own gender group. The upper panels report our results for France, while the bottom ones report the corresponding US figures in Guvenen et al. (2022a). Table 3 reports growth rates at selected points of the distribution for France and the US. [20] The increases in mean and median lifetime earnings in France documented in the previous section are reflected throughout the whole distribution: unlike for the U.S., there were gains

[20]Table A.3 in the Appendix provides a more detailed set of figures obtained from our data.

over the period for all percentiles. There is however some considerable heterogeneity in the magnitude of the gains across percentiles.

Figure 4: Selected percentiles of lifetime earnings, by cohort and gender: France and US

(a) Men France (b) Women France (c) Men US (d) Women US



Notes: The graphs display selected percentiles of the distribution of lifetime earnings for successive cohorts. The top graphs are our own computations for France, those at the bottom are for the US and come from Guvenen et al. (2022a), Figure 3. Left panels (a) and (c) are for men, and right panels (b) and (d) are for females.

For men and focusing on the same cohorts as Guvenen et al. (2022a) (i.e. 1967-1983), we observe an evolution in earnings that is more favorable to the p10 (cumulated growth of 4.2%) compared to the p90 (1.8%), which reflects the decrease in labor income inequality that took place in France following the social unrest of May 68 and up to the early 80s.[21] This contrasts with the US where Guvenen et al. (2022a) document a strong decrease for the p10 (-20%) and an increase for the p90 (+10%). As documented above for mean and median lifetime earnings, we tend to find large gains for the earlier cohorts (i.e.

[21]For a historical perspective see Atkinson et al. (2011) and Garbinti et al. (2018).

Table 3: Lifetime earnings growth for various percentiles: France & the U.S. (1967-1983)

	France		US	
	Men	Women	Men	Women
p10	4.17	6.75	-19.77	16.31
Median	5.36	19.41	-10.34	32.67
p90	1.82	13.68	9.98	40.04
p99	-2.29	19.56	17.48	107.57

Notes: This table reports the growth rates (in %) in lifetime earnings between the 1967 cohort and the 1983 one, for both France and the US, for various percentiles of the distribution. The figures from the US come from Guvenen et al. (2022a), Table 1.

1967 to 1973) and small gains for the younger ones (1973 to 1987). The pattern of gains differs across the distribution: it is rather flat for the bottom percentiles and U-shaped at the top. In particular, when broadening the period up to the end of the 80s (Figure 4), the cumulative evolution appears roughly similar for the p10 and the p90, which reflects the increase in the p90 observed for the younger cohorts, leading to higher inequality in lifetime earnings for the recent cohorts.

For women, we observe a larger increase at the top, with the rate of growth of lifetime earnings being about twice as large for the p90 as for the p10 over the 1967-1983 cohorts (6.7% for the p10 versus 13.7% for the p90). This pattern of faster growth for women at the top than at the bottom of the distribution is also observed in the US, although there both the increases for women and the gap between the top and the bottom are much larger than in France (+16% for the p10 vs. +49% for the p90). Interestingly, in France, for the first cohorts, women at the bottom experienced an earnings loss that is not present in the US and could be explained by different selection patterns. Notably, this is a period in which in the US female selection into the labor market started to shift from being negative to being positive, which could explain considerable growth at the bottom; see Mulligan and Rubinstein (2008). There is no evidence of such a shift in France, and it is possible that the reduction in lifetime earnings at the bottom of the distribution in the late 1960s/early 1970s is due to weaker positive selection as female labor market participation increased.[22]

4.2 Inequality in lifetime earnings

We go further in the analysis of lifetime earnings inequality by studying various inequality indicators (Figure 5). The top left-hand side panel depicts the p90/p50 ratio, the top right-

[22]Unfortunately, there is no comparable study for France that identifies whether or not there has been a change in the sign of selection.

hand one reports the p50/p10 ratio, and the bottom panels report the p90/p10 ratio and the Gini coefficient. We report these measures for women, men, and the entire population. The blue lines marked with squares correspond to lifetime inequality among men, the red lines (circles) correspond to lifetime inequality among women, and the grey ones (diamonds) correspond to the entire population.

Consistently with our findings on the evolution of the different percentiles, inequality at the top of the distribution, as measured by the p90/p50 ratio, exhibits a U-shaped pattern for the overall population. Inequality first fell and then rose, exhibiting roughly the same level for the last as for the first cohorts. Changes are largest for women, while the overall p90/p50 ratio follows closely that for men, capturing the fact that the share of women in the p90 is small. Despite the similarities, the patterns for men and women are driven by different dynamics, notably for the older cohorts. For males, the decrease for the first cohorts is due to an increase in p50 with stability of p90 (see Table A.3), and this is followed by an increase in p90 with stability of p50 for the younger cohorts. For women, the dynamics are driven by the growth of p90, which is below that of the p50 for older and above it for younger cohorts. The dynamics of inequality are more pronounced for women and less pronounced for men and the overall population. This is the result of two offsetting effects: an increase in inequality across women and a decrease in the gender earnings gap.[23]

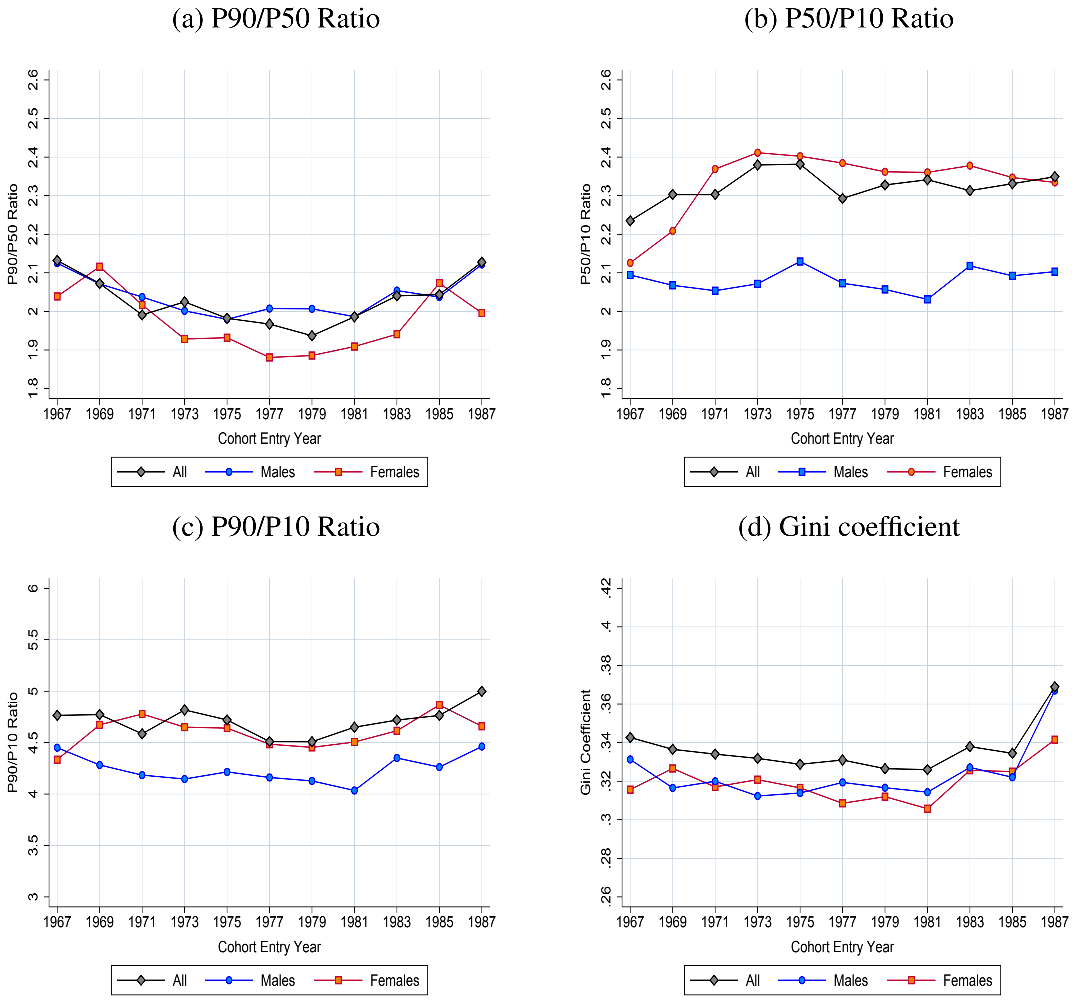
At the bottom of the distribution, the dynamics of inequality–captured by the p50/p10 ratio—indicate that inequality for the whole population is large and driven by that for females. For men, the p50/p10 fluctuates with no trend. Unlike in the U.S. where, as we saw, the p10 earnings declined roughly twice as fact as median earnings over 16 cohorts, in France both magnitudes grew at comparable rates. The minimum wage, which in France is high and paid to a large share of the labor force provided a floor that prevented economic shocks from resulting in lower wages.[24] As a result, employment tends to be the margin of adjustment (see for example Blanchard (2002)). Figure A.2 in the Appendix shows that male years of work declined for the cohorts entering the labor market in the years after the 1973 oil crisis. For women, we find two distinct periods: an increase in inequality for the first cohorts (up to that of 1973) and then a stabilization. The increase is likely the result of two factors. On the one hand, women's hourly wages rose for those at the top of the distribution. This may be the result of an increased access to top occupations and of weaker wage discrimination within occupations compared to previous cohorts. On the other, and as we will see below, the increase in female labor force participation was accompanied by a higher prevalence of part-time employment, adding higher hours-of-

[23] See subsection 5.3 for further discussion of the gender earnings gap.

[24] See Gautier et al. (2022) for the minimum wage institutional setting in France, as well as Figure A.1 in the Appendix for trends in the minimum wage.

work inequality to the underlying wage inequality.[25]

Figure 5: Inequality indicators by cohort and gender, lifetime earnings, France



Notes: The graphs display selected percentiles ratios and the Gini coefficient computed on the distribution of lifetime earnings for successive cohorts. All graphs report the series for the whole population (All), as well as for men and women separately.

The bottom two panels of Figure 5 (p90/p10 ratio and Gini coefficient) show an overall U-shaped pattern with a net increase in inequality for younger cohorts. This implies a higher level of inequality for the youngest than for the oldest cohorts for both the overall population and within each gender group. Although the exact turning point varies and is somewhat dependent on the measure used, inequality in lifetime earnings declined for the cohorts that entered the job market before the late seventies and increased for those who entered afterwards.

Guvenen et al. (2022a) report various measures of inequality that all indicate an increase in lifetime earnings inequality within a cohort both for males and for females in

[25] See Checchi et al. (2023) on the contribution of working-hours inequality to earnings inequality.

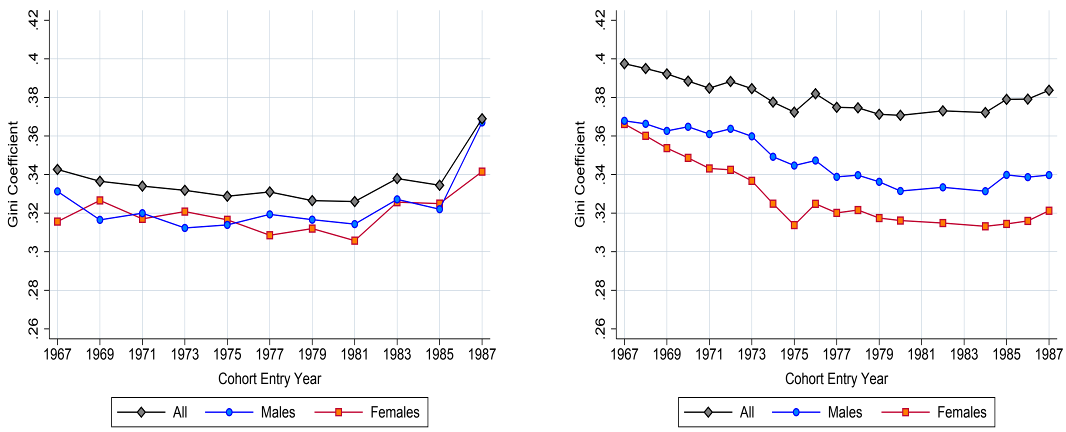
the US. Overall inequality varies much less, increasing for some measures (standard deviation of logs and p90/p50) and falling for others (interquartile ratio and p90/p10). This is the result of higher within-group inequality for both sexes and lower between-group inequality, as female earnings partially caught up with those of men. Both the changes and the levels of inequality are much greater in the US. For example, for the entire population, the p90/p50 ratio grew from 2.3 to 2.7 in the US, while in France it went from 2.13 to 1.94, and back to 2.13. As is the case with median lifetime incomes, in the US a flat overall trend seems to be the result of sharp gendered dynamics and the very substantial catching up of women to men both in terms of level of earnings and their dispersion. In contrast, in France, both overall inequality measures and those for each gender follow roughly similar patterns.

4.3 Cross-sectional versus lifetime inequality

How does inequality in lifetime earnings compare with that obtained in the cross-section? To answer this question we use our earnings data to compute a measure of cross-sectional inequality and compare it to that reported above. Figure 6 reports again the Gini coefficient of lifetime earnings and that obtained in the cross-section for the period 1967-1987. The cross-section uses the earnings observed in the DADS data for workers aged between 25 and 55 in, say, 1967, then 1968.[26]

Figure 6: Cross-sectional versus lifetime inequality, France

(a) Gini coefficient of lifetime earnings (b) Gini coefficient of cross-sectional earnings



Notes: The graphs display Gini coefficients computed on the distribution of lifetime earnings for successive cohorts on panel (a); and on the cross-sectional distribution of yearly earnings on panel (b). The sample for the latter is the entire population of individuals reported in the DADS. Each graph reports the series computed for the whole population, as well as on subsets of men and women, separately.

[26]The cross-sectional measures use the same selection rule as for our main sample.

As we would have expected, the Gini coefficient is systematically higher in the cross-section, ranging between 37.1 and 39.7 for the entire population, while the Gini for lifetime earnings lies between 32.6 and 36.9. The lower level of inequality compared to the cross-section indicates that both earnings mobility over time and the fact that individuals have non-employment spells result in less dispersion in earnings than when we take a snapshot. There are nevertheless important similarities. First, the magnitude of the changes is similar for both measures, which fluctuate in a 3 and 4 Gini-point band. Second, in both cases, we observe a U-shaped pattern, with inequality initially declining and then increasing. Of course, our measure of lifetime incomes includes incomes that go up to 2017, so the Gini coefficient on panel (a) is affected by earnings in years after 1987. Figure A.4 in the Appendix reports the cross-sectional Gini coefficient for the period up to 2017 and shows that it fluctuated within the same range without displaying a clear trend.

Figure 6 also shows that, for both measures, inequality is greater in the entire population than for either men or women. The Gini coefficient for lifetime earnings shows similar dynamics for the three groups and similar values for men and women. In the cross-section, we find much larger fluctuations for the Gini for women than for men, largely due to a considerable reduction in inequality amongst women between 1967 and 1978. For lifetime incomes we observe a reduction of inequality between the 1967 and the 1981 cohorts of women. The opposite holds for men: the cross-section displays a falling Gini up to 1980, while the Gini of lifetime earnings declined only from the 1967 to the 1973 cohort. In conclusion, although the broad pattern is the same–a U-shaped one–the dynamics of the cross-section are not able to predict in a precise way how inequality in lifetime earnings changes over time.

5 Explaining the dynamics of lifetime earnings across cohorts

In this section, we further explore the data in order to explain the dynamics of lifetime earnings. We first assess the factors driving the increase in mean lifetime earnings observed between the 1967 and the 1987 cohorts, for men and women. We then turn to the analysis of the aspects that have affected the gender gap.

There are various factors that could contribute to the rise in average lifetime earnings across different cohorts. First, the evolution of working time could be a key factor, encompassing changes in the number of years worked and the frequency of part-time employment. Second, different cohorts may have different characteristics, particularly concerning education, as the period under consideration has been marked by a substantial expansion of educational attainment. Our data also allows us to explore geographical differences across individuals. Lastly, the returns to characteristics may have changed over time. For example, technological change that favours the high-skilled may have increased the returns to certain degrees and reduced those to others.

To examine the role played by different factors, we focus on the determinants of *mean* lifetime earnings and run the equivalent of a wage regression except that our left-hand side variable is the individual's lifetime earnings rather than his or her wage. Hence we estimate

$$y_{i(c)} = \alpha_c + \beta_c X_i + \varepsilon_i \tag{2}$$

where $y_{i(c)}$ is the lifetime income of individual i born in cohort c, X_i are the characteristics of the individual, β_c are the returns to characteristics which we allow to vary across cohorts, and ε_i is an error term. The variables in X_i are time-invariant and comprise two sets of variables. The first group of regressors describes the employment history of the individual and consists of the proportion of years in which the individual has worked in (i) a full-time job, (ii) a part-time job, and (iii) in the Paris region (i.e., the region called *Ile de France* or IDF). The reason for taking into account the fraction of the working-life spent in the Paris region is that this is, by far, the largest agglomeration in France and is characterised by higher wages than the rest of the country. The second set of variables are obtained from the census: the highest educational degree obtained,[27] whether the individual has ever been married or declared to be in a couple in a wave of the census, and whether the individual has ever had children. These are variables traditionally used when examining the determinants of (cross-sectional) earnings. In subsection 5.2 we will consider an additional variable, the place of birth of individuals.[28]

These regressions allow us to perform a counterfactual exercise in which we compute a counterfactual measure of lifetime earnings by using cohort-specific coefficients but maintaining the composition of the cohort constant in terms of its characteristics. That is, the counterfactual earnings are given by

$$\hat{y}_c^X = \alpha_c + \beta_c \bar{X}_{1967} \tag{3}$$

where $\hat{y}_c^X$ is the counterfactual mean earnings of cohort c when we substitute its characteristics by the average characteristics of the 1967 cohort. Alternatively, we can allow the characteristics to change keeping constant the coefficients (at the value estimated for the 1967 cohort), that is:

[27] The categories available are no degree, elementary education, junior high school, professional high school, standard high school, bachelor, and master or more.

[28] Although we have information on the individual's occupation and industry each year, we do not use this information as it varies over time.

$$\hat{y}_c^{\beta} = \alpha_c + \beta_{1967}\bar{X}_c. \tag{4}$$

These two expressions allow us to gauge to what extent the increase in lifetime earnings is due to changes in the characteristics of those employed, and if so which ones, or to the return to those characteristics.

5.1 The effects of declining returns to education and increasing (part-time) working time

We start by looking at education and working time. Table 4 reports the regression coefficients for men based on the specification of Equation 2 (see Table A.4 for the results for women). Our variables of interest are generally significant and have the expected signs. Individuals who have worked more years have higher lifetime earnings, especially if they worked full time while having spent a greater share of their working years in the Paris region also increases earnings. The various educational categories have positive coefficients, implying higher earnings as compared to those without any diploma. Having ever been in a couple and ever had children has a positive coefficient. This marriage premium is a well-established stylized fact (cf. e.g., Antonovics and Town (2004) or Juhn and McCue (2017)).

Several of the coefficients change across cohorts. For example, the return to years of work full-time increases for younger cohorts. The key change in the regressions is seen in the coefficients on educational levels. The significance of the coefficient on an elementary school degree diminishes, implying its return is equivalent to that of having no schooling, while those on Junior High, Professional, High School, and Bachelor's degrees roughly halve between the 1967 and 1987 cohorts.[29] In contrast, the coefficient for a master's degree, which for the early cohorts was roughly of the same magnitude as that on a bachelor's degree, remained stable. This implies that in the case of the older cohorts, both degrees yielded similar returns in the job market, but for the younger cohorts, the return on a master's degree was between two and three times as high as that for a bachelor's degree. The notable reduction in the return to a bachelor's degree could be the result of supply or of demand forces, as the increase in the supply of workers with such degrees would tend to reduce their wage, while selection implies lower unobserved ability of those obtaining the degrees in latter cohorts.

The regression for women (Table A.4) displays similar results concerning both the coefficients on years of full-time work and diplomas, although in both cases the coefficients

[29] For instance, the coefficient associated with having a bachelor's degree declined from 22.19 to 9.81.

Table 4: The determinants of lifetime earnings for men

VARIABLES	(1) 1967	(2) 1969	(3) 1971	(4) 1973	(5) 1975	(6) 1977	(7) 1979	(8) 1981	(9) 1983	(10) 1985	(11) 1987
% Years Full Time	29.16***	29.42***	30.98***	32.36***	32.29***	30.29***	30.07***	28.40***	30.64***	32.60***	35.33***
	(1.741)	(1.718)	(1.682)	(1.535)	(1.505)	(1.499)	(1.401)	(1.566)	(1.796)	(1.546)	(4.016)
% Years Part Time	15.13***	11.81***	13.48***	4.689	11.59***	5.186**	4.468*	0.701	1.922	8.314***	11.00*
	(3.631)	(3.311)	(3.053)	(2.850)	(2.619)	(2.628)	(2.396)	(2.590)	(2.937)	(2.396)	(6.271)
% Years Paris Region	7.978***	6.966***	8.978***	8.548***	5.902***	7.765***	7.844***	8.625***	8.691***	7.439***	13.57***
	(0.741)	(0.692)	(0.706)	(0.640)	(0.645)	(0.697)	(0.624)	(0.689)	(0.813)	(0.669)	(1.711)
Elementary	1.762**	2.172**	1.336	1.179	0.607	0.487	0.919	-0.406	-0.728	0.202	1.029
	(0.874)	(0.888)	(0.879)	(0.876)	(0.857)	(0.960)	(0.987)	(1.153)	(1.520)	(1.349)	(4.521)
Junior High	6.623***	7.860***	8.243***	7.382***	4.853***	4.535***	3.584***	3.185***	2.757*	3.640***	3.394
	(1.374)	(1.246)	(1.273)	(1.213)	(1.246)	(1.337)	(1.136)	(1.206)	(1.416)	(1.227)	(3.222)
Professional	4.673***	3.704***	3.256***	3.263***	2.695***	2.267***	2.463***	2.156**	2.245**	1.810**	2.076
	(0.758)	(0.780)	(0.790)	(0.765)	(0.718)	(0.802)	(0.803)	(0.845)	(0.945)	(0.777)	(2.039)
High School	12.06***	12.06***	9.177***	8.320***	7.715***	6.739***	7.395***	6.248***	5.908***	6.436***	5.994**
	(0.973)	(0.942)	(0.960)	(0.912)	(0.857)	(0.926)	(0.919)	(0.955)	(1.086)	(0.900)	(2.413)
Bachelor	22.19***	19.04***	19.17***	15.46***	15.68***	11.18***	11.71***	10.64***	9.656***	10.06***	9.814***
	(1.019)	(1.008)	(0.998)	(0.940)	(0.903)	(1.073)	(1.011)	(1.056)	(1.212)	(0.960)	(2.465)
Master	27.45***	23.52***	22.93***	23.06***	22.10***	24.81***	23.93***	22.20***	23.38***	23.85***	32.63***
	(1.641)	(1.472)	(1.287)	(1.114)	(1.058)	(1.051)	(0.976)	(1.030)	(1.151)	(0.946)	(2.457)
Dipl Missing	3.071***	4.990***	4.901***	4.587***	5.001***	5.640***	8.060***	8.652***	5.545***	4.479***	3.262
	(1.082)	(1.130)	(1.251)	(1.192)	(1.223)	(1.206)	(1.283)	(1.401)	(1.577)	(1.289)	(3.277)
Ever Couple	3.353**	1.874	2.051	1.742	1.779	3.421***	3.705***	2.234**	3.263***	3.102***	3.259
	(1.304)	(1.306)	(1.325)	(1.118)	(1.087)	(1.066)	(0.933)	(0.933)	(1.060)	(0.842)	(2.296)
Ever Children	0.0842	1.914***	1.972***	2.392***	1.463**	0.862	0.455	1.098**	0.627	1.568***	2.807**
	(0.654)	(0.670)	(0.693)	(0.629)	(0.621)	(0.607)	(0.513)	(0.521)	(0.602)	(0.508)	(1.310)
Coupl Missing	1.739	-0.0434	-1.051	2.306	0.732	-0.736	1.958	1.353	2.457	3.085**	4.514
	(1.448)	(1.520)	(1.644)	(1.535)	(1.482)	(1.493)	(1.374)	(1.412)	(1.532)	(1.225)	(3.298)
Constant	-14.44***	-14.15***	-15.42***	-15.95***	-14.95***	-13.64***	-13.94***	-11.05***	-13.22***	-15.64***	-20.01***
	(1.914)	(1.908)	(1.909)	(1.727)	(1.676)	(1.652)	(1.581)	(1.700)	(1.897)	(1.638)	(4.308)
Observations	1,821	1,931	2,434	2,647	2,598	2,459	2,651	2,548	2,765	2,753	2,905
R-squared	0.452	0.422	0.400	0.422	0.405	0.429	0.459	0.412	0.359	0.447	0.177

Notes: The table displays regressions of male lifetime earnings for successive cohorts between 1967 and 1987, on a set of control variables. These include labor supply measures: percentage of years worked full time and years worked part-time; dummies for highest education level from Elementary to Master (with the reference category being no education at all); whether individuals have been in a couple or have had children throughout their lives; and the percentage of years they have lived in the Paris region. Dummies for missing observations of Diploma and couple status are included as well. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

are lower. For women, the coefficient on years of part-time work rises sharply across cohorts, doubling between the first and the last one, while Table 4 indicates that there has been a decline for men. This increase in the returns in part-time work for women contrasts with existing evidence for the UK that the so-called *part-time penalty* has increased over time.[30] The latter has been shown to have been largely due to rising wage inequality, which has been much greater in the UK than in France. The fall in the part-time penalty that we observe in France may also be explained by the introduction of the 35-hour week that reduced differences between full- and part-time jobs. Younger cohorts spent more time working under the 35-hour regime, thus explaining the lower part-time penalty they exhibit.[31] The coefficients on having ever been in a couple or had a child are negative

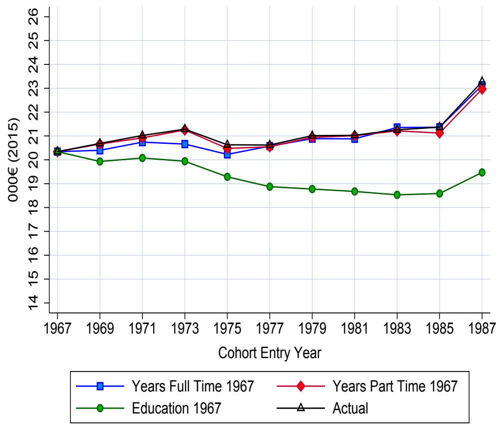
[30]The part-time penalty is defined as the difference in hourly earnings between full- and part-time employees when controlling for a number of characteristics. Manning and Petrongolo (2008) examine the dynamics of the penalty in the UK between the mid-70s and the early 2000s and find that the penalty has increased.

[31]The legislation became effective in 2000, implying that from the 1971 cohort individuals in the sample

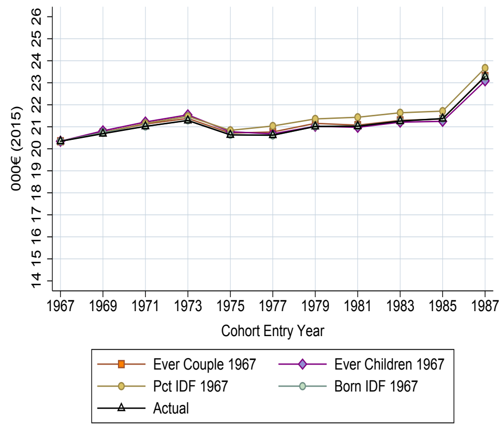
and significant when we do not include years of work, but lose their significance once we control for working time, indicating that the motherhood penalty occurs largely through the induced reduction of working time and years.

Figure 7: Counterfactual Lifetime Earnings, men

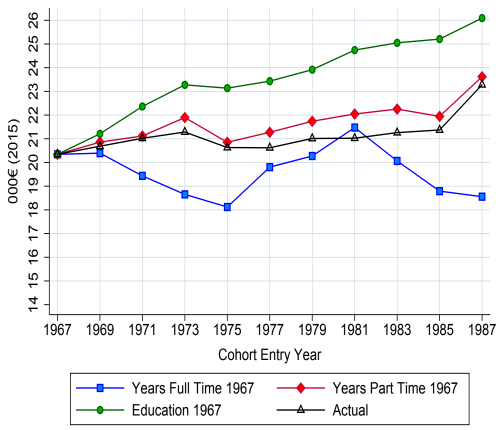
(a) Endowments: Working time and Education



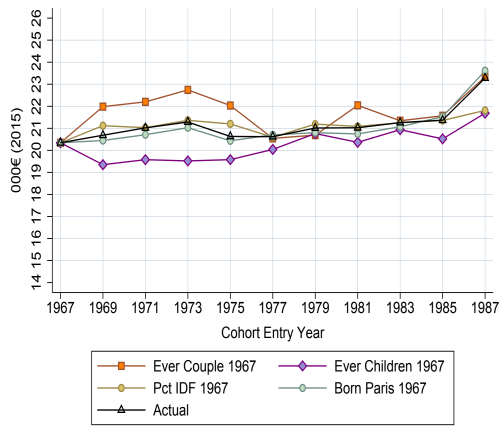
(b) Endowments: Demographics



(c) Coefficients: Working time and Education



(d) Coefficients: Demographics



Notes: The graphs display average lifetime earnings computed for successive male cohorts between 1967 and 1987 against counterfactual earnings. These are computed using the same regressions model as in Table 4 where either endowments (panels a and b) or coefficients (panels c and d) of one or several variables of interest have been fixed at their value in the regression for cohort 1967. In practice we start by estimating the model in 1967 and store its coefficients, then we estimate the model for successive years. We then compute average earnings by replacing either the coefficient(s) or the endowment(s) of our variable(s) of interest, with the coefficient(s) or the endowment(s) from the regression on the 1967 cohort. Note that for endowments we input the average endowments of 1967 to all individuals. For example, panel a) displays how average lifetime earnings would have evolved for cohorts after 1967 had they either worked the same number of years full-time as cohort 1967 (blue), worked the same number of years part-time (red), or had the same education achievements (green).

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were affected, with the youngest cohort having spent over half of their working-life under the 35-hour regime.

Figure 7 reports our counterfactual exercises. In panels (a) and (b) we use the actual regression coefficients for each cohort and keep the relevant endowment at the level observed in the 1967 cohort (Equation 3). Panels (c) and (d) report the results when we change one of the coefficients to that obtained for the 1967 cohort (Equation 4). The top two panels indicate that the most important change in endowments is the increase in educational attainment. In fact, given the fall in the return to all educational qualifications other than a master's degree, if the labor force had retained the distribution of education observed for the 1967 cohort, lifetime earnings would have declined over the period instead of growing mildly. More precisely, they would have declined from the 1971 cohort onward, increasing again for the last cohort to a level close to but below that observed in 1967. In other words, one of the key factors driving the increase in lifetime earnings has been the increase in educational attainment as the share of the population with at least a high-school diploma increased by 15 percentage points across the cohorts; see Figure A.5 in the Appendix.

The increase in years of full-time employment also plays a role for the early cohorts. As we show in the Appendix (see Figure A.2), total years worked increased up to the 1975 cohort, and our simulations indicate that if the early cohorts had worked as many years full-time as the 1967 cohort, earnings growth would have been slower. Panel (b) also indicates that the regional distribution of employment has been important, albeit to a lesser degree than education. The fraction of employees working in the Paris region fell from the 1975 cohort onward, and this has implied slower earnings growth than would have occurred otherwise.

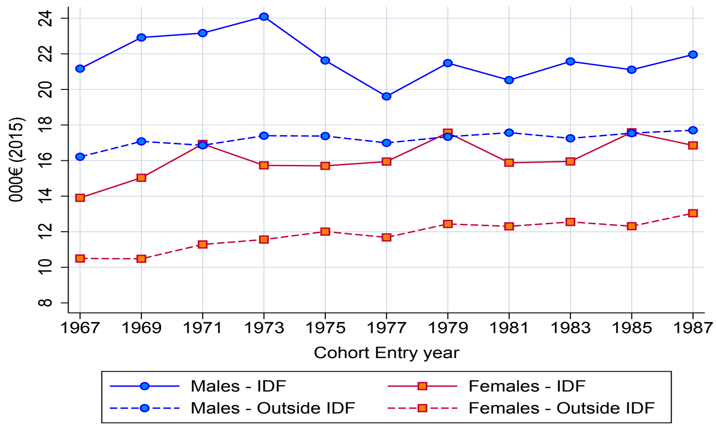
The bottom panels keep one of the regression coefficients constant at the level obtained for the 1967 cohort. The most notable result is the fall in the returns to education, apparent in the fact that when we keep those returns constant counterfactual earnings grow at a much faster rate than they actually did. Had the returns to education remained at their 1967 level, earnings growth between the 1967 and the 1987 cohorts would have been 28%, that is, six times as fast as the growth of mean earnings we actually observe. As we saw in Table 4, these results are driven by the decline in the returns to all educational categories except 'masters degree or more', which remained roughly constant.

5.2 The geography of lifetime earnings

We turn next to the role of geography. A recent literature has examined the importance of geographical location for inter-generational mobility, and identified the effect that the place where an individual grew up has on their likelihood to move up the income scale (see Chetty et al. (2014)). Our data allows us to link the information on earnings coming from firms with the census, so that we can identify an individual's place of birth and consider whether it has any effect on their lifetime earnings.

Given the importance of Paris and its surrounding region, the so-called *Ile-de-France* or IDF, in terms of employment and labor productivity, we consider two possible locations: the Paris Region (*Ile-de-France*) and the provinces. Individuals are then classified as having been born in the Paris region or outside it.[32] Having split the sample, we computed median lifetime earnings for each of these groups, which are depicted in Figure 8.

Figure 8: Lifetime earnings by birth location



Notes: The figure displays median lifetime earnings for men (circles) and women (squares), with the population having been split between those born in the Paris region (Ile de France (IDF, continuous lines) and elsewhere (dashed lines).

The figure indicates a large gap depending on whether individuals are born in the Paris region or not. For men, there is a gap of about 6 000 euros for the earlier cohorts, i.e. lifetime earnings are 35 % higher for those born in the Paris region than for other men. The dynamics indicate that this gap first increased to 38% (6 700 euros) for the 1973 cohort) and then narrowed to 20% to 24% (2 950 to 4 200) for the last four cohorts. A surprising feature is that while the lifetime earnings of men born outside the Paris region have grown steadily, growing by 9.1% over the period, lifetime earnings for those in the Paris region grew by less (3.6%) and present much wider fluctuations. Fast growth for the 1967 to 1973 cohorts was followed by a sharp decline that implied that those entering the labor market in 1977 had lower lifetime earnings than those entering 10 years earlier. A slow recovery meant that the earnings of the 1967 cohort were only attained by the 1985 one, and those of the cohort with the highest lifetime earnings in our sample–men born in the Paris region entering the labor market in 1973— were not attained by any other cohort

[32]Our data reports place of birth at the department level *département*, with France consisting of 101 *départments*, which are then grouped into regions. *Ile de France* is one of these regions and can be considered to be the commuting zone of Paris. We considered various specifications, for example, having three categories for the place of birth (Paris, large cities, other), but the results indicated little difference across locations other than the Paris region (*Ile-de-France*).

in our sample. The sharp decline for the 1973 to 1977 cohorts of men born in the Paris region is most likely the result of the first oil crisis, yet this shock had only a mild effect on the earnings of men born outside Paris. A possible explanation is that those born–and hence often working–outside the Paris region tend to work in more traditional occupations that were less affected by the global macroeconomic crisis. The slow recovery from 1977 onwards of the earnings of males born in the Paris region could be related to changes in the composition of the population in this region, notably relating to longer and more frequent unemployment spells and to changes in the skill distribution as migration rose.

For women, there is also a large gap between those born in the Paris region or outside it. The lifetime earnings of those born in Paris are 32.5% higher than those of other women for the oldest cohort. Growth rates of 21.1 and 24.2 percent, respectively, imply a slight convergence so that the gap is 29.1% for the 1987 cohort. As is the case for men, women born outside the Paris region exhibit steady growth without much change for the cohorts entering during the first oil crisis. The earnings of women born in the Paris region fluctuate more, with a decline for those entering in the early-70s, thought much milder than for men.

There are different reasons why place of birth can give advantages in terms of earnings. Being born in the Paris region may allow individuals different educational opportunities, with those in the capital having greater educational attainment and thus higher earnings. If there are mobility costs, those born in the Paris region are also more likely to work there, and since the region pays the highest earnings,[33] birth location may simply be capturing where individuals work. To examine in more detail the effect of place of birth and the mechanisms through which it operates we estimate again earnings regressions including a dummy variable for whether individuals are born in the Paris region.

Table 5 presents the coefficients of interest of various specifications, with the upper panel reporting the results for men and the lower panel those for women. To understand why place of birth matters we consider three specifications. The first one includes place of birth as well as previously used controls other than education and years spent working in the Paris region. We next add as a regressor the percentage of years worked in the Paris region, while the third specification also includes our measure of educational attainment.

Consider first the results for men. Panel A indicates, as we saw graphically, a considerable advantage of being born in the Paris region. Our estimates indicate that annualized earnings increase by between 4 000 and 7 700 euros, with considerable fluctuations across cohorts. When we control for the percentage of years worked in the Paris region (Panel B), the regressions indicate that this is key. The coefficient on this variable is large and

[33] See Bonnet and Sotura (2021) for a historical perspective on regional income in France based on yearly income data.

Table 5: Place of birth, place of work, and lifetime earnings

					Males						
	(1) 1967	(2) 1969	(3) 1971	(4) 1973	(5) 1975	(6) 1977	(7) 1979	(8) 1981	(9) 1983	(10) 1985	(11) 1987
					Panel A						
Born in Paris Region	4.908***	5.909***	7.703***	7.047***	5.906***	4.094***	6.687***	6.580***	5.822***	3.997***	7.086***
	(0.871)	(0.886)	(0.770)	(0.717)	(0.714)	(0.767)	(0.712)	(0.751)	(0.851)	(0.736)	(1.711)
Education	no	no	no	no	no	no	no	no	no	no	no
					Panel B						
Born in Paris Region	-0.374	1.516	2.233***	1.274	1.660**	-1.348	1.262	1.650**	-0.386	-1.976**	-3.536*
	(0.933)	(0.940)	(0.858)	(0.799)	(0.816)	(0.846)	(0.808)	(0.828)	(0.955)	(0.817)	(1.924)
% Years in Paris Region	12.28***	9.848***	11.64***	11.77***	8.546***	12.10***	11.00***	11.11***	13.25***	12.95***	22.31***
	(0.969)	(0.861)	(0.906)	(0.819)	(0.843)	(0.909)	(0.851)	(0.886)	(1.021)	(0.881)	(1.987)
Education	no	no	no	no	no	no	no	no	no	no	no
					Panel C						
Born in Paris Region	-0.555	1.521*	1.476*	1.269*	0.874	-1.154	0.941	1.406*	0.756	-1.601**	-2.844
	(0.784)	(0.809)	(0.757)	(0.705)	(0.714)	(0.729)	(0.682)	(0.722)	(0.859)	(0.698)	(1.837)
% Years in Paris Region	8.236***	6.392***	8.198***	7.884***	5.441***	8.370***	7.330***	7.912***	8.278***	8.310***	15.04***
	(0.826)	(0.756)	(0.811)	(0.739)	(0.747)	(0.795)	(0.727)	(0.780)	(0.939)	(0.769)	(1.956)
Education	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
					Females						
	(1) 1967	(2) 1969	(3) 1971	(4) 1973	(5) 1975	(6) 1977	(7) 1979	(8) 1981	(9) 1983	(10) 1985	(11) 1987
					Panel A						
Born in Paris Region	2.693***	1.919***	3.466***	2.870***	3.861***	3.618***	3.595***	2.674***	2.980***	3.654***	3.848***
	(0.554)	(0.594)	(0.450)	(0.465)	(0.445)	(0.441)	(0.466)	(0.427)	(0.533)	(0.463)	(0.530)
Education	no	no	no	no	no	no	no	no	no	no	no
					Panel B						
Born in Paris Region	0.0983	-0.873	1.138**	0.805	1.290**	0.414	0.767	-0.319	-1.535***	0.0760	-0.995*
	(0.608)	(0.612)	(0.525)	(0.540)	(0.511)	(0.509)	(0.561)	(0.476)	(0.588)	(0.497)	(0.573)
% Years in Paris Region	5.919***	6.783***	4.714***	4.248***	5.098***	6.279***	5.222***	6.386***	9.732***	8.259***	10.80***
	(0.675)	(0.617)	(0.580)	(0.590)	(0.536)	(0.549)	(0.602)	(0.520)	(0.654)	(0.541)	(0.632)
Education	no	no	no	no	no	no	no	no	no	no	no
					Panel C						
Born in Paris Region	-0.128	-0.844	0.867*	0.687	0.965**	0.339	0.315	-0.457	-1.332**	0.0484	-0.942*
	(0.549)	(0.564)	(0.489)	(0.489)	(0.440)	(0.467)	(0.507)	(0.424)	(0.519)	(0.429)	(0.502)
% Years in Paris Region	5.325***	5.540***	4.012***	3.162***	4.281***	5.332***	4.864***	5.271***	7.432***	6.071***	8.183***
	(0.612)	(0.576)	(0.541)	(0.539)	(0.463)	(0.509)	(0.545)	(0.469)	(0.589)	(0.475)	(0.565)
Education	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Notes: The table displays regressions of male and female lifetime earnings for all cohorts between 1967 and 1987, on a set of control variables. We sequentially consider a dummy for whether individuals are born in the Paris region, the percentage of years they have worked in this region, and education variables. The latter are dummies for highest education level from Elementary to Master (with the reference category being no education at all). All regressions include controls for labor supply measures (% of years worked full-time and years worked part-time) and whether individuals have been in a couple or have had children (see Table A.5 and Table A.6). Dummies for missing observations of Diploma and couple status are also included. Reference category: Individuals who have not been born and have never worked in the Paris region. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

highly significant, while that on place of birth becomes much smaller, insignificant for half of the cohorts. In Panel C, the third specification indicates that part of the effect is occurring through education. Once we include our education measures, the coefficient on place of birth is mostly insignificant, while that on years worked in the Paris region retains its significance but falls by about 30%. That is, being born in the Paris region confers an advantage that is due both to it leading to higher educational attainment and to the fact that those individuals born in the Paris region tend to spend more years working there.

For women, being born in the Paris region also confers an earnings advantage. As is the case for men, controlling for years worked in the Paris region and education renders the coefficient on being born in the Paris region much smaller and for most cohorts not significantly different from zero. Including education variables reduces the coefficient on years worked in the Paris region by between 10 and 26%. As is the case for education, there are considerable differences in the returns to location for women and men. Comparing the first line of regression coefficients in each panel, we can see that the advantage conferred to women by being born in the Paris region is about half of that of men for all cohorts. The coefficient on the percentage of years spent in the Paris region is also about twice as high for men as for women, both when we do not and when we do control for education.

Interestingly, Table 5 indicates that, although there are some fluctuations, the coefficients are quite stable across cohorts and genders. In contrast to education, we find no narrowing of the gap in the returns to being born or working in the Paris region for men and women, and we find no trend in these returns across cohorts. This indicates that while place of birth and work is an important factor shaping lifetime earnings for a given cohort, they do not play a significant role in explaining the dynamics of average earnings nor the gender earnings gap.[34]

5.3 Gender gaps in lifetime earnings

The last aspect we explore is the evolution of the gender gap in lifetime earnings. Both in the US and in France, the lifetime gender gap has narrowed across cohorts as can be seen in Figure 9 which reports the ratio of female to male lifetime earnings for each cohort for France (our own computations) as well as for the US (as reported by Guvenen et al. (2022a)). Women's lifetime earnings as a percentage of those of men are far larger in France than in the US for all cohorts, increasing from 64% to 68% in France between the 1967 and the 1987 cohorts (versus from 42% to 61% in the US over the 1967-1983 cohorts). Women in the early French cohorts thus display higher relative earnings than their US counterparts, which only reach the ratio we observe in France for the 1967 cohort by the 1983 cohort. These figures are consistent with existing evidence using cross-sectional data that finds a lower wage gap in France.[35]

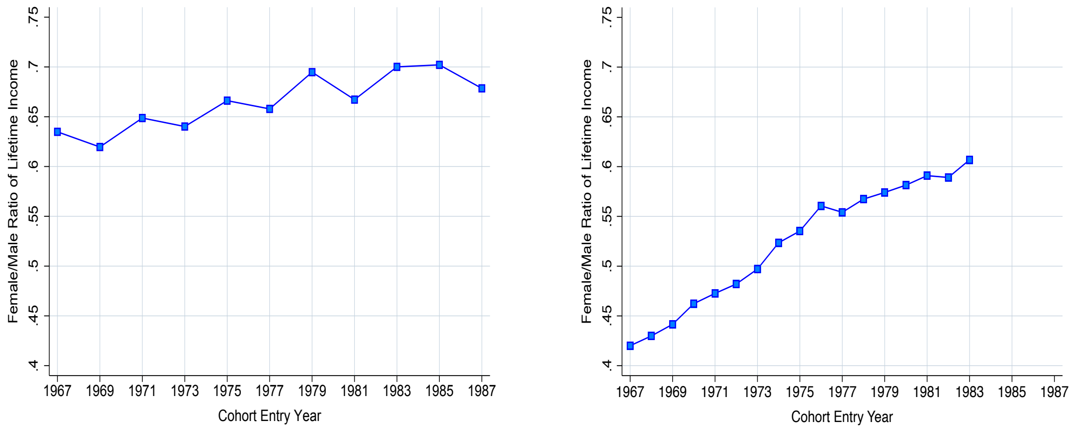
In order to understand what factors drove the increase in relative female lifetime earnings in France, we perform an Oaxaca decomposition of the gender gap across cohorts, reported in Figure 10. The gender gap is defined as the (log of) male over female lifetime earnings, with the regressions for the earnings equations being those reported in the

[34] Although there are considerable fluctuations in the coefficients, the data imply a slight downward trend in the coefficient on being born in the Paris region and a slight upward trend in that on the percentage of years worked in the Paris region (see Figure A.6).

[35] For example, Olivetti and Petrongolo (2008) find a gender gap in hourly wages of 32% for the US and 12% for France in 1999. See also Kunze (2018) for evidence on OECD countries, and in particular the sharp decline in the wage gap for the US over the period 1970 to 2015.

Figure 9: Female Lifetime earnings of women relative to men's

(a) France (b) US

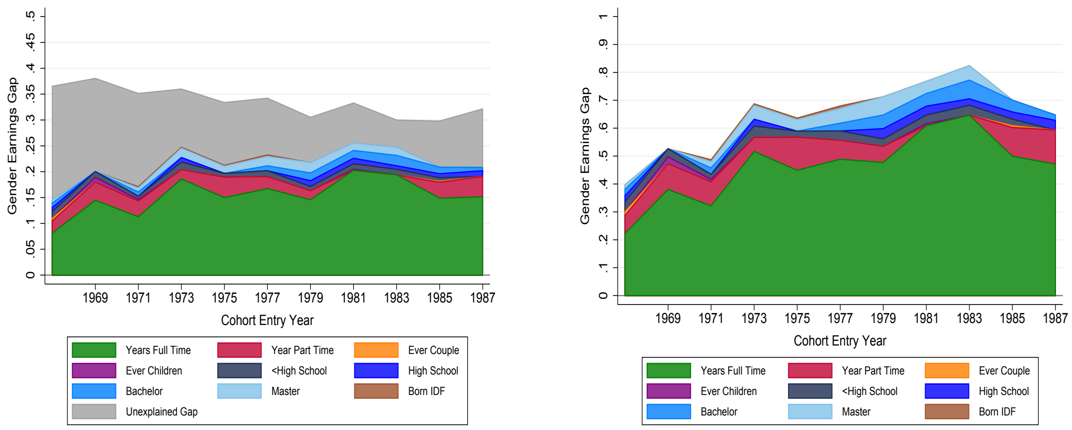


Notes: The figures display the ratio between female and male lifetime earnings, for successive cohorts. Panel (a) reports results for France, and panel (b) for the US, which graph comes from Guvenen et al. (2022a).

bottom specification of each panel of Table 5. The left panel depicts the absolute contributions of the various factors, while the right panel depicts the relative ones.

Figure 10: Oaxaca decomposition: Gender gap

(a) Decomposition of the gender gap: Absolute (b) Decomposition of the gender gap: Relative



Notes: The figure displays the results of an Oaxaca-Blinder decomposition of the gap in lifetime earnings between males and females, using males as the reference group. Panel (a) displays the evolution of the gender wage gap in absolute terms, and its decomposition between its explained (colored areas at the bottom), and unexplained components (top gray area). For example, the bottom green area shows that differences in the number of years worked full-time between males and females are responsible for a 10 to 20 percent difference in earnings between the two groups of individuals over the period. Panel (b) displays the same series but in percentage terms of the total gap including the unexplained component, which itself is not represented, but corresponds to the difference between the colored area and 1.

The first thing to note is that the unexplained contribution has declined, both in absolute terms and as a share of the total. It accounted for 60% of the gap for the early cohorts and for between 20 and 35% for younger ones. This can also be seen by inspecting the regression results, which indicate that returns to characteristics for women have become more similar to those for men for the younger than for the older cohorts. This contrasts with work that, using cross-sectional data, finds that the reduction in the gap in returns to characteristics (notably to education) has played a small role in the convergence of female to male earnings.[36] A possible explanation for the difference between the existing cross-sectional and our lifetime earnings results is the fact that the former control for occupation, thus implying that what is measured is the gender gap in returns to education *within* an occupation. Since the nature of our data implies that we cannot control for occupation–a time-varying characteristic– our regressions are capturing returns to education that include the choice of occupation. The finding that these returns are more similar for the younger cohorts implies that women with certain educational attainment are making occupational choices more similar to those of men for the younger than for the older cohorts.

It does not come as a surprise that much of the gap is explained by the differences in working time, as is the case in cross-sectional data.[37] What is remarkable are its dynamics. The contribution of working time (full and part-time together) has increased across cohorts, both in absolute and relative terms. In fact, working time gaps accounted for only 30% of the gender gap for the 1967 cohort yet were 60% of the gap for the 1987 one. Two factors can explain this. On the one hand, although there was an increase in the average number of years worked by women, which went from 23 in the 1967 cohort to 25 in the 1987 cohort (out of 31 years, see Figure A.2), men also increased the average number of years worked by about a year, implying only moderate convergence. On the other, much of the increase in years worked by women was in part-time employment. In fact, our counterfactual exercises for women show that working time alone explains only a small fraction of the increase in female lifetime earnings (see Figure A.7 in the Appendix). In contrast, the contribution of *Born IDF*, which captures both the effect of having been born in the Paris region (Ile-de-France) and of the percentage of years spent working there, plays a very minor role as men and women tend to have roughly the same characteristic along these dimensions.

The second important aspect is the increase in educational attainment. The share of women with bachelor's or further diplomas increased faster than that of men, accounting for some of the convergence. Simultaneously, we observe large changes in the relative returns to education. For the 1967 cohort, the returns to a bachelor's and a master's degree are, respectively, 2.7 and 2.4 times higher for men than for women. For the 1985

[36] See, for example, Blau and Kahn (2017) for the US over the period 1980-2010 and Meurs and Ponthieux (2006) for an analysis of monthly earnings in France over the period 1990-2002.

[37] See, for example, Blau and Kahn (2017) and Meurs and Ponthieux (2006).

cohort, the returns to a bachelor are 1.5 and those to a master 1.8 times higher for men than for women (these figures increase to 1.7 and 2.2 for the 1987 cohort, an exceptional year in terms of male educational returns).

Overall, our data indicate that when we compare lifetime earnings between men and women, the fast increase in female educational attainment and the reduction in the gap in the returns to education have been key aspects in closing the gender gap. The former aspect is in line with existing evidence at the cross-sectional level, while the latter is not found in cross-sectional studies. In contrast, our data indicate that the increase in female labor force participation has not been a major source of convergence both because the number of years worked did not increase much more than for men and due to women in employment being more likely to work part-time in the younger than in the older cohorts.

6 Conclusion

This paper uses a long administrative data panel covering the cohorts that entered the labor market (i.e. were aged 25) between 1967 and 1987 to compute individual lifetime earnings and study their dynamics. Our administrative data allow us not only to reconstruct earnings throughout the career but also to have information on individual characteristics that help us understand these dynamics. Moreover, using the methodology employed by Guvenen et al. (2022a) to compute lifetime earnings for the US, we can compare trends across the two countries.

We find two main results concerning the dynamics of lifetime earnings in the two countries. First, both countries display similar patterns for median lifetime earnings for the entire population, a roughly flat trend since the late 1960s/1970s, yet these hide marked differences in the dynamics by gender. We find that in France the overall flat curve results from moderate increases for males and somewhat faster earnings growth for women, together with a sharp increase in female participation. In contrast, Guvenen et al. (2022a) show that for the US it is the result of large losses for men and even larger gains for women.

Second, in both countries, recent cohorts display increasing lifetime earnings inequality. In France, inequality is low and displays a U-shaped pattern, with lifetime earnings inequality first falling and then increasing, starting with the cohorts that entered the labor market around the 1980s. This pattern differs from those in the US where Guvenen et al. (2022a) report higher initial inequality in lifetime earnings and a steady increase across cohorts. However, the trends we identify for the youngest cohorts raise the question of whether France is also on a path of growing inequality, albeit with a lag compared to the US.

To better understand the dynamics of lifetime earnings we have performed two analyses. The first consists in examining age profiles, and we find a dramatic change in the yearly earnings profile across the life cycle. From the 1973 cohort onward initial earnings declined compared to earlier cohorts, although this was compensated by faster earnings growth between ages 35 and 55. Despite roughly constant lifetime earnings across the relevant cohorts, this change in the age profile could have important consequences, notably for access to the housing market, as the reduction in earnings for the youngest cohorts is concentrated in the years in which individuals are likely to form a family.[38]

Our data also allows us to explore the importance of demographic characteristics in explaining the dynamics of lifetime earnings. We find a fall in the returns to education and show that, combined with the changes in educational attainment across cohorts, it plays a key role in shaping lifetime earnings across cohorts in France. Moreover, the differential increase in working time (both regarding the number of years worked and the frequency of part-time employment) for men and women account for about 60% of the gender gap in lifetime earnings for the 1987 cohort, compared to only 30% for the 1967 cohort. In contrast, although we find a large effect of place of birth on lifetime earnings within a given cohort, this factor does not play a role in understanding the dynamics across cohorts.

[38] See for instance Bonnet et al. (2018) for the rise in inequality among young households in getting on to the property ladder, and Garbinti and Savignac (2020), Garbinti and Savignac (2022) for the increasing role of parental wealth over time in accessing home-ownership.

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Appendix

A Additional tables and figures

This Appendix provides additional tables and figures mentioned in the text.

Table A.1: Annual median growth in earnings by cohort, France

Cohort	Men			Women		
	Median earnings growth between					
	25 and 35 yo	35 and 45 yo	45 and 55 yo	25 and 35 yo	35 and 45 yo	45 and 55 yo
1967	0.876	0.062	0.044	0.879	0.156	0.092
1977	0.224	0.148	0.102	0.203	0.164	0.116
1983	0.252	0.217	0.113	0.195	0.225	0.151
1987	0.402	0.220	0.125	0.298	0.258	0.154

Notes: This table reports the cumulative growth rates in median earnings between ages 25-35, 35-45, and 45-55 for selected cohorts. Note that because the 1983 data are missing, for the 1983 cohort we compute the growth rate for 26-35 year olds. The figures from the US are from Guvenen et al. (2022a).

Table A.2: Growth in undiscounted (LTE) and discounted median lifetime earnings (Disc LTE): France and the US

	France				US			
	Men		Women		Men		Women	
	LTE	Disc LTE	LTE	Disc LTE	LTE	Disc LTE	LTE	Disc LTE
1967-73	5.50	6.26	3.83	5.29	-2.60	-2.66	13.09	12.93
1973-83	-0.95	-1.21	2.94	2.58	-5.43	-6.01	10.27	10.55
1967-83	4.50	4.97	6.88	8.01	-7.89	-8.51	24.70	24.85
1973-87	0.22	-0.32	4.47	3.78				
1967-87	5.74	5.92	8.47	9.27				

Notes: This table reports the growth rates (in %) in lifetime earnings between various cohorts. It reports growth rates for undiscounted and discounted earnings. For the US, the bottom row reports the growth rate across the 1967 and 1983 cohorts. The figures from the US come from Guvenen et al. (2022a).

Table A.3: Growth rates of cohorts median lifetime incomes: Selected percentiles

		Averages		Selected percentiles								
		Mean	**Median**	**p5**	**p10**	**p25**	**p40**	**p60**	**p75**	**p90**	**p95**	**p99**
Entire population												
67-73	Cumulative	2.86	6.02	-4.22	-0.42	8.14	6.16	5.99	5.40	0.68	-1.76	-11.49
	Annualised	0.41	0.86	-0.60	-0.06	1.16	0.88	0.86	0.77	0.10	-0.25	-1.64
73-87	Cumulative	8.62	1.66	5.57	2.98	-0.16	2.18	0.54	2.71	6.83	11.67	27.42
	Annualised	1.23	0.24	0.80	0.43	-0.02	0.31	0.08	0.39	0.98	1.67	3.92
67-87	**Cumulative**	**11.73**	**7.79**	**1.11**	**2.54**	**7.97**	**8.47**	**6.56**	**8.27**	**7.56**	**9.71**	**12.78**
	Annualised	1.68	1.11	0.16	0.36	1.14	1.21	0.94	1.18	1.08	1.39	1.83
67-83	Cumulative	3.88	5.09	-2.17	1.53	7.93	7.02	4.40	4.37	0.56	0.34	-4.39
	Annualised	0.55	0.73	-0.31	0.22	1.13	1.00	0.63	0.62	0.08	0.05	-0.63
Men												
67-73	Cumulative	4.63	7.88	4.66	9.07	8.58	8.46	8.82	5.66	1.61	-1.22	-9.17
	Annualised	0.66	1.13	0.67	1.30	1.23	1.21	1.26	0.81	0.23	-0.17	-1.31
73-87	Cumulative	9.37	-0.18	-1.50	-1.68	1.06	1.01	0.52	3.25	5.81	14.72	29.52
	Annualised	1.34	-0.03	-0.21	-0.24	0.15	0.14	0.07	0.46	0.83	2.10	4.22
67-87	**Cumulative**	**14.44**	**7.68**	**3.10**	**7.23**	**9.73**	**9.56**	**9.38**	**9.10**	**7.51**	**13.32**	**17.65**
	Annualised	2.06	1.10	0.44	1.03	1.39	1.37	1.34	1.30	1.07	1.90	2.52
67-83	Cumulative	4.51	5.36	-1.72	4.17	8.15	7.14	5.67	4.71	1.83	2.34	-2.29
	Annualised	0.64	0.77	-0.25	0.60	1.16	1.02	0.81	0.67	0.26	0.33	-0.33
Women												
67-73	Cumulative	5.51	10.71	-8.68	-2.40	2.16	8.06	9.53	7.38	4.72	5.18	3.362
	Annualised	0.79	1.53	-1.24	-0.34	0.31	1.15	1.36	1.05	0.67	0.74	0.48
73-87	Cumulative	15.92	11.16	22.36	14.83	12.61	11.22	8.94	9.91	15.04	29.67	51.19
	Annualised	2.27	1.59	3.19	2.12	1.80	1.60	1.28	1.42	2.15	4.24	7.31
67-87	**Cumulative**	**22.31**	**23.06**	**11.74**	**12.07**	**15.04**	**20.19**	**19.32**	**18.02**	**20.47**	**36.39**	**56.26**
	Annualised	3.19	3.29	1.68	1.72	2.15	2.88	2.76	2.57	2.92	5.20	8.04
67-83	Cumulative	15.25	19.41	1.79	6.76	12.29	16.92	14.17	13.13	13.68	20.31	19.56
	Annualised	2.18	2.77	0.26	0.97	1.76	2.42	2.02	1.88	1.95	2.90	2.79

Notes: This table reports the cumulative growth and annualized growth rates in moments of the lifetime earnings distribution across cohorts. We report growth rates for the mean, median, and selected quantiles of the lifetime earnings distributions for men and women separately. Different periods are reported in order to highlight the dynamics and compare our results with those of Guvenen et al. (2022a).

Table A.4: The determinants of lifetime earnings for women

VARIABLES	(1) 1967	(2) 1969	(3) 1971	(4) 1973	(5) 1975	(6) 1977	(7) 1979	(8) 1981	(9) 1983	(10) 1985	(11) 1987
% Years Full Time	21.83***	21.58***	25.33***	23.98***	25.20***	24.14***	25.54***	25.61***	25.93***	27.31***	28.00***
	(1.332)	(1.270)	(1.074)	(1.034)	(0.873)	(0.918)	(0.953)	(0.862)	(1.098)	(0.926)	(1.135)
% Years Part Time	8.094***	7.906***	12.44***	11.20***	14.51***	12.67***	13.26***	14.20***	12.79***	16.17***	15.96***
	(1.818)	(1.731)	(1.516)	(1.395)	(1.149)	(1.159)	(1.172)	(1.039)	(1.329)	(1.109)	(1.342)
% Years Paris Region	5.256***	5.187***	4.532***	3.564***	4.825***	5.535***	5.062***	5.014***	6.657***	6.096***	7.662***
	(0.536)	(0.526)	(0.455)	(0.457)	(0.391)	(0.425)	(0.443)	(0.403)	(0.507)	(0.420)	(0.492)
Elementary	0.308	-0.0341	-0.0690	0.363	0.768	0.198	0.467	-0.0734	-0.0871	1.077	0.0788
	(0.725)	(0.653)	(0.628)	(0.630)	(0.532)	(0.589)	(0.777)	(0.676)	(0.929)	(0.893)	(1.281)
Junior High	2.380**	3.717***	2.490***	2.975***	2.519***	2.119***	2.458***	1.251*	1.352*	2.317***	1.743**
	(0.933)	(0.920)	(0.773)	(0.779)	(0.684)	(0.697)	(0.836)	(0.673)	(0.800)	(0.686)	(0.862)
Professional	2.291***	2.066***	1.969***	2.248***	2.679***	1.831***	1.944***	1.335**	1.603**	1.797***	0.956
	(0.726)	(0.641)	(0.609)	(0.605)	(0.512)	(0.550)	(0.698)	(0.565)	(0.657)	(0.537)	(0.698)
High School	6.005***	5.495***	3.850***	4.230***	4.876***	3.896***	5.015***	3.724***	3.222***	4.290***	3.284***
	(0.802)	(0.761)	(0.687)	(0.666)	(0.573)	(0.606)	(0.730)	(0.589)	(0.701)	(0.564)	(0.727)
Bachelor	8.201***	5.742***	7.180***	7.227***	8.042***	6.690***	5.844***	5.150***	5.698***	6.220***	5.887***
	(0.924)	(0.822)	(0.755)	(0.701)	(0.607)	(0.650)	(0.760)	(0.621)	(0.721)	(0.582)	(0.764)
Master	11.38***	10.09***	9.438***	13.42***	14.44***	9.103***	12.33***	10.40***	14.29***	13.31***	14.54***
	(1.613)	(1.235)	(1.007)	(0.974)	(0.788)	(0.743)	(0.848)	(0.672)	(0.796)	(0.625)	(0.788)
Dipl Missing	1.400	1.078	1.006	2.336**	1.820**	2.385***	3.048***	2.101**	1.656	3.081***	2.684***
	(0.919)	(0.850)	(0.968)	(0.953)	(0.848)	(0.881)	(1.003)	(0.892)	(1.132)	(0.861)	(1.041)
Ever Couple	0.731	-0.527	0.472	1.245	0.243	-0.801	0.572	1.363**	0.193	0.883	0.984
	(0.641)	(0.681)	(0.689)	(0.779)	(0.613)	(0.703)	(0.751)	(0.595)	(0.699)	(0.598)	(0.639)
Ever Children	0.640	0.110	-0.294	-0.311	-0.243	0.732*	0.267	-0.0566	0.234	0.390	0.0702
	(0.450)	(0.448)	(0.419)	(0.469)	(0.406)	(0.395)	(0.412)	(0.321)	(0.395)	(0.314)	(0.382)
Coupl Missing	1.162	-0.337	1.334	0.220	0.526	1.087	-0.413	0.567	1.884*	1.838**	0.171
	(0.857)	(0.915)	(0.960)	(1.145)	(0.950)	(0.954)	(1.019)	(0.863)	(1.081)	(0.842)	(0.934)
Constant	-7.088***	-5.011***	-7.962***	-7.771***	-8.901***	-7.125***	-8.777***	-9.113***	-8.340***	-11.11***	-10.75***
	(1.256)	(1.254)	(1.163)	(1.193)	(0.964)	(1.059)	(1.210)	(0.987)	(1.224)	(1.035)	(1.225)
Observations	847	879	1,329	1,513	1,566	1,623	1,771	1,744	1,877	2,053	2,153
R-squared	0.537	0.564	0.552	0.524	0.633	0.558	0.537	0.582	0.525	0.591	0.551

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: The table displays regressions of female lifetime earnings for successive cohorts between 1967 and 1987, on a set of control variables. See notes Table 4

Table A.5: The determinants of lifetime earnings for men: The role of birth place

VARIABLES	(1) 1967	(2) 1969	(3) 1971	(4) 1973	(5) 1975	(6) 1977	(7) 1979	(8) 1981	(9) 1983	(10) 1985	(11) 1987
Born Paris region	-0.555	1.521*	1.476*	1.269*	0.874	-1.154	0.941	1.406*	0.756	-1.601**	-2.844
	(0.784)	(0.809)	(0.757)	(0.705)	(0.714)	(0.729)	(0.682)	(0.722)	(0.859)	(0.698)	(1.837)
% Years Paris region	8.236***	6.392***	8.198***	7.884***	5.441***	8.370***	7.330***	7.912***	8.278***	8.310***	15.04***
	(0.826)	(0.756)	(0.811)	(0.739)	(0.747)	(0.795)	(0.727)	(0.780)	(0.939)	(0.769)	(1.956)
% Years Full Time	29.14***	29.52***	31.17***	32.47***	32.35***	30.20***	30.09***	28.56***	30.70***	32.49***	35.24***
	(1.742)	(1.717)	(1.684)	(1.536)	(1.506)	(1.499)	(1.401)	(1.568)	(1.797)	(1.546)	(4.015)
% Years Part Time	15.11***	11.96***	13.48***	4.819*	11.72***	5.230**	4.458*	0.680	1.957	8.146***	10.93*
	(3.631)	(3.310)	(3.051)	(2.850)	(2.621)	(2.628)	(2.396)	(2.589)	(2.937)	(2.395)	(6.270)
Ever Couple	3.349**	1.902	2.055	1.759	1.803*	3.434***	3.707***	2.198**	3.255***	3.119***	3.277
	(1.304)	(1.306)	(1.324)	(1.117)	(1.087)	(1.065)	(0.932)	(0.932)	(1.060)	(0.842)	(2.296)
Ever Children	0.0934	1.899***	1.963***	2.354***	1.459**	0.876	0.452	1.144**	0.637	1.531***	2.745**
	(0.654)	(0.669)	(0.693)	(0.629)	(0.621)	(0.606)	(0.513)	(0.521)	(0.602)	(0.508)	(1.311)
Elementary	1.804**	2.112**	1.226	1.116	0.568	0.552	0.889	-0.451	-0.744	0.192	1.044
	(0.876)	(0.888)	(0.880)	(0.876)	(0.857)	(0.961)	(0.987)	(1.153)	(1.520)	(1.348)	(4.520)
Junior High	6.680***	7.828***	8.143***	7.269***	4.801***	4.541***	3.514***	3.097**	2.728*	3.670***	3.450
	(1.377)	(1.245)	(1.273)	(1.214)	(1.247)	(1.337)	(1.137)	(1.206)	(1.417)	(1.227)	(3.221)
Professional	4.701***	3.681***	3.088***	3.220***	2.662***	2.312***	2.413***	2.088**	2.219**	1.853**	2.159
	(0.759)	(0.779)	(0.794)	(0.765)	(0.719)	(0.802)	(0.804)	(0.845)	(0.946)	(0.776)	(2.040)
High School	12.11***	12.01***	9.081***	8.255***	7.662***	6.725***	7.321***	6.162***	5.874***	6.512***	6.060**
	(0.976)	(0.941)	(0.960)	(0.912)	(0.858)	(0.926)	(0.920)	(0.956)	(1.086)	(0.900)	(2.412)
Bachelor	22.22***	19.00***	19.00***	15.40***	15.63***	11.26***	11.63***	10.51***	9.653***	10.13***	9.871***
	(1.020)	(1.007)	(1.001)	(0.940)	(0.903)	(1.074)	(1.012)	(1.057)	(1.212)	(0.959)	(2.465)
Master	27.42***	23.55***	22.82***	23.06***	22.04***	24.83***	23.89***	22.15***	23.40***	23.83***	32.61***
	(1.642)	(1.471)	(1.287)	(1.113)	(1.059)	(1.051)	(0.976)	(1.030)	(1.151)	(0.946)	(2.457)
Dipl Missing	3.060***	5.020***	4.928***	4.697***	5.065***	5.633***	8.040***	8.612***	5.577***	4.370***	3.074
	(1.082)	(1.129)	(1.251)	(1.193)	(1.224)	(1.206)	(1.283)	(1.400)	(1.577)	(1.289)	(3.278)
Coupl Missing	1.733	0.00438	-0.918	2.441	0.811	-0.805	2.070	1.445	2.497	3.086**	4.521
	(1.448)	(1.519)	(1.644)	(1.536)	(1.483)	(1.493)	(1.376)	(1.412)	(1.532)	(1.224)	(3.297)
Constant	-14.43***	-14.26***	-15.51***	-16.04***	-15.02***	-13.59***	-13.95***	-11.17***	-13.28***	-15.50***	-19.85***
	(1.914)	(1.907)	(1.909)	(1.727)	(1.676)	(1.652)	(1.581)	(1.700)	(1.899)	(1.638)	(4.309)
Observations	1,821	1,931	2,434	2,647	2,598	2,459	2,651	2,548	2,765	2,753	2,905
R-squared	0.452	0.423	0.401	0.422	0.406	0.430	0.460	0.413	0.359	0.448	0.178

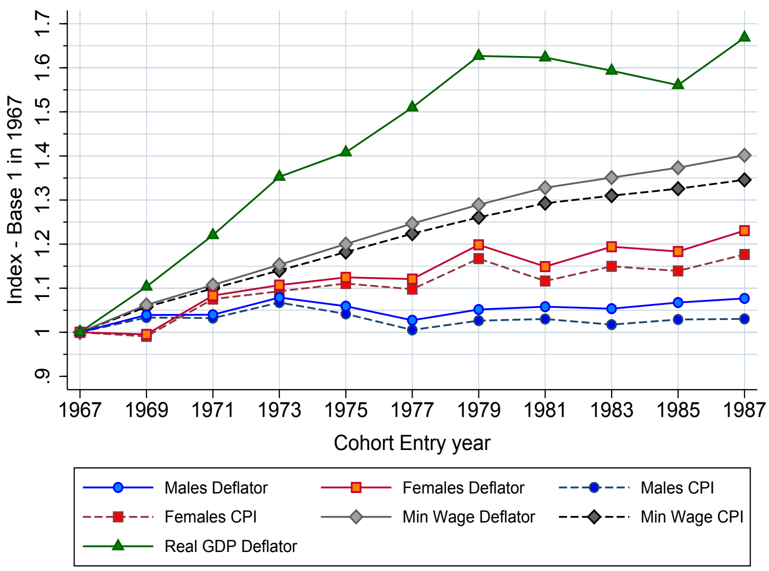
Notes: The table displays regressions of male lifetime earnings for all cohorts between 1967 and 1987, on a set of control variables. These include labor supply measures: percentage of years worked full time and years worked part-time; dummies for highest education level from Elementary to Master (ref. category: no education); whether individuals have been in a couple or have had children; whether individuals are born in the Paris Region, and the percentage of years they worked there. Dummies for missing observations of Diploma and couple status are also included. Reference category: Individuals who have not been born and have never worked in the Paris region. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table A.6: The determinants of lifetime earnings for women: The role of birth place

VARIABLES	(1) 1967	(2) 1969	(3) 1971	(4) 1973	(5) 1975	(6) 1977	(7) 1979	(8) 1981	(9) 1983	(10) 1985	(11) 1987
Born Paris region	-0.128	-0.844	0.867*	0.687	0.965**	0.339	0.315	-0.457	-1.332**	0.0484	-0.942*
	(0.549)	(0.564)	(0.489)	(0.489)	(0.440)	(0.467)	(0.507)	(0.424)	(0.519)	(0.429)	(0.502)
% Years Paris region	5.325***	5.540***	4.012***	3.162***	4.281***	5.332***	4.864***	5.271***	7.432***	6.071***	8.183***
	(0.612)	(0.576)	(0.541)	(0.539)	(0.463)	(0.509)	(0.545)	(0.469)	(0.589)	(0.475)	(0.565)
% Years Full Time	21.80***	21.53***	25.46***	24.08***	25.36***	24.19***	25.55***	25.58***	25.81***	27.31***	27.82***
	(1.338)	(1.269)	(1.076)	(1.036)	(0.875)	(0.921)	(0.953)	(0.863)	(1.098)	(0.927)	(1.139)
% Years Part Time	8.057***	7.780***	12.65***	11.33***	14.73***	12.74***	13.28***	14.19***	12.62***	16.17***	15.72***
	(1.826)	(1.731)	(1.519)	(1.397)	(1.152)	(1.164)	(1.173)	(1.039)	(1.329)	(1.111)	(1.347)
Ever Couple	0.727	-0.533	0.475	1.294*	0.189	-0.808	0.572	1.361**	0.227	0.884	1.000
	(0.642)	(0.680)	(0.689)	(0.779)	(0.613)	(0.704)	(0.752)	(0.595)	(0.698)	(0.599)	(0.639)
Ever Children	0.646	0.130	-0.348	-0.359	-0.261	0.728*	0.249	-0.0570	0.201	0.390	0.0535
	(0.451)	(0.448)	(0.420)	(0.470)	(0.406)	(0.395)	(0.413)	(0.321)	(0.395)	(0.314)	(0.382)
Elementary	0.310	0.0210	-0.135	0.333	0.697	0.172	0.474	-0.0658	-0.0600	1.076	0.0975
	(0.725)	(0.653)	(0.629)	(0.630)	(0.533)	(0.590)	(0.777)	(0.676)	(0.928)	(0.894)	(1.281)
Junior High	2.391**	3.716***	2.404***	2.943***	2.460***	2.098***	2.446***	1.265*	1.341*	2.314***	1.824**
	(0.934)	(0.919)	(0.774)	(0.779)	(0.683)	(0.698)	(0.836)	(0.673)	(0.798)	(0.686)	(0.863)
Professional	2.292***	2.099***	1.885***	2.215***	2.601***	1.805***	1.934***	1.363**	1.627**	1.793***	1.021
	(0.726)	(0.641)	(0.610)	(0.605)	(0.512)	(0.551)	(0.699)	(0.565)	(0.656)	(0.538)	(0.699)
High School	6.009***	5.589***	3.727***	4.190***	4.818***	3.871***	5.006***	3.754***	3.236***	4.286***	3.374***
	(0.803)	(0.763)	(0.690)	(0.666)	(0.573)	(0.607)	(0.730)	(0.590)	(0.700)	(0.565)	(0.728)
Bachelor	8.211***	5.740***	7.080***	7.199***	7.933***	6.659***	5.837***	5.164***	5.728***	6.217***	5.942***
	(0.926)	(0.821)	(0.757)	(0.701)	(0.608)	(0.651)	(0.760)	(0.621)	(0.720)	(0.583)	(0.765)
Master	11.38***	10.06***	9.437***	13.40***	14.41***	9.092***	12.32***	10.42***	14.26***	13.31***	14.59***
	(1.614)	(1.234)	(1.006)	(0.974)	(0.787)	(0.743)	(0.849)	(0.672)	(0.795)	(0.626)	(0.788)
Dipl Missing	1.406	1.064	1.057	2.398**	1.969**	2.364***	3.073***	2.074**	1.532	3.078***	2.658**
	(0.920)	(0.849)	(0.968)	(0.953)	(0.849)	(0.881)	(1.004)	(0.893)	(1.131)	(0.862)	(1.041)
Coupl Missing	1.149	-0.378	1.405	0.273	0.428	1.122	-0.396	0.551	1.781*	1.839**	0.196
	(0.859)	(0.915)	(0.960)	(1.145)	(0.950)	(0.955)	(1.020)	(0.863)	(1.080)	(0.842)	(0.933)
Constant	-7.062***	-4.956***	-8.007***	-7.858***	-8.945***	-7.154***	-8.771***	-9.092***	-8.178***	-11.11***	-10.60***
	(1.261)	(1.253)	(1.162)	(1.194)	(0.963)	(1.060)	(1.210)	(0.987)	(1.224)	(1.036)	(1.227)
Observations	847	879	1,329	1,513	1,566	1,623	1,771	1,744	1,877	2,053	2,153
R-squared	0.537	0.565	0.553	0.524	0.634	0.558	0.537	0.583	0.526	0.591	0.551

Notes: Regressions of female lifetime earnings for all cohorts between 1967 and 1987. See note Table A.5

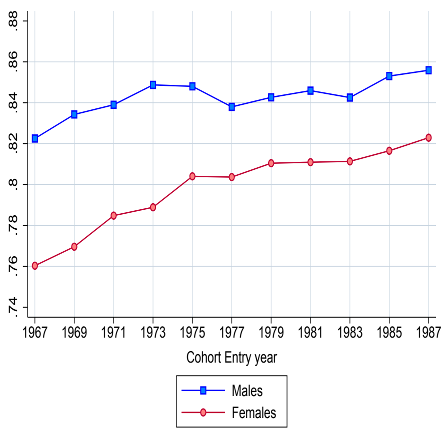
Figure A.1: GDP, median lifetime earnings and the minimum wage with different price indices



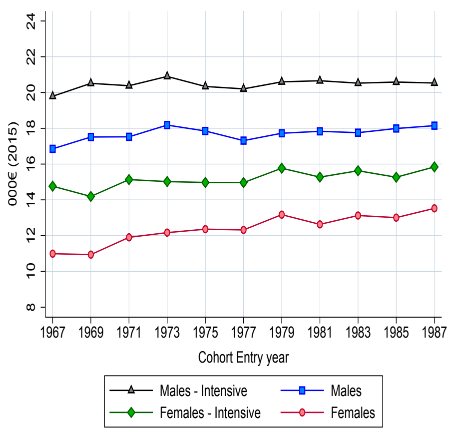
Notes: The graph displays series of median lifetime earnings, minimum wage and real GDP, indexed at one in 1967. CPI series were deflated using the consumer prince index while Deflator series were deflated using the personal consumer expenditures price index.

Figure A.2: Lifetime income by cohort, intensive and extensive margin

(a) Percentage of years worked



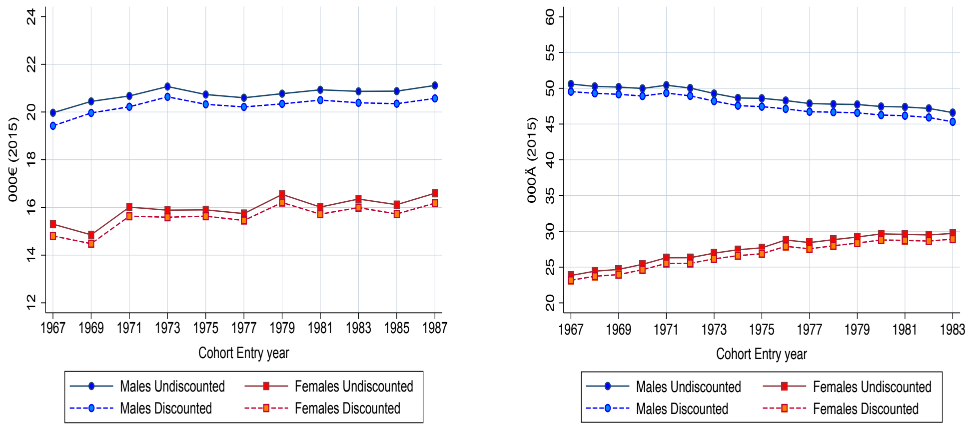
(b) Lifetime earnings



Notes: Panel (a) displays the percentage of years worked over the lifetime (either 28 29 and 30 years depending on the number of missing years) for a cohort of each gender that entered the labor market in a given year. Panel (b) displays the median lifetime earnings each gender-cohort as in Figure 1 (blue and red lines), as well as the median of the intensive margin of lifetime earnings for a gender-cohort that entered the labor market in a given year (blue and green lines) as defined as the average lifetime income per year worked.

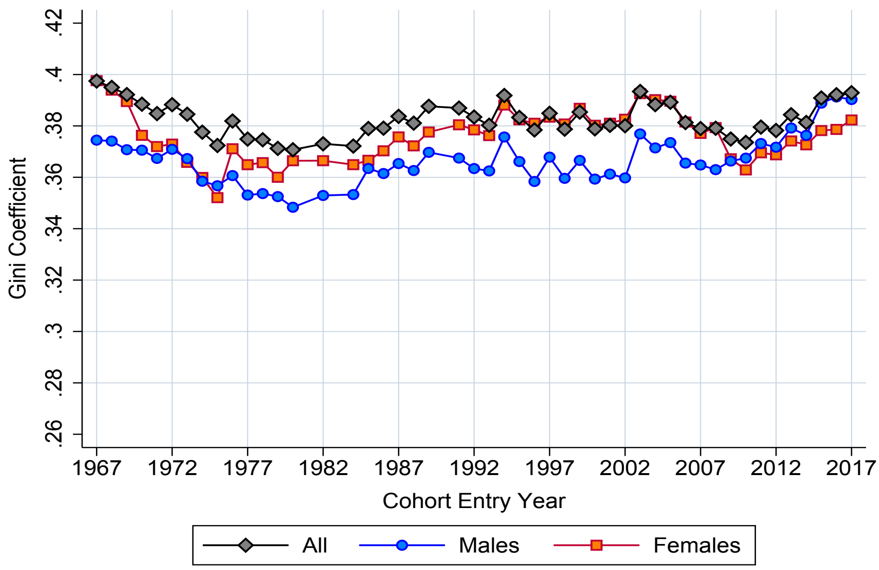
Figure A.3: Discounted median lifetime earnings by cohort, France and the US

(a) France (b) US



Notes: The figure depicts undiscounted and discounted lifetime earnings for men in France and the US. To compute discounted lifetime earnings, ”hypothetical” median lifetime earnings are computed by attributing to a hypothetical individual in each cohort the median lifetime earning observed at each age and then computing their lifetime earnings.

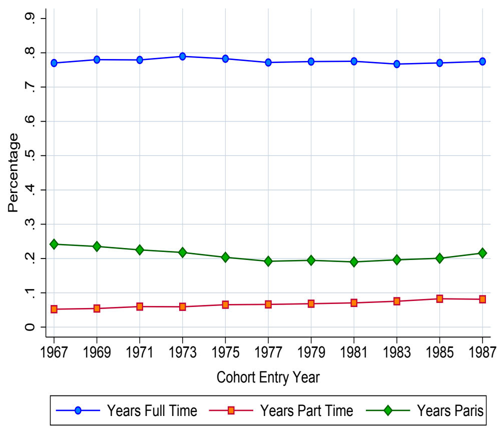
Figure A.4: Cross-sectional inequality: 1967-2017



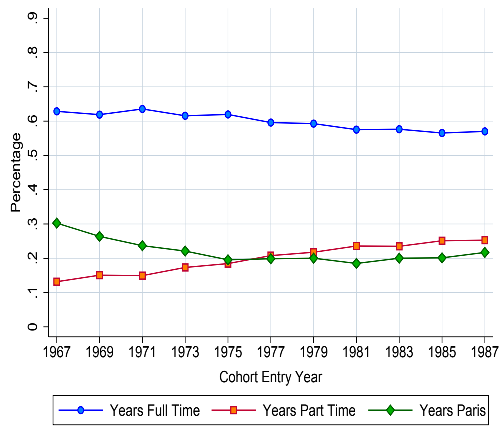
Notes: The figure displays the evolution of Gini coefficients over time, computed for successive cross sections of yearly earnings, for all individuals, as well as males and females separately.

Figure A.5: Endowments across cohorts

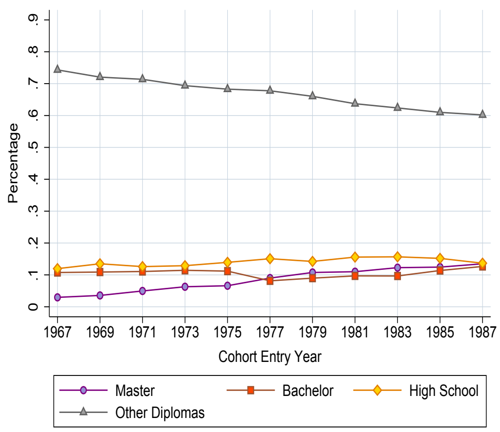
(a) Years of work, men



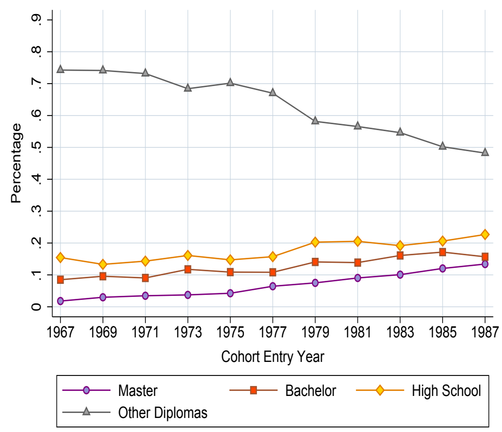
(b) Years of work, women



(c) Diplomas, men

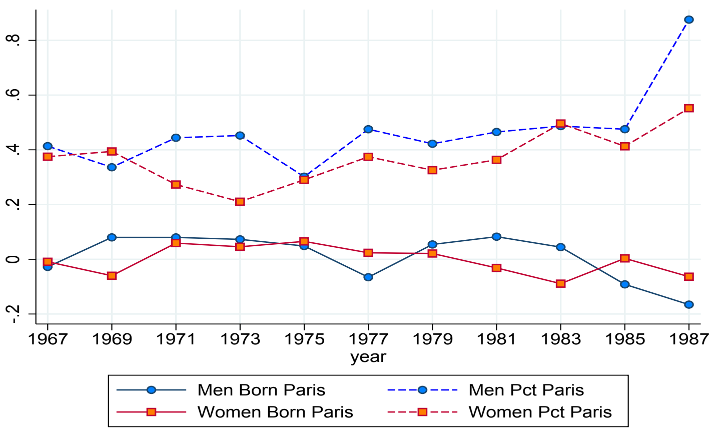


(d) Diplomas, women



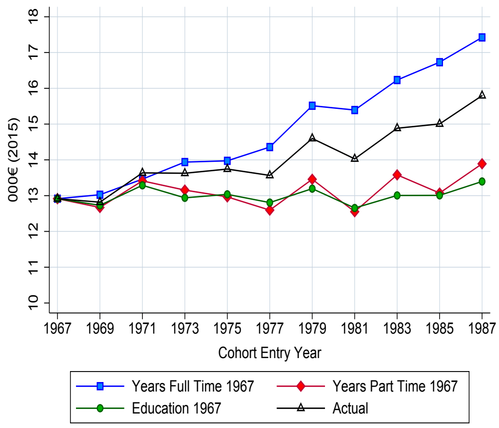
Notes: The top graphs show the endowments of median individuals across male (left) and female (right) cohorts for the number of years worked full-time and part-time, as well as years spent working in *Ile-de-France*, the most populated and central French region that includes the capital Paris. The bottom graphs display the percentage of individuals by male (left) and female (right) cohorts with specific degrees. Note that Master indicates individuals with a Master degree or above. While Other diplomas regroups either vocational/technical high school diplomas, or diplomas of lower degree than high school.

Figure A.6: Regression coefficients on Being Born in the Paris region and Percentage Years Spent in the Paris region by Cohort, by Gender

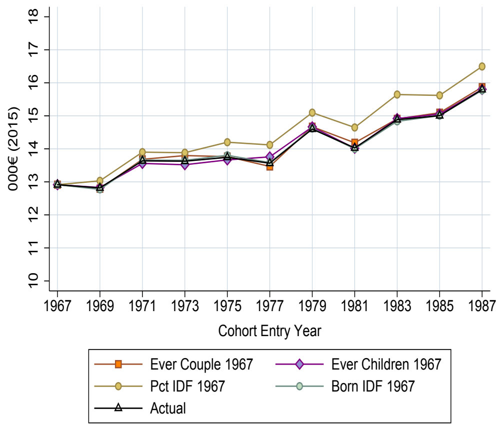


Notes: The figure displays coefficient estimates of the variables being born in the Paris region (Ile-de-France, IDF) and percentage of years spent working in the Paris region (IDF) from regressions of life time earnings for the successive cohorts that entered the labor market between 1967 and 1987. The coefficients used are those reported in the last line of each panel of Table A.5 and Table A.6. Since lifetime earnings change over time, for each cohort we have divided the coefficients by the mean lifetime earnings estimated when the location variables are set to zero.

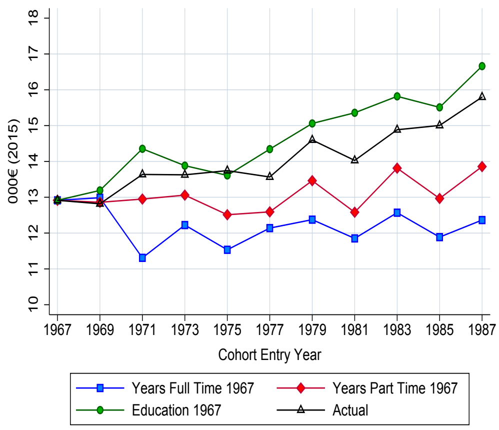
Figure A.7: Counterfactuals, women



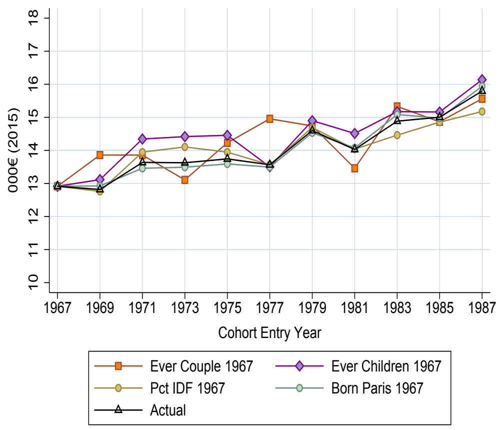
(a) Endowments: Working time and Education



(b) Endowments: Demographics



(c) Coefficients: Working time and Education



(d) Coefficients: Demographics

Notes: Notes: The graphs display average lifetime earnings computed for successive male cohorts between 1967 and 1987 against counterfactual earnings. These are computed using the same regressions model as in Table 4 where either endowments (panels a and b) or coefficients (panels c and d) of one or several variables of interest have been fixed at their value in the regression for cohort 1967. In practice we start by estimating the model in 1967 and store its coefficients, then we estimate the model for successive years. We then compute average earnings by replacing either the coefficient(s) or the endowment(s) of our variable(s) of interest, with the coefficient(s) or the endowment(s) from the regression on the 1967 cohort. Note that for endowments we input the average endowments of 1967 to all individuals. For example, panel a) displays how average lifetime earnings would have evolved for cohorts after 1967 had they either worked the same number of years full-time as cohort 1967 (blue), worked the same number of years part-time (red), or had the same education achievements (green).