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Explaining the Dynamics of the Gender Gap in Lifetime Earnings *

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Abstract

Using a long administrative panel dataset for France, we analyse the dynamics and drivers of the narrowing gender gap in lifetime earnings (LTE) for cohorts born after WWII. We find that the level, trends, and distribution of gender differences in LTE contrast sharply with those observed in the US, and that these differences are more marked than when we compare cross-sectional gender gaps. We show that this reflects a specific pattern in which both men and women experienced earnings gains over the whole distribution (with the exception of the very top), in contrast with the US, where the same cohorts of men experienced earnings losses in the three bottom quartiles of the distribution. We then decompose the changing role of various factors (e.g., working (part) time, education, occupation, geographical location) in shaping the evolution of the gender LTE gap in France. The contribution of unobserved factors decreases across cohorts and increases along the distribution, remaining larger at the top, consistent with a glass ceiling effect. Meanwhile, the impact of observed factors rises, mostly due to the decline in the years worked full time by women, which has slowed gender convergence. Differences in educational attainment contribute to a lesser extent, as the gender gap in returns to education has narrowed.

JEL Classification: *J16, J31, J62*

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

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1 Introduction

Figures on the gender pay gap regularly hit the headlines and often play a key role in promoting the principle of equal pay for equal work.[1] The academic literature has focused extensively on both the narrowing and the persistence of the cross-sectional gender pay gap in developed countries. 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. Moreover, as Goldin et al. (2017) notes, *"the gender earnings gap is a shifting statistic"* over the life-cycle. Therefore, a broader perspective based on lifetime earnings, i.e., examining the earnings of several cohorts over their life cycle, can significantly enrich the analysis of the long-term dynamics of the gender earnings gap.

In this paper, we analyse the dynamics and drivers of the decline in the gender gap in lifetime earnings for cohorts born after the Second World War in a large European country, France. The analysis of the dynamics and distribution of lifetime earnings has been limited by data availability, and most recent contributions have focused on the US (Kopczuk et al. (2010), Guvenen et al. (2022) or Ozkan et al. (2023)). However, based on cross-sectional data, it is well documented that both the evolution of average earnings and their dispersion have followed different paths in Western European economies compared to the US. First, the cross-sectional gender pay gap in the US is larger than in other countries, including France.[2] Second, over the second half of the 20^{th} century, the cross-sectional gender pay gap fell more in the United States than in Western European countries (e.g. Blau and Kahn (2008), Olivetti and Petrongolo (2008), Blau and Kahn (2017), or Kunze (2018)). This paper is the first to assess whether these point-in-time gender differences accurately reflect life-cycle differences, offering a novel perspective on the long-term trends that have shaped gender inequality across different contexts and cohorts.

Our contribution to the literature is twofold. First, we compute the gender gap in lifetime earnings and its distribution, for a large number of cohorts in France, and provide a direct comparison with the US, based on Guvenen et al. (2022). This comparison is of particular interest, as France is, relative to the US, a country characterized both by a

1. For instance the Directive (EU) 2023/970 of the European Parliament and of the Council of 10 May 2023 states that employers with at least 100 workers should regularly report on pay by publishing sex-disaggregated data.

2. According to the OECD database, for the year 2019, the gender gap (in terms of median annual earnings) levels at 18.5 in the US, compared to 12.1 for France.

low level of cross-sectional inequality [3] and by limited intra-generational mobility. [4] Our paper hence contributes to understanding how these two features shape lifetime earnings, and affect the comparisons in terms of gender differences. Second, using the richness of our administrative data for France, we assess the role of various determinants (working time, education, family composition, and location) in explaining the dynamics of the gender gap in lifetime earnings since the 1960s.

Our analysis relies on a long administrative panel dataset that combines firm-level and census information. This allows us, firstly, to produce the first series of lifetime earnings at the individual level for France, and secondly to assess the role of different factors in shaping both the evolution and distribution of the gender gap in lifetime earnings using Oaxaca-Blinder decompositions. For comparison purposes, we follow closely Guvenen et al. (2022) in terms of sample selection and lifetime earnings computation. Following their approach, we measure lifetime earnings over 31 (potential) working years, from age 25 to 55. Our core sample consists hence of the cohorts born between 1942 and 1964, who turned 25 years old between 1967 and 1989. Throughout this paper, we refer to cohorts by the year in which they turned 25.

We start by documenting, for the first time, the evolution of the gender gap in lifetime earnings in France, and show that both the level and the trends in the (median) gender gap in lifetime earnings contrast sharply with those observed in the US. In addition, we show that the differences between France and the US are magnified when looking at the dynamics of the gender gap in lifetime earnings compared to cross-sectional data. Throughout the period, the gender gap in lifetime earnings remains significantly smaller in France than in the US, and there is no convergence at the end of the period, despite the greater narrowing observed in the US. There are also important differences in the distribution of the gap between the two countries. In France, the gap is U-shaped across the distribution (i.e. the gender ratio is inverse U-shaped), with the smallest gap observed around the 70-75 percentiles, while in the US the smallest gap is observed at the bottom of the earnings distribution. Moreover, while in the US there is a striking narrowing of the gender gap for the whole distribution (except at the very top), we observe that in France it narrows only at the top and bottom of the distribution for the youngest cohorts. Drawing on the existing literature that highlights cross-country differences in the cross-sectional gender gap, we synthesize key findings and examine the institutional factors that may drive these disparities. We explore in particular the role of the minimum wage and collective bargaining, as

3. See e.g. Atkinson (2003), Alvaredo et al. (2018), Garbinti et al. (2018), or Bozio et al. (2024).
4. See Aghion et al. (2023), Kramarz et al. (2022), or Loisiel and Sicsic (2023).

well as the main cross-country differences in labor market participation.

Second, we show that this evolution of the gender gap reflects very different patterns of lifetime earnings in France compared to the US. In France, lifetime earnings have increased throughout the distribution for both men and women.[5] In contrast, in the US, men below the median have experienced losses. In France, the evolution of men's lifetime earnings is more favorable to those at the bottom of the distribution as compared to those at the top, reflecting the reduction in income inequality that took place after the social unrest of May 1968 until the early 1980s. For women, we find increases in lifetime earnings throughout the distribution, with larger gains at the top, although smaller than in the US.

Third, using a Oaxaca-Blinder decomposition, we show how the role of various factors (working time and part-time employment, education and occupation, family composition, and geographical location) in shaping the gender gap in lifetime earnings in France has changed over time. We find, firstly, that the contribution of unobserved factors decreases across cohorts and increases across the distribution. For early cohorts, it accounts for 60% of the gap, whereas for younger cohorts, it ranges from 20% to 30%. At the bottom of the distribution, the unexplained part is small and contributes little to the gap. In contrast, it is larger at the top (though declining across cohorts), consistent with a glass ceiling effect. This large decrease in the unexplained part has been accompanied by a rise in the impact of observable factors. The most important effect is due to working time and, more specifically, to the decline in the years worked full time by women, which slowed down the convergence across genders. Our results point towards a striking pattern: gender differences in working time accounted for only 28% of the gap for the oldest cohort, while it represents 77% of the gap for the youngest one. Notably, the increase in years worked by women over the course of their careers across cohorts was exclusively in part-time employment, suggesting that the rise in women's labor force participation has not been a source of convergence in France.

Education also contributes to explaining the gender gap in lifetime earnings, albeit to a lesser extent. We find a decrease in the returns to all educational attainments other than a Master's degree (and above) for both men and women, while the gender gap in returns has narrowed, though remains substantial. Such result contrasts with previous work based on cross-sectional data, which found that the declining returns to characteristics, particularly education, play a limited role in explaining the gender convergence. We argue that such differences are likely to be due to endogenous occupational choices. Indeed, the findings

5. Except for men at the very top.

that the returns to education are more similar across genders for younger cohorts than for older ones suggest that women with a given level of education are making occupational choices that increasingly resemble those of men. Adding the share of years that an individual spent working in a white-collar occupation to the analysis, allows us to show that it is an important factor contributing to the reduction of the gender gap at the top of the distribution. [6]

Lastly, we examine the role of geographical location. We show that the greater the number of years the individual spent working in Paris, the higher their lifetime earnings are, for both men and women. This captures both the advantages of being born in the Paris region (such as better educational opportunities) and the benefits of working in Paris, where firms may be more productive. However, we find no narrowing of the gender gap in the returns to being born or working in the Paris region.

Related literature. Our paper is related to the extensive literature analysing the sources of the evolution of the cross-sectional gender pay gap. [7] While existing studies focus on annual earnings, we provide the first in-depth analysis of gender differences in lifetime earnings across multiple cohorts, tracking their entire careers from ages 25 to 55. A recent contribution by Meurs and Pora (2019) provides a detailed analysis of the evolution of the cross-sectional gender pay gap in France since the 1960s and highlights the role that maternity plays in the persistence of the gender pay gap even in recent years as it impacts women's participation and hours worked. We complement their results by showing that working time, particularly part-time work, has become an increasingly important driver of the gender earnings gap. By documenting this growing role of part-time work across cohorts, our results also contribute to the understanding of the mechanisms behind the low intergenerational income mobility in France, as identified by Kenedi and Sirugue (2023). [8]

We also contribute to the literature on the drivers of cross-country differences in the gender earnings gap, which has so far been based on cross-sectional data, e.g. Blau and Kahn (2008), Olivetti and Petrongolo (2008), Christofides et al. (2013), Blau and Kahn (2017), Kunze (2018), or Dolado et al. (2020). By comparing the evolution of the gender gap in lifetime earnings in France with that in the US, we provide new insights into long-term trends and drivers of the gender pay gap. In particular, we emphasize the importance

6. Except for the 99th percentile.

7. See, among others, Goldin (2014), and Ngai and Petrongolo (2017), as well as Coudin et al. (2018), Meurs and Pora (2019), Gobillon et al. (2015), Gobillon et al. (2022), Meurs (2023), and Palladino et al. (2025) for France.

8. There is also a literature looking at intra-generational mobility over the life-cycle, e.g. Kopczuk et al. (2010) and other references listed in footnote 4. While mobility is not the focus of this paper, we nevertheless provide evidence in Appendix subsection B, showing changes in the age profile over cohorts.

of the gender differences in the number of years worked over the lifecycle in explaining cross-country patterns. These findings highlight the need for more cross-country analysis based on lifetime earnings to assess long-term dynamics of the gender pay gap across different contexts.

As already discussed, our methodological approach to compute lifetime earnings relies on detailed administrative panel data covering a large number of cohorts and is closely related to Guvenen et al. (2022). There are only a few other empirical papers analysing lifetime earnings based on detailed administrative data, comparing measures of income inequality with cross-sectional measures, but without focusing on the gender gap and its evolution across cohorts: Björklund (1993) for Sweden between 1950 and 1990, Aaberge and Mogstad (2015) for Norway and cohorts born between 1942 and 1944, and Bönke et al. (2015) and Corneo (2015) for Germany and cohorts born between the mid-1930s and end-1960s. While there has been a long-standing interest in lifetime earnings because of their central role in human capital theory, data limitations explain why the empirical literature on the dynamics of lifetime earnings remains limited, especially with regard to the gender earning gap. [9]

The rest of the paper is organized as follows. Section 2 presents the data. In Section 3, we present the key stylized facts of this paper, showing the dynamics of the gender gap in lifetime earnings and of its distribution in France, compared to one observed for the US. Based on the existing literature, we discuss the main factors that could explain the cross-country differences. In Section 4, we assess the main drivers of the gender gap in lifetime earnings in France, and their evolution over cohorts. Section 5 concludes.

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

9. To overcome data limitations, some work use models of earnings dynamics based on parametric assumptions 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. However, beyond the methodological differences, their analysis focuses on the late 1990s, whereas we are interested in the long-run dynamics of lifetime earnings.

and firm characteristics, the *Déclaration annuelle des données sociales* or DADS, and which covers the period 1967-2019. These data are combined with registry data indicating dates of birth, marriage, and death, and with census data. [10] We use a sample of the EDP that corresponds to 0.5% of the population. [11] The observations for 1981, 1983, and 1990 are missing as data were not collected in those years. [12] Our data have several advantages. Due to its large sample size, the EDP allows for a detailed analysis that can take into account heterogeneity across generations and qualifications. Furthermore, there is no top-coding of earnings in our data. [13]

Earnings include all wage and salary income supplied by employers. They are reported net of all social security contributions but not of income taxes. Since our data are provided by firms, we have particularly reliable information on labor earnings, but lack information on 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. Firm data are matched to the census, allowing 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. (2022). Following standard practice in the literature as well as their approach, we consider only prime-age workers, i.e. those aged 25 to 55 years. Hence, following Guvenen et al. (2022), 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 1964 (i.e.

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

11. More precisely, initially the dataset covered only individuals born in the first four days of October of even years, though the sample was progressively increased over time. In order to be consistent across cohorts, we select for all cohorts individuals born on those dates.

12. 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.

13. 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.

55 in 2019). This restriction is due to the need to observe individuals over their entire lifetime, i.e. for the 31-year period between ages 25 and 55. We hence have data on 12 cohorts spanning over 22 years.

Our sample selection rule is as close as possible to that of Guvenen et al. (2022). We follow these authors in restricting the sample to those still alive at 55. [14] We also restrict our sample to individuals employed by private companies, individual entrepreneurs, and public companies subject to private law. Guvenen et al. (2022) focus on ”commerce and industry” workers, which exclude agriculture, forestry and fishing, hospitals, educational services, social service, religious organizations, private households, and public administration. Occupational categories in our dataset are only available at a more aggregated level and this forces us to do a slightly different exclusion of workers. We exclude those working in agriculture, forestry and fishing, for private households and in the public sector (which include those in public administration). However, while in France the vast majority of those working in hospitals and (all levels of) education are public servants and hence excluded from our sample, there are some individuals providing education and hospital services privately. Because they appear in a broad service category we are unable to identify them. A number of robustness checks indicate that broadening the occupations included is not a concern. [15]

A potential concern is that earnings may not be observed in certain years, as individuals leave the DADS dataset 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; hence after those dates we can see if the individual disappears from the sample because it switches jobs into those categories. Unfortunately, we cannot distinguish between being non-employed or self-employed. As a result, we cannot determine whether missing earnings are due to a transition to self-employment.

Following procedures common in the literature that impose restrictions on wages to mitigate sample bias, we focus on individuals for whom we have “sufficient” data. We follow Guvenen et al. (2022) 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. [16] This

14. This selection criterion is potentially a concern as the probability of early death is correlated with earnings. There is a positive correlation between income at age 25-35 and the probability to be alive at age 55 conditional on having lived past 35, both for women and for men. However, it is small: a linear probability model implies that doubling the individual’s earnings when they are 25 to 35 years old increases the probability of reaching 55 by 1.1% for men and by 0.5% for women. We estimated (annualized) lifetime earnings for the sample including those who do not reach age 55 (available upon request). The series for men are slightly lower than those reported here for all cohorts, but the dynamics are unchanged.

15. In our dataset, information on individuals employed by the public sector or by natural persons (rather than by firms) are only included from 1988 and 2009, respectively. 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.

16. We use the restrictions, 507*0.25*the minimum hourly wage or 455*0.25*the minimum hourly wage.

ensures sufficient labor market attachment. The final sample has 1.2 million individual-year observations, consisting of 12 cohorts comprising between 2,668 and 5,474 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. [17] Our choice of deflator has been made following that in Guvenen et al. (2022), 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 Key stylized facts on the gender gap in lifetime earnings

In this section, we report the evolution of the gender gap in lifetime earnings in France, how it differs from that observed in the US for the same cohorts, and discuss the main sources of these cross-country differences in the light of the existing literature.

3.1 Comparing the gender gap in lifetime earnings in France and in the US

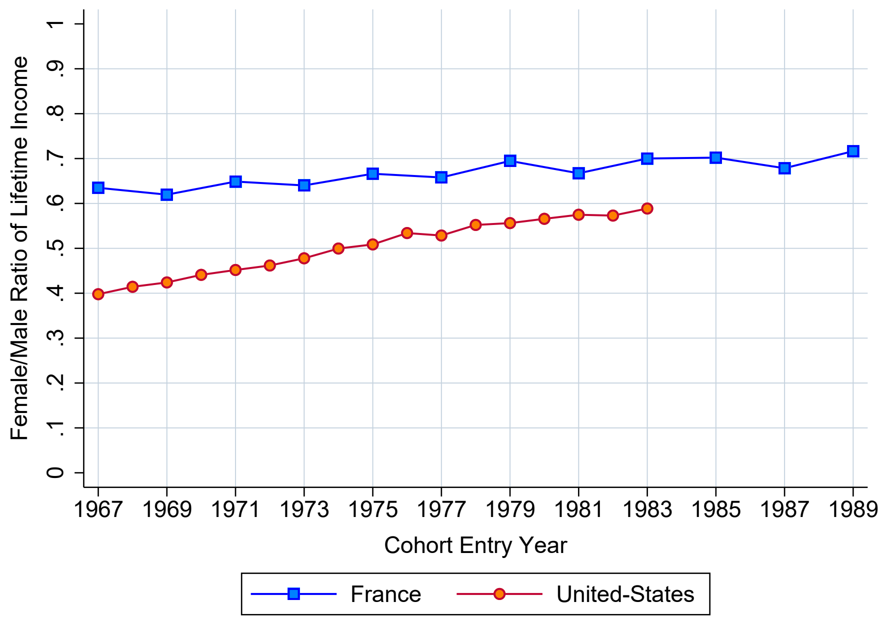
Both the level and the trend of the gender gap in median lifetime earnings that we obtain for France contrast sharply with those observed in the US. Figure 1 reports our estimates of median lifetime earnings of women as a share of those of men for France by cohorts, with a higher share indicating a lower gender gap. It also shows the estimates for

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. (2022) 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.

17. 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)).

the US obtained by Guvenen et al. (2022). The horizontal axis denotes the cohort defined by the year in which they turned 25.

Figure 1 – Lifetime earnings of women relative to men's

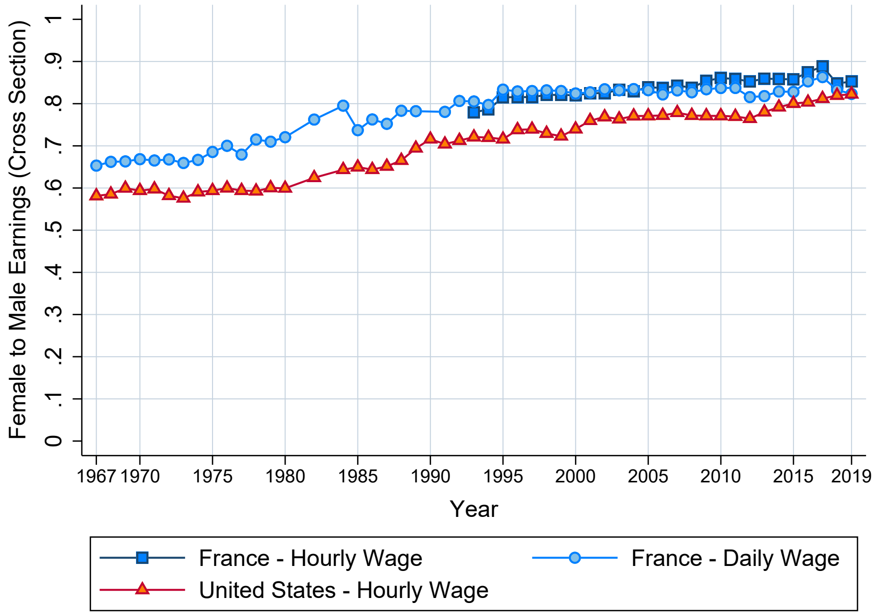


Notes: The figure displays the ratio of female to male median lifetime earnings, for cohorts entering the labor market between 1967 and 1987. The (blue) line with squares denote our results for France, the (red) line with circles those for the US, which come from Guvenen et al. (2022).

In our data, women's median lifetime earnings were 63% of those of men for the oldest cohort (1967) and reach about 70% for the younger one (1989). For all cohorts, it represents a much larger share than that observed in US data, where it grew from 40% for the 1967 cohort, to 58% for the 1983 one. The youngest cohort for which we have data for the two countries, that of 1983, exhibits a sizably larger female earnings ratio in France than in the US (70% as compared to 58%). Our data indicate that over the 23-year period that we consider, women's relative lifetime earnings grew in France, albeit at a much slower pace in France than in the US.

A large literature has consistently documented the lower gender gap in Western European countries compared to the US based on cross-sectional gender data (see among others, Olivetti and Petrongolo (2008), Blau and Kahn (2017), and Kunze (2018)). To further illustrate this point, Figure 2 reports the ratio of female to male hourly (or daily) wages when we consider annual data. We report the ratios for the period 1967 to 2019, using our data for France and data from the Census and CPS for the US. While the earnings ratio is higher in France than in the US, the two countries follow similar patterns. It is therefore particularly striking that when examining lifetime earnings (Figure 1), we find that the cross-country differences are magnified. Firstly, the level of these cross-country

Figure 2 – The cross-sectional gender ratio



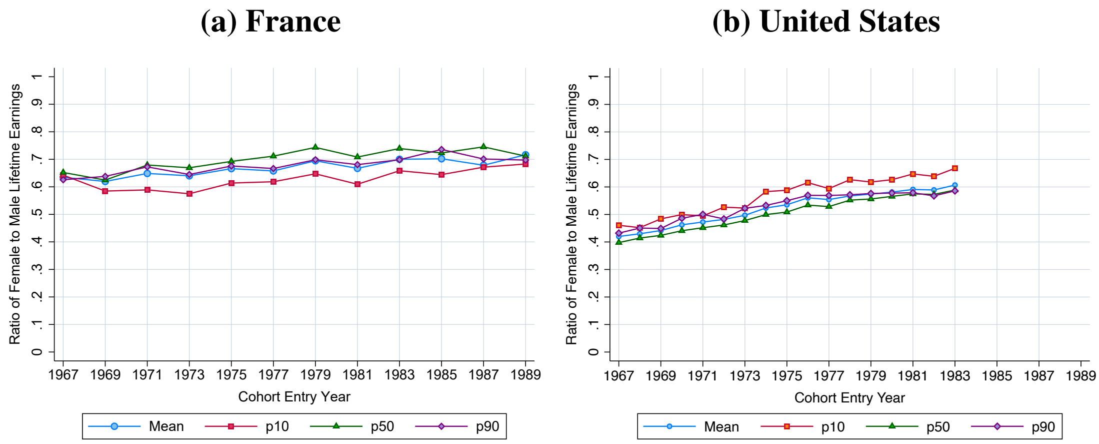
Notes: The figure displays the ratio of female to male cross-sectional wages for full-time workers from 1967 to 2019. The data for the US is for hourly wages. For France, hours worked are only available from 1993, hence we also report daily earnings, which are available for the entire period. US Source: Stuart (2024)'s calculations based on U.S. Census Bureau Analysis of Current Population Survey, Annual Social and Economic Supplements. Sample contains workers aged 15 and above, working at least 50 weeks per year and 35 hours per week.

differences is higher, and secondly, the evolution of the gender gap is notably different in France from that in the US.

We further explore the differences between France and US in the dynamics of the gender gap in lifetime earnings through its heterogeneity across the distribution. Recent literature has shown that whether the cross-sectional wage gap is wider at the top ("glass ceilings") and/or at the bottom of the wage distribution ("sticky floors") depends on the country (e.g. Christofides et al. (2013), Redmond and Mcguinness (2019)). However, no cross-country comparison has examined the heterogeneity of the gender gap in lifetime earnings across the distribution. To address this, we compute the gap in lifetime earnings at various percentiles, where individuals are ranked within the distribution of their own gender group. Figure 3 summarizes the data by reporting gender gaps for the mean, as well as the 10th, 50th, and 90th percentiles of the distribution of lifetime earnings in both France (using our data) and the US (based on the results in Guvenen et al. (2022)), while Figure 4 depicts the gender gaps across the entire distribution. [18]

18. We are grateful to Greg Kaplan for providing the detailed data for the US.

Figure 3 – Gender Ratios at Various Percentiles - France versus US



Notes: The graphs display the evolution of the ratio of female to male lifetime earnings computed at different percentiles and the mean across successive cohorts between 1967 and 1989 for France (Panel a) and the United States (Panel b).

For both countries the data presented in Figure 3 indicate that the trends reported above for the median are also apparent at other points of the distribution, with the US displaying initially low but fast-growing female relative earnings and France an initially high ratio but slow growth. The behavior at the bottom of the distribution differs markedly, with the gender gap for the p10 being the largest (i.e. lowest ratio) in France and the lowest in the US when compared with other points in the distribution for each cohort.

Figure 4 depicts the gender gap in lifetime earnings across the entire distribution, for France (panel a) and the US (panel b). In both panels, the left-hand-side figure reports the gap for the 1967 to 1977 cohorts and the right-hand-side one that for the 1979-1989 ones.

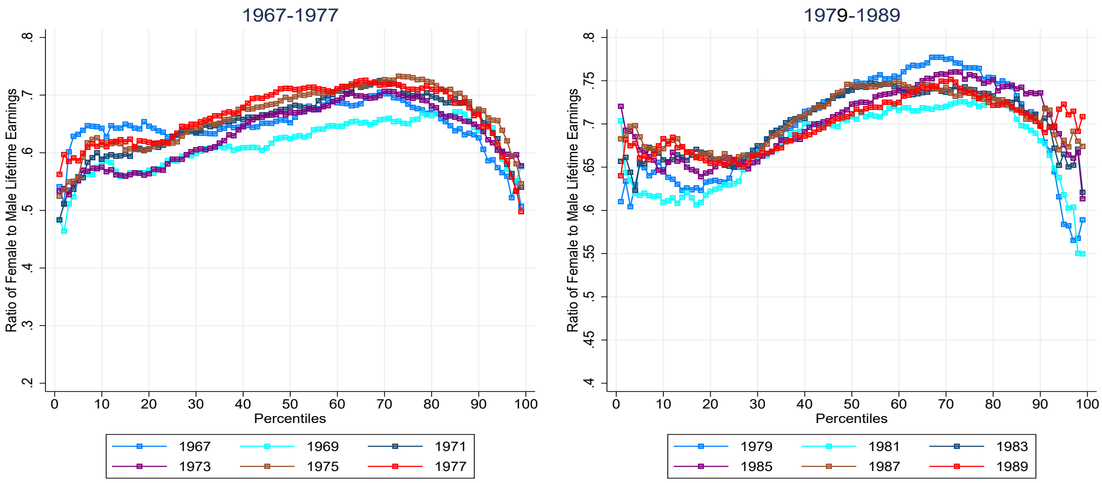
We find strong differences between France and the US when comparing the profile of lifetime earnings across the whole distribution. For France, the gender ratio in lifetime earnings is inverse-U shaped across the distribution (i.e. the gap is U-shaped) but this is less pronounced for the youngest cohorts than for the oldest ones. [19] The smallest gap is observed around the 70-75th percentile for most cohorts (and for the 80th for the 1969 one). The large gender gap in lifetime earnings observed at the very top and at the very bottom fall sharply for the youngest cohorts making it flatter. [20] This patterns contrast markedly with those in the US, where the gap is J-shaped with the gap being smallest at

19. The gap in lifetime earnings is more pronounced across the distribution for the older than for the younger cohorts. For older cohorts, the gap is considerably larger at the top than at the bottom of the distribution. In contrast, for the 1989 cohort, the gap is largest around the 20th percentile (36%), lowest for the 75th percentile at around 25%, and is about 30% at the very top.

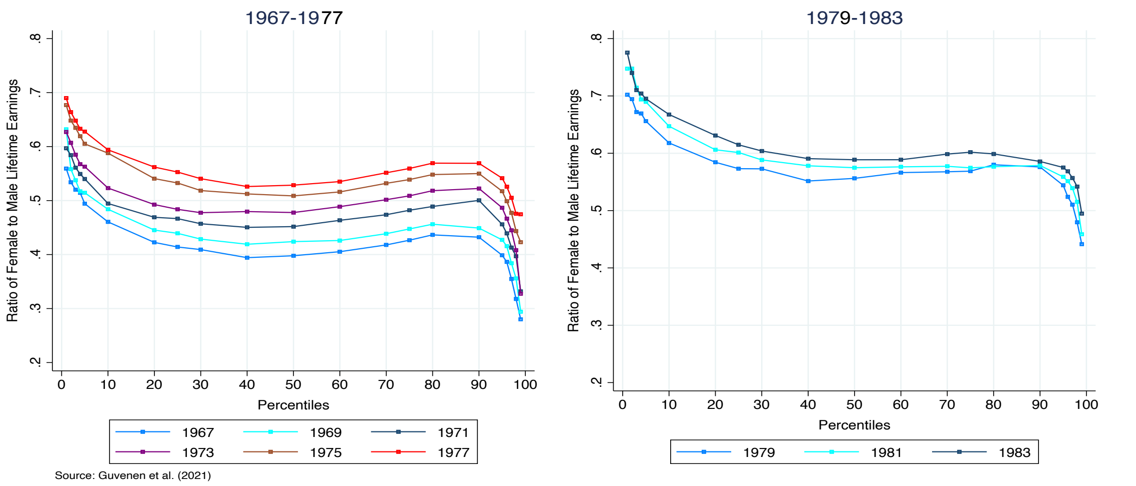
20. Indeed, the extent of the decline in the gender gap across cohorts varies considerably. This decline is more pronounced at the top than at the bottom of the distribution. The trend is almost flat at the 25th percentile (with the gap going from 37% to 35%), becoming steeper as we move up the distribution, with a fall from 49% to 31% at the 99th percentile.

Figure 4 – Gender ratios in lifetime earnings along the whole distribution

(a) France



(b) United States



Notes: Panel (a) displays the ratio of female to male lifetime earnings over the distribution of earnings in France across cohorts that entered the labor market between 1967 and 1989. Panel (b) displays the same statistic for selected percentiles of the distribution of lifetime earnings in the United States for cohorts between 1967 and 1983. For the U.S., the figures were provided to us by Greg Kaplan as part of the replication package for Guvenen et al. (2022).

the bottom of the distribution. In addition, there is a striking narrowing of the gender gap across the cohorts for the whole distribution in the United States, except at the top, where the gender gap remains remarkably stable across the post-1977 cohorts.

3.2 Country-Specific Patterns in the Light of the Literature

Several factors have been discussed in the literature to explain the cross-country differences in the *cross-sectional* gender pay gap. Blau and Kahn (2008) argue that the gender-specific factors (such as education, experience, discrimination) appear unlikely to account for the higher wage gap in the US. Instead, the differences in the gender pay ratio between the US and other countries may be driven by institutional factors affecting the distribution of wages, such as differences in sectoral heterogeneity and in the wage institutions. Such an assessment is in line with the papers showing that gender differences in industry and occupations play a key role in explaining the earnings gap, while factors related to human capital and discrimination tend to play a more modest role (Blau and Kahn (2017)). In particular, firm-specific wage premiums are an important source of wage inequality and the between-firm sorting channel explains part of the gender wage gap, as it leads to labour market segmentation of women into firms with lower wages (see among others Card et al. (2015), Casarico and Lattanzio (2024), Card et al. (2025) and for France, Coudin et al. (2018) and Palladino et al. (2025)).

Focusing on European countries, Christofides et al. (2013) show that the “unexplained part” of the gender gap is correlated with country-specific policies and institutions, and in particular wage setting institutions.[21] Wage setting institutions are relatively centralized in France, with a key role played by the national minimum wage and mandatory collective bargaining at the industry level.[22] In contrast to European systems, individual companies are key players in the US collective bargaining system (Jäger et al. (2024)). Deunionization and the decrease in the minimum wage (relative to the median wage) have been important in explaining changes in the distribution of wages in the US (e.g. Acemoglu et al. (2001), DiNardo et al. (1996), Fortin and Lemieux (1997), Lee (1999)). While the minimum wage has fallen sharply in the United States (from 51% to 32% of the median wage between 1967 and 2018), it has steadily risen in France, from 42.4% to 61% over the same period (see Figure A.2). Increases in the minimum wage translate into higher pay at the bottom of the earning distribution, where women are over-represented, and contribute to wage compression, which contributes to the reduction of the cross-sectional gender gap in France.[23]

Participation in the labour market can be an important source of cross-country differences. Olivetti (2014) documents that the labor force participation of women grew monotonically in the United States over the 20^{th} century, while France displays a slightly N-shaped pattern with a peak in the 1920s. Over our period of interest, the female par-

21. See also Matteazzi et al. (2018) for European countries.

22. See Fougère et al. (2018) for a detailed presentation of wage setting institutions in France.

23. See Kramarz et al. (2022). There are also spillover effects of the national minimum wage on the sectoral wage floors and on the earnings distribution (Fougère et al. (2018) and Aeberhardt et al. (2012)). Fougère et al. (2018) explain that these spillover effects are larger in France compared to those observed in the US.

ticipation rate increased steadily in both France and the US, but remained higher in the US throughout the period (see Figure A.3). Patterns of participation can be the result of differences in the structural transformations faced by each country, in particular the pace of the shift from agriculture to industry and then to services (Goldin (2024), Ngai and Petrongolo (2017), Ngai et al. (2024)). Cultural differences (e.g. Fernández (2007), Fernández (2013) or Fogli and Veldkamp (2011)), country-specific legislation affecting directly female activities or supporting the principle of equal pay for women and men (Bailey et al. (2024), Doepke et al. (2025)), as well as differences in part-time work, motherhood penalty, education and gender differences in returns to education may also explain country-specific gender gap developments.[24]

With these institutional factors in mind, in the next section, we analyze the changing role of several factors in explaining the narrowing of the gender gap in lifetime earnings in France. Our choice of focus is determined by the variables available in our data, which include working time, education, occupation, geographic location, as well as marital status and children.

4 Explaining the gender gap in lifetime earnings

In this section, we first analyse gender trends in lifetime earnings in order to understand the underlying forces explaining the narrowing of the gender gap in France and how this differs from the US case. We then estimate the role of several factors in explaining the lifetime earnings for men and women across cohorts, including working time, education and occupation, or geographic location. Using Oaxaca-Blinder decompositions, we show the changing role of various mechanisms across cohorts and across the distribution.

4.1 Gender trends in lifetime earnings

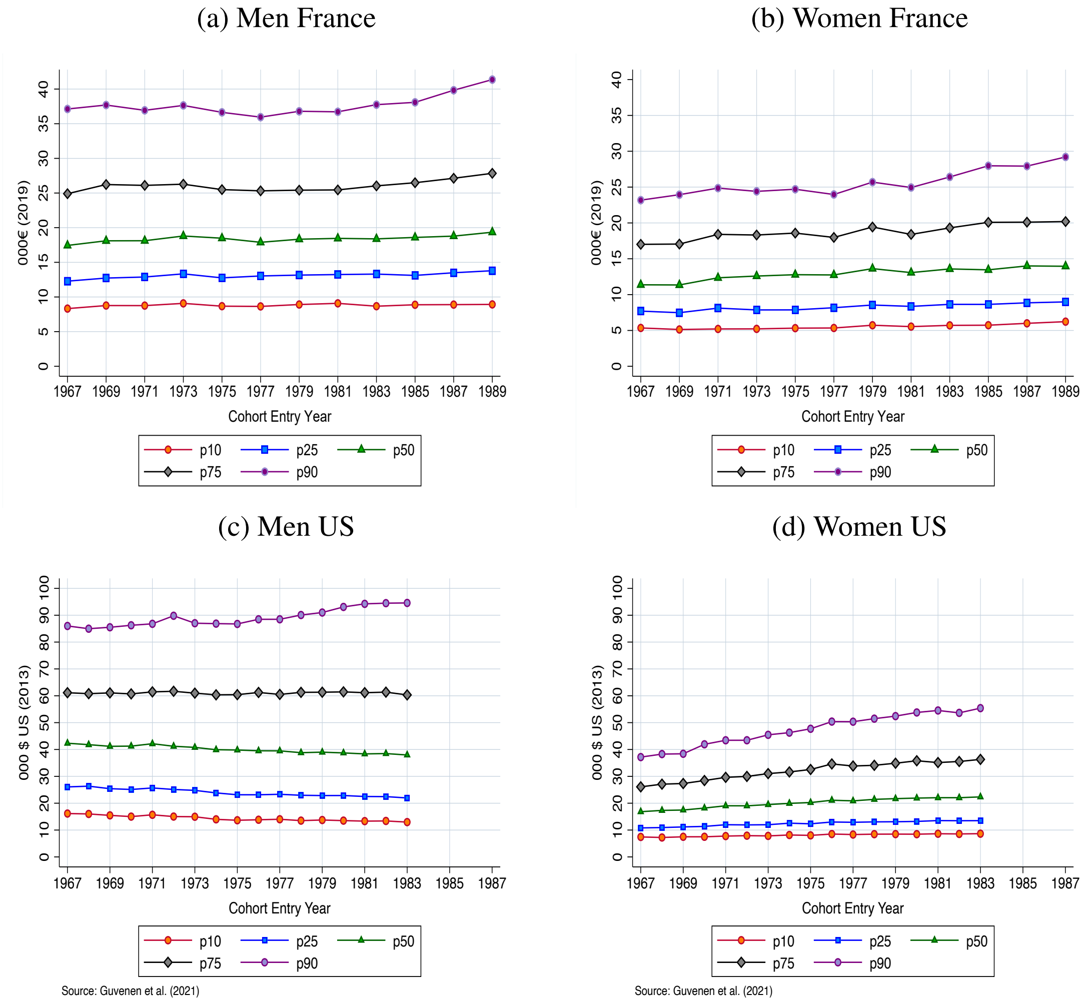
To understand the underlying forces behind the gender gap patterns, Figure 5 displays lifetime earnings for the 10th, 25th, 50th, 75th, and 90th percentiles of the distribution of lifetime earnings for men and women separately.[25] The upper panels show our results for France, while the lower panels present the corresponding figures for the US from Guvenen et al. (2022). Table 1 reports growth rates at selected points of the distribution for

24. See Meurs and Pora (2019) for a presentation of the main changes in gender pay equality legislation in France since the late 1960s. They also document that the persistence of the cross-sectional gender pay gap in France is related to the consequences of motherhood and reflects adjustments in mothers' working time.

25. Further discussion of inequality in lifetime earnings within each gender group is provided in Appendix C.

France and the US. [26] In France, we observe an increase in lifetime earnings throughout the whole distribution, both for men and women, except at the very top for men. In contrast, the figure reports the striking finding that in the post-1967 cohorts in the US, men below the 75th percentile experienced significant losses.

Figure 5 – Selected percentiles of lifetime earnings, by cohort and gender: France and 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. (2022), Figure 3. Left panels (a) and (c) are for men, and right panels (b) and (d) are for females. The data are in euros for France and dollars for the US.

For men, focusing on the cohorts common to both our data and that of Guvenen et al. (2022) (i.e. 1967-1983), we observe a more favorable evolution of earnings at the 10th percentile (cumulative growth of 4.2%) than at the 90th percentile (1.7%). This pattern reflects the decrease in labor income inequality that occurred in France following the

26. Table A.2 in the Appendix provides a more detailed set of figures obtained from our data.

Table 1 – Lifetime earnings growth for various percentiles: France & the U.S. (1967-1983)

	France		US	
	Men	Women	Men	Women
p10	4.17	6.76	-19.77	16.31
p25	8.31	12.3	-6.63	29.24
Median	5.43	19.46	-10.34	32.67
p75	4.54	13.48	14.28	46.75
p90	1.69	13.95	9.98	40.04
p99	-2.21	24.79	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. (2022), Table 1.

social unrest of May 68 and up to the early 80s.[27] This contrasts with the US, where Guvenen et al. (2022) document a strong decrease for the p10 (-20%) and an increase for the p90 (+10%). For mean and median lifetime earnings, we find large gains for the earlier cohorts (i.e. 1967 to 1973) and smaller gains for the younger ones (1973 to 1989). The pattern of gains differs across the distribution: it is monotonic for the bottom percentiles and U-shaped at the top. In particular, when broadening the period up to the end of the 80s (Figure 5), the cumulative earnings growth is roughly similar for the p10 and the p90. This reflects the increase in the earnings of the p90 observed for the younger cohorts, leading to higher inequality in lifetime earnings for the most recent cohorts.

In France, for women, we observe a larger increase at the top, with the growth rate of lifetime earnings being about twice as large for the p90 as for the p10 over the 1967-1983 cohorts (+6.8% for the p10 versus +14% for the p90). This pattern of faster growth for women at the top as compared to those at the bottom of the distribution is also observed in the US, although there both growth rates across cohorts and the gap between the top and the bottom are much larger than in France (+16% for the p10 vs. +40% 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 as women with high educational attainment started entering the labor force; 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

27. For a historical perspective see Atkinson et al. (2011) and Garbinti et al. (2018).

in the late 1960s/early 1970s is due to weaker positive selection as female labor market participation increased. [28]

We now return to the gender gaps reported in Figure 3. In France, women's earnings are furthest from those of men at the bottom of the distribution. In fact, for the cohorts entering in the 1970s, women's relative earnings at the 10th percentile decreased compared to the 1967 cohort (from 0.64 to 0.57). A possible explanation for this is that, in France, the minimum wage is high and binding, implying that differences in lifetime earnings at the bottom are largely due to years and hours worked. Below, we explore the role of working time, as well as other factors such as education, occupation and geography, in shaping the dynamics of the gender lifetime earnings gap.

4.2 Assessing the changing role of determinants of the gender gap

The richness of the French data allows us to examine which factors account for the observed gender gap in lifetime earnings and its dynamics. First, we have information on working time, including the number of years and the days worked per year, as well as on the prevalence of part-time employment. Second, men and women may differ in characteristics, particularly in terms of 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, and to account for family composition and the presence of children at home.

To examine the role of these different factors, we 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:

$$y_{i(g,c)} = \alpha_{gc} + \beta_{gc} X_i + \varepsilon_i \tag{2}$$

where $y_{i(g,c)}$ is the (log of) lifetime earnings of individual i born in cohort c of gender g, X_i are the characteristics of the individual, β_{gc} are the returns to characteristics which we allow to vary across cohorts and genders, 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. 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 characterized by higher wages than the rest of the country, but also by allowing individuals to accumu-

28. Unfortunately, there is no comparable study to Mulligan and Rubinstein (2008) that identifies whether or not there has been a change in the sign of selection in France.

late human capital that can result in higher earnings even once they move.[29] The second set of variables is obtained from the census: the highest educational degree obtained,[30] 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. Note that although we have information on the individual's occupation and industry each year, we do not use it in our core regressions as it varies over time, although below we provide some robustness analysis including occupations. The results of these estimates are discussed in subsubsection 4.2.1 below.

The resulting regressions allow us to perform a Oaxaca-Blinder decomposition, with the gender gap being expressed as

$$\bar{y}_{mc} - \bar{y}_{fc} = (\bar{X}_{mc} - \bar{X}_{fc})\beta_{mc} + (\beta_{mc} - \beta_{fc})\bar{X}_{fc}. \tag{3}$$

where $\bar{y}_{mc}$ and $\bar{y}_{fc}$ are, respectively, the average male and female (log of) lifetime earnings for cohort c and $\bar{X}_{gc}$ the average characteristics of cohort c of gender g. Note that for indicator variable regressors, such as diplomas, the decomposition depends on the base category. To prevent this choice from distorting our results, we normalize indicator variables relative to the mean, following Yun (2005). We perform this decomposition considering differences in average lifetime earnings and for selected percentiles of the distribution in subsubsection 4.2.2 to show the changing role of these various factors on the gender gap both across cohorts and across the distribution.

4.2.1 The changing determinants of lifetime earnings across cohorts

In this section, we present the results of regressions based on Equation 2 for men and women. In both cases, we find striking changes in the coefficients across cohorts. In particular, we show that there is a decrease in the returns to all educational attainments other than a Master's degree (and higher) for both men and women, while the gender gap in returns to education is decreasing but remains large. We also find a surprising increase in the returns to working part-time for women, which we discuss.

Table 2 reports the regression coefficients for men and women for selected cohorts and variables.[31] Our variables of interest are generally significant and have the expected

29. See Elass et al. (2024) for the effect of working experience gained in Paris. In Appendix E, we consider an additional variable, whether the individual was born in the Paris region, and explore its impact on earnings.

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

31. See Table A.3 and Table A.4 for the full results.

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 has a positive coefficient for men, this 'marriage premium' being a well-established stylized fact (cf. e.g., Antonovics and Town (2004) or Juhn and McCue (2017)), and having children tends to display a positive though often insignificant coefficient. In contrast, for women, both variables have insignificant coefficients, the 1977 cohort being the only one for which we find a significant and positive one. In fact, when we exclude working time from the regressions (regression not reported but available upon request), marriage and children have negative and highly significant coefficients that lose their significance once we control for overall years worked and part-time. This indicates that much of the child penalty is due to the intensive and extensive labor supply choices of mothers. [32]

For men, several of the coefficients change markedly across cohorts. For example, the return to years worked full-time increases for younger cohorts. The most striking change in the regressions concerns the coefficients on educational levels. The coefficient on a bachelor's degree more than halved between the 1967 and 1989 cohorts, declining from 23 to 9. In contrast, that on 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 over two 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. A large literature argued that skilled-biased technical change has increased the education wage premium and this may have affected most those at the very top of the distribution (Lindley and Machin (2016)). On the supply side, the increase in the share of workers with bachelor's degrees would tend to reduce their wage even with constant ability, while selection into higher education implies that unobserved ability is, on average, likely to be lower for those obtaining the degrees in younger cohorts, thus lowering average earnings. [33]

The regressions for women display similar results concerning both the coefficients on

32. See Kleven et al. (2024) for a discussion of the child penalty and cross-country evidence.

33. In Appendix subsection D we present several counterfactual exercises. Based on equation 2, we compute a counterfactual measure of lifetime earnings by using cohort-specific coefficients while keeping either the cohort's composition (in terms of characteristics such as education and working time, ... taken at their average values for the 1967 cohort) or the coefficients themselves (set at the values estimated for the 1967 cohort) constant. One of these exercises indicates that, given the fall in the return to all educational qualifications other than a master's degree, if the labor force had maintained the distribution of education observed for the 1967 cohort, lifetime earnings of men would have declined over the period instead of growing mildly (see Figure D.1).

Table 2 – Determinants of lifetime earnings by cohort and gender

	Men			Women		
	(1) 1967	(2) 1977	(3) 1989	(4) 1967	(5) 1977	(6) 1989
% Years Full Time	29.61***	31.23***	29.17***	22.58***	24.97***	23.10***
	(1.754)	(1.545)	(1.585)	(1.378)	(0.950)	(1.844)
% Years Part Time	14.91***	5.276*	2.124	8.373***	13.11***	9.201***
	(3.717)	(2.715)	(2.741)	(1.880)	(1.199)	(2.279)
% Years Paris	8.253***	8.048***	7.250***	5.437***	5.726***	9.179***
	(0.767)	(0.721)	(0.812)	(0.555)	(0.440)	(1.042)
High School	12.51***	6.973***	6.389***	6.212***	4.030***	3.767**
	(1.007)	(0.958)	(1.279)	(0.830)	(0.627)	(1.724)
Bachelor	22.97***	11.57***	9.306***	8.484***	6.920***	5.775***
	(1.055)	(1.110)	(1.308)	(0.956)	(0.672)	(1.768)
Master	28.15***	25.67***	22.60***	11.77***	9.417***	14.40***
	(1.698)	(1.087)	(1.256)	(1.669)	(0.769)	(1.806)
Ever Couple	3.476**	3.509***	3.978***	0.756	-0.829	0.430
	(1.350)	(1.102)	(1.095)	(0.663)	(0.728)	(1.445)
Ever Children	0.0674	0.920	-0.526	0.662	0.758*	0.937
	(0.677)	(0.627)	(0.663)	(0.466)	(0.408)	(0.839)
Observations	1,822	2,461	3,130	847	1,623	2,344
R-squared	0.453	0.429	0.335	0.537	0.558	0.205

Notes: The table displays regressions of male lifetime earnings for successive cohorts between 1967 and 1987 (see Table A.3 and Table A.4 for the full results), 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.

years of full-time work and diplomas, although in both cases the coefficients are lower than for men. The gender gap in the returns to education falls across cohorts, but remains large, with the return to either a bachelor's or a master's degree being 60% higher for men than for women for the youngest cohort, while for the oldest one they were, respectively, 2.7 and 2.4 times higher for men than for women.

For women, the coefficient on years of part-time work rises sharply across cohorts, doubling between the 1967 and the 1987 ones, though it declines again for the 1989 cohort; see Table A.4.[34] This increase in the returns in part-time work for women contrasts

34. Our counterfactual exercise in Appendix subsection D also illustrates the crucial role played by the

with existing evidence for the UK where the so-called *part-time penalty* has increased over time.[35] This decline has been largely attributed 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.[36]

4.2.2 Decomposing gender gaps in lifetime earnings

The Oaxaca-Blinder decomposition of the gender gap across cohorts (Equation 3) is reported in Figure 6.[37] The left panel depicts the absolute contributions of the various factors, while the right panel depicts the relative ones. In Figure 7, we complement our analysis by reporting additional Oaxaca-Blinder decompositions for the 25th, 50th, 75th, 90th, 95th, and 99th percentiles.

The unexplained component: decreasing across cohorts, and increasing across the distribution

The first point to note is that the unexplained contribution has declined over time, both in absolute terms and as a share of the total (Figure 6). It accounted for 60% of the gap for the early cohorts but for between 20 and 35% for younger ones. This trend is also evident in 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. Social and institutional changes are often cited as key drivers of shifts in the unexplained part of the gender gap, particularly through anti-discrimination policies (notably those on equal pay), evolving attitudes toward occupational access and promotions (see e.g., Meurs and Pora (2019) and Christofides et al. (2013)).

Another striking result is that the higher up we are in the distribution, the larger the unexplained part of the gap becomes (Figure 7). For the 25th percentile, the unexplained part is small and accounts for little of the overall gap, which is almost solely explained

endowment effect associated with the number of years working full-time: if women of the youngest cohorts had worked has many years full-time as those in the older cohort, their earnings would have risen considerably faster, by +35% instead of +23%; see Figure D.2.

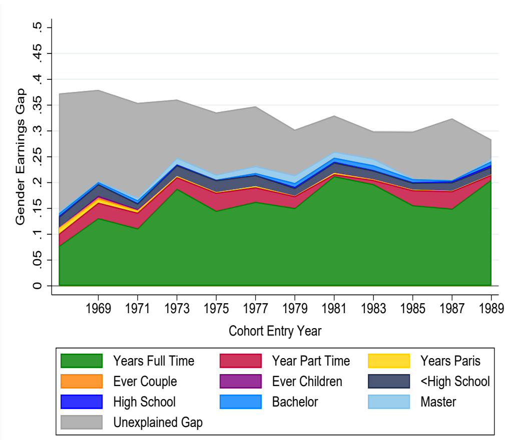
35. The part-time penalty is defined as the difference in hourly earnings between full- and part-time employees when controlling for a number of characteristics. Manning and Petrongolo (2008) examine the dynamics of the penalty in the UK between the mid-70s and the early 2000s and find that the penalty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

36. The legislation became effective in 2000, implying that the 1971 cohort is the first one to have been affected, with the youngest cohort having spent over half of their working life under the 35-hour regime.

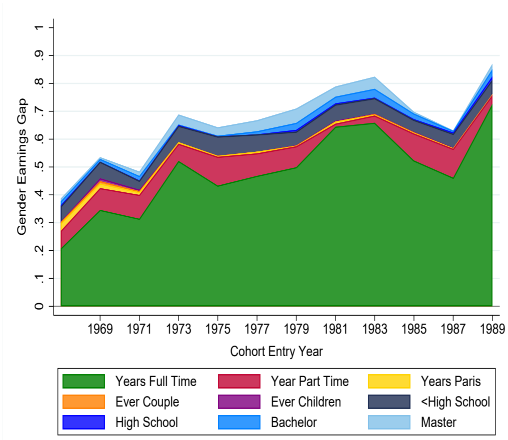
37. The regressions for the earnings equations being those reported in Table A.3 and Table A.4 in the Appendix.

Figure 6 – Oaxaca-Blinder decomposition of the Gender gap

(a) Decomposition of the gender gap: Absolute



(b) Decomposition of the gender gap: Relative



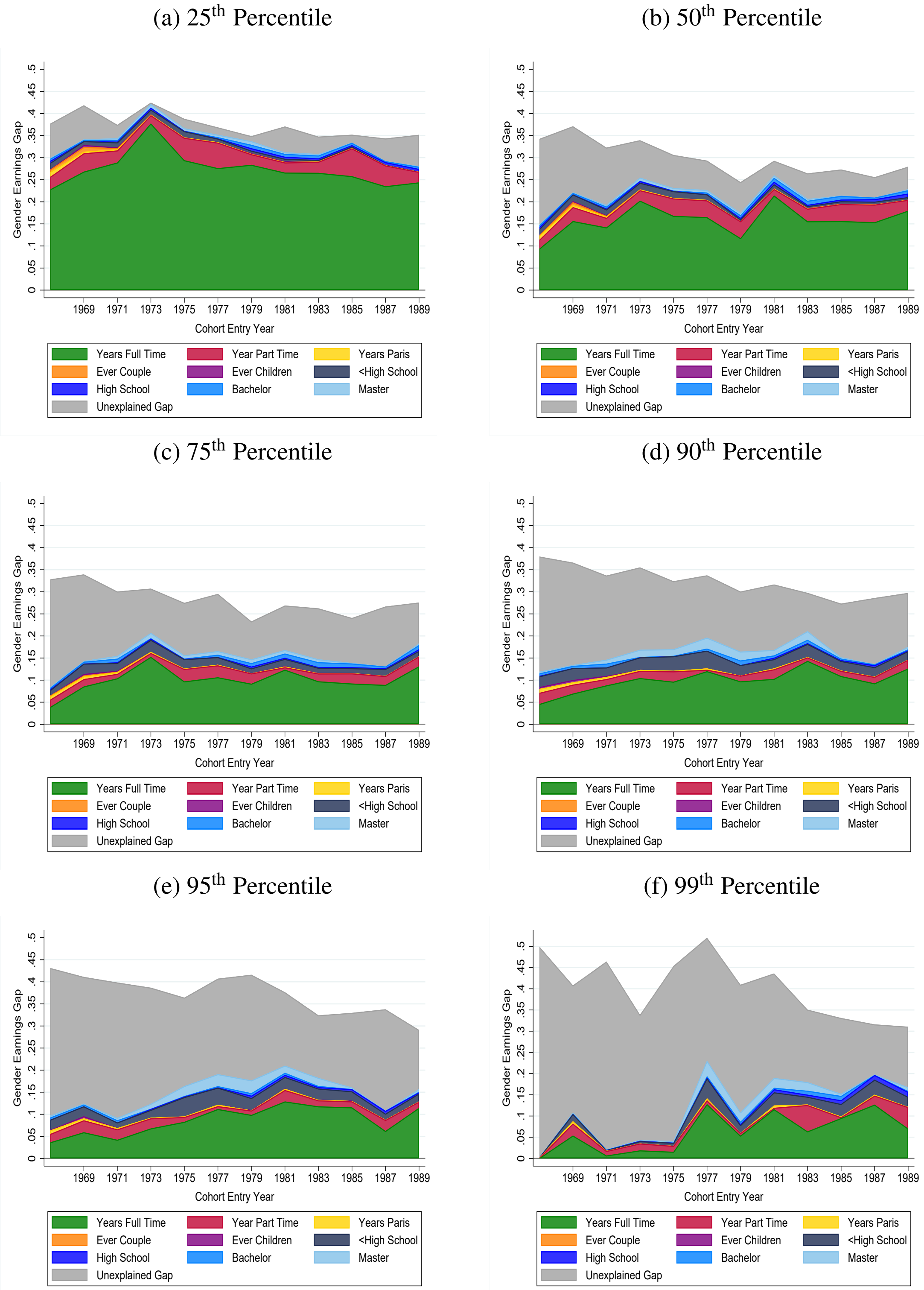
Notes: The figure displays the results of an Oaxaca-Blinder decomposition of the gap in lifetime earnings between males and females using a prior regression with pooled data as a reference. Panel (a) displays the evolution of the gender wage gap in absolute terms, and its decomposition between its explained (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 underlying regressions are reported in Table A.3 and Table A.4.

by differences in working time. This is not surprising. At any point in time, about 20% of those employed are receiving the minimum wage, hence the bottom quartile of the distribution of lifetime earnings will spend most of their working life at that wage level and consequently all differences in lifetime earnings stem primarily from the number of years worked and whether they do so full- or part-time. Our decomposition indicates that the gender gap is largely driven by women's lower share of years in full-time work, which accounts for approximately 70% of the gap. At the median, we observe a pattern similar to that found for mean earnings. The unexplained gap was initially larger at the median than at the 25th percentile, accounting for about half of the gap, but it declined across the cohorts. This reduction drove the overall reduction in the gap, being partly offset by an increase in the component due to differences in working time.

The size of the unexplained component is large higher up in the distribution, consistent with a glass-ceiling effect which cannot be explained by differences in endowments. Across all reported top percentiles, we observe a decline over time in the unobserved component, which accounted for the vast majority of the gap at the very top among older cohorts.

Overall, the large decline in the unexplained part has been accompanied by an in-

Figure 7 – Oaxaca Decomposition of the Gender Gap at Selected Percentiles



Notes: The figure displays the results of an Oaxaca-Blinder decomposition of the gap in lifetime earnings between males and females using a prior regression with pooled data as a reference. All panels display 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) at selected percentiles.

crease in the explained component, which has slowed the earnings convergence between genders. The most significant factor is working time, particularly the decline in the number of years worked full-time, although there was also a (much smaller) increase in the contribution from differences in educational attainment.

A countervailing force: the increasing role of part-time work for women

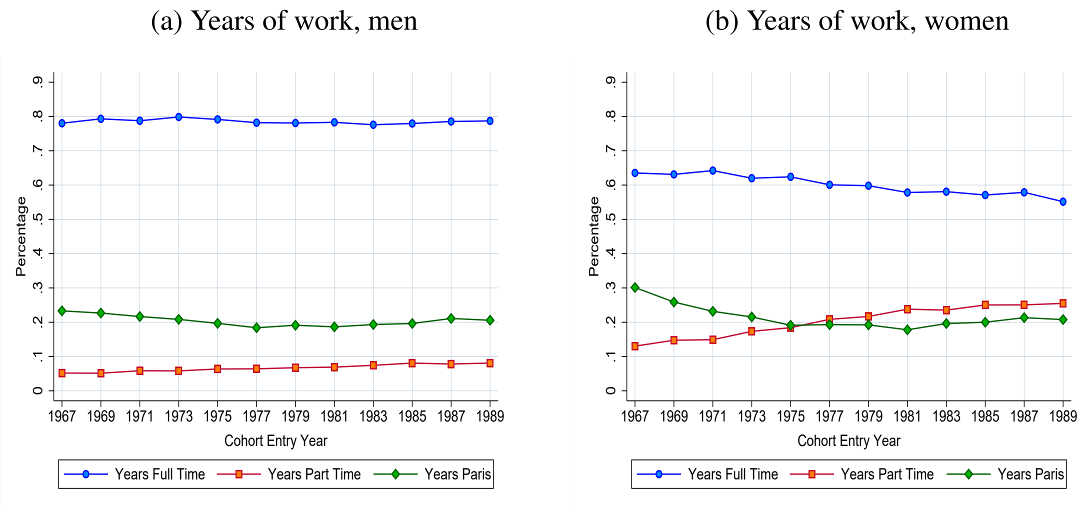
We have previously shown that much of the gap is explained by differences in working time, in line with what is observed in cross-sectional data.[38] What is particularly remarkable, however, is its dynamics.

The results reported in Figure 6 indicate that the contribution of working time (full and part-time together) has increased across cohorts, both in absolute and relative terms. Working time gaps account for only 28% of the gender gap for the 1967 cohort, yet they represent 77% of the gap for the 1989 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 23.6 in the 1967 cohort to 25.7 in the 1989 cohort,[39] men also increased the average number of years worked by about a year and a half (from to 25.6 to 27.2), implying only moderate convergence. On the other hand, the increase in years worked by women was exclusively in part-time employment. In fact, the share of years spent working full-time declined steadily across cohorts from 63% in the oldest one to 57% in the youngest. Hence, our results suggest that, in France, the increase in female labor force participation has not been a source of convergence in lifetime earnings.

In contrast to changes in women's labor force participation, differences in trends in working time appear to explain part of the divergent dynamics of the gender gap in lifetime earnings observed in France and the US. In the latter, women initially worked four fewer years than men (22 rather than 26)[40], with the difference narrowing to two years over the cohorts examined. As the authors argue, this implied that "the gap in lifetime earnings declined by more than its cross-sectional counterpart". By comparison, in France, the gap in overall years worked was initially smaller, at 2 years (23.6 and 25.6 years), fell by only 0.5 percentage points, and was accompanied by a shift from full- to part-time work. These dynamics in working time imply that the gap in lifetime earnings decreased less than in the cross-section of both earnings and hourly wages.[41]

38. See, for example, Blau and Kahn (2017) and Meurs and Ponthieux (2006).
39. Out of 31 years, see Figure A.4
40. As reported in Guvenen et al. (2022), footnote 30.
41. Because they use social security data, Guvenen et al. (2022) have no information on working hours or type of contract, hence it is not possible to gauge in their data the role of part-time employment. For evidence on the reduction in the gender gap in participation in the US since the 1950s see Blau and Kahn (2017), Figure 3.

Figure 8 – Endowments across cohorts: Working time



Notes: The 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 the Paris region *Ile-de-France*, the most populated and central French region.

The combined roles of education and occupation

The contribution of education to the gap increased up to the mid-1980s cohorts (Figure 6), despite a context of educational expansion.[42] During this period, the gap in educational attainment was initially small (with women being almost as educated as men) and eventually reversed, with women becoming more educated than men (Figure 9). The increase in the contribution of education to the gender gap in lifetime earnings thus reflects the persistence of a significant gender gap in returns to education, as shown in Table 2.[43]

Our results contrast with work using cross-sectional data, which 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.[44] A possible explanation for the difference between these cross-sectional findings and our lifetime earnings results is that the former typically control for occupations and industry, thus measuring the gender gap in returns to education *within* an industry-occupation category. This could also explain the large unexplained component of the gender gap at the top of the distribution we observe.

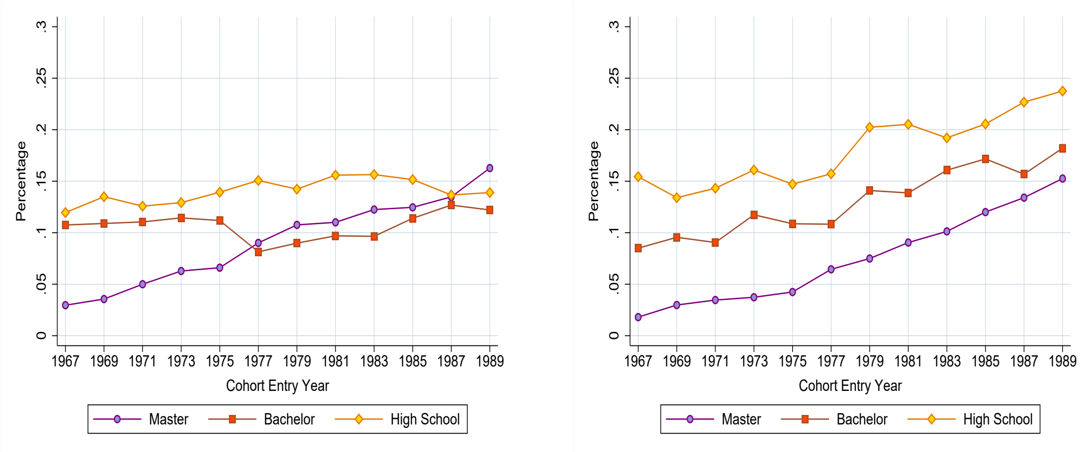
42. See Garnier et al. (1989), Duru-Bellat and Merle (2000) or Merle (2002) on the evolution of the French education system.

43. This observation suggests that differences in gender gaps between France and the US may partly be driven by distinct patterns of selection into employment, as already discussed in subsection 4.1. Mulligan and Rubinstein (2008) show that in the US, in the 1970s, women with lower education attainment were more likely to enter employment, whereas in the 1990s, it was primarily highly educated women who did so. Although no comparable study exists for France, the trends in Figure 9, which displays educational attainment across cohorts, suggest that the share of employed women with the highest level of education (master or more) was almost as large as for men.

44. 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.

Figure 9 – Educational endowments across cohorts

(a) Diplomas, men (b) Diplomas, women



Notes: The graphs display the percentage of individuals by male (left) and female (right) cohorts with specific degrees. Note that "Master" indicates individuals with a Master's degree or above. While "Other diplomas" regroups either vocational/technical high school diplomas, or diplomas of a lower degree than high school.

The rationale for not controlling for the individual's occupations is twofold. First, individuals change occupations during their working life, so occupation is not a time-invariant individual characteristic. Second, occupational choices are endogenous career decisions, hence, our decomposition captures the differences in earnings between men and women while treating occupations as an outcome based on their education level. By not including occupations, we allow the occupational choice to be an endogenous decision that can vary across cohorts. Our regressions thus capture returns to education that include differences in the choice of occupation and industry between the genders. The finding that these returns are more similar for younger cohorts than for older ones implies that, conditional on education, women are making occupational choices that are more similar to those of men in the younger cohorts than in the older ones.

To further investigate these mechanisms, we compute the proportion of years that the individual spent working in a specific occupation. In Appendix A (Figure A.5 and Figure A.6), we report the decomposition when controlling for the share of years that the individual spent working in a white-collar occupation in our regressions.[45] When examining the average gender gap in lifetime earnings (Figure A.5), we find that including years in a white-collar occupation reduces the unexplained part of the gap. However, this

45. The White Collar occupation corresponds to the category *cadres* in the French Socio-Professional Classification (PCS). In practice it is not only a category, but also a status of recognition inside companies, which many employees consider as an objective for their career trajectories. Becoming a *cadre* can often be a prerequisite for moving to upper positions within and across firms. As a consequence it can be a potential "glass ceiling" for women.

component displays a flat trend across cohorts, indicating that, on average, changes in occupational trajectories are not responsible for the reduction in the gender gap across cohorts.

Sharp differences emerge when we examine different points of the distribution (Figure A.6). As expected, this variable plays no role for the 25th percentile, where the share of individuals holding white-collar occupations is very small, and has a modest and roughly constant contribution to the gender gap at the 50th percentile. In contrast, including years employed in a white-collar occupation absorbs a large part of the unexplained variation at the top of the distribution. Except for the 99th percentile, this is an important factor contributing to the reduction of the gender gap across cohorts. One possible explanation for this is the presence of a glass ceiling, which has weakened over time: differences in lifetime earnings at the top could be due to differences in the likelihood of being promoted to higher-paying occupations.

Geographical heterogeneity

Lastly, we also investigate the potential role of years spent working in Paris (see Figure 8) in curbing gender convergence, as the greater the number of years the individual spent working in Paris, the higher their lifetime earnings are (see Table 2).[46] For the 1967 cohort, 22% of men in our sample worked in Paris, and this share declines slightly to reach 20% for the 1977 one and barely changed afterwards. In contrast, for the first cohort, 30% of women worked in Paris, indicating strong selection into employment on the basis of location. As more women entered the labor force, this share declined steadily, reaching 19% for the 1981 cohort, and remained around 20% afterwards. However, we find no narrowing of the gap in the returns to being born or working in the Paris region.

5 Conclusion

Using a long administrative panel dataset for France, we provide the first in-depth analysis of the level, trend, and distribution of the gender gap in lifetime earnings, and analyse their key drivers.

Our empirical contribution relies on multiple cohorts born between 1942 and 1964, tracking their entire careers from ages 25 to 55. Comparing our results with the US case, we find that the gender gap in lifetime earnings has remained significantly smaller in France throughout the period. Moreover, while the US has seen a striking narrow-

46. This captures both the effect of having been born in the Paris region, which can confer, for example, educational advantages, and that from years spent working in Paris, potentially in more productive firms. See Appendix E, where we examine in detail the role of location for lifetime earnings.

ing of the gap between cohorts across the whole distribution (except at the very top), in France, we observe a sharp narrowing only at the top and bottom of the distribution for the youngest cohorts. We show that these patterns reflect fundamental differences in lifetime earnings dynamics between the two countries. In France, lifetime earnings have increased across the entire distribution for both men and women. [47] In contrast, in the US, men below the median have experienced losses.

We show how the influence of various factors (working time and part-time employment, education and occupation, family composition, and geographical location) has changed across cohorts in shaping the evolution of the gender gap in lifetime earnings in France. First, the contribution of unobserved factors decreases across cohorts but increases across the distribution. Second, this sharp decline in the unexplained part has been accompanied by a growing role of observable factors. The most important effect comes from working time and, more specifically, from the decline in the years worked full time, which has slowed down the convergence across genders. Third, differences in educational attainment also play a role, albeit to a lesser extent.
Our results point to a variety of mechanisms affecting gender convergence in lifetime earnings. At the bottom of the distribution, the minimum wage helps reduce earnings disparities, while working time remains the primary driver of the gender gap in lifetime earnings. At the top, our results are consistent with a glass-ceiling effect, which has weakened over time. In addition, the increase in educational attainment and the narrowing of the gender gap in returns to education have also contributed to the reduction in the lifetime earnings gap.

While there has been a long-standing interest in lifetime earnings, data limitations explain why the empirical literature on the dynamics of lifetime earnings remains limited. Our findings highlight the need for more cross-country analysis based on lifetime earnings to assess long-term dynamics of the gender pay gap across different contexts.

47. Except for men at the very top.

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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	0.875	0.062	0.044	0.879	0.156	0.092
1977	0.224	0.147	0.102	0.203	0.164	0.116
1983	0.251	0.216	0.113	0.197	0.225	0.151
1989	0.424	0.219	0.117	0.331	0.267	0.138

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

Table A.2 – 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	2.98	6.03	-4.16	-0.42	8.21	6.22	5.98	5.42	1.18	-1.57	-9.91
	Annualised	0.99	2.01	-1.39	-0.14	2.74	2.07	1.99	1.81	0.39	-0.52	-3.30
73-89	Cumulative	7.03	3.98	12.20	6.89	1.70	3.12	3.11	4.63	9.67	9.14	15.02
	Annualised	0.88	0.50	1.52	0.86	0.21	0.39	0.39	0.58	1.21	1.14	1.88
67-89	**Cumulative**	**10.22**	**10.25**	**7.52**	**6.44**	**10.05**	**9.54**	**9.28**	**10.30**	**10.96**	**7.43**	**3.62**
	Annualised	0.93	0.93	0.68	0.59	0.91	0.87	0.84	0.94	1.00	0.68	0.33
67-83	Cumulative	4.11	5.26	-2.29	1.69	8.07	7.18	4.43	4.71	0.86	0.83	-1.19
	Annualised	0.51	0.66	-0.29	0.21	1.01	0.90	0.55	0.59	0.11	0.10	-0.15
Men												
67-73	Cumulative	4.58	7.80	4.59	9.07	8.58	8.45	8.77	5.50	1.39	-1.16	-9.17
	Annualised	1.53	2.60	1.53	3.02	2.86	2.82	2.92	1.83	0.46	-0.39	-3.06
73-89	Cumulative	5.83	2.90	0.85	-1.66	3.40	3.95	2.88	5.98	9.90	9.97	13.77
	Annualised	0.73	0.36	0.11	-0.21	0.42	0.49	0.36	0.75	1.24	1.25	1.72
67-89	**Cumulative**	**10.67**	**10.92**	**5.48**	**7.25**	**12.27**	**12.73**	**11.90**	**11.81**	**11.43**	**8.70**	**3.34**
	Annualised	0.97	0.99	0.50	0.66	1.12	1.16	1.08	1.07	1.04	0.79	0.30
67-83	Cumulative	4.60	5.43	-1.72	4.17	8.31	7.23	5.70	4.54	1.69	2.36	-2.21
	Annualised	0.57	0.68	-0.21	0.52	1.04	0.90	0.71	0.57	0.21	0.29	-0.28
Women												
67-73	Cumulative	6.10	10.72	-8.68	-2.40	2.16	8.06	9.84	7.65	5.27	6.16	9.12
	Annualised	2.03	3.57	-2.89	-0.80	0.72	2.69	3.28	2.55	1.76	2.05	3.04
73-89	Cumulative	18.48	10.86	27.39	19.31	14.24	12.21	9.43	10.24	19.67	28.92	32.06
	Annualised	2.31	1.36	3.42	2.41	1.78	1.53	1.18	1.28	2.46	3.61	4.01
67-89	**Cumulative**	**25.71**	**22.74**	**16.33**	**16.44**	**16.71**	**21.25**	**20.20**	**18.68**	**25.98**	**36.87**	**44.10**
	Annualised	2.34	2.07	1.48	1.49	1.52	1.93	1.84	1.70	2.36	3.35	4.01
67-83	Cumulative	15.91	19.46	1.79	6.76	12.30	17.40	14.26	13.48	13.95	22.32	24.79
	Annualised	1.99	2.43	0.22	0.84	1.54	2.18	1.78	1.69	1.74	2.79	3.10

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. (2022).

Table A.3 – 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	(12) 1989
% Years Full Time	29.61***	30.39***	30.75***	33.13***	31.99***	31.23***	31.19***	29.44***	31.15***	32.60***	35.33***	29.17***
	(1.754)	(1.763)	(1.693)	(1.555)	(1.489)	(1.545)	(1.436)	(1.555)	(1.828)	(1.552)	(4.068)	(1.585)
% Years Part Time	14.91***	12.05***	11.58***	4.094	10.13***	5.276*	4.747*	0.644	1.042	7.016***	9.914	2.124
	(3.717)	(3.409)	(3.068)	(2.845)	(2.626)	(2.715)	(2.466)	(2.595)	(3.006)	(2.429)	(6.411)	(2.741)
% Years Paris	8.253***	7.216***	9.145***	8.814***	6.114***	8.048***	8.133***	8.912***	8.917***	7.354***	13.91***	7.250***
	(0.767)	(0.716)	(0.727)	(0.662)	(0.668)	(0.721)	(0.646)	(0.713)	(0.844)	(0.684)	(1.766)	(0.812)
Elementary	1.844**	2.248**	1.358	1.189	0.612	0.506	0.949	-0.423	-0.643	0.156	1.090	-0.738
	(0.904)	(0.919)	(0.908)	(0.906)	(0.887)	(0.993)	(1.021)	(1.194)	(1.579)	(1.397)	(4.676)	(2.241)
Junior High	6.859***	8.133***	8.492***	7.653***	5.018***	4.690***	3.708***	3.404***	2.875*	3.662***	3.454	2.348
	(1.423)	(1.288)	(1.317)	(1.255)	(1.291)	(1.383)	(1.175)	(1.249)	(1.468)	(1.271)	(3.331)	(1.771)
Professional	4.841***	3.827***	3.321***	3.377***	2.782***	2.350***	2.547***	2.215**	2.451**	1.839**	2.214	2.100*
	(0.784)	(0.807)	(0.817)	(0.792)	(0.744)	(0.829)	(0.831)	(0.875)	(0.980)	(0.804)	(2.106)	(1.125)
High School	12.51***	12.48***	9.485***	8.577***	7.929***	6.973***	7.651***	6.463***	6.231***	6.595***	6.246**	6.389***
	(1.007)	(0.974)	(0.992)	(0.943)	(0.888)	(0.958)	(0.951)	(0.989)	(1.127)	(0.932)	(2.493)	(1.279)
Bachelor	22.97***	19.70***	19.83***	16.00***	16.22***	11.57***	12.09***	11.00***	10.10***	10.43***	10.24***	9.306***
	(1.055)	(1.042)	(1.032)	(0.972)	(0.935)	(1.110)	(1.046)	(1.093)	(1.259)	(0.992)	(2.545)	(1.308)
Master	28.15***	24.33***	23.52***	23.90***	22.83***	25.67***	24.75***	22.96***	24.29***	24.66***	33.78***	22.60***
	(1.698)	(1.522)	(1.326)	(1.152)	(1.096)	(1.087)	(1.009)	(1.067)	(1.196)	(0.978)	(2.540)	(1.256)
Dipl Missing	3.144***	5.097***	4.439***	4.681***	5.015***	5.726***	8.346***	8.844***	6.446***	4.522***	3.260	2.735
	(1.120)	(1.165)	(1.274)	(1.228)	(1.267)	(1.244)	(1.327)	(1.449)	(1.633)	(1.334)	(3.387)	(2.283)
Ever Couple	3.476**	1.933	2.296*	1.800	1.804	3.509***	3.826***	2.329**	3.000***	3.164***	3.364	3.978***
	(1.350)	(1.351)	(1.361)	(1.156)	(1.125)	(1.102)	(0.965)	(0.966)	(1.099)	(0.871)	(2.375)	(1.095)
Ever Children	0.0674	1.964***	2.126***	2.448***	1.476**	0.920	0.478	1.097**	0.661	1.651***	2.879**	-0.526
	(0.677)	(0.693)	(0.716)	(0.651)	(0.643)	(0.627)	(0.530)	(0.539)	(0.626)	(0.526)	(1.355)	(0.663)
Coupl Missing	1.778	-0.0273	-0.732	2.389	0.720	-0.721	2.023	1.438	2.049	3.267**	4.747	2.303
	(1.498)	(1.572)	(1.665)	(1.584)	(1.534)	(1.543)	(1.421)	(1.462)	(1.588)	(1.268)	(3.411)	(1.470)
Constant	-14.48***	-14.57***	-14.98***	-16.16***	-14.18***	-14.03***	-14.50***	-11.46***	-12.93***	-15.09***	-19.65***	-11.22***
	(1.955)	(1.964)	(1.944)	(1.758)	(1.689)	(1.706)	(1.626)	(1.712)	(1.957)	(1.655)	(4.397)	(1.944)
Observations	1,822	1,932	2,447	2,651	2,599	2,461	2,651	2,548	2,771	2,757	2,907	3,130
R-squared	0.453	0.422	0.399	0.423	0.404	0.429	0.461	0.414	0.356	0.448	0.177	0.335

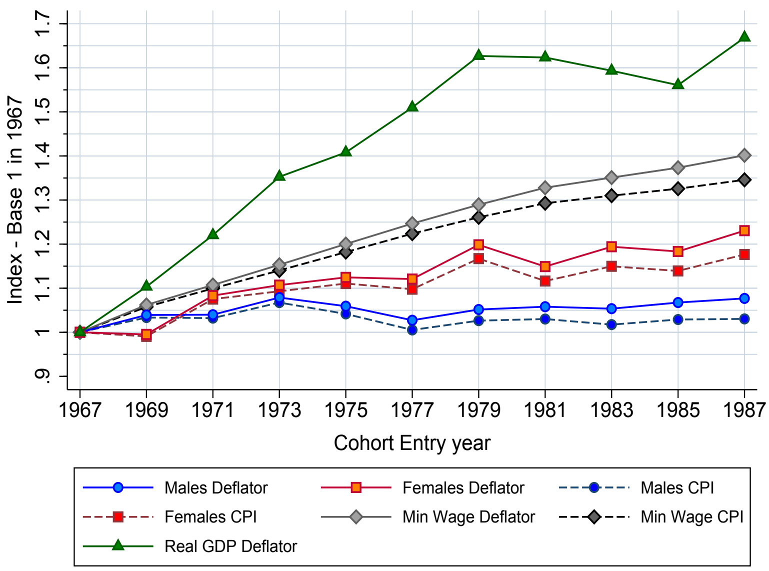
Notes: The table displays regressions of male lifetime earnings for successive cohorts between 1967 and 1989, on a set of control variables. These include labor supply measures: percentage of years worked full time and years worked part-time; dummies for highest education level from Elementary to Master (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 worked in the Paris region. Dummies for missing observations of Diploma and couple status are included as well. Standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

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	(12) 1989
% Years Full Time	22.58***	22.88***	25.44***	25.83***	26.69***	24.97***	26.21***	26.45***	27.33***	28.00***	28.32***	23.10***
	(1.378)	(1.289)	(1.059)	(1.049)	(0.881)	(0.950)	(0.984)	(0.891)	(1.100)	(0.941)	(1.157)	(1.844)
% Years Part Time	8.373***	8.720***	12.05***	12.65***	15.73***	13.11***	13.45***	14.65***	13.64***	16.42***	15.72***	9.201***
	(1.880)	(1.773)	(1.528)	(1.430)	(1.165)	(1.199)	(1.211)	(1.074)	(1.349)	(1.132)	(1.365)	(2.279)
% Years Paris	5.437***	5.339***	4.710***	3.825***	4.973***	5.726***	5.250***	5.193***	6.996***	6.195***	7.862***	9.179***
	(0.555)	(0.546)	(0.477)	(0.481)	(0.401)	(0.440)	(0.459)	(0.417)	(0.527)	(0.432)	(0.510)	(1.042)
Elementary	0.319	-0.0119	-0.0369	0.316	0.792	0.205	0.516	-0.0754	-0.378	1.135	0.0653	-0.810
	(0.750)	(0.677)	(0.660)	(0.663)	(0.546)	(0.609)	(0.799)	(0.700)	(0.969)	(0.928)	(1.328)	(2.882)
Junior High	2.462**	3.879***	2.611***	2.985***	2.556***	2.192***	2.571***	1.295*	1.081	2.355***	1.809**	1.886
	(0.965)	(0.955)	(0.812)	(0.819)	(0.703)	(0.721)	(0.861)	(0.696)	(0.833)	(0.710)	(0.894)	(2.267)
Professional	2.370***	2.140***	2.034***	2.399***	2.759***	1.894***	2.048***	1.374**	1.363**	1.856***	1.002	1.808
	(0.751)	(0.664)	(0.640)	(0.636)	(0.525)	(0.569)	(0.717)	(0.584)	(0.684)	(0.557)	(0.724)	(1.686)
High School	6.212***	5.842***	4.026***	4.295***	5.013***	4.030***	5.211***	3.854***	2.968***	4.462***	3.407***	3.767**
	(0.830)	(0.788)	(0.722)	(0.700)	(0.588)	(0.627)	(0.750)	(0.609)	(0.730)	(0.585)	(0.753)	(1.724)
Bachelor	8.484***	5.945***	7.444***	7.419***	8.300***	6.920***	6.007***	5.331***	5.572***	6.430***	6.130***	5.775***
	(0.956)	(0.853)	(0.794)	(0.737)	(0.624)	(0.672)	(0.781)	(0.643)	(0.751)	(0.604)	(0.792)	(1.768)
Master	11.77***	10.50***	9.549***	13.83***	14.83***	9.417***	12.78***	10.76***	14.34***	13.82***	15.09***	14.40***
	(1.669)	(1.283)	(1.058)	(1.024)	(0.810)	(0.769)	(0.873)	(0.695)	(0.828)	(0.649)	(0.817)	(1.806)
Dipl Missing	1.448	1.205	1.545	2.493**	1.934**	2.467***	3.151***	2.166**	1.323	3.178***	2.712**	3.404
	(0.951)	(0.882)	(1.000)	(1.001)	(0.872)	(0.911)	(1.035)	(0.923)	(1.171)	(0.895)	(1.079)	(3.247)
Ever Couple	0.756	-0.547	0.427	1.319	0.240	-0.829	0.544	1.410**	0.184	0.858	1.008	0.430
	(0.663)	(0.707)	(0.724)	(0.819)	(0.631)	(0.728)	(0.775)	(0.615)	(0.726)	(0.622)	(0.663)	(1.445)
Ever Children	0.662	0.161	-0.213	-0.249	-0.251	0.758*	0.257	-0.0627	0.243	0.437	0.0567	0.937
	(0.466)	(0.465)	(0.440)	(0.493)	(0.418)	(0.408)	(0.427)	(0.332)	(0.412)	(0.326)	(0.396)	(0.839)
Coupl Missing	1.203	-0.350	1.187	0.234	0.557	1.125	-0.470	0.587	1.944*	1.912**	0.201	0.166
	(0.886)	(0.952)	(1.007)	(1.204)	(0.978)	(0.987)	(1.054)	(0.893)	(1.124)	(0.875)	(0.968)	(1.819)
Constant	-7.332***	-5.647***	-7.659***	-8.913***	-9.703***	-7.371***	-8.864***	-9.390***	-8.714***	-11.24***	-10.55***	-6.020**
	(1.299)	(1.289)	(1.176)	(1.231)	(0.980)	(1.096)	(1.242)	(1.020)	(1.260)	(1.061)	(1.254)	(2.400)
Observations	847	881	1,331	1,514	1,567	1,623	1,774	1,745	1,881	2,058	2,153	2,344
R-squared	0.537	0.571	0.550	0.532	0.645	0.558	0.535	0.582	0.533	0.594	0.549	0.205

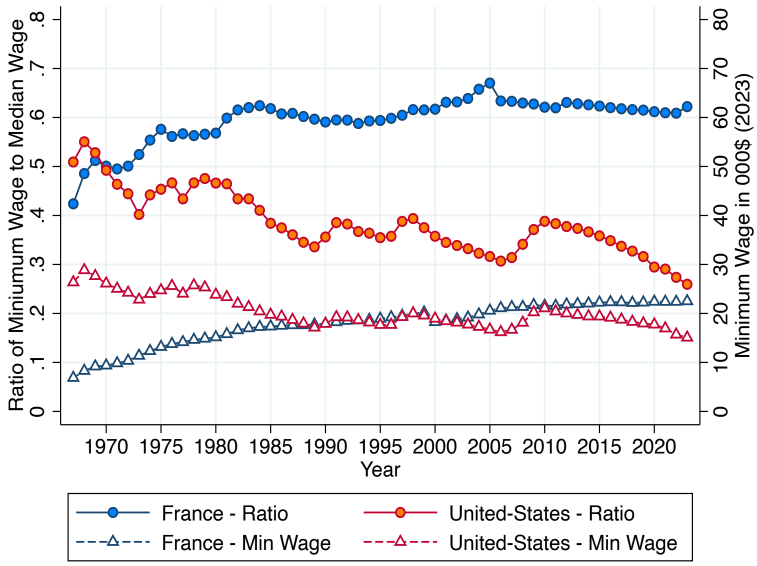
Notes: The table displays regressions of female lifetime earnings for successive cohorts between 1967 and 1989, on a set of control variables. See notes Table A.3

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



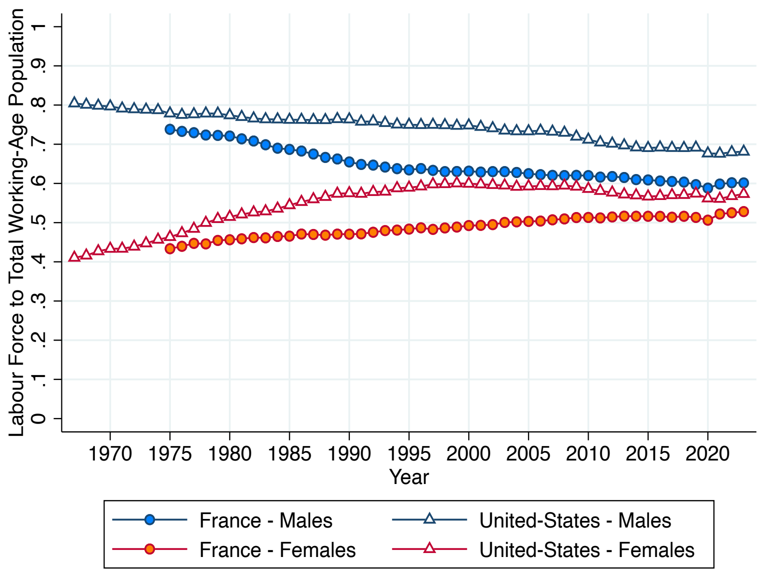
Notes: The graph displays series of median lifetime earnings, minimum wage and real GDP, indexed at one in 1967. CPI series were deflated using the consumer prince index while Deflator series were deflated using the personal consumer expenditures price index.

Figure A.2 – Minium Wage Relative to Median Wage, France and United-States



Notes: The graph displays series of the legal minimum wage as well as its ratio to the median wage, separately for France and the United-States. Series are expressed in 2023 thousands US dollars, and converted from euros using the current exchange rate. The data is from OECD, available in its website .

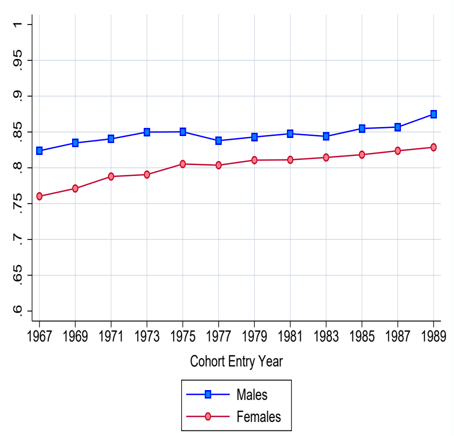
Figure A.3 – Labor Force Participation by Gender, France and the United States



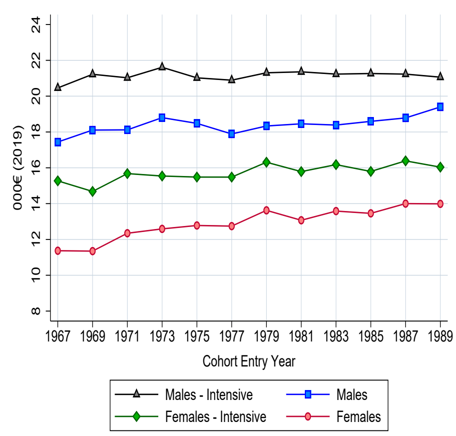
Notes: The graph displays time series of the ratio of the working population to the total working-age population by gender and country, as provided by the OECD website.

Figure A.4 – Lifetime income by cohort, intensive and extensive margin

(a) Percentage of years worked



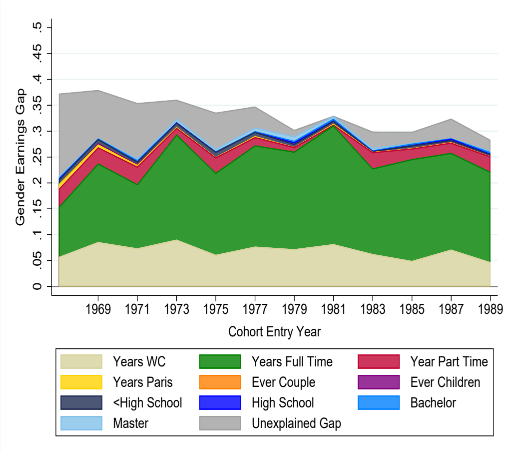
(b) Lifetime earnings



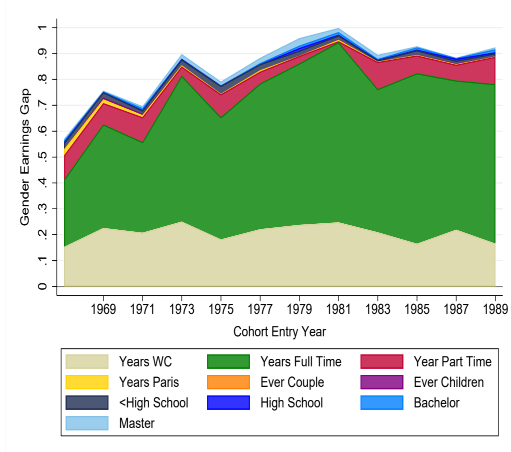
Notes: Panel (a) displays the percentage of years worked over the lifetime as a share of the number of possible years (ranging between 28 and 31 depending on the number of missing years) for a cohort of each gender that entered the labor market in a given year. Panel (b) displays the median lifetime 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) and defined as the average lifetime income per year worked.

Figure A.5 – Oaxaca-Blinder decomposition: Gender gap - Including White Collar Years

(a) Decomposition of the gender gap: Absolute



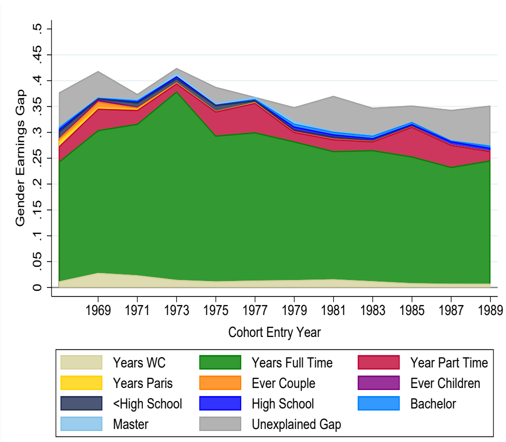
(b) Decomposition of the gender gap: Relative



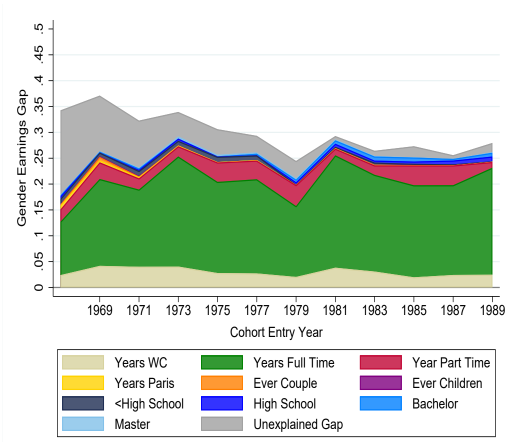
Notes: The figure displays the results of an Oaxaca-Blinder decomposition of the gap in lifetime earnings between males and females using a prior regression with pooled data as a reference. Panel (a) displays the evolution of the gender wage gap in absolute terms, and its decomposition between its explained (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 between 10 to 20 percent of the 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.

Figure A.6 – Oaxaca-Blinder Decomposition of the Gender Gap at Selected Percentiles - Including White Collar Years

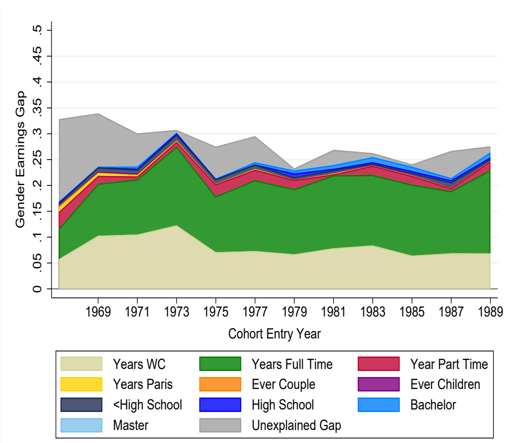
(a) 25th Percentile



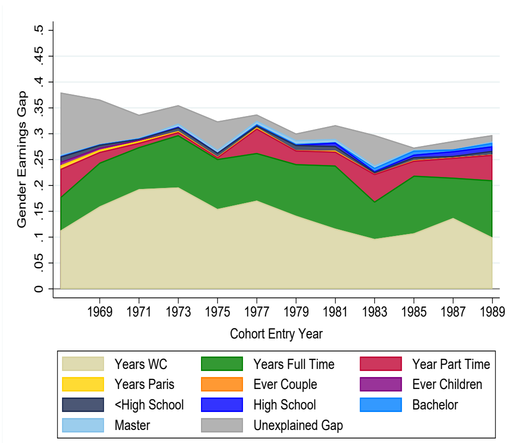
(b) 50th Percentile



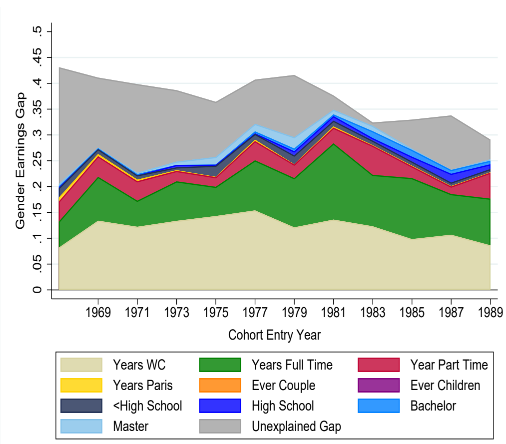
(c) 75th Percentile



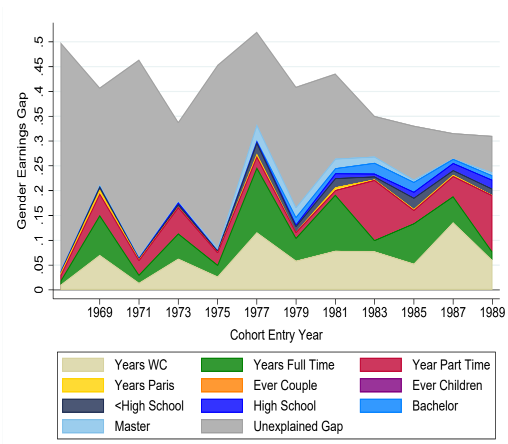
(d) 90th Percentile



(e) 95th Percentile



(f) 99th Percentile



Notes: The figure displays the results of an Oaxaca-Blinder decomposition of the gap in lifetime earnings between males and females using a prior regression with pooled data as a reference. All panels display 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) at selected percentiles.

B Cross-sectional versus lifetime earnings

This Appendix examines how similar the dynamics of lifetime earnings are to those obtained when we look at a cross-section of individuals. Before doing that, we report age profiles for men and women, which help us understand the dynamics behind the cross-section.

In Figure B.1 we plot median earnings at each age for each of the cohorts we observe, separately for males and females. The dashed lines guide us through a cohort's lifetime. The colored 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. Note that missing data points are due to data not being collected in 1981, 1983, and 1990.

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. (2022) 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. (2022). 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 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.

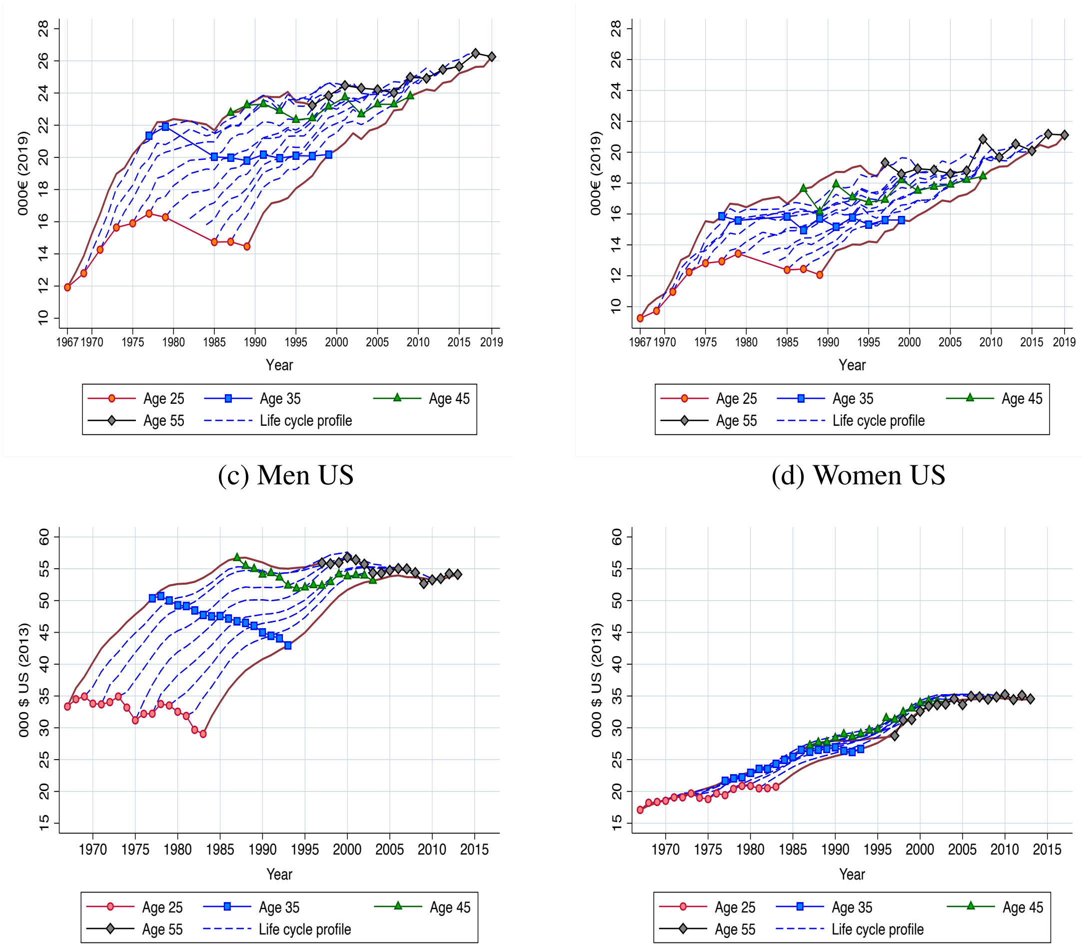
Men in the 1967 cohort experienced an increase in wages of 88% between ages 25 and 35 and of only 21% between ages 35 and 55. For the 1989 cohort, these figures were respectively 41% and 30%. This implies that although earnings roughly doubled for both cohorts between age 25 and age 55, for the oldest 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 half in the two subsequent ones. 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.

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

Figure B.1 – Age profiles of median earnings by cohort

(a) Men France

(b) Women France



(c) Men US

(d) Women US

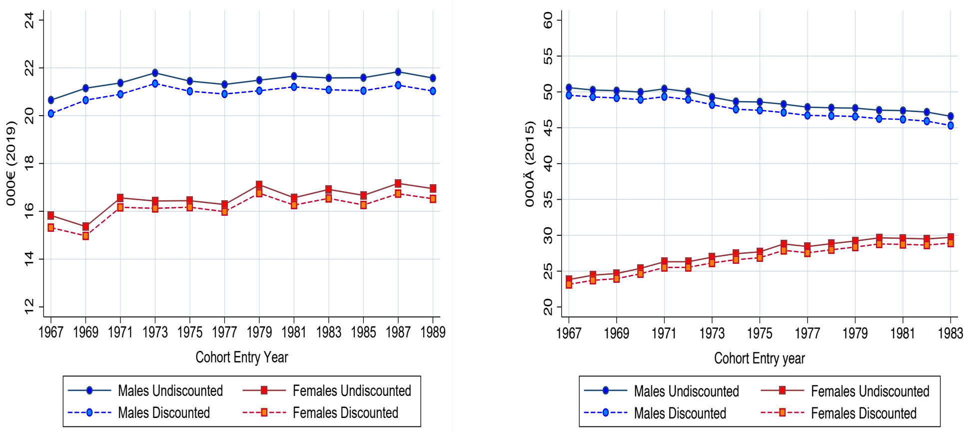
Sources: Our own computations for France, Guvenen et al. (2022) for the US.
Notes: Panels (a) and (c) display the age profiles of male cohorts in France and the US, respectively; Panels (b) and (d) display the age profiles of female cohorts in France and the US, respectively. Each dot represents the 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.

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. A notable difference with the US is 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 growth rates for the earnings of 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); see, for example, Hakim (1993). 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 (Altonji and Blank (1999) and Meurs and Ponthieux (2006)). 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.

Figure B.2 – 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.

To highlight the importance of changes over the life-cycle, we compute a discounted value of lifetime earnings, which are reported in Figure B.2. 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 B.1 for both France and the US. 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 1989 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.

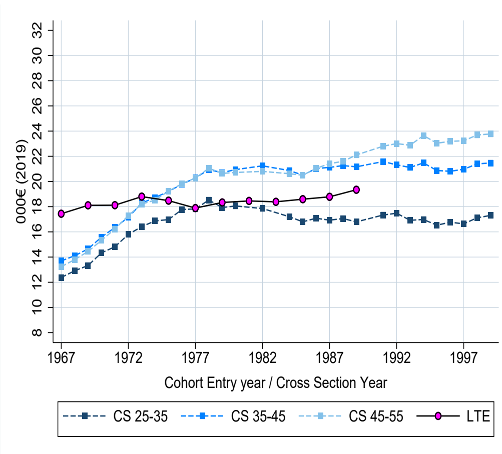
Figure B.3 compares lifetime earnings in France with cross-sectional earnings computed for various age groups for both men and women. We consider three groups, 25 to 35 year-olds, 35 to 45 year-olds, and 45 to 55 year-olds, and compute for each group median and mean earnings in a particular year. For 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, 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. We report cross-sectional earnings from 1967 to 1997.

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 earning losses compared to earlier cohorts since the 1970s, while those aged 45 to 55 have seen consistent earnings gains.

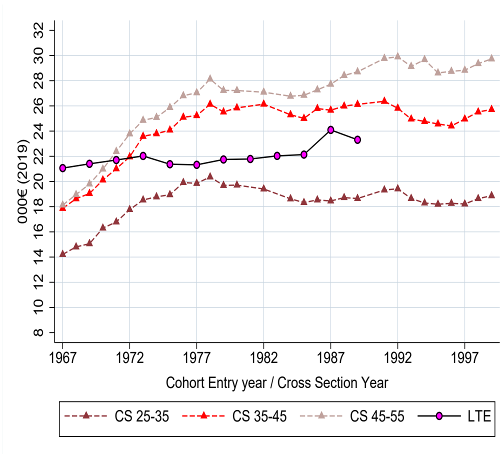
Panels (c) and (d) of Figure B.3 perform the same analysis for women. Growth is faster than for men, but otherwise the graphs display similar dynamics. It is particularly striking that initially median earnings in the cross-section are virtually identical for all age groups. They then grow together up 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.

Figure B.3 – Approximations of Lifetime Earnings by Earnings at Selected Age Periods

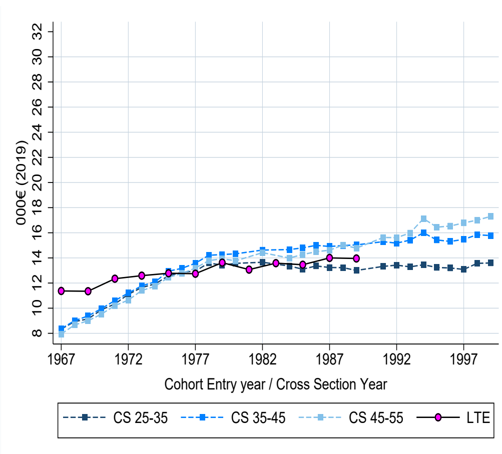
(a) Median - Men



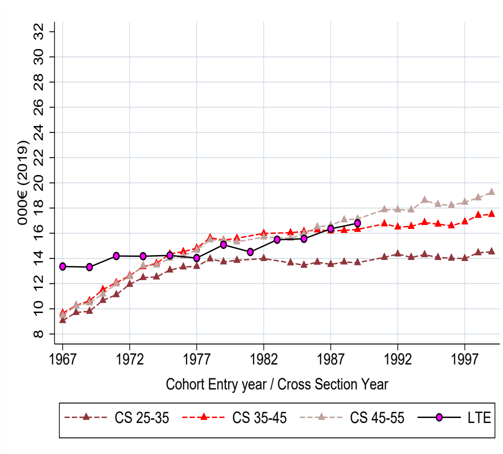
(b) Mean - Men



(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.

C Inequality in lifetime earnings

This appendix examines further the dynamics of lifetime earnings inequality. We start by reporting various inequality indicators in Figure C.1. The top left-hand side panel depicts the p90/p50 ratio, the top right-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.

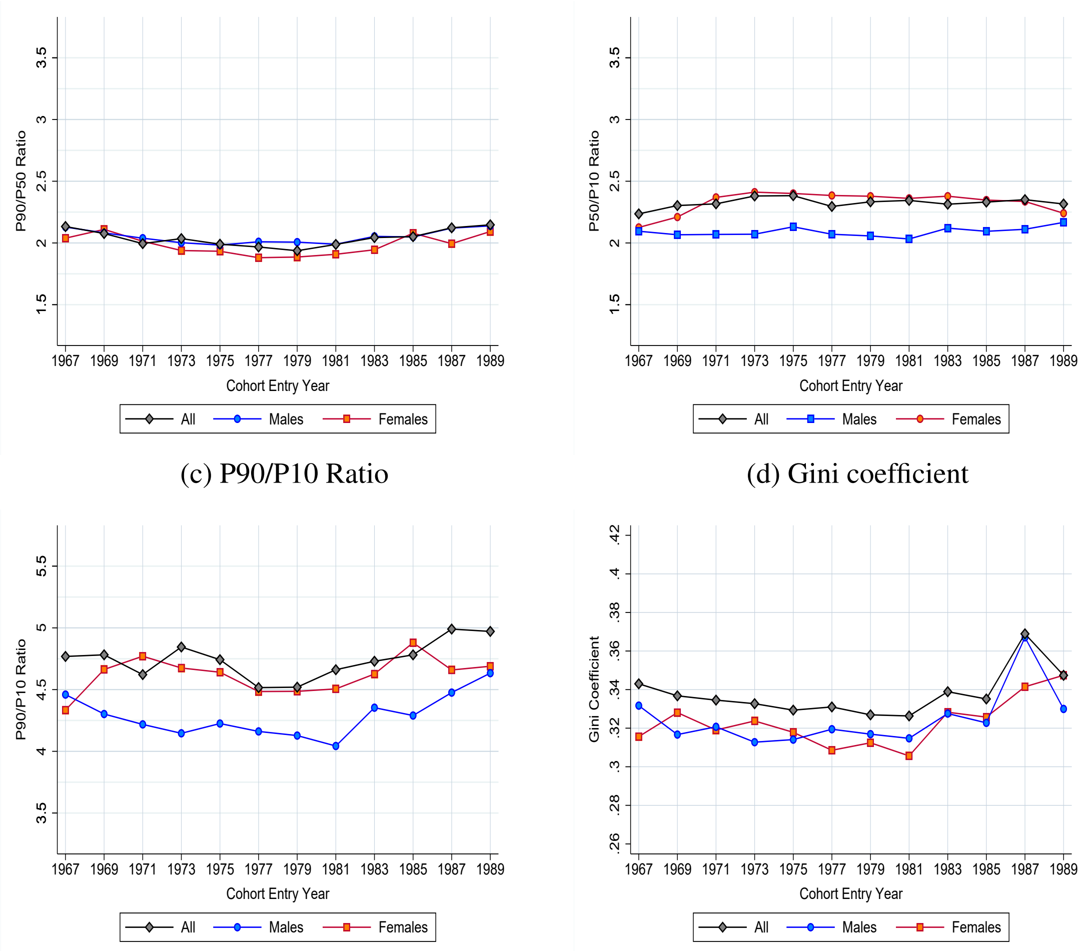
Figure C.1 – Inequality indicators by cohort and gender, lifetime earnings, France

(a) P90/P50 Ratio

(b) P50/P10 Ratio

(c) P90/P10 Ratio

(d) Gini coefficient



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.

Inequality at the top of the distribution, as measured by the p90/p50 ratio, exhibits a U-shaped pattern for the overall population. 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. 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.

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. 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. Figure A.4 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. On the other, the increase in female labor force participation was accompanied by a higher prevalence of part-time employment, adding higher hours-of-work inequality to the underlying wage inequality.

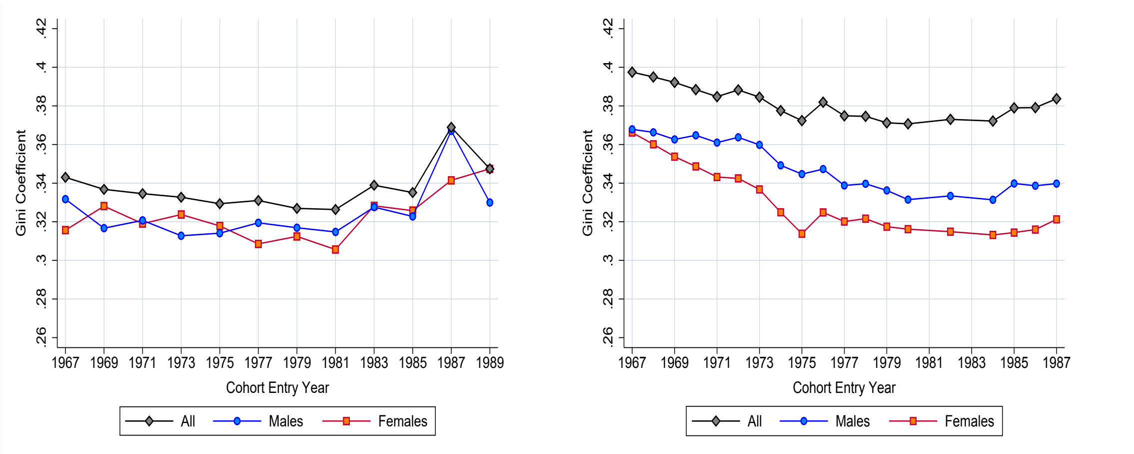
The bottom two panels of Figure C.1 (p90/p10 ratio and Gini coefficient) show an overall U-shaped pattern with a net increase in inequality for younger cohorts. This implies a higher level of inequality for the youngest than for the oldest cohorts for both the overall population and within each gender 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.

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

We next examine how inequality in lifetime earnings compares with that obtained in the cross-section. We use our earnings data to compute a measure of cross-sectional inequality. Figure C.2 reports the Gini coefficient of lifetime earnings and that obtained in the cross-section for the period 1967-1989. The cross-section uses the earnings observed in the DADS data for workers aged between 25 and 55 in, say, 1967, then 1968. The cross-sectional measures use the same selection rule as for our main sample.

Figure C.2 – Cross-sectional versus lifetime inequality, France

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

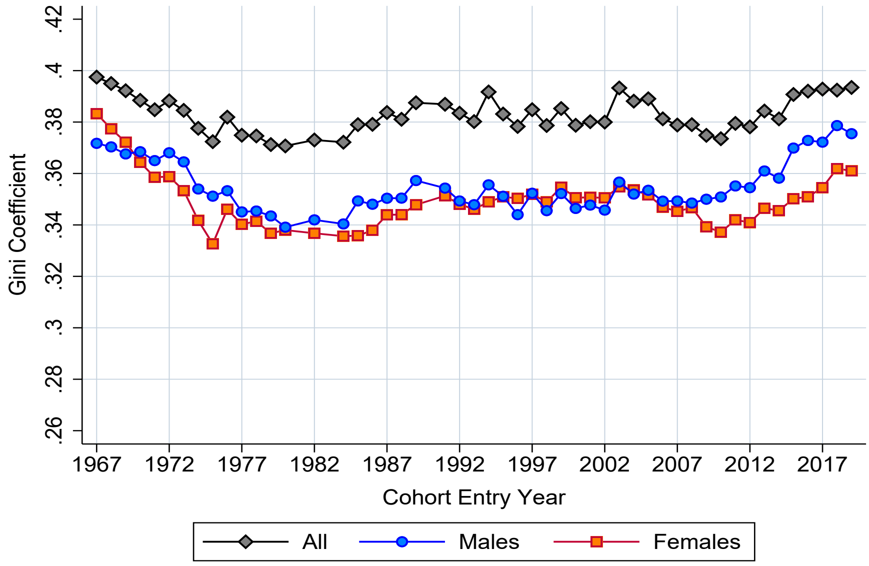


Notes: The graphs display Gini coefficients computed on the distribution of lifetime earnings for successive cohorts on panel (a); and on the cross-sectional distribution of yearly earnings on panel (b). The sample for the latter is the entire population of individuals reported in the DADS. Each graph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

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 2019, so the Gini coefficient on panel (a) is affected by earnings in years after 1989. Figure C.3 reports the cross-sectional Gini coefficient for the period up to 2019 and shows that it fluctuated within the same range without displaying a clear trend.

Figure C.2 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

Figure C.3 – Cross-sectional inequality: 1967-2019



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.

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.

D Counterfactual exercises

This appendix performs a number of counterfactual exercises. Equation 2 allows us to 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

$$\hat{y}_c^X = \alpha_c + \beta_c \bar{X}_{1967} \tag{A.1}$$

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:

$$\hat{y}_c^\beta = \alpha_c + \beta_{1967} \bar{X}_c. \tag{A.2}$$

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.

Figure D.1 reports our counterfactual exercises for men. 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 (**??**). Panels (c) and (d) report the results when we change one of the coefficients to that obtained for the 1967 cohort (Equation A.2). 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 9.

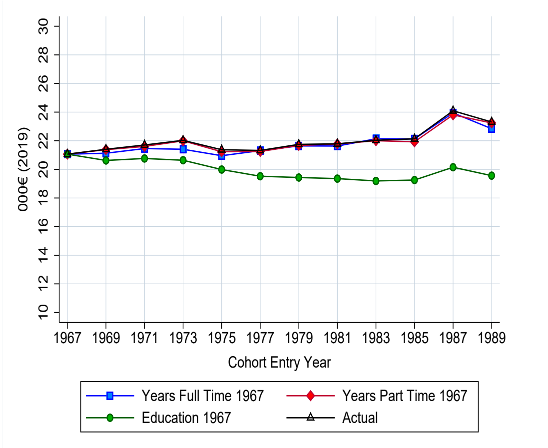
The increase in years of full-time employment also plays a role for the early cohorts. As can be seen in Figure A.4, total years worked increased up to the 1975 cohort, and our simulations indicate that if the early cohorts had worked as many years full-time as the 1967 cohort, earnings growth would 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. These results are driven by the decline in the returns to all educational categories except 'masters degree or more', which remained roughly constant.

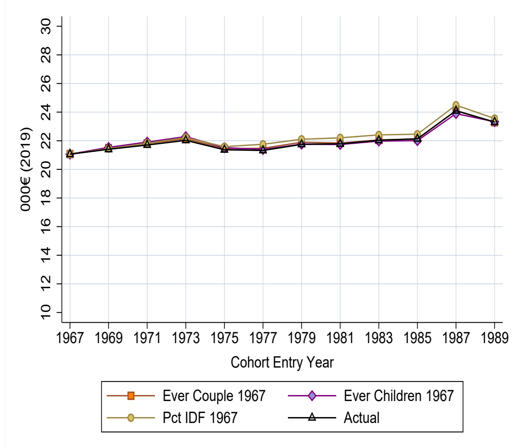
The counterfactuals for women are reported in Figure D.2. Increased educational attainment is accompanied by a reduction in the gender gap in the returns to education, which explains much of the catch up with men. Changes in working time have been particularly important for the dynamics of female lifetime earnings. Our counterfactuals indicate that if women in the youngest cohorts had worked as many years full-time as those in the older cohorts, their earnings would have risen considerably faster.

Figure D.1 – Counterfactual Lifetime Earnings, men

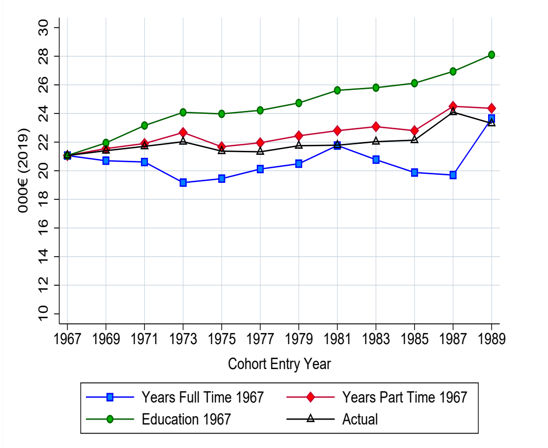
(a) Endowments: Working time and Education



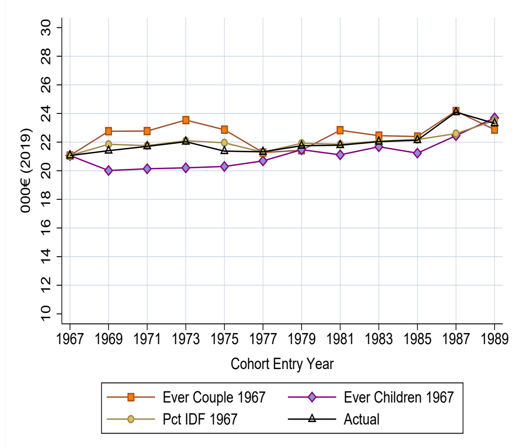
(b) Endowments: Demographics



(c) Coefficients: Working time and Education



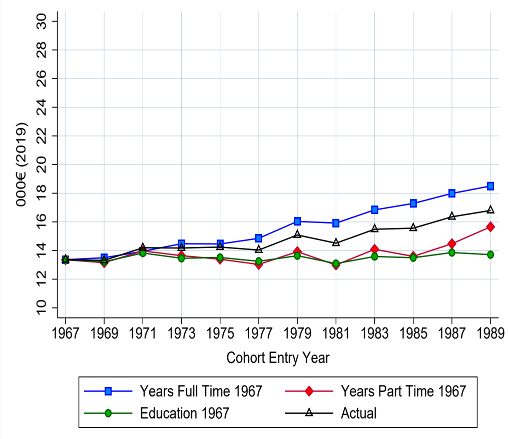
(d) Coefficients: Demographics



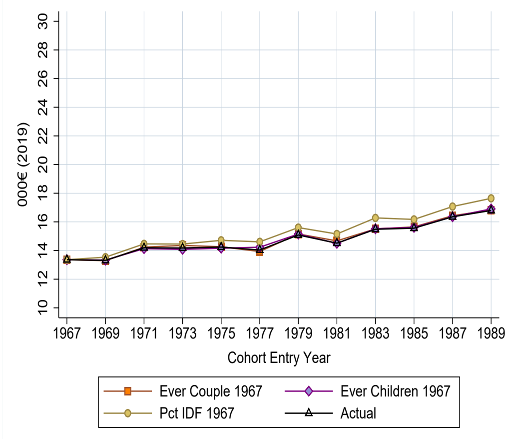
Notes: The graphs display average lifetime earnings computed for successive male cohorts between 1967 and 1987 against counterfactual earnings. These are computed using the same regressions model as in Table A.3 where either endowments (panels a and b) or coefficients (panels c and d) of one or several 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).

Figure D.2 – Counterfactual Lifetime Earnings, women

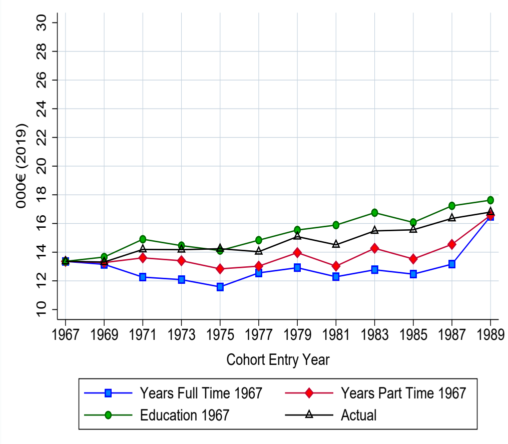
(a) Endowments: Working time and Education



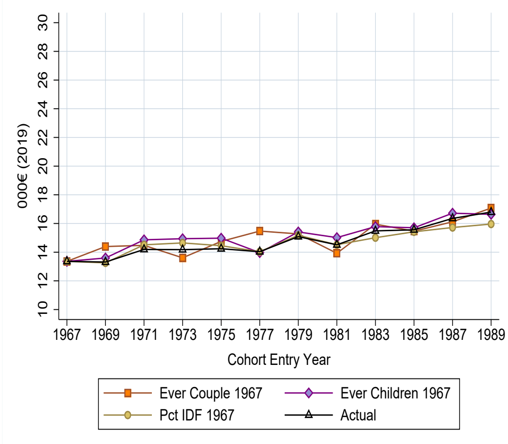
(b) Endowments: Demographics



(c) Coefficients: Working time and Education



(d) Coefficients: Demographics



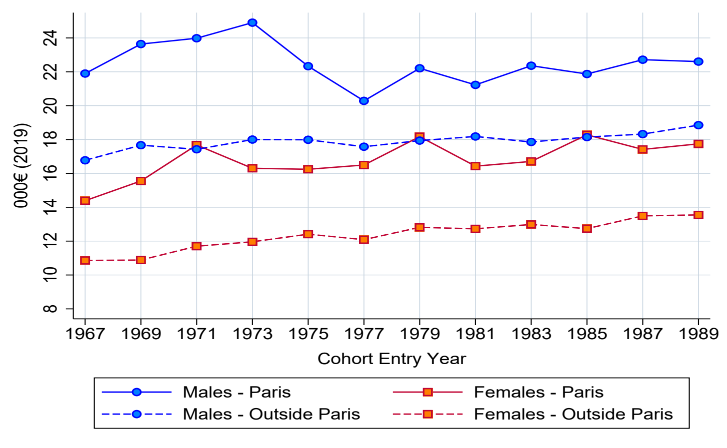
Notes: Notes: The graphs display average lifetime earnings computed for successive male cohorts between 1967 and 1987 against counterfactual earnings. These are computed using the same regressions model as in Table A.3 where either endowments (panels a and b) or coefficients (panels c and d) of one or 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).

E The geography of lifetime earnings

This appendix examines 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* (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.[48] Having split the sample, we computed median lifetime earnings for each of these groups, which are depicted in Figure E.1.

Figure E.1 – 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 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

48. 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*).

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 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, birth location may simply be capturing where individuals work (see Bonnet and Sotura (2021) for a historical perspective on regional income in France based on yearly income data.). 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 E.1 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

Table E.1 – 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	(12) 1989
Panel A												
Born in Paris Region	5.102***	6.120***	7.997***	7.127***	6.099***	4.243***	6.925***	6.808***	6.234***	4.018***	7.269***	5.537***
	(0.901)	(0.917)	(0.795)	(0.739)	(0.740)	(0.793)	(0.737)	(0.778)	(0.881)	(0.759)	(1.768)	(0.860)
Education	no	no	no	no	no	no	no	no	no	no	no	no
Panel B												
Born in Paris Region	-0.353	1.573	2.480***	1.166	1.671**	-1.392	1.266	1.722**	-0.0934	-2.083**	-3.695*	-0.247
	(0.965)	(0.972)	(0.887)	(0.822)	(0.846)	(0.875)	(0.837)	(0.857)	(0.990)	(0.847)	(1.988)	(0.956)
% Years in Paris Region	12.67***	10.19***	11.70***	12.25***	8.865***	12.53***	11.43***	11.47***	13.52***	12.96***	22.99***	12.47***
	(1.002)	(0.891)	(0.931)	(0.845)	(0.873)	(0.940)	(0.882)	(0.916)	(1.059)	(0.904)	(2.049)	(0.988)
Education	no	no	no	no	no	no	no	no	no	no	no	no
Panel C												
Born in Paris Region	-0.549	1.576*	1.648**	1.189	0.862	-1.194	0.948	1.463*	1.130	-1.722**	-2.965	-0.628
	(0.811)	(0.836)	(0.783)	(0.725)	(0.741)	(0.754)	(0.706)	(0.747)	(0.891)	(0.723)	(1.899)	(0.868)
% Years in Paris Region	8.508***	6.622***	8.281***	8.194***	5.658***	8.674***	7.614***	8.171***	8.299***	8.291***	15.44***	7.564***
	(0.855)	(0.782)	(0.835)	(0.762)	(0.774)	(0.822)	(0.753)	(0.807)	(0.975)	(0.789)	(2.019)	(0.921)
Education	yes	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	(12) 1989
Panel A												
Born in Paris Region	2.785***	1.950***	3.621***	3.058***	3.950***	3.743***	3.729***	2.772***	3.090***	3.715***	3.923***	5.282***
	(0.573)	(0.617)	(0.471)	(0.487)	(0.458)	(0.457)	(0.483)	(0.441)	(0.553)	(0.478)	(0.549)	(1.006)
Education	no	no	no	no	no	no	no	no	no	no	no	no
Panel B												
Born in Paris Region	0.102	-0.952	1.200**	0.864	1.291**	0.429	0.795	-0.328	-1.713***	0.0370	-1.063*	0.340
	(0.629)	(0.636)	(0.550)	(0.566)	(0.526)	(0.526)	(0.581)	(0.493)	(0.613)	(0.515)	(0.594)	(1.115)
% Years in Paris Region	6.123***	7.039***	4.877***	4.505***	5.239***	6.495***	5.414***	6.615***	10.21***	8.382***	11.11***	11.28***
	(0.699)	(0.642)	(0.606)	(0.618)	(0.550)	(0.568)	(0.624)	(0.538)	(0.679)	(0.557)	(0.655)	(1.183)
Education	no	no	no	no	no	no	no	no	no	no	no	no
Panel C												
Born in Paris Region	-0.132	-0.927	0.926*	0.750	0.951**	0.350	0.325	-0.472	-1.478***	0.0187	-1.010*	-0.498
	(0.568)	(0.586)	(0.514)	(0.515)	(0.453)	(0.483)	(0.525)	(0.439)	(0.544)	(0.445)	(0.520)	(1.088)
% Years in Paris Region	5.508***	5.727***	4.155***	3.386***	4.437***	5.516***	5.046***	5.459***	7.861***	6.185***	8.422***	9.424***
	(0.633)	(0.598)	(0.567)	(0.568)	(0.475)	(0.526)	(0.564)	(0.485)	(0.615)	(0.490)	(0.585)	(1.172)
Education	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

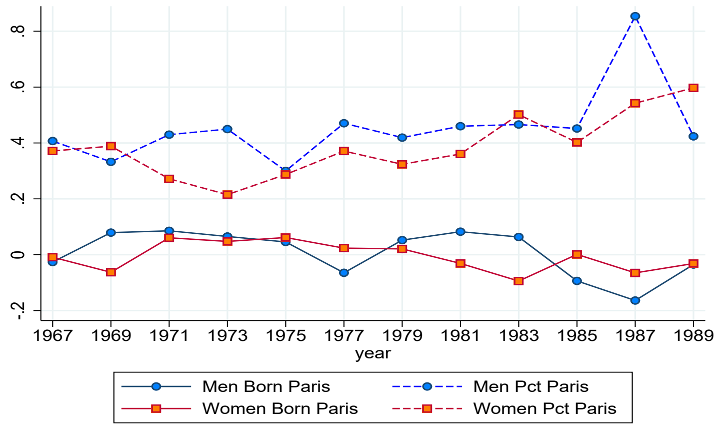
Notes: The table displays regressions of male and female lifetime earnings for all cohorts between 1967 and 1989, on a set of control variables. We sequentially consider a dummy for whether individuals are born in the Paris region, the percentage of years they have worked in this region, and education 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. 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, *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

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 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.

Figure E.2 – 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 and percentage of years spent working in the Paris region from regressions of life time earnings for the successive cohorts that entered the labor market between 1967 and 1989. Since the average lifetime earnings change across cohorts, for each cohort we have divided the coefficients by the mean lifetime earnings estimated when the location variables are set to zero.

Interestingly, Table E.1 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. 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, as reported in Figure E.2.

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