Inequality and Earnings Dynamics in France: National Policies and Local Consequences

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July 2022

Abstract

This paper provides new stylized facts about labor earnings inequality and dynamics in France for the period 1991-2016. Using Linked Employer-Employee Data, we show that (i) Labor inequality in France is low compared to other developed countries and has been decreasing until the financial crisis of 2009 and increasing since then. (ii) Women experienced high earnings growth, in particular at the bottom of the distribution, in contrast to the stability observed for men. Both result from a decrease in labor costs at the minimum wage and an increase in the hourly minimum in the aftermath of the 35h workweek policy. (iii) Top earnings (top 5 and 1%) grew moderately while very top earnings (top .1 and .01%) experienced a much higher growth. (iv) Inequality between and within cohorts follow the same U-shaped pattern as global inequality: it decreased before 2009 and then increased until 2016. (v) Individual earnings mobility is stable between 1991 and 2016, and very low at the top of the distribution. (vi) The distribution of earnings growth is negatively skewed, leptokurtic, and varies with age. Then, studying earnings dispersion both within and between territories, we document strong differences across cities as well as between urban and rural areas, even after controlling for observable characteristics. We also observe a continuous decrease in earnings inequality between cities as well as between rural and urban territories. However, the higher price increases in rural territories attenuates this convergence. Finally, we document a strong reduction in inequality within rural and remote territories, again driven by changes at the bottom of the wage distribution.

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§We would like to thank Fatih Guvenen, Luigi Pistaferri, and Gianluca Violante for initiating and coordinating this ambitious project. We also thank Serdar Ozkan and Sergio Salgado for there tremendous work on harmonizing the core statistics, as well as Pierre Boyer, Pauline Carry, Bertrand Garbinti, Gautier Lenfant and seminar participants at the Global Repository of Income Dynamics Conferences at Stanford SITE (2019) and held virtually (2020) for helpful comments and suggestions. We also thank our guest editor, Luigi Pistaferri, as well as two anonymous referees for their very insightful and constructive comments on a previous version of this article. This paper has been conducted in collaboration with the CASD with special thanks to Kamel Gadouche, Marie Vidal and Raphaëlle Fleureux for their help and support. The access to the French administrative data has been made possible within a secure environment offered by the CASD (Ref. 10.34724/CASD). This paper has received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme: Grant Agreement: 741467 FIRMNET.

1 Introduction

"How can you lead a country which has 258 sorts of cheeses?" is an often cited Général de Gaulle's sentence that summarizes the tensions prevailing in France between a centralized government and its multiple localities with varied specific traits.[1] These tensions are a constituting feature of French history (see Weber (1976) for a historical perspective on some aspects of such tensions) and they regularly erupt, as evidenced by the "yellow vests" protests which took place at the end of our study period.

With this background in mind, we try to offer a systematic investigation of labor earnings inequality and dynamics over the 1991 to 2016 period, documenting the differences between men and women as well as on the differences between the national and the local levels. This paper is part of the Global Repository of Income Dynamics project, which two main objectives are: (i) to produce harmonized statistics to compare inequality and earnings dynamics between countries and over time (ii) to zoom in on some specific features of each country, such as informal jobs in Latin America, social benefits in Sweden and, in our case, the role of geography when it interacts with National (central) labor market policies in shaping earnings inequality in France.

We may start with the following question in mind: How is France different from other countries in the project? We believe that French labor market is characterized by a steady state with high unemployment and moderate growth. The large share of the GDP dedicated to "social shock absorbers" tends to smooth both ups and downs. Low-wage workers are "protected" by a high minimum wage which has had adverse effects on their employment (see Kramarz & Philippon (2001)). Between 1991 and 2016, our period of interest, there were major reforms of the labor market institutions which had a strong impact on inequality: massive increases in the minimum wage in association with the reduction of the workweek to 35 hours. At the same time, there was a strong reduction of the cost of low-wage workers (elimination of employer-paid payroll taxes) to attenuate the impact of the two previous reforms on unemployment. But, maybe counter-intuitively, France is the only European country with a clear

[1] Charles de Gaulle, cited in Mignon (1962)

decrease in inequality over the period, in particular for women.

As mentioned above, France has a highly centralized State implementing policies that apply to all territories. These policies are decided within a densely populated capital, Paris, which concentrates most economic and public decision-making centers. However, it also has a huge number of small municipalities with very heterogeneous economic conditions with little leeway in deciding their social and economic fates. As we argue below, it led to local tensions and many localized protests over our sample period. Because of these social tensions, it is important to understand the disparities in earnings across space as well as their evolution over time.

In this paper, we combine Employer-Employee data on labor earnings to census data on educational attainment to study earnings inequality and dynamics between 1991 and 2016. We find that the strong increase in the minimum wage at the beginning of the 2000s, in the aftermath of the reduction of the workweek to 35h and the suppression of all employer-paid payroll taxes around the minimum wage, translates into a marked increase in bottom percentiles of the earnings distribution (the 10th percentile in particular) in the 2000s. This increase induces a decrease in inequality, defined as the differential between the 90th and the 10th percentile (P90-10), until the financial crisis when the bottom percentile stagnates and the other percentiles tend to increase. Upper-tail inequality explains only a small share of the variations observed as the differential between the 90th and the 50th percentile (P90-50) remains almost constant over the sample period. This extends to other 95th and 99th since their growth is comparable to that of lower ones. However, the very top percentiles (including P99.9 and above) display very high growth.

The above changes hide extremely different trends for men versus women. For the former, wage growth is low, in particular at the bottom of the distribution implying increasing inequality since the financial crisis. For the latter, wage growth is higher at all percentiles but particularly so at the bottom. Hence, for females, inequality decreased until the financial crisis and increased only moderately since 2009. It resulted in a decrease in the (unconditional) gender pay gap by a third.

Once we decompose earnings into hours worked and hourly wages, the 35-hour working week implied a mechanical reduction in hours for all except for women at

the bottom of the wage distribution. The decrease in inequality for women described above is therefore driven both by an increase in hours and a higher increase in hourly wage for the bottom percentiles.

Inequality between cohorts, defined as the P90-10 for individuals born a given year, follows a similar pattern. The increase at the bottom of the distribution until the end of the 2000's also caused a decrease in inequality for men and women aged 25 years-old. However, the trend has reversed since the financial crisis. We observe increasing inequality both within and between cohorts since then.

Turning to earnings changes, we find a moderate increase in the dispersion in individuals' earnings growth rate for both men and women. Going beyond the first-order and second-order moments, the earnings changes distribution is characterized by negative skewness and high excess kurtosis. Skewness is clearly pro-cyclical (i.e. the distribution is more negatively skewed during recessions), as observed in the U.S. (see Guvenen et al. (2014)). We also find that wage mobility is pretty low in France, especially when compared to Scandinavian countries (see other articles in this issue, in particular Friedrich et al. (2021) for Sweden, Halvorsen et al. (2021) for Norway, and Leth-Petersen & Sæverud (2022) for Denmark). Earnings mobility is very stable over the sample period as in other European countries (see for example Bell et al. (2021), Drechsel-Grau et al. (2021), and Hoffmann et al. (2021)). Other features are similar to those observed in the U.S.: the log-density of residual earnings growth has double Pareto tails, negative skewness and excess kurtosis are both increasing with age (see Guvenen et al. (2015)).

We finally find huge differences in earnings between cities, especially at the top of the distribution. While bottom percentiles are pretty similar in most cities, top percentiles are much higher in Paris and strongly decrease with city size. These differences are only partially explained by observable characteristics such as age, education, occupations, firm size or the industry structure. These differences have been reduced over the period of interest for bottom percentiles but have increased for top percentiles. We also find large differences between and within territories (i.e. Paris, other centers, suburbs, rural, and remote municipalities). In particular, we observe a strong reduction in inequality within rural and remote municipalities over the sample period and a decrease of the gap in median earnings between these

localities and the other urban territories.

Related literature: Earnings Inequality and Mobility in France

Verdugo (2014) provides a study of earnings inequality that spans 1950 to 2008, focusing mainly on men employed full-time full-year in the private sector. Inequality increased between 1950 and 1965 both at the bottom and at the top of the earnings distribution. Then, inequality tended to decrease both at the bottom of the wage distribution (the 1968 massive increases in the minimum wage) and at the top starting in the nineties (the supply of educated individuals massively increased then). Charnoz et al. (2014) confirms the latter result, showing in particular the strong decrease in the returns to skills associated with increased supply and the lack of evidence for skilled biased technical change (in stark contrast with other countries). Guillot et al. (2020) extends the previous analysis until 2015. In an interesting twist, the focus moves to a comparison between inequality in terms of labor cost and in terms of net earnings, the former including both employer and employee-paid payroll taxes when the latter excludes them. The results show that labor cost inequality increased by 8% between 1967 and 2015 while net wage inequalities decreased by 25%. These changes are directly caused by the continuous increase in the minimum wage as well as reforms of the structure of payroll taxes with taxes decreasing for low-wage workers and increasing at the top of the distribution. Godechot (2012) examines the 1975-2007 period and focuses on top percentiles, insisting on its changing composition: a decline in the number of CEOS but an increase in lower-rank managers, top athletes, with managers in the finance industry accounting for almost half of the rise at the top. Recently, Pora & Wilner (2020) decomposes earnings growth into the growth of wages and that of working time. They insist, as we will do here, on the role of working time in earnings volatility, in the aftermath of the various workweek reductions. All these papers used the French administrative data (DADS).

A wave of papers, following Piketty's lead, provides results on income inequality using tax data. Piketty (2003) shows that wage inequality has been very stable in the long run (1901-1998) when the secular decline in income inequality is essentially

due to capital income and the two world wars. Furthermore, the top 1% and 10% wage shares are stable since 1980. Garbinti et al. (2018) complements this analysis for the period 1900 to 2014. The article presents "Distributional National Accounts" (using national accounts, tax and survey data) with a focus on pre-tax income.[2] The top 10% share of total income has decreased between 1900 and the beginning of the eighties, but increased since then. The middle 40% share (i.e. workers with earnings between the median and the 90th percentile) increases until WWII, but is almost stable until mid 1990s, and decreasing since. They also observe a continuous increase in the bottom 50% as well as an increase in the top 0.1% and the top 0.01% between the beginning of the 1980's and 2000's (with a decrease since). As for the labor income, the top 10% share has been decreasing since the mid-60s when the top 1% decreased until the beginning of the 90's but increased since then. Interestingly, women increased their presence within the top fractiles of the labor income.

The present article does not examine the role of transfers on earnings inequality. However, Bozio et al. (2020) shows that most of the long-term (1900-2018) decline in inequality in France is due to the fall in pretax inequality, resulting in low values of inequality as compared to the U.S. Focusing on gross earnings is therefore relevant to study inequality in France.

Finally, our paper provides several measures of earnings mobility and studies their evolution since 1991. Buchinsky et al. (2003) complements our analysis by examining measures of earning mobility based either on ranks in the income distribution or on Francs for periods of 3 years (using DADS between 1967 and 1999). Their results suggest a decrease in mobility over time. Using Panel data allowing to track the tax returns of all French tax residents over time, Aghion et al. (2019) find a rank-rank correlation of total income of .83 between 2011 and 2015. Contrary to our results, they find no large differences between men and women, except at the bottom of the distribution where mobility is higher for men.

The remainder of this paper is organized as follows. Section 2 provides institutional details on the French labor market, describes the data and provides some

[2]Hence, before all taxes and transfers, except pensions and unemployment insurance.

descriptive statistics. We then present our main results on earnings inequality and dynamics in Section 3. Finally, Section 4 provides complementary statistics on earnings inequality between and within various French territories. Section 5 concludes.

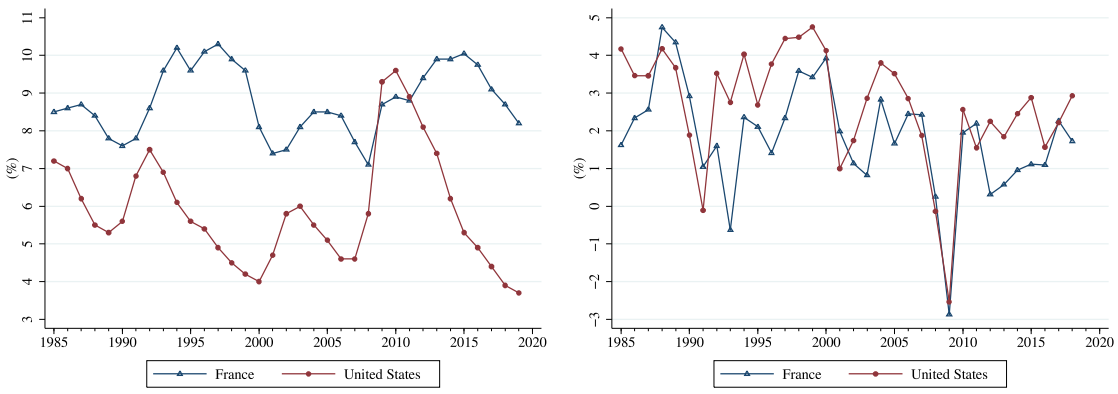
2 Institutions and Data

2.1 The French Labor Market Institutions

Figure 1 presents, on the left (A), the unemployment rate in France and in the United States over the period 1985-2019 and, on the right (B), the GDP growth rate for the same countries. As can be seen from the Figure, the unemployment rate in France has been staying consistently between 7.5% and 10% over the last 30 years (with one exception, 7%, in 2000). Expansions appear unable to decrease unemployment below this point, and recessions do not seem to have the same effect as, for instance, in the United States where unemployment between a trough and a peak can increase by 5 points when in France the increase is 2.5 points. GDP growth rates, however, vary mostly in sync (with that of France being lower by one point during expansions). During our analysis period, France has witnessed two recessions, in 1993 and 2008 but one expansion, around 2000 when the US had more expansion years.

Figure 1 – The French Business Cycle

(A) Unemployment Rate (B) GDP Growth Rate



Note: Figure 1 plots against time: (a) the unemployment rate, (b) the growth rate of the GDP, for France and the United States. Source: INSEE and BLS for the unemployment rates. The World Bank for the GDP.

The inability to decrease the unemployment rate in good times to, say, 5 or 6% as in other countries, together with the inability to generate as much growth as in the US, must be questioned. At least, these two questions will be in the back of our mind when exploring earnings dynamics and inequality.

We then provide a brief description of the main institutional features of the French labor market. First, as in multiple other European countries, there are two main types of labor contracts: permanent and temporary. In 2017, 88% of the wage workers have a permanent contract while 87% of the new hires are made under temporary contracts. This rate has steadily increased since 1993 when it represented 76% of the new hires. The duration of these contracts tend to be short and the use of extremely short term contracts has strongly increased over the past decades. In 2017, almost one third of the temporary contracts last only one day.

Second, part-time jobs have been increasing for both women and men. In 2016, 30.1% of women and 8.2% of men had part-time jobs. It was respectively 23.4% and 4% in 1990.[3]

Finally, the participation rate strongly increased since the middle of the 1980s, mostly driven by the oldest age groups and women, as depicted in Appendix Figure B.1. Women participation rate managed to increase from the 1990s on while men's strongly decreased due to the low participation of older age groups. In particular, pre-retirement plans in the 80s pushed down participation of people above 55, especially for men. Recent pension reforms in the 2000s and 2010s had a huge impact and partially reversed this last tendency.

For our analysis period (1991-2016), two policies had a huge effect on all labor market outcomes. We start by describing the changes in the minimum wage policy. Then, we explain those on the workweek.

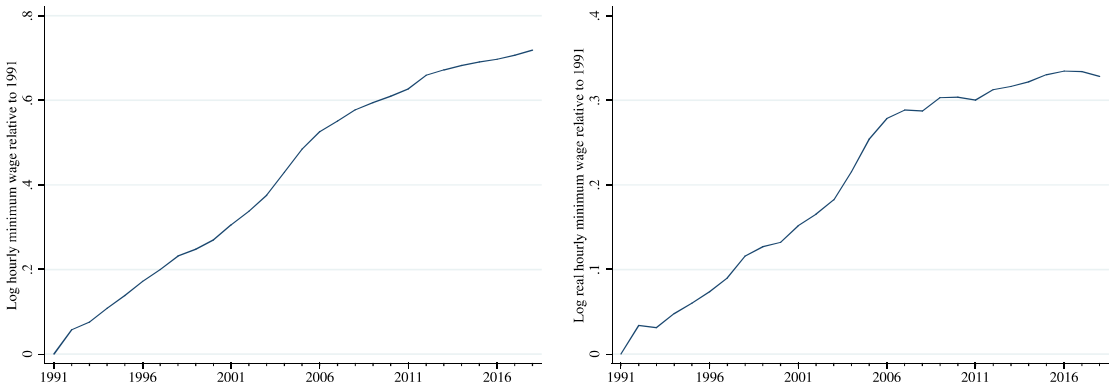
The debates on minimum wages that took place in the 1990s in the United States tend to obscure why the French case was one of a dramatically high minimum wage with adverse employment effects (Kramarz & Philippon (2001)). For employers at least, the minimum wage by itself is only one part of the story. What really matters

[3]See "Emploi, chômage, revenus du travail", INSEE, 2020.

is the total labor cost i.e. the wage plus the payroll taxes (see Saez et al. (2019) and Huttunen et al. (2013) for the employment effects of payroll taxes in Sweden and Finland). These payroll taxes comprise two components, one paid by the worker and one paid by the firm.[4]

Figure 2 – Nominal and Real Minimum Wage Over Time

(A) Nominal Minimum Wage (B) Real Minimum Wage



Note: Figure 2 plots against time: (a) the nominal hourly minimum wage, (b) the real hourly minimum wage in France. All statistics are normalized to 0 in 1991. Source: INSEE.

Figure 3 – Labor Cost at Minimum Wage

Note: The labor cost is the sum of the gross wage and of the employer's contributions. All statistics are normalized to 100 in 1980. Source: "*Rapport à la Commission des comptes de la sécurité sociale de juin 2009*".

Until the beginning of the 1990s, France was characterized by both a very high

[4]In the end, obviously everything is paid by the firm but these different payroll taxes may have different destinations. For minimum wage workers, every component is mandated by the law, with no possible trade off except on hours and employment.

minimum wage and extremely high labor costs at the bottom of the wage distribution. It is still characterized by a very high minimum wage since the ratio of the net minimum wage to the median wage is equal to .63 in 2015, one of the highest in the OECD. Indeed, as Figure 2 shows, the nominal and the real value of the minimum wage increased dramatically, by respectively 100% and 40%, between 1991 and 2016. However, as evidenced by Figure 3, the total labor cost barely budged thanks to the very strong decrease in employers' contributions in the 1990's and the 2000's. These contributions are now virtually equal to zero. We will see in Section 3.1 that this strong increase in the minimum wage, especially since the middle of the 2000's, had a big impact on earnings inequality.

We describe in Appendix A the various steps of the workweek reduction and the path to 35 hours that took place mostly between 1998 and 2001. Importantly, wage compensation schemes and wage moderation agreements were implemented at the same time so that monthly wages stayed constant in the short-term and did not increase too rapidly in the longer-run. Labor costs for low-wage workers did not increase too strongly thanks to the payroll tax exemptions that were expanded in those years.

Until 2005, when all minimum wages were unified, there existed a flurry of SMICs[5] depending on the moment the firm reduced the workweek. As depicted in Appendix Figure A.1, the reduction of the workweek was followed by a strong increase in the minimum wage between 2002 and 2005, the highest over our period of interest.

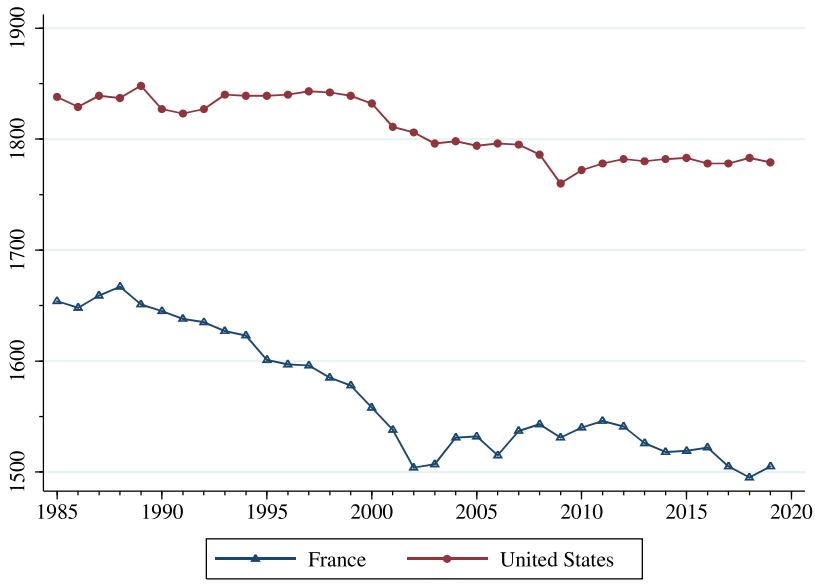
As can be seen on Figure 4, hours in France were decreasing at a brisk rate in the years preceding the implementation of the 35 hours workweek. Then, they stabilized from 2002 on. In the US though, hours decreased too, at a lower rate and annual working time today is much higher than in France as it was in the 1980s. We will come back to this question of hours and to its impact on earnings inequality later in our analysis.

We also detail in Online Appendix I.1 the sequence of social movements that took

[5] *Salaire Minimum de Croissance*

place in France over the last 20 years: from urban riots in 2005, red caps in Brittany, to the yellow vests recently. We attempt to show that each of these movements was an expression of disagreements with Paris, seen as the central administrative power, when it tried to impose a new carbon-style tax on trucks or increase taxes on gasoline to fight global warming. The government, legislating from a city benefiting from excellent infrastructure and well-connected to the rest of France and the world, was seen as out of touch by most citizens living in the countryside without much infrastructure (public transport, in particular) and forced to use their cars every day. Paris-imposed one-size-fits-all decisions are indeed less-well accepted that they once were.

Figure 4 – Average Annual Working Time



Note: Figure 4 plots against time the average annual number of hours worked in France and in the United States. The average is computed using both men and women. Source: OECD.

2.2 The French Employer-Employee Data

In what follows, we use the DADS[6], the French Linked Employer-Employee Data source over the period 1991-2016. These administrative data are based on mandatory employer reports of the earnings of each employee subject to French payroll taxes. It comprises all employer's and their (declared) employees. In each year t, the data

[6] *Déclaration Annuelle des Données Sociales*

comprise information on year $t-1$ and year t. Because of legal constraints the full panel version does not include all workers. The so-called Panel combines a random sample (individuals born in October of an even year) from the DADS with data on central government public employees, similarly selected.[7] In addition, the panel can be matched to the EDP[8], a sample (individuals born the first 4 days of October) of the various Censuses which allows to recover information on the level of education. Around 13% of the workers from the DADS can be matched to census data (see Abowd et al. (1999)).

The sample we use in what follows covers private sector and public sector workers, excluding civil servants working for the central State.[9] The self-employed are not covered in the DADS. Furthermore, we cannot track the unemployed, in particular unemployment benefits are not available. According to the French Statistical Office (INSEE), wage employment represented 89.25% of total employment in 2019.[10] Finally, data on employees working outside of metropolitan France (e.g. overseas territories), employees working in the agricultural sector, or for private individuals (e.g. maids, gardeners, etc.) are not included in the DADS over the whole study period. We exclude them from our sample. We also exclude apprentices, interns, and people working for the clergy.

The data available to researchers are aggregated at the job spell level (in an establishment in a given year for a given individual). Hence, our data on earnings use this employment (job) spell level. For each individual, we define total earnings in year t as the sum of earnings across all employment spells in that year. We measure earnings using their gross definition (i.e. net labor earnings plus workers' mandatory social contributions). This measure includes the sum of wages, over-time hours, paid leaves, bonuses, in-kind benefits, and several kinds of compensations (sickness, short-time work, severance payments, etc.). It does not include stock options nor

[7] The sample size was multiplied by two in 2002 by including individuals born in October of an odd year.

[8] *Echantillon Démographique Permanent*

[9] The civil servants working for the State are not available in the comprehensive Employer-Employee data before 2009 so we exclude them from the core analysis. We only consider them in Appendix Section I.4 where we study the evolution of public employment in different locations using the Panel DADS. We always keep observations of civil servants working in hospitals and local governments.

[10] The share of wage employment stayed high over the period of interest. Between 1990 and 2002, it slightly increased from 87.6% to 91.2%. We then observe a small decrease since the beginning of the 2000's until today.

employer-paid payroll taxes. Earnings are expressed in 2018 euros deflated using the CPI computed by the French Statistical Office (INSEE).

In line with other countries requirements for this project, we impose a minimum level of annual earnings for an individual to be included in the data. More precisely, an observation must have earnings above the equivalent of 260 hours paid at the French minimum wage.[11] Appendix Table B.1 depicts the annual minimum earning threshold for the period of interest and Appendix Figure B.2 plots the share of individuals with earnings below this minimum threshold. Every year, we exclude between 6 and 7% of the observations of the sample. Interestingly, this share is slightly decreasing over time while the income threshold is increasing due to the rising minimum wage.[12] This suggests that the decrease in inequality observed in Section 3.1 is not mechanically driven by the tightening of the income threshold. We also observe a strong increase in the share of excluded individuals in 1994. For unknown reasons, the share of jobs which cannot be matched to their individual identifier is higher in 1994, resulting in more individuals with earnings below the threshold.[13] It is likely to explain the peculiar patterns observed at the bottom of the distribution for this year.[14]

In the remaining of the paper, we will use four measures of earnings to study inequality and earnings dynamics. First, the raw real earnings are computed using total annual worker compensation deflated by the French national price index. Second, we use two measures of residual earnings which take into account (i) the evolution of the age structure and (ii) the evolution of the age structure and of educational attainment. To do so, we regress the raw real log earnings on a full set of age dummies (respectively age dummies and four education groups[15]) separately for men and women. We also construct a measure of permanent earnings defined as the

[11] It corresponds approximately to a part-time job for one quarter.

[12] In addition, we computed the share of excluded observations for alternative minimum earnings thresholds. Using either 200 hours or 300 hours paid at the French minimum wage (baseline: 260 hours) would lead to exclude respectively 5.5% and 7.2% of the sample. These statistics suggest that the share of excluded observations does not vary much around the threshold.

[13] This feature was also noted by other scholars using the same data (see Cottet (2022)).

[14] We also excluded around 3,000 observations with abnormally high gross earnings when compared to both earnings observed over the preceding years and current net earnings. Including these observations leads to erratic changes in the P99.9 and P99.99 between 2005 and 2007, which are inconsistent with the variations observed in the comprehensive DADS.

[15] We divide education into four groups: less than high school, high school diploma, two-year college diploma and advanced university degree. Education is only available for workers in the Panel DADS merged with the EDP.

average earnings of a worker over a period of 3 years.[16] Permanent earnings in year t is defined only for workers with earnings above the minimum threshold in year t and at least two out of three years. We then residualize the log of this measure using the same procedure as for residualized earnings.[17] Finally, we compute one and five-year forward (residual) log earnings growth for workers with earnings above the minimum threshold in years t and $t+k$ (with $k \in \{1, 5\}$).

The main statistics are computed using three samples: the cross-sectional (CS), the longitudinal (LX) and the heterogeneity (H) samples. The CS sample includes all workers between 25 and 55 years old who have raw real annual earnings above the minimum earnings threshold in the current year. The LX sample includes all workers of the CS sample who have a measure of one and/or five-year residual earnings changes. Finally, the H sample includes all workers of the LX sample with a permanent earnings measure. We denote the full time period available for the analysis (i.e. 1991-2016) by Tmax.

We present elements on the earnings distribution in Appendix Table B.2 for the Panel DADS. Descriptive statistics on the number of observations, the age distribution and the level of education are shown in Appendix Table B.3. In particular, there was a massive increase in the level of education of the workforce during the period, with a doubling of the share of university graduates between 1995 and 2015 (see Charnoz et al. (2014), Nimier-David (2022), and Verdugo (2014) on the impact of the expansion of higher education on wages and local development in France).

2.3 French Cities and Territories

As we mentioned in the previous Section, social movements that took place in France over the last 20 years appear to have a local origin (see Online Appendix I.1 for more details). Hence, we will directly examine how different cities and territories are affected by earnings inequality.

As a first and preliminary step, we present now the concepts that will be used to characterize this spatial dispersion. In particular, we will use repeatedly categories

[16] Permanent earnings is computed backward: it is the average of labor earnings between t and $t-2$.

[17] In what follows, permanent earnings is computed using only age dummies.

that should help us approximate cities or territories. Indeed, the empirical analyses of Section 4 rely on across-cities and across-territories comparisons. In particular, we will characterize inequality between "urban areas" or between urban and rural "territories". Hence we define these concepts in the following paragraphs. But, first we present some basic facts about French local administrative structure.

France is mostly seen as a centralized country with a capital, Paris, much larger than any other French city and where most of its administration is located. However, France is also a country with the highest number of municipalities in Europe: almost 35,000 against around 11,000 in Germany or in the United Kingdom. Most municipalities are small, with an average size of 1,800 inhabitants and a median of less than 500. For years, there has been some political desire to reduce this number.[18] However, this desire did not convert into real actions.

To perform comparisons across geographical units, in particular cities, we aggregate municipality-level data at the "urban area" level using the boundaries defined by the French Statistical Institute (INSEE) as of 2010. An *urban area* comprises a core center with at least 1,500 jobs and adjacent municipalities among which at least 40% of the employees work in the core center. Urban areas are typically smaller than commuting zones except for the largest cities such as Paris, Lyon, and Marseille.

There were 771 urban areas in 2015 which included 85% of the population.[19] Their size ranged from around 2,400 inhabitants in Bellême to 12.5M in Paris. Due to its size, much larger than any other French urban area, and its strong heterogeneity, we run a specific analysis for Paris's urban area. More precisely, we divide Paris's urban area into three parts: the municipality of Paris, the close and the distant suburbs.[20]

Urban areas provide a reasonable approximation of cities and are useful to compare their relative convergence or divergence when examining earnings inequality. Nevertheless, these urban areas (as their name indicates) do not cover the whole territory and exclude rural areas. In addition, this view of cities as urban areas

[18]See Tricaud (2020).

[19]We exclude areas "000", "997" and "998" which include municipalities that do not belong to urban areas.

[20]The municipality of Paris is composed of its twenty districts. The close suburbs include all the municipalities of the "unité urbaine" (urban unit) of Paris, while excluding the Paris municipality. Finally, distant suburbs are composed of the municipalities of the urban area which are not included in the "unité urbaine" of Paris. We define urban units in the following paragraphs.

precludes making differences between city centers and suburban areas for example.

To get a comprehensive view of labor earnings dynamics between territories, we divide French municipalities into five groups of "territories": rural areas, suburban areas, remote municipalities, central municipalities, and Paris.

We explain now how these territories are defined. A city might include one or multiple municipalities. When there is only one municipality, the city is classified as a "Remote Area". When it includes several municipalities, these are divided into Central and Suburban municipalities based on their size.[21] Due to its prominent size and role in the French economy, we exclude Paris from Central municipalities and study it separately.

Municipalities are classified by the French statistical institute into the above 5 categories based on the urban unit they belong to.[22] An *urban unit* is defined as a group of municipalities with a total population of at least 2,000 inhabitants and with a continuity of the built-up area. Rural municipalities are municipalities which do not belong to an urban unit.

Since people may have different jobs in different locations, we compute our statistics based on the residency location, measured at the municipality-level. If people change within a year, we define residency as the one associated with the highest paying job. The variable on municipality of residency is available since 1993 so we start our geographic analysis at this date.[23]

[21] Central municipalities are either the biggest municipality if its population comprises at least 50% of the city's population or the biggest municipality and all the municipalities with a population at least equal to 50% of the biggest municipality.

[22] As a result, Paris refers to the urban unit of Paris when considered for across-territories comparisons.

[23] For this specific Section, we exclude people living in Corsica because the precise place of residency is not available every year. Hence, our across cities and across territories statistics will restrict to continental France. The number of urban areas considered decreases from 771 to 759 when we exclude Corsica from the sample.

3 Earnings Inequality and Dynamics

3.1 Inequality

3.1.1 The Distribution of Earnings Over Time

We begin our analysis by studying the main features of the earnings distribution in France and its evolution over the 1991 to 2016 period. In the core of the paper, we present separately the results for men and women. Results for the combined sample of men and women can be found in Appendix C. Figure 5 presents the various percentiles of the distribution of earnings.[24]

First, we see little wage growth for men, except for the very top percentiles (P99.9 and P99.99, see Figure 5C). However, there is clearly much higher growth for women at all percentiles, and most striking at the very bottom of the distribution. This rapid increase at the bottom of the distribution coincides with the strong increase of the minimum wage that took place at the beginning of the 2000s. Indeed, women at the 10th and 25th percentiles of the earnings distribution have hourly wages close to the minimum wage.[25]. Finally, we observe that the growth at very top percentiles is also slightly higher for women than for men (see Figure 5D). Between 1991 and 2016, the top 0.1% increased by 57% for women (43% for men) compared to 42% (respectively 2%) for the 10th percentile.

The consequences of these trends in the various percentiles can be seen on Figure 6 which presents simple measures of inequality. Most striking, in particular when compared to many other developed countries, the higher growth of the bottom percentiles entails a decrease in inequality (defined as the differential between the 90th and the 10th percentiles) for women over the period. It is mostly due to a decrease in P50-10 while P90-50 stays essentially constant over time. This results in comparable levels of inequality for men and women at the end of the period. However, inequality tends to increase since the financial crisis, most particularly for men, again driven by the bottom of the earnings distribution. The recent increase in the percentiles at or above the median contrasts with the decrease, for men, and the decreasing

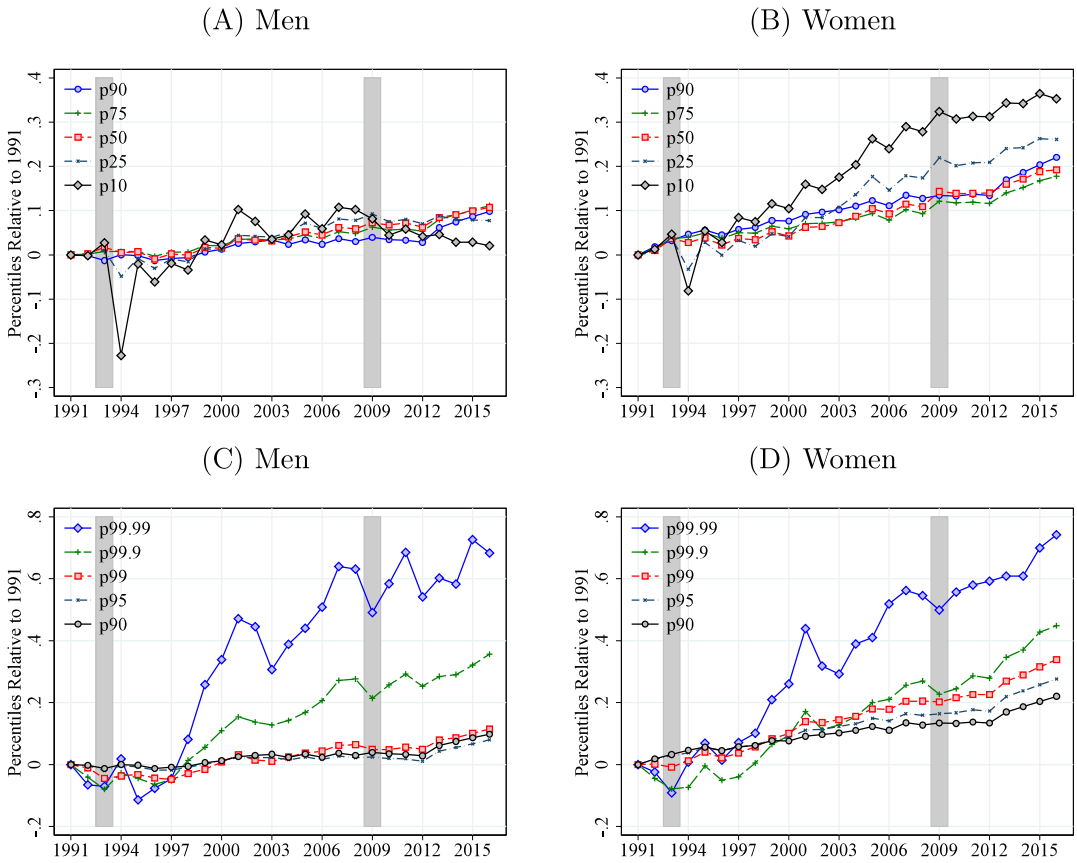
[24]We would like to recall the sampling problem that took place in 1994 which may induce the observed dip. As a result, we will not comment on the results for this year.

[25]In the following Section, we decompose labor earnings into hours and hourly wage to assess the contribution of these two factors to earnings inequality.

growth, for women, of the 10th percentile since 2009.[26]

Interestingly, the level of inequality is relatively low in France compared to other developed countries. The P90-10 differential of log labor earnings is on average 171 log points for men and 177 log points for women over our sample period, a level much lower than what is found in the United States and comparable to that of Norway (see McKinney et al. (2021) and Halvorsen et al. (2021)). It also appears to be close to that prevailing in a Gaussian distribution, especially for women (the P90-10 is close to 2.56 Standard Deviation). However, and in stark contrast with the Gaussian distribution, the distribution of earnings is not symmetric. It is negatively (left) skewed, in particular for women (i.e. P90-50 is much lower than P50-10).

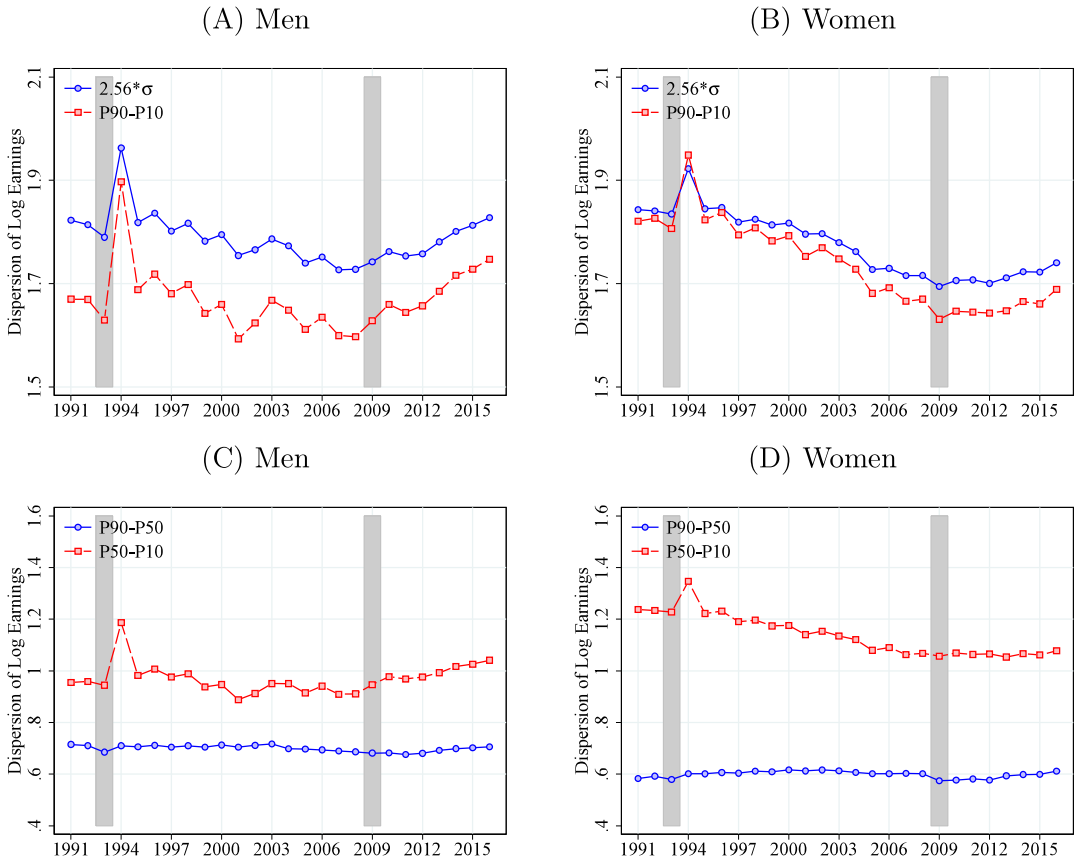
Figure 5 – Change of Percentiles of the Log Real Earnings Distribution



Note: Using real raw log earnings and the CS+TMax sample, Figure 5 plots against time the following variables: (a) Men: P10, P25, P50, P75, P90 (b) Women: P10, P25, P50, P75, P90, (c) Men: P90, P95, P99, P99.9, P99.99, (d) Women: P90, P95, P99, P99.9, P99.99. All percentiles are normalized to 0 in the first available year. Shaded areas represent recession years. Dataset: Panel DADS.

[26]Results for the combined sample of men and women are displayed in the Appendix Figure C.1. Again, most of the growth is concentrated at the bottom and at the very top of the earnings distribution. The rapid increase of the 10th percentiles during the 2000s translates into a decrease in inequality until the 2009 financial crisis when the trend reversed.

Figure 6 – Earnings Inequality



Note: Using real raw log earnings and the CS+TMax sample, Figure 6 plots against time the following variables: (a) Men: P90-10 and 2.56*SD of log income (b) Women: P90-10 and 2.56*SD of log income (c) Men: P90-50 and P50-10, (d) Women: P90-50 and P50-10. Shaded areas represent recession years. 2.56*SD corresponds to P90-10 differential for a Gaussian distribution. Dataset: Panel DADS.

While previous measures focused on *within*-gender inequality, we now turn to inequality *between* genders. To do so, we compute the log differential between men and women earnings, using either mean or median earnings. Appendix Figures C.2 plots the unconditional gender pay gap defined as the difference in men and women earnings without taking into account neither workers' nor jobs' characteristics. First, we observe large differences in earnings between men and women. Mean and median earnings are respectively 43% and 29% higher for men than for women in 1991. We then observe a decrease of more than a third in the gender pay gap over the period of interest due to the higher growth for women at all percentiles described in Figure 5.[27]

Using residual earnings yields essentially identical trends in earnings inequality, when controlling either for age or age and education (see Appendix Figures C.3

[27]We find a similar decrease in the gender pay gap when using the hourly wage instead of total labor earnings.

and C.4). The increase in bottom percentiles is even more pronounced compared to other percentiles when we account for compositional changes. In addition, there is no increase in inequality since the financial crisis once we control for the evolution of the age composition of the workforce and of educational attainment.

Other measures of inequality yield very similar conclusions. Appendix Figure C.5 displays the evolution of the income share (A) by quintile and (B) for top percentiles. The first quintile increases until 2009 before decreasing while the top quintile declines during the financial crisis and increases since then. Very top percentiles (above the 90th percentile) experience a very similar pattern. The Gini coefficient is almost stable until 2003. It then slightly decreases between 2003 and 2009 before increasing continuously until 2016 (see Appendix Figure C.6). Again, the trends differ by gender. For men, the gini coefficient is almost constant until 2009 and increasing since then. For women, we observe a decrease between 2002 and 2009 followed by a continuous increase.

Finally, the distribution of earnings is (unsurprisingly) fat-tailed as we see from Appendix Figures C.7 and C.8. The linear relationship between (log) earnings and the log of the counter cumulative distribution[28] suggests that the right-tail of the distribution has a Pareto shape. The strong increase in very top percentiles over time, depicted in Figure 5, translates into a thickening of the right-tail (associated with a decrease in the slope coefficient in absolute value) between 1995 and 2015. Similar results are obtained for the two cut-offs at 1 and 5%. Interestingly, the slope is smaller in absolute value for men; the top tail being thicker for men than for women.

To conclude, variations in inequality seem to be only mildly related to the business cycle and, apparently, mainly driven by changes in institutions such as the strong increase in minimum wage over the period. Women, who are more likely to be minimum wage workers, have particularly benefited from these reforms which translated into a strong reduction in inequality.

[28]The counter cumulative distribution is defined as one minus the cumulative distribution function of labor earnings.

3.1.2 Inequality and the Reduction of the Working Week

Because hours are available since 1993, we are able to contrast wages, hourly wages, and hours on the sub-period 1993-2016. Hours and hourly wages are computed for people with non-missing hours for all their jobs in the given year. Appendix Figures D.1 and D.2 plot respectively the annual number of hours worked, as a share of a full time job, and the hourly wage for various percentiles of the earnings distribution. About hours worked, we observe notable differences between men and women at the bottom of the earnings distribution. Men with earnings close to the 25th percentile work full time (45% of a full time for the 10th percentile) while it is only 2/3 of a full time (respectively 1/3) for women. Looking at the trends, men with low earnings tend to work less over time while hours are increasing for women at the 10th and 25th percentiles. The overall decrease in hours between 1999 and 2002 is extensively discussed below. Turning to hourly wages, we observe that workers with earnings lower or equal to the median tend to earn similar hourly wages. This is especially the case for women where hourly wages are very close to the minimum wage. It results that women's differences in earnings at the bottom of the distribution are mainly driven by the number of hours worked, not by their hourly wage. The dispersion of hourly wage by income percentiles is higher for men, especially at the top of the earnings distribution.

We now discuss the impact of the reduction of the working week on labor earnings. Appendix Figure D.3 shows, on the left, the evolution of the number of hours worked for various percentiles of the earnings distribution and, on the right, the evolution of the hourly wage for the same percentiles. The first panel corresponds to the full population when the next two panels are for men and women, respectively.

On Appendix Figure D.3A, we clearly see the impact of the reduction of the workweek for those percentiles at or above the median that worked 39 hours in 1993 and moved to 35 hours from 2002 on. The behavior of hours for the deciles below median are more erratic but also follow this downward tendency. Contrasting men and women clearly shows that men with income below the median tend to work less hours in the aftermath of the workweek reduction, whereas it is the opposite for women with income below the median.

The hourly wages increase very clearly and consistently across the earnings distribution over the period. For men, the increase is smaller than for women and starts because of the workweek reduction whereas women increase their hourly wages before, at, and after the workweek reduction. This results in a 20% increase in hourly wages for men but in a 30% increase for women between 1993 and 2016. Interestingly, the 10th percentile for women closely follows the evolution of the minimum wage. Hence, the moderate increase in labor earnings, especially for men, described in the previous Section results from a 10% reduction in hours compensated by a stronger increase in hourly wage. Differences between men and women can be explained by both a higher increase in hourly wage and a smaller decrease in hours for women, especially at the bottom of the earnings distribution.

Finally, we turn to the impact of hours and hourly wages on inequality. To do so, we decompose the variance of the log labor earnings (y_{it}) into the variance of the log number of hours worked (h_{it}), the variance of the log hourly earnings (w_{it}) and the covariance between the two using the following formula:

$$\text{Var}(\log(y_{it})) = \text{Var}(\log(h_{it})) + \text{Var}(\log(w_{it})) + 2\text{Cov}(\log(h_{it}), \log(w_{it})) \quad (1)$$

Appendix Figure D.4 plots the decomposition for men and women separately. The figures confirms the much lower variance in (log) hourly wages but higher variance in (log) hours for women. The decrease in the variance of earnings described in the previous Section comes from a clear decrease of the variance of (log) hours, especially for women, a smaller decrease in (log) hourly earnings, together with a moderate increase in the covariance between hours and hourly wages.

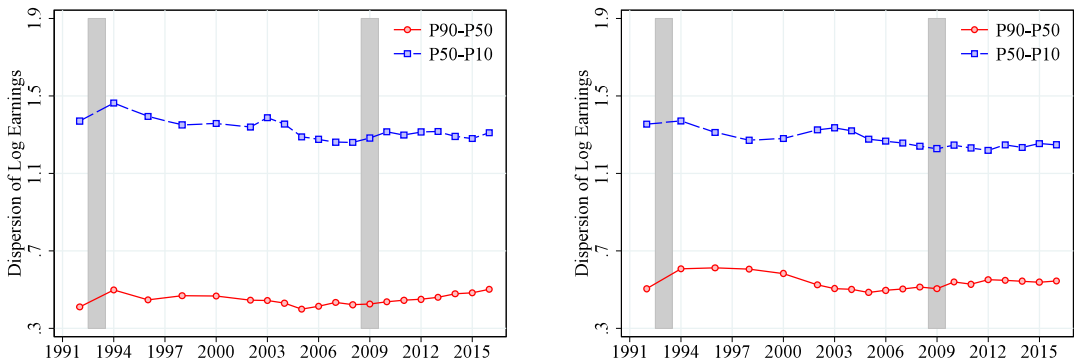
3.1.3 Inequality Between Cohorts

In this Section, we study how inequality compares between cohorts and how it evolves over the life-cycle of various cohorts. Indeed, the trends described in the previous two sections can be due to variations in initial conditions at labor market entry and/or variations in earnings dispersion over the life cycle. Figure 7 plots the P90-50 and the P50-10 every year for workers at age 25. Figures 7A and 7B show that the distributions are very similar for men and women at age 25, contrary to

what was found in Figure 6. Indeed, lower-tail inequality is smaller and upper-tail inequality is higher when workers of all ages (25-55) are included when compared to what we see at age 25. This pattern is much more pronounced for men than for women. As in Section 3.1.1, we observe a decrease in inequality over time for workers entering the labor market, essentially driven by the bottom P50-10 (in particular for men). We also observe a moderate increase in the P90-50 for men since the financial crisis.

Figure 7 – Initial Earnings Inequality (at age 25)

(A) Men (B) Women

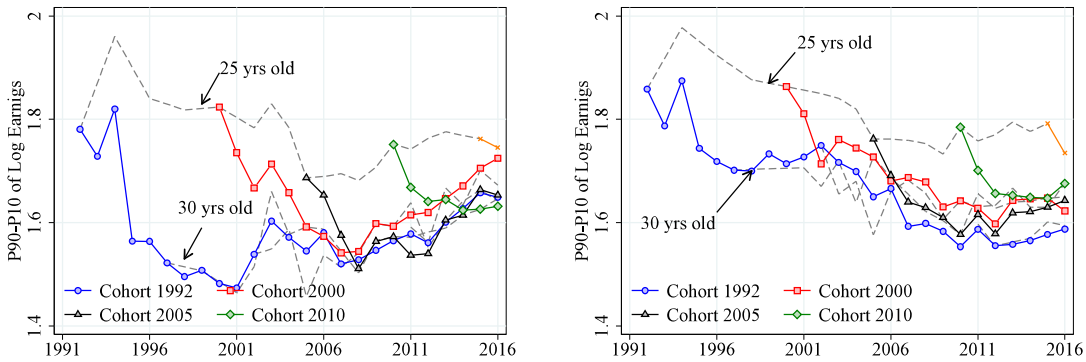


Note: Using real raw log earnings and the CS+TMax sample, Figure 7 plots against time the following variables: (a) Men: P90-50 and P50-10 at age 25, (b) Women: P90-50 and P50-10 at age 25. Shaded areas represent recession years. Dataset: Panel DADS.

We then study how the P90-10 differential evolved over the life cycle for several cohorts of workers. Figure 8 shows that inequality was much higher at age 25 than at age 30 in the 1990's. This gap has been decreasing over time and has become small in the late 2000's, mainly because of the reduction in inequality at age 25. Furthermore, the life-cycle inequality of cohorts is decreasing for women and is U-shaped for men. Similar to what was found previously, within cohorts inequality has decreased until the financial crisis and increased since then for male workers (respectively stagnate for female workers).

Figure 8 – Life-Cycle Inequality Over Cohorts

(A) Men (B) Women



Note: Using real raw log earnings and the CS+TMax sample, Figure 8 plots against time the following variables: (a) Men: P90-10 over the life cycle for all cohorts available, (b) Women: P90-10 over the life cycle for all cohorts available. The dashed grey lines plot the P90-10 for people aged 25, 30, and 35 in the year given in the x-axis. The four remaining lines plot the evolution of the P90-10 over time for specific cohorts. Dataset: Panel DADS.

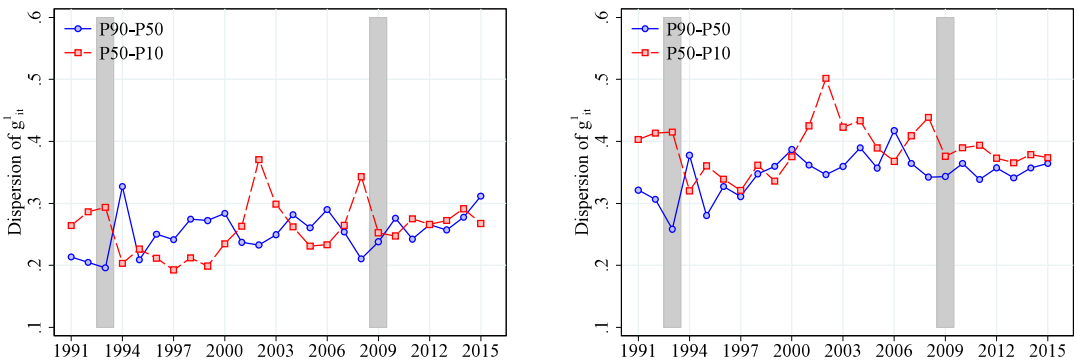
3.2 Earnings Changes

3.2.1 The Distribution of Earnings Changes Over Time

We study here the evolution over the sample period of the distribution of earnings changes after controlling for age. The results are presented in Figures 9 for the one-year growth and in Appendix Figure E.1 for the five-year growth. We use the P90-10 as a measure of earnings growth volatility and decompose it into right tail dispersion (P90-50) and left tail dispersion (P50-10) separately for men and women.

Figure 9 – Dispersion of One-Year Log Earnings Changes

(A) Men (B) Women



Note: Using residual one-year earnings changes (controlling for age) and the LX sample, Figure 9 plots against time the following variables: (a) Men: P90-50 and P50-10, (b) Women: P90-50 and P50-10. Shaded areas represent recession years. Dataset: Panel DADS.

First, we find that the cross-sectional dispersion of the one-year growth rate of residualized earnings is higher for women than for men. This gap is likely due, at

least in part, to maternity leave and to the higher probability for women to work in part-time jobs. Second, the income volatility is slightly increasing over time, in particular for men. Using the above mentioned decomposition, we observe that most of the growth is due to the increase of the right tail dispersion while the left tail dispersion is almost constant over the period. Third, left and right tail dispersion tend to move in opposite directions over the business cycle. The P50-10 increases strongly before recessions while the P90-50 declines.[29] As a result, recessions are associated with a higher probability of large downward movements and a smaller probability of large upward movements. Nevertheless, variations in left tail dispersion are usually higher than variations in right tail dispersion implying some countercyclicality of the P90-10 (i.e. more dispersion in periods of low GDP growth). Turning to the five-year growth rate, we observe a moderate increase for men over the period and an inverted-U shape for women. In addition, comovements observed between left and right tail dispersion are even stronger using the five-year growth rate.

We then discuss the shape of the earnings growth distribution. Appendix Figures G.1 and G.2 display graphically (and very clearly) that the distribution of both one and five-year residual earnings changes are very far from a normal distribution.[30] The distribution is negatively skewed: the left tail of the distribution is longer than the right tail. As a results, the "bad" shocks (below the mean) are larger in absolute terms than the "good" shocks. In addition, the distribution is leptokurtic since the coefficient of kurtosis is much higher than 3, the level observed for a normal distribution. Hence, workers experience much more small and extreme changes than what would imply a normal distribution, and much less middling ones. Furthermore, dispersion is larger for women but kurtosis is larger for men. Very similar conclusions can be drawn from the study of the five-year earnings growth distribution, except that the kurtosis, albeit high, is smaller for both men and women.

Appendix Figures G.3 and G.4 plot the log-densities of one and five-year earnings growth. We observe that the distribution has Pareto tails at the top and bottom

[29]The one year delay between the variations of the P50-10 or the P90-50 and GDP growth is due to the fact that earnings growth is computed forward while GDP growth is computed backward.

[30]The red dotted line plots the density of a normal distribution with similar variance as in our data.

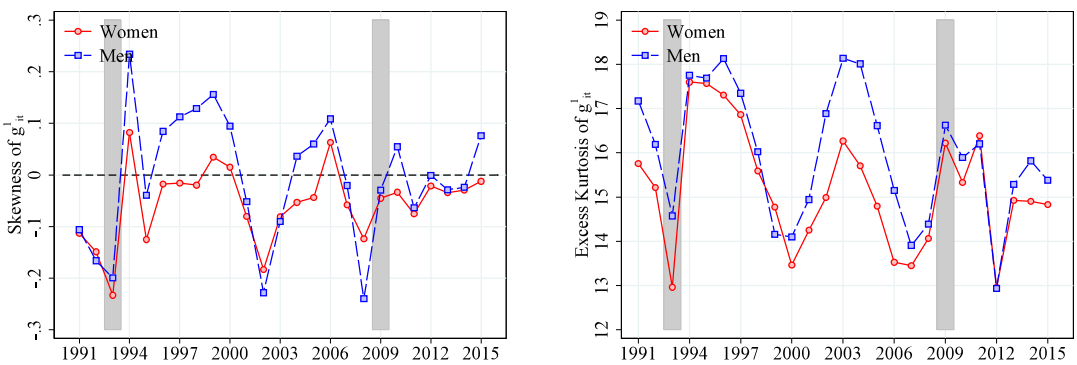
of the distribution. This result is consistent with previous papers for the United-States (see Guvenen et al. (2015)). In Table G.1, we report the main coefficients (slope, skewness, and kurtosis for the whole population) over several years. We observe a clear thinning of the (two) tails over time as evidenced by the increase of the coefficients in absolute value. The message is similar for both the one-year and the five-year growth measures.

3.2.2 Higher Order Moments of the Distribution

In this Section, we study the second, third and fourth order moments of the distribution of earnings growth. Figure 10 depicts the evolution of (A) the Kelley skewness and (B) the Excess Crow-Siddiqui kurtosis of the one-year changes of residualized earnings over time. These two statistics provide measures of skewness and kurtosis based on percentiles, hence robust to extreme values. We find that skewness is pro-cyclical: negative during recessions and positive in expansions. In addition, there is much less variation for women than for men. As for the kurtosis, no clear pattern emerges; it is low during our first recession but high during the second one and the nature of its fluctuations is hard to interpret.[31]

Figure 10 – Skewness and Kurtosis of 1-Year Log Earnings Changes

(A) Kelley Skewness (B) Excess Crow-Siddiqui Kurtosis



Note: Using residual one-year earnings changes (controlling for age) and the LX sample, Figure 10 plots against time the following variables: (a) Men and Women: Kelley skewness, (b) Men and Women: Excess Crow-Siddiqui kurtosis calculated as $\frac{P97.5-P2.5}{P75-P25} - 2.91$ where the first term is the Crow-Siddiqui measure of Kurtosis and 2.91 corresponds to the value of this measure for Normal distribution. Shaded areas represent recession years. Dataset: Panel DADS.

In Figure 11, we condition our various statistics using a measure of "permanent

[31]Results for the five-year growth rate are displayed in Appendix Figure E.2

earnings".[32] We look at the P90-10 differential in the first panel, at the Kelley skewness in the second, and at the Crow-Siddiqui kurtosis in the third. Each time results for men are presented in the left column when those for women in the right one. Hence, Figure 11 allows to study uncertainty that workers with same gender, age and permanent earnings face.

Our measure of dispersion (P90-10) follows a clear U-shaped pattern for men. It is highest at the bottom and very top of the permanent income distribution for both men and women. It is also mildly decreasing with age, especially for women at a young age.

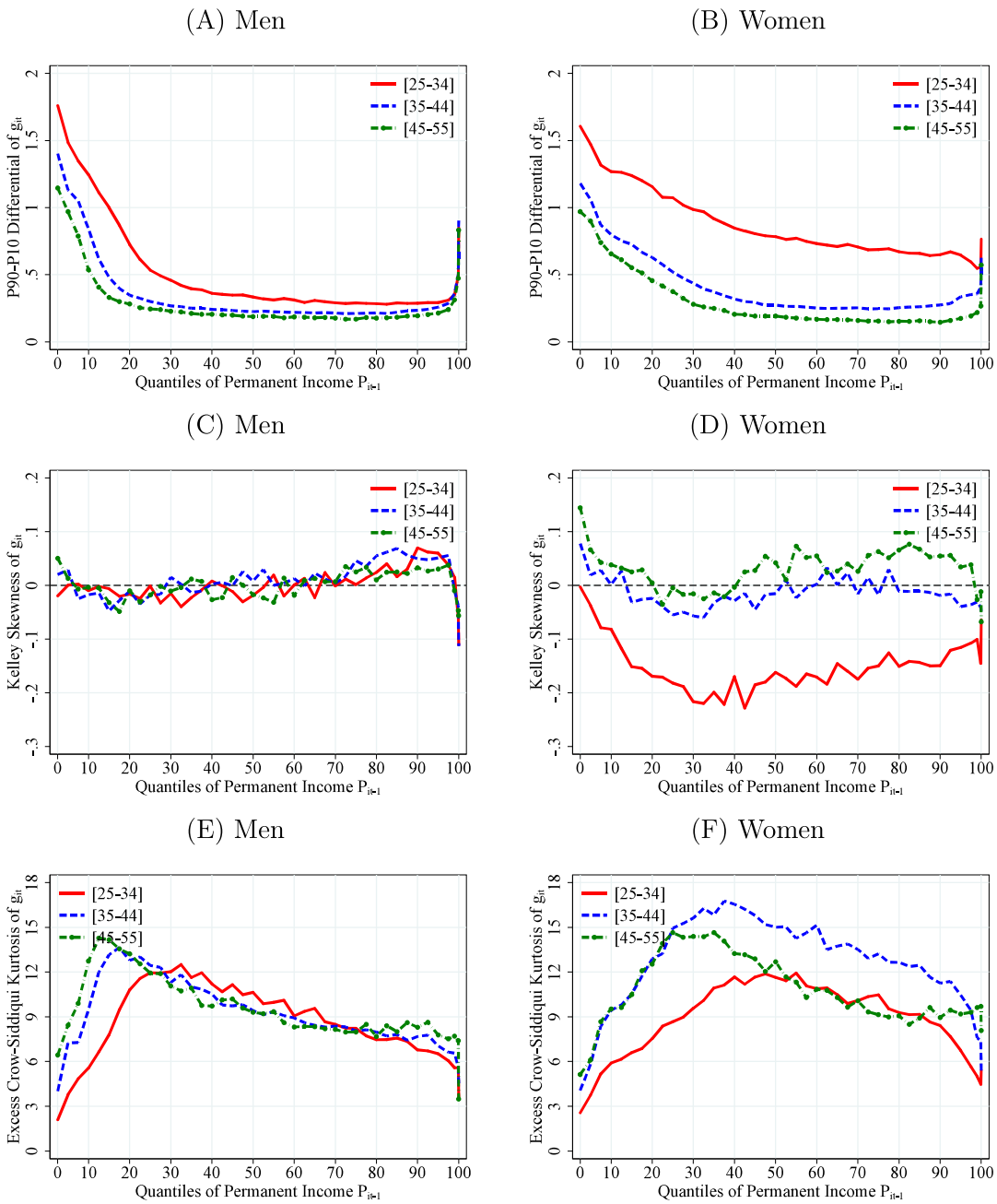
The measure of Skewness is essentially flat for male, except at the very top. The pattern is identical at all ages. By contrast, skewness is very strongly negative for women in the younger age group (25-34) for almost all quantiles of the permanent income distribution. However, it is rather flat for the two other (older) age groups (35 and above).

Finally, the Crow-Siddiqui kurtosis has an inverted U-shape across the quantiles of the permanent income distribution with a maximum below the median. This pattern holds for both men and women as well as for all age groups.

We compute similar statistics using now the five-year earnings changes. Results are presented in Appendix Figure E.3. The P90-10 differential looks pretty similar to that of the one-year change. However, Kelley skewness is much more negative and much less flat (U-shaped in fact) than its one-year equivalent. Finally, the kurtosis has again an inverted U-shape. However, the magnitude of the kurtosis is similar for men but smaller for women for the five-year change than it is for the one-year one.

[32]Permanent earnings are defined as the average of non-missing earnings between t and t-2 net of age and year effects separately by gender.

Figure 11 – Dispersion, Kelley Skewness and Excess Crow-Siddiqi Kurtosis of One-Year Log Earnings Changes by Age Group



Note: Using residual one-year earnings changes and the H sample over the period 1994-2015, Figure 11 plots against permanent income quantile groups the following variables for the 3 age groups: (a) Men: P90-10, (b) Women: P90-10, (c) Men: Kelley Skewness, (d) Women: Kelley Skewness, (e) Men: Excess Crow-Siddiqui kurtosis, (f) Women: Excess Crow-Siddiqui kurtosis. Excess Crow-Siddiqui kurtosis calculated as $\frac{P97.5-P2.5}{P75-P25} - 2.91$ where the first term is the Crow-Siddiqui measure of Kurtosis and 2.91 corresponds to the value of this measure for Normal distribution. Dataset: Panel DADS.

In Appendix Figures E.4 and E.5, we present (standardized) measures of the moments of the earnings changes using their standard deviation, their skewness, and their kurtosis. These measures are computed on the whole distribution rather than using percentiles. Hence, they are more likely to be sensitive to extreme values

in contrast to those above.

Nevertheless, these standardized measures yield results that are pretty consistent with the P90-10 differential, the Kelley skewness, and the excess Crow-Siddiqui kurtosis. Indeed, using either the P90-10 or the standard deviation give a similar U-shape pattern. Similarly, both skewness and Kelley skewness are negative for the one-year and the five-year growth. Finally, both measures of our fourth-order moment display high excess kurtosis, the magnitude being even higher using kurtosis directly (as expected).

3.3 Earnings Mobility

We now focus on individual-level earnings mobility measured over 5 to 10 years, as well as its change over the sample period. Our first results are presented in Figure 12. They give the 10-year mobility rate, measured as the mean percentile in the "ten-years after" distribution as a function of the position in the initial permanent earnings distribution.[33] The use of a measure of permanent income allows us to mitigate concerns about a mechanical relationship due to a reversion to the mean. The black (thin dotted) line shows what would be observed in a world without mobility. Results for men are presented on the left when those for women are shown on the right. For the 10-year mobility measure, we divide the population into two age groups.

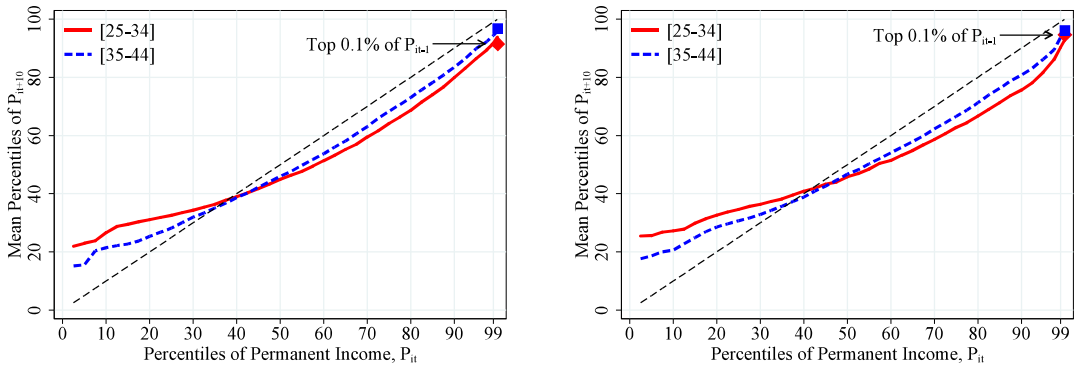
As expected, we observe upward mobility at the bottom of the distribution until the 40th percentile. As observed in most mobility studies, we also see that mobility is decreasing with income at the top, most particularly at the very top percentiles. Again, unsurprisingly, mobility is larger for the younger age group as well as for females (less so at the very top percentile though).

The Appendix Figure F.1 that focuses on 5-year mobility yields essentially similar conclusions.

[33] In this Section, we use a slightly modified version of the permanent earnings. We keep individuals with earnings above the minimum threshold for at least one year (two in the previous definition). We hence also include in our sample workers with little attachment to the labor market.

Figure 12 – Evolution of 10-Year Mobility Over the Life Cycle

(A) Men (B) Women

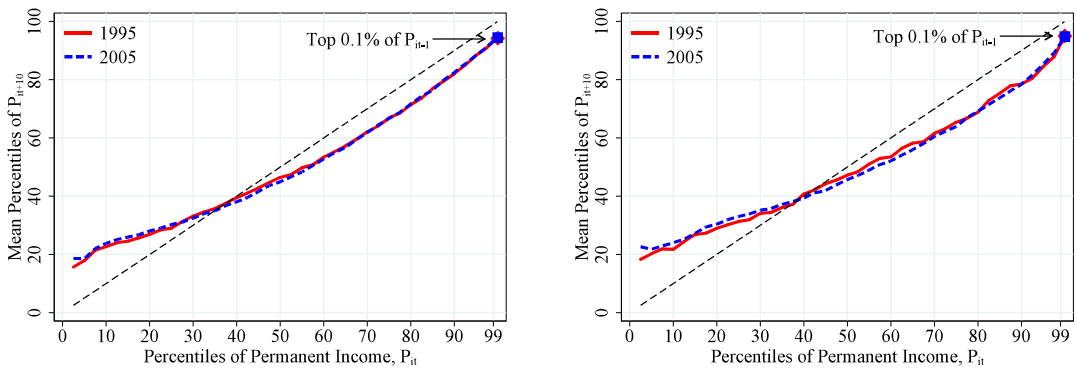


Note: Using permanent income and the H sample over the period 1993-2006, Figure 12 plots the average rank-rank mobility for two age groups separately for men and women over the period 1993-2006. The 45-degree (dashed black) line corresponds to the case of perfect immobility: workers stay on average at the same percentile after 10 years. Dataset: Panel DADS.

Figure 13 presents these 10-year mobility measures at two points in time, 1995 and 2005 (the starting years). Mobility is constant over time for both men and women. The Appendix Figure F.2 shows a small increase in 5-year mobility for both men and women, including at the very top.

Figure 13 – Evolution of 10-Year Mobility Over Time

(A) Men (B) Women



Note: Using permanent income and the H sample, Figure 13 plots the average rank-rank mobility in 1995 and 2005 separately for men and women. The 45-degree (dashed black) line corresponds to the case of perfect immobility: workers stay on average at the same percentile after 10 years. Dataset: Panel DADS.

In order to study more systematically the changes in (relative) mobility over time, we perform a rank-rank correlation analysis using the following regression:

$$\mathrm{R}_{perm,i,t+k} = \beta_0 + \beta_1 \times \mathrm{R}_{perm,i,t} + \epsilon_{i,t} \tag{2}$$

where $\mathrm{R}_{perm,i,t}$ is the rank in the permanent earnings distribution of individual i

in year t. The coefficient β_1 provides the degree of relative labor earnings mobility. The Appendix Figure F.3 plots coefficient β_1 for each sample year. The estimated value over the period is .8 (se: .0002). In addition, the coefficient barely moves over the period of interest with small ups around recessions and downs in periods of higher growth. We repeat the exercise by age group and by gender (see Appendix Figure F.4). Consistent with our previous results, relative mobility is lower for older workers and higher for women. In anticipation of our analysis of French territories (just below), Appendix Figure F.5 shows that relative earnings mobility is larger in Paris than in other territories in 1995, but all such mobility numbers converge across territories (decreasing markedly in Paris and slightly increasing everywhere else).

4 Geographic Disparities in France

In this Section, we examine the spatial dimension of inequality. We start with an analysis of Urban Areas, our measure of cities. We then turn to territories, as defined in Section 2.3.

4.1 Inequality Between Urban Areas

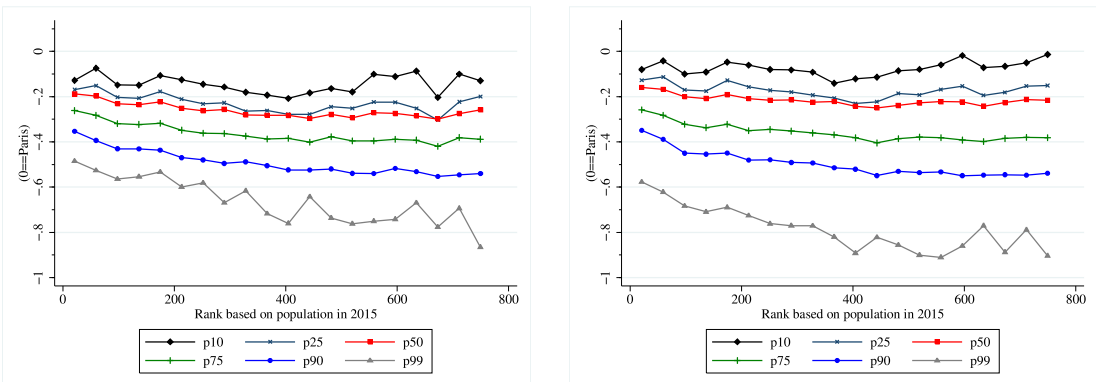
Figure 14 presents our first assessment of inequality between cities. We rank the 759 urban areas by size (population in 2015), Paris being the first. Then, we present various percentiles of the real raw log-earnings distribution across these cities, using a bin-scatter plot. All percentiles are displayed in difference from the Paris urban area. On the left, we show the distribution for 2001 and, on the right, that for 2016. We use the comprehensive DADS (rather than the panel) in order to maximize the number of observations.

In both 2001 and 2016, the bottom of the distribution (the 10th percentile) is almost indistinguishable from that of Paris, across all cities; a reflection of the prevalence of the minimum wage for low-earnings workers. This result masks interesting disparities: even though Lyon (2nd in size) or Bordeaux (5th) low-earners are not very different from the Paris ones, those in Marseilles (3rd) or Dunkirk (40th) make

17% less than in Paris. Above this first decile, the gap is clearly increasing when city size decreases (moving from the left to the right of the x-axis of each Figure). For instance, the worker at the 99th percentile in Lyon (2nd) makes 31% less than the corresponding worker in Paris, but the gap increases to 44% in Marseilles or Bordeaux and to 61% in Dunkirk. Because Paris's urban area also includes poor areas, the gap between Paris per se and other cities is a lower bound for each percentile shown on Figure 14. We will come back to this point in Section 4.5 where we compare levels and trends in labor earnings between the municipality of Paris and its suburbs. Finally, the gap is clearly largest for the top of the distribution, and is larger in 2016 than in 2001. On the other hand, the gap at the bottom of the distribution is closing over the period (in Dunkirk, for instance, it decreases to 6%). However, the small differences in earnings at the bottom of the distribution may mask large differences in employment rates and job loss rates between areas (Bilal 2020).

Figure 14 – Between-Urban Areas Inequality

(A) 2001 (B) 2015



Note: Using raw log earnings for men and women, Figure 14 plots against city rank the difference between the log earnings of a person in percentile p in urban area a relative to the log earnings of a person in the same percentile in the earnings distribution of Paris. The difference is computed for the $10^{th}, 25^{th}, 50^{th}, 75^{th}, 90^{th}, 99^{th}$ percentiles for the periods: (a) 2000-2002, (b) 2014-2016. City rank is based on 2015 census population. Observations are the 759 French urban areas. Data are displayed using a bin-scatter. Dataset: panel DADS.

In Appendix Figure H.1, we examine the same question but controlling for demographic characteristics (gender, age, education), job characteristics (hours and occupation) and firms characteristics (4-digit industry code and firm size). Adding controls strongly decreases the gaps between percentiles as well as the slopes across cities, making these lines almost flat. The gap becomes very small at the bottom of the distribution (less than 5%) while it stays significant for top percentiles. Unsur-

prisingly, controls matter more for top percentiles that for those at the bottom, a reflection of a larger homogeneity of observable characteristics of individuals in the latter.

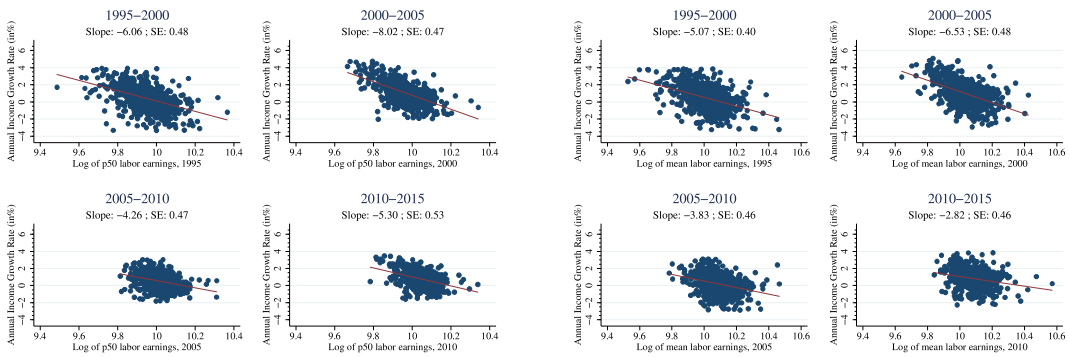
4.2 The Convergence of the "Poorest" Areas

In the previous analysis, we focused on inequality across cities at given points in time. We now turn to how our measures of inequality across cities evolved over time. To characterize cities, we use median and mean labor earnings. We decompose our sample period into four sub-periods: 1995-2000, 2000-2005, 2005-2010, and 2010-2015. For each measure, we plot in Figure 15 the initial level of earnings of the urban area on the horizontal axis (i.e. labor earnings in the first year of the sub-period). Then, we plot the corresponding annual income growth rate over the sub-period on the vertical axis.

The negative slope parameter, reported for each sub-period and for both measures of earnings, attests of the strong convergence that took place between areas during the 1995 to 2015 period. We indeed observe a strong compression of cities' mean and median earnings over the period.

Figure 15 – Convergence of Log Earnings Between Urban Areas

(A) Median Labor Earnings (B) Mean Labor Earnings



Note: Using the real raw labor earnings of both men and women, Figure 15 plots for four sub-periods the correlation between the growth rate of: (a) median labor earnings, (b) mean labor earnings, and the log of labor earnings for the first year of the sub-period. Observations are the 759 French urban areas. Median and mean earnings are computed at the urban area level. The coefficients and the red line correspond to the linear regression of the growth rate on the log of the initial level of labor earnings. For each sub-period, the annual growth rate is trimmed at the 1% level. Standard errors are robust to heteroscedasticity. Dataset: Panel DADS.

When performed on the whole period, the slope coefficients are respectively equal

to -2.71 for the mean and to -3.19 for the median measure. Furthermore, convergence appears to be higher at the beginning of the period and decreasing recently. This faster convergence between 1995 and 2005 clearly corresponds to the major reforms – reduction of the workweek, increase in minimum wage, decrease in total labor cost at the minimum wage – described in Section 2.1.

Results shown on Figure 14 and Figure 15 present complementary (rather than contradictory) evidence. At the bottom of the distribution, convergence is strong in particular with respect to Paris. However, at the top and the very top of the distribution, divergence is also very strong. To give a unified assessment of this phenomenon using a common metric, we computed the sum across urban areas of the squared difference in earnings with respect to Paris at different percentiles, in 2001 and in 2016. The numbers are presented in Appendix Table H.1. The measured difference shrinks at the bottom and even in the middle of the distribution but widens at the top (95th and 99th percentiles). In another attempt to provide a unified view of these opposing phenomena, we reproduced Figure 15 using the size of urban areas rather than their initial income level. Resulting estimates demonstrate the same convergence in particular for the smallest areas (see Online Appendix Table I.1). However, growth rates in the smaller zones are quite dispersed (less so in the large ones). Hence, size does not suffice to summarize earnings dynamics in small areas.

We then turn to inequality between Territories, including both urban and rural areas. In Figure 16, we plot the log difference in (A) median, (C) mean earnings, between Paris and the other territories.[34] Figures 16B and 16D plot the evolution of these log differences normalized to 0 in 1993.[35] As before, we observe a huge gap in earnings between Paris and other territories, in particular for the mean. There is also differences between territories, in particular, the gap is smaller for the suburbs whereas it is very large and almost the same in the three other territories at the start of the period (using both measures of earnings).

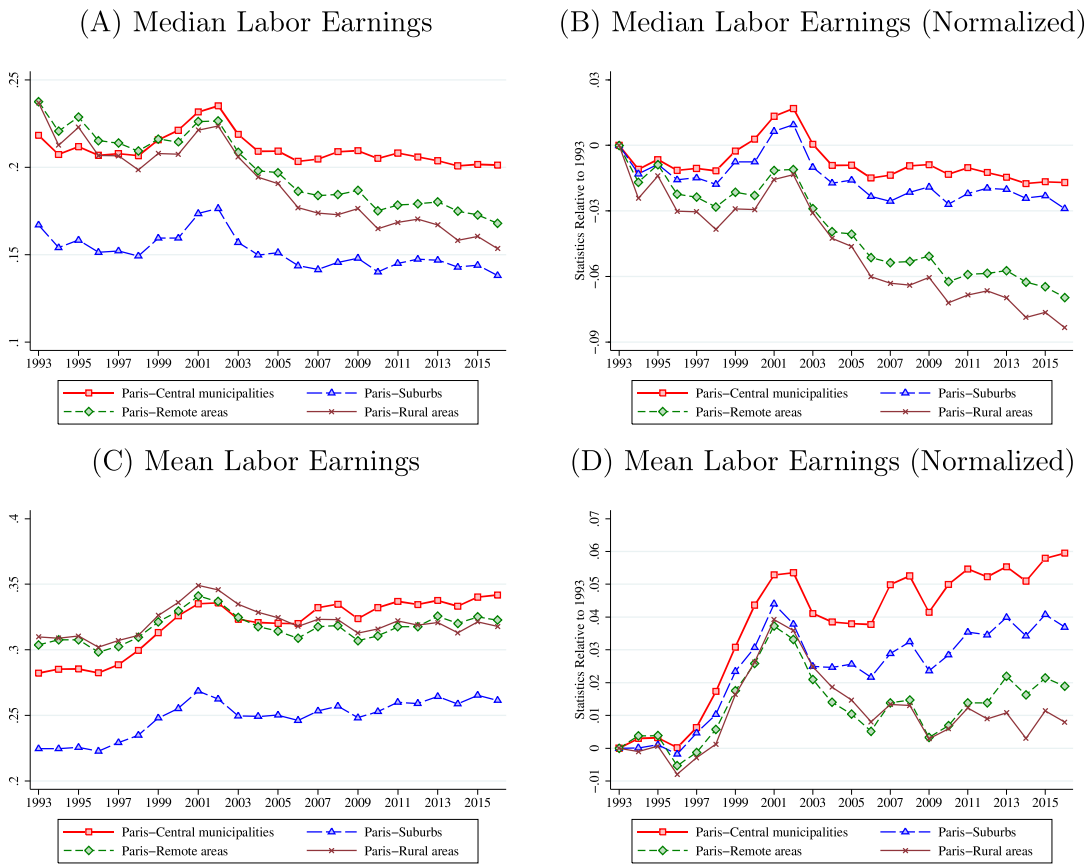
[34]Since we use the word "territories", it implies that we refer to Paris as a urban unit. We also classify municipalities as central, suburbs, remote, and rural based on the urban unit they belong to.

[35]The place of residence is only available in the data since 1993. As a result, we focus on the period 1993-2016 thereafter.

Over the years, we observe a strong reduction in the gap between the urban unit of Paris and the other territories when we use our median earnings measure implying a convergence between territories. However, the gap with Paris grows when using our mean earnings measure, a reflection of the higher growth of the top of the distribution in Paris (e.g. P99) compared to other territories.

The normalized numbers, in Figures 16B and 16D, complement these results. The gap using the median stays almost constant between Paris and central municipalities as well as suburbs but constantly decreases between Paris and rural areas as well as between Paris and remote areas. By contrast, all gaps increase using normalized mean labor earnings until 2001. They then stabilize at their 2001 level in both central municipalities and suburbs. They decrease and go back to their mid-90s level in remote and rural areas.

Figure 16 – The Urban Unit of Paris vs. the Rest



Note: Using the real raw log labor earnings of both men and women, Figure 16 plots against time the differential between: (a) median labor earnings in Paris and in other territories, (b) median labor earnings in Paris and in other territories normalized to 0 in 1993, (c) mean labor earnings in Paris and in other territories, (d) mean labor earnings in Paris and in other territories normalized to 0 in 1993. Territories and Paris are defined using urban units. Dataset: Panel DADS.

The different dynamics just described can be amplified or attenuated by local

trends in prices (see for example Diamond & Moretti (2021)). All previous statistics were computed using the national price index and implicitly assumed similar price dynamics across territories. Unfortunately, the French Statistical Office does not produce local price indices on a regular basis. However, during the 1998-2012 period, INSEE experimented and computed Consumer Price Indexes (CPIs) for the different city sizes. These local CPIs take into account both differences in consumption between areas (in particular due to the uneven distribution of occupations over the territory) and differences in local prices. They were computed for six groups of urban units: rural units, urban units with less than 20,000 inhabitants, urban units with a population between 20,000 and 100,000 inhabitants, urban units with more than 100,000 inhabitants (excluding the one for Paris), the Paris urban unit excluding Paris municipality, and finally the municipality of Paris. Appendix Figure H.2 replicates Figure 16D using the municipality of Paris as our reference group and for the period 1998-2012. We present in the Figure the evolution of mean earnings using the national price index (A), and the same evolution but using the local price indices (B). We first observe that the divergence between the municipality of Paris and the other urban units is increased when using local CPIs compared to national CPI. We also observe more similar tendencies between urban units. Whereas the gap between Paris and rural municipalities was growing more slowly than in other territories when using the national CPI, this is much less so when using local CPIs.[36] A faster growth of the local CPI in rural areas explains these differential changes. As pointed out by Chauvet-Peyrard (2013), most of the difference in inflation between territories is due to the consumption basket of the households rather than different trends in prices for similar goods. Indeed, workers in rural areas dedicate a much higher proportion of their income to transportation, heating and a higher one to alcohol and tobacco. As a result, they were adversely affected by the rapid increase in gasoline and fuel prices and to a lesser extent from cigarette prices than workers in Paris.

Unfortunately, this exercise is limited since the price index we use only imperfectly reflects a fraction of the variation in housing prices. More precisely, it incorporates variations in rents as well as variations in housing-related consumption

[36]Similar conclusions can be drawn when using median earnings rather than mean earnings.

(water, electricity, and gas in particular). However, owners are, in France, a majority when roughly 40% of households are tenants, with almost half of them living in social housing.

To further compare these territories, we present two sets of statistics, on minimum wage workers and on job-to-job mobility, for every year of our sample period.

Figure 17 shows the fraction of minimum wage workers by year and territory. These workers are defined by their hourly wage, comprised between .95 and 1.2 times the national minimum wage. The evolution is parallel for all territories with an increase between 2002 and 2006 which coincides with the strong increase in the minimum wage. However, the starting point differs with Paris having the lowest share of minimum wage workers, then suburban areas, whereas the fraction is at least 15% in all other territories. From 2006 on, this fraction stabilizes and even slightly decreases except in Paris again where it slightly increases. As a result, we observe a convergence in the share of minimum wage workers between the five Territories, especially since the mid-2000's. Looking at the fraction by gender, we observe both a much lower share of minimum wage workers and a much lower dispersion between territories for men; the gap between men and women being the smallest in Paris. However, both men and women experience the same trends as described for the joint sample (see Online Appendix Figure I.2).

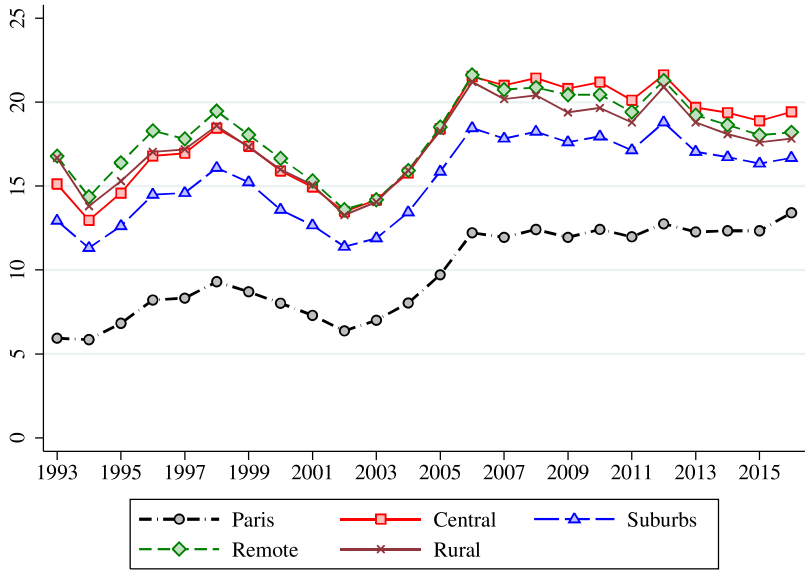
Figure 18 presents job-to-job mobility statistics by territory of origin, i.e. including both within and between territories moves, from 1993 to 2015. A move entails a change of establishment between t and $t+1$. As expected for a dense territory with more jobs and firms, mobility is highest in Paris' urban unit. It is lowest in rural areas, again an unsurprising result in a less dense territory. For all territories though, the changes are strictly parallel and pro-cyclical (with a maximum in 2000). Job-to-job mobility steadily decreases from 2001 on in all territories, a potential reflection of equalized opportunities within territories, as we will see in Section 4.4.

Employees working full-time[37] in t, experience similar trends but have a much lower mobility rate: around 14% in Paris and 9% in other territories. This large gap results from the inclusion in our main sample of many low-earners, most likely

[37]We define full-time workers as worker working full-time at least 350 days during the year.

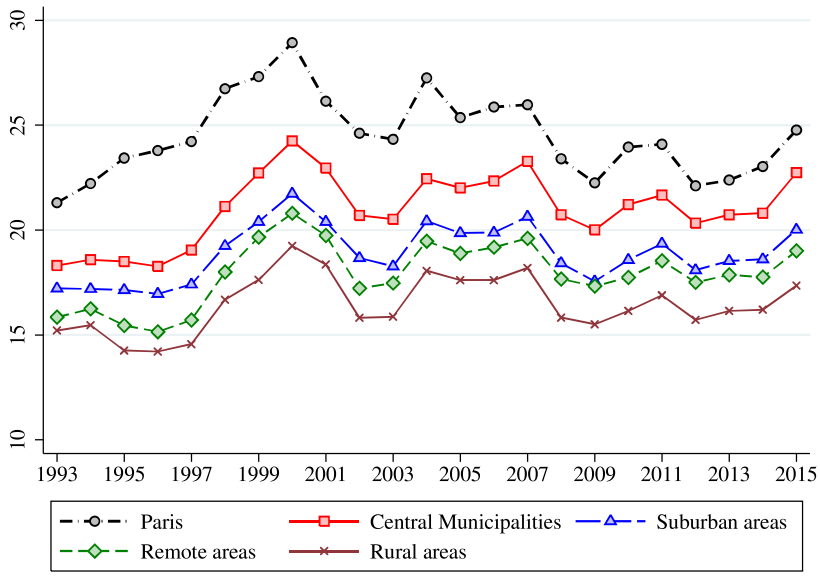
to experience periods of unemployment and to be hired under very short-term contracts. Using firm-to-firm mobility does not alter the above results (mobility larger in Paris, smaller in rural areas) with between 13% and 20% of workers moving every year.

Figure 17 – Share of Minimum Wage Workers by Territory



Note: Using the real raw log labor earnings of both men and women, Figure 17 plots the evolution over time of the share of minimum wage workers according to their place of residency. The share of minimum wage workers is defined as the share of employees with hourly earnings between .95 and 1.2 times the national minimum wage. Territories and Paris are defined using urban units. Dataset: Panel DADS.

Figure 18 – Job to Job Mobility by Territory



Note: Figure 18 plots the evolution over time of the share of workers who change plant between two consecutive years. Each share is computed based on the place of residency before the change happened, irrespective of the place of residency after the change. For each individual in the data, we consider only the highest paying job. Territories and Paris are defined using urban units. Dataset: Panel DADS.

4.3 Geographic Mobility

In this Subsection, we focus on geographic mobility in complement to our previous analysis of job-to-job mobility.

Geographic mobility mostly takes place between municipalities (most likely within a commuting zone) rather than between commuting zones (see Online Appendix Figure I.3). We first describe the mobility between territories (BT-mobility hereafter): moves between, say, Paris and Rural areas and their impact on earnings.

In line with common perception, mobility from Paris is half as likely (2.5% per year) as from each other territory (5-6% per year in 1993, slightly increasing to 6-8% in 2015). And mobility to Paris, the largest destination in line again with common perception, mostly comes from central municipalities rather than from more remote places (see Online Appendix Figure I.4). Such geographic mobility takes place at a relatively young age. To better characterize those workers moving to different places, we plot the average percentile (rank of permanent earnings) of movers by area of destination (see Online Appendix Figure I.5). Indeed, workers moving to Paris have the largest average percentile (57th in 1993), followed by workers moving

to suburban areas (54th in 1993), and other destinations (52th in 1993). The ranking is unchanged over the sample period but the average percentile decreases constantly (to 54th in Paris and 48-50th for other destinations).[38]

To give a fuller view of mobility, we contrast earnings growth for the stayers and for the movers. Online Appendix Figure I.6 shows the 5-year (log) earnings growth distribution for stayers (in Paris, rural territories, and in Province[39]). The distribution is very similar in Province and Rural territories: leptokurtic with negative skewness. The distribution in Paris is less peaked and exhibits less negative skewness. Online Appendix Figure I.7 show similar distributions for movers (again between these three origins/destinations). In contrast with stayers, moves to Paris induce a right shift in the 5-year (log) earnings growth distribution with the associated thickening of the right tail (upwards mobility) whereas mobility from Paris has the opposite consequence (downwards mobility). For movers to and from destinations other than Paris, the earnings distributions do not shift much, very much similar to those observed for stayers, albeit with a decreased fraction of zero earnings growth (less peaked).

4.4 The Decrease in Within Territories Inequality

In this section, we study how inequality evolved within the six territories considered. Figures 19 and 20 present changes for various percentiles of the log real earnings distribution, in difference with 1993, for men on the left side, and women on the right side of the Figures. Results for Paris, central municipalities, and suburbs are shown in the first of the two Figures when those for remote and rural municipalities are given in the second Figure.

Results are pretty striking. First, wage growth is quite low for men, and even negative for the bottom percentiles, for all territories. By contrast, wage growth is quite strong for women in all territories. The contrast between men and women is even stronger when looking at the bottom percentiles, especially the 10th per-

[38] A similar analysis using residual ranks yields similar results.

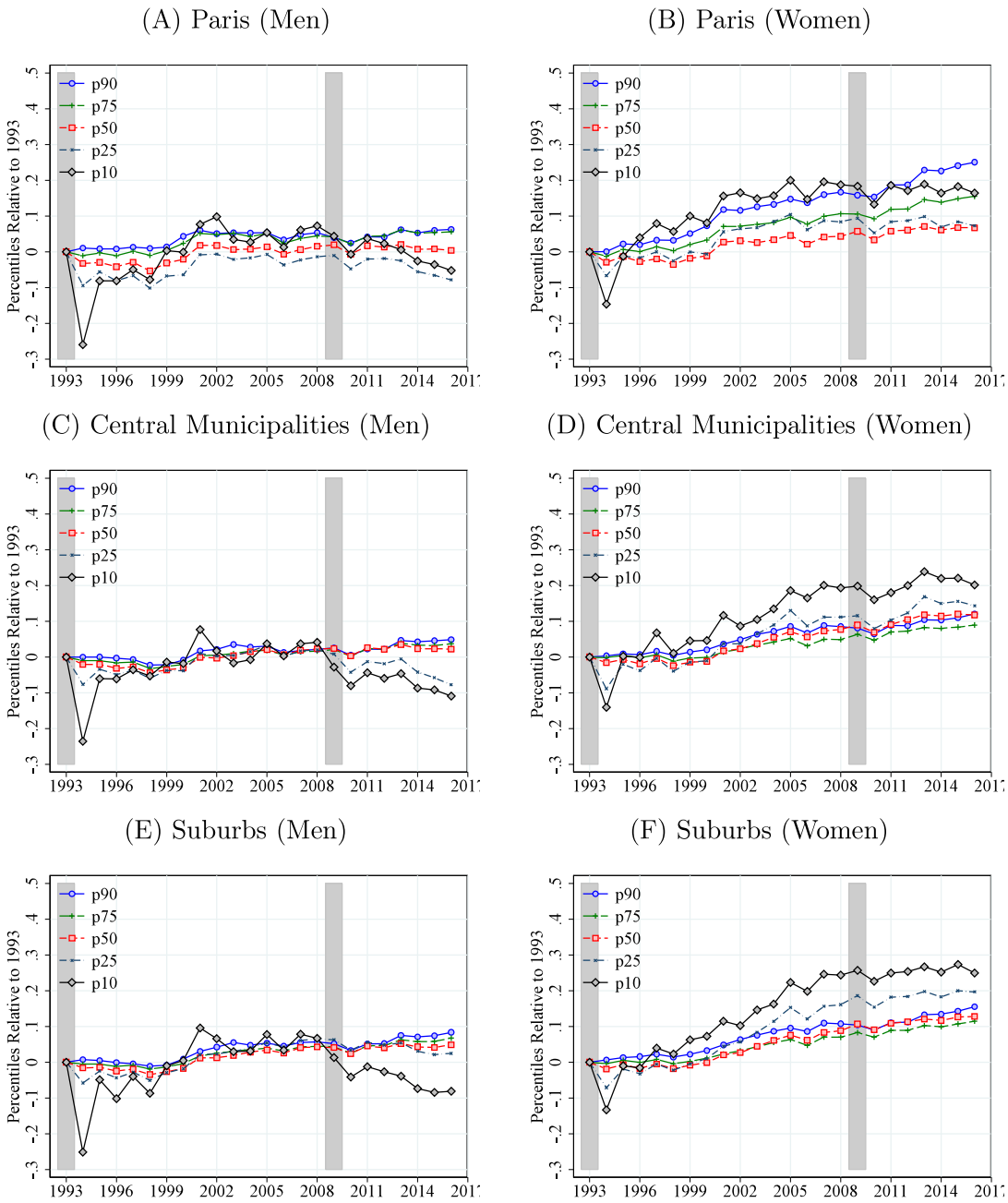
[39] To make graphics easier to read, we focus on three territories: the urban unit of Paris, rural territories and the other territories that we denote "Province".

centile. Even more strikingly, this wage growth is largest for rural territories, then remote when the more urban territories look quite similar: strong growth at the bottom percentiles (but not as strong as that in rural and remote territories). Paris is once more different: wage growth is largest for women at the top percentile (P90).

A direct consequence of these results (confirmed by Appendix Figures H.3 and H.4) is the decrease in inequality for women in all territories, except for Paris, at least until 2009. As seen above, the decrease is much larger in rural and remote territories. These Figures also show the moderate decrease in inequality for men until 2009. Inequality increases since then, with inequality being back or even above its 1993 level.

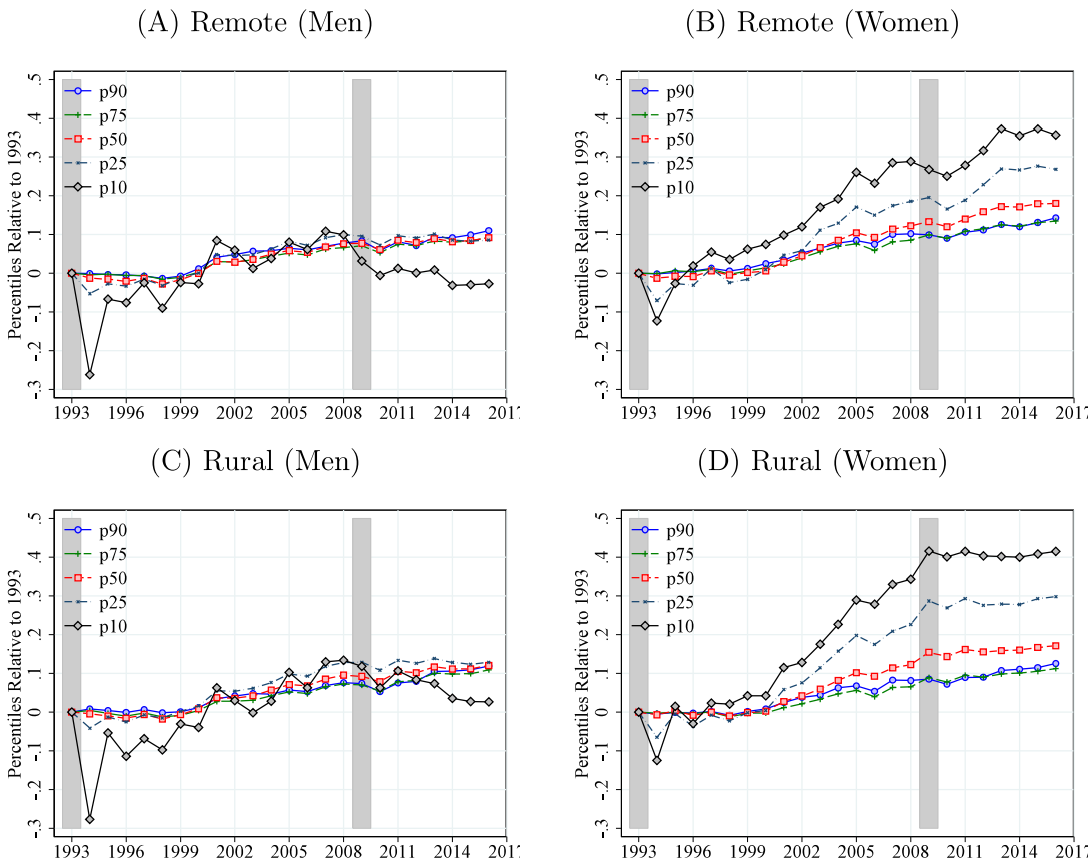
Turning to inequality *levels*, the difference between the 90th and 10th percentiles is much higher in Paris than in other territories where this difference looks pretty similar. However, inequality for men is pretty well ordered: much lower in rural and remote areas, intermediate in suburbs and central municipalities, and extremely high for Paris. The level of inequality is much lower for men in rural territories than it is for women but the two converge at the end of our sample period. Finally, inequality is higher in Paris for men than it is for women.

Figure 19 – Change of Percentiles of the Log Real Earnings Distributions by Territory



Note: Using real raw log earnings separately for men and women, Figure 19 plots against time the P10, P25, P50, P75, P90 for: (a-b) the urban unit of Paris, (c-d) central municipalities and (e-f) the suburbs. All statistics are normalized to 0 in the first available year. Territories and Paris are defined using urban units. Shaded areas represent recession years. Dataset: Panel DADS.

Figure 20 – Change of Percentiles of the Log Real Earnings Distributions by Territory (continuation)



Note: Using real raw log earnings separately for men and women, Figure 20 plots against time the P10, P25, P50, P75, P90 for: (a-b) remote municipalities, (c-d) rural municipalities. All statistics are normalized to 0 in the first available year. Territories and Paris are defined using urban units. Shaded areas represent recession years. Dataset: Panel DADS.

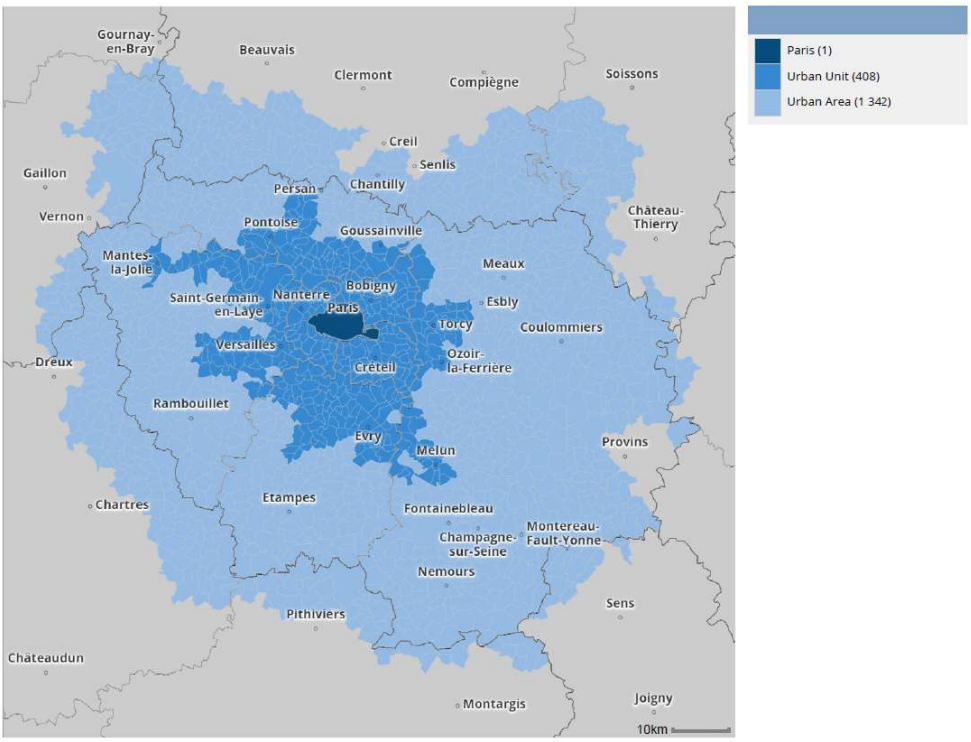
Recent political events in France have placed earnings inequality but also on employment and its evolution in the public sector under the spotlight. In particular, almost always stemming from the recent protests was a demand to increase public services in remote and rural areas. Its origin was the perceived decrease in the supply of State-provided services, to the point of their disappearance, in these territories.

As a complement to our results on earnings inequality by territory, Online Appendix Section I.4 provides evidence on the evolution of public services across space and over time, proxied by public employment. We study its changes in the aggregate as well as for the three types of public sector employment: State civil servants, local civil servants, and hospital civil servants. Furthermore, we contrast these changes across territories.

4.5 Paris: the Center, the Suburbs, and its Outskirts

Because the Paris urban area is so large, comprising Paris municipality per se, Paris's suburbs, and a large set of land that includes rural municipalities, we present in this subsection results for these three zones. These three areas are presented on the Figure 21 with the dark blue showing the municipality of Paris, in medium blue Paris's urban unit (as defined in Section 2.3), a unit that includes 408 municipalities, and in light blue the rest of Paris's urban area, which includes 1,342 municipalities.

Figure 21 – Paris and its Surroundings



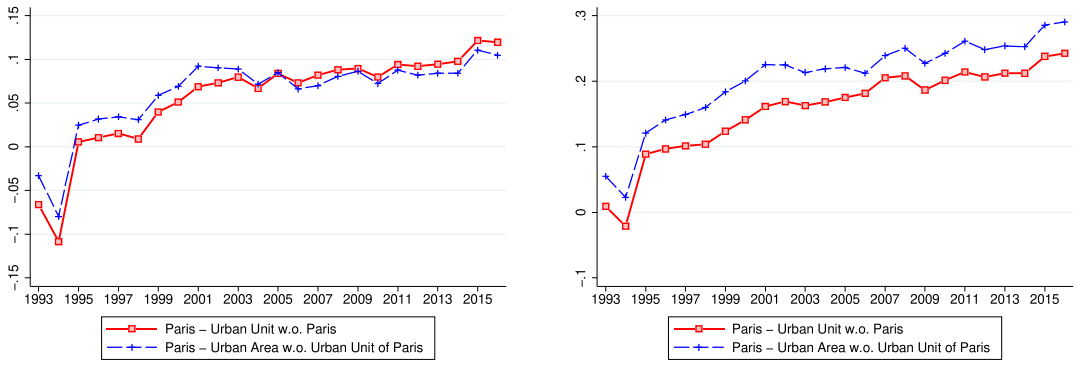
Note: Figure 21 plots Paris and its surburbs. Numbers in parenthesis correspond to the number of municipalities.

Figure 22 plots the median (A) and the mean (B) log earnings differential between the municipality of Paris and its suburbs (the urban unit without Paris) and between the municipality of Paris and Paris's urban area (without Paris full urban unit) over the 1993 to 2015 period. For both measures, the differential increases implying that inequality between Paris and its suburbs or its outskirts increases steadily, potentially because Paris intra-muros includes a top of the distribution that has very strongly increased over the period. While the gap with the municipality of Paris was low at the beginning of the period, the difference amounts to

25% for mean earnings (respectively 12% for median) in 2016. Interestingly, the trends and levels are very comparable in both suburbs and outskirts. As a result, previous results on between-areas inequality should be interpreted keeping in mind the strong divergence between the municipality of Paris and the rest of France.

Figure 22 – Paris center vs. its surroundings

(A) Median (B) Mean



Note: Using raw log earnings for men and women, Figure 22 plots against time: (a) the median, (b) the mean, labor earnings differential between Paris and its suburbs. Paris corresponds to the municipality of Paris. Dataset: panel DADS.

5 Conclusion

The French labor earnings inequality and dynamics over the last 25 years have been shaped by labor market institutions and their changes: strong increase in the minimum wage, sharp decrease in labor costs at and around the minimum wage, the implementation of the 35-hours workweek, resulting in the absence of a rising inequality. Even if the top 0.1% or 0.01% increased more than lower percentiles, as was observed in other countries, the lessons from France should not be centered on the top but on the bottom of the distribution, in particular for women who clearly benefited from the increase in the hourly minimum wage. Indeed, women often employed in part-time jobs increased hours (inducing a potential supply effect), in contrast to men, while labor costs at the minimum wage decreased (inducing a potential demand effect). A more complete analysis of the bottom of the French earnings distribution is clearly needed.

The above changes seem to have had interesting and, again, counter-intuitive consequences on the inequality between territories: the smaller urban areas have

converged (in terms of median or mean earnings) to the larger ones. Furthermore, rural and remote territories have witnessed a clear decrease in inequality at the bottom of the earnings distribution. Finally, these remote or rural territories do not seem to have been "abandoned" by the central State, as often stated in these territories: public employment increased there over the period, both in local public jobs and public hospitals. All these developments in these territories are a far cry from public perception.

The tensions between centralized institutions deciding most policy changes and local entities (municipalities, constituencies) have generated reactions, even protests, to these changes that question policy-making and how resulting outcomes are perceived. In particular, those individuals closer to the middle of the earnings distribution do not seem to have benefited from these labor market policies. They also do not seem to have been aware of the positive changes in public employment, in a context where hospitals were closed and municipalities forced to regroup (see Tricaud (2020)). Were the Yellow Vests protests an echo from the populist movements that emerged in many other countries, in particular the United States?

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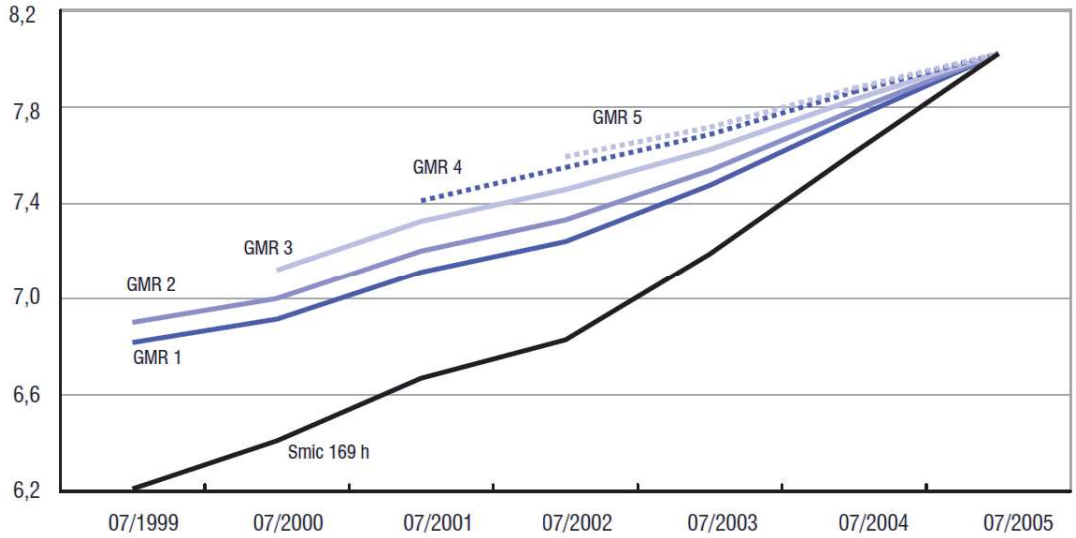
Appendices

A The Reduction of the Workweek

At the end of the 1990s, the Jospin government, with Martine Aubry as Minister of Labor, decided to fulfill an electoral promise and to go to 35 hours. Discussions between the government, which included the green party, and business unions were tense. Negotiations started within various industries and firms. But, at some point, Martine Aubry enacted a law essentially forcing firms above 20 employees to come up with some agreement with their workers' unions or delegates. In addition, various incentives and subsidies were proposed at different moments in time. For instance, in June 1998, the so-called Aubry I laws gave establishments incentives to reduce their workweek and create or preserve employment in exchange for large subsidies. In order to receive these subsidies, firms had to reduce hours by at least 10% in order to attain an average weekly duration of 35 hours. In such a case, employment creation had to amount to 6% of total employment. A "defensive" aspect also allowed firms to receive subsidies to avoid economic separations or collective dismissals. The 2000 law, Aubry II, offered payroll tax subsidies for all firms that decided to go to 35 hours per week. Hence, among firms with more than 20 employees, at the beginning of the 21st century, various agreements prevailed. Some firms were still at 39 hours and had to pay overtime, others went to 35 hours between June 1998 and January 2000 and received incentives and subsidies, others refused the incentives (but received some "structural" subsidies) even though they went to 35 at similar dates (the so-called Aubry II forerunners). Firms also went to 35 hours after January 2000, receiving only the "structural" subsidies. Finally, remaining firms went to 35 hours and decided to receive no subsidies.

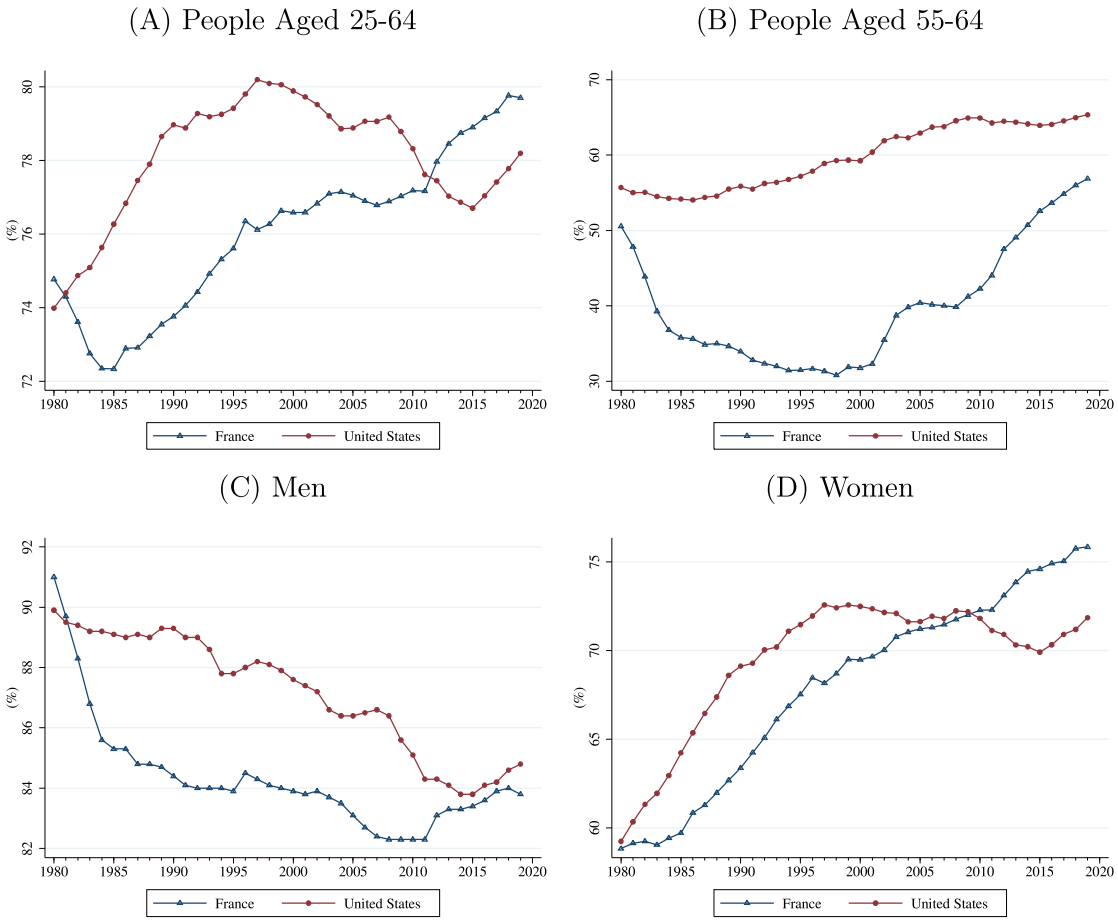
Figure A.1 – The Several Minimum Wages in the 2000s



Note: Figure A.1 plots against time the five hourly minimum wages (GMR) for workers working 35 hours a week and the hourly minimum wage for workers working 39 hours a week (Smic 169h). Values are expressed in euros. GMR stands for "Garantie Mensuelle de Rémunération". GMR 1-5 are applicable to firms which started reducing their worker's workweek respectively between: (1) 06/1998-06/1999 (2) 07/1999-06/2000 (3) 07/2000-06/2001 (4) 07/2001-06/2002 (5) in 07/2002. Source: Malik Koubi and Bertrand Lhommeau, *"Les salaires en France"*, 2007, Ministry of Labor. Go back to main text

B Data and Descriptive Statistics

Figure B.1 – Participation Rate



Note: Figure B.1 plots against time the participation rate for: (a) people aged between 25 and 64, (b) people aged between 55 and 64, (c) men aged 25-64, (d) women aged 25-64. Source: OECD. Go back to main text

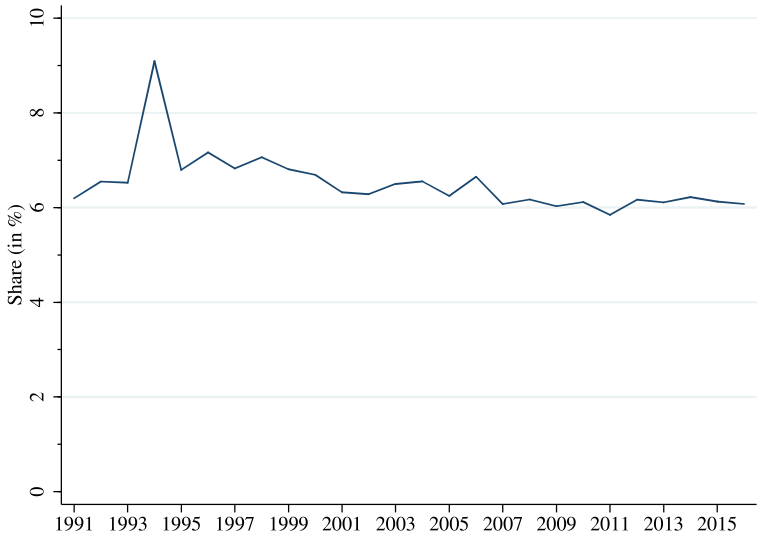
Table B.1 – Minimum Earnings Threshold

Year	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
Threshold	1850	1913	1909	1941	1964	1992	2024	2077	2100	2111	2153	2182	2220

Year	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Threshold	2295	2385	2444	2468	2466	2505	2506	2498	2529	2539	2553	2574	2585

Note: Table B.1 displays for each year the minimum labor earnings threshold in euros 2018. Go back to main text

Figure B.2 – Share of Observations Below the Minimum Earnings Threshold



Note: Figure B.2 displays for each year the share of observations with annual earnings below the minimum labor income threshold displayed in Table B.1. Dataset: Panel DADS. Go back to main text

Table B.2 – Earnings Distribution in France (Panel DADS)

(a) Total Population

Year	P1	P5	P10	P25	P50	P75	P90	P95	P99	P99.9
1995	2,403	4,455	7,553	16,026	23,270	31,838	44,691	58,033	99,798	194,779
2005	2,933	5,386	8,873	17,595	24,382	33,178	47,000	60,675	106,531	236,190
2015	3,148	5,679	9,036	18,021	25,749	35,165	50,150	64,506	113,020	266,795

(b) Men

Year	P1	P5	P10	P25	P50	P75	P90	P95	P99	P99.9
1995	2,565	5,423	9,516	18,612	25,415	35,139	51,483	67,704	115,618	227,547
2005	3,111	6,357	10,647	20,156	26,571	36,476	53,346	69,892	123,907	281,434
2015	3,244	6,172	9,992	20,293	27,879	38,578	56,254	72,921	131,998	327,918

(c) Women

Year	P1	P5	P10	P25	P50	P75	P90	P95	P99	P99.9
1995	2,286	3,749	6,005	12,576	20,385	28,135	37,182	43,981	67,681	120,424
2005	2,809	4,667	7,398	14,595	21,773	29,419	39,734	48,360	77,769	147,850
2015	3,072	5,273	8,189	15,903	23,677	31,669	43,096	53,878	89,108	185,495

Note: Table B.2 shows summary statistics for CS sample separately for (a) total population, (b) men and, (c) women. Dataset: Panel DADS. Go back to main text

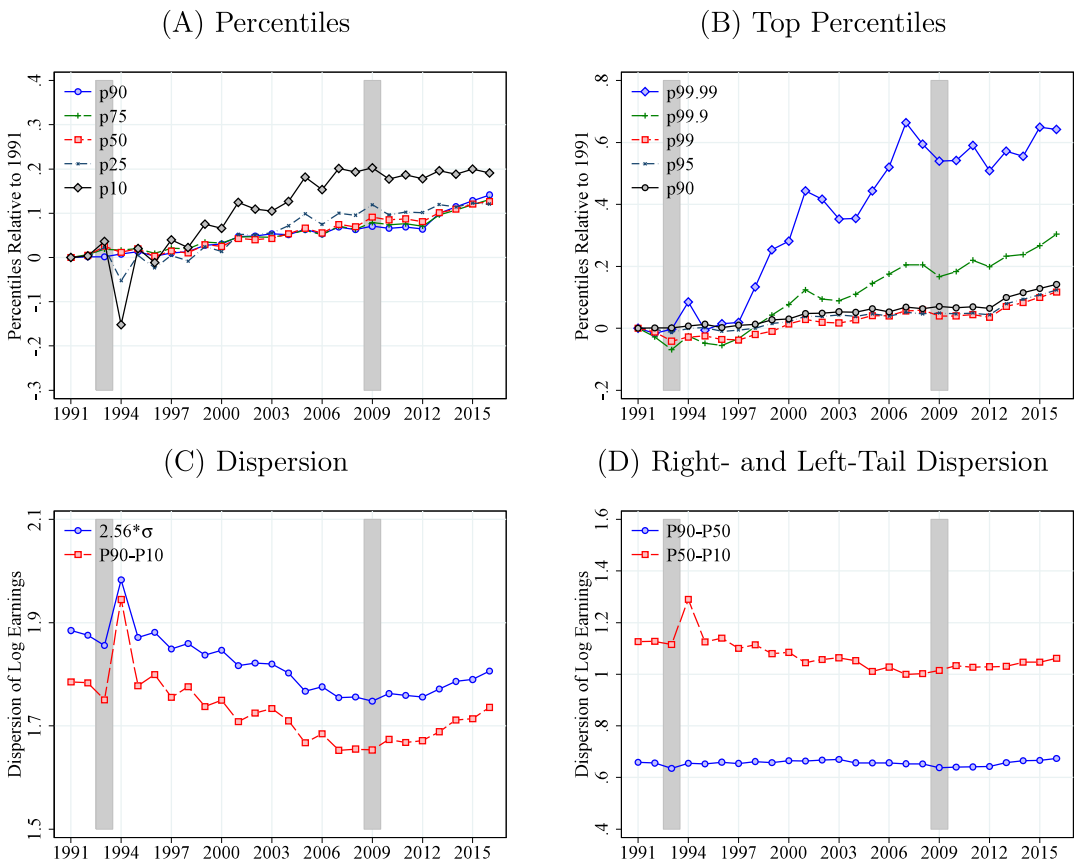
Table B.3 – Descriptive Statistics

Year	Obs. (Mill)	Mean Income Men	Mean Income Women	Women % Share	Age Shares % [25,35]	Age Shares % [36,45]	Age Shares % [46,55]	Education Shares % <HS	Education Shares % HS	Education Shares % CD	Education Shares % >CD
1995	.58	29,896	21,772	43.2	37.7	35.1	27.2	67.8	13.9	10.7	7.7
2015	1.38	33,062	25,999	47.7	34.7	32.8	32.5	43.6	21.8	18.6	16.0

Note: Table B.3 shows descriptive statistics for CS sample. We construct four groups of workers based on their highest diploma. <HS are workers with less than a high school diploma, HS are workers with a high school degree, CD are workers with a two-year college diploma and >CD are workers with an advanced university degree. Dataset: panel DADS. Go back to main text

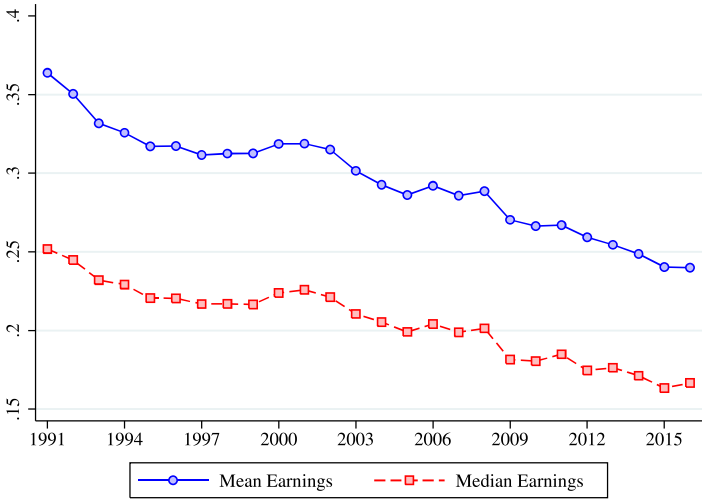
C Inequality

Figure C.1 – Distribution of Log Real Earnings in the Population



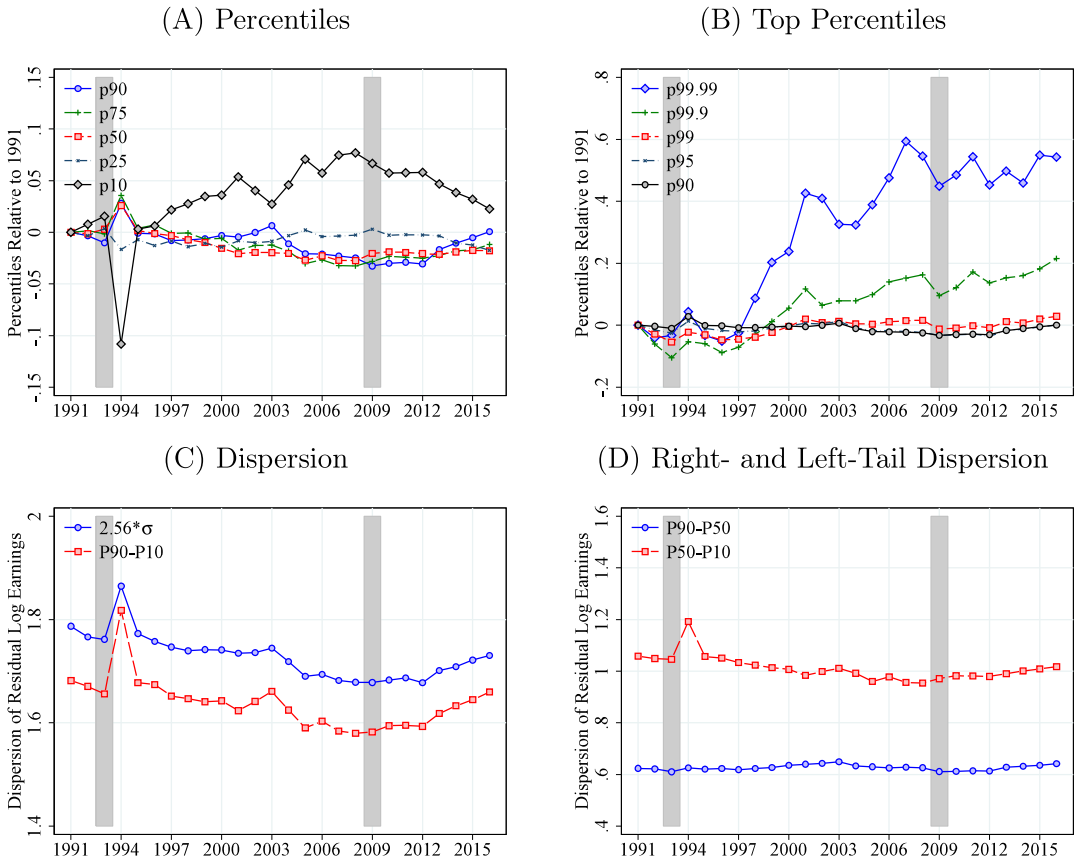
Note: Using raw log earnings and the CS+TMax sample, Figure C.1 plots against time the following variables: (a) Men and women: P10, P25, P50, P75, P90 (b) Men and women: P90, P95, P99, P99.9, P99.99, (c) Men and women: P90-10 and 2.56*SD of log income, (d) Men and women: P90-50 and P50-10. All percentiles are normalized to 0 in the first available year. 2.56*SD corresponds to P90-10 differential for a Gaussian distribution. Shaded areas represent recession years. Dataset: Panel DADS. Go back to main text

Figure C.2 – Unconditional Gender Pay Gap



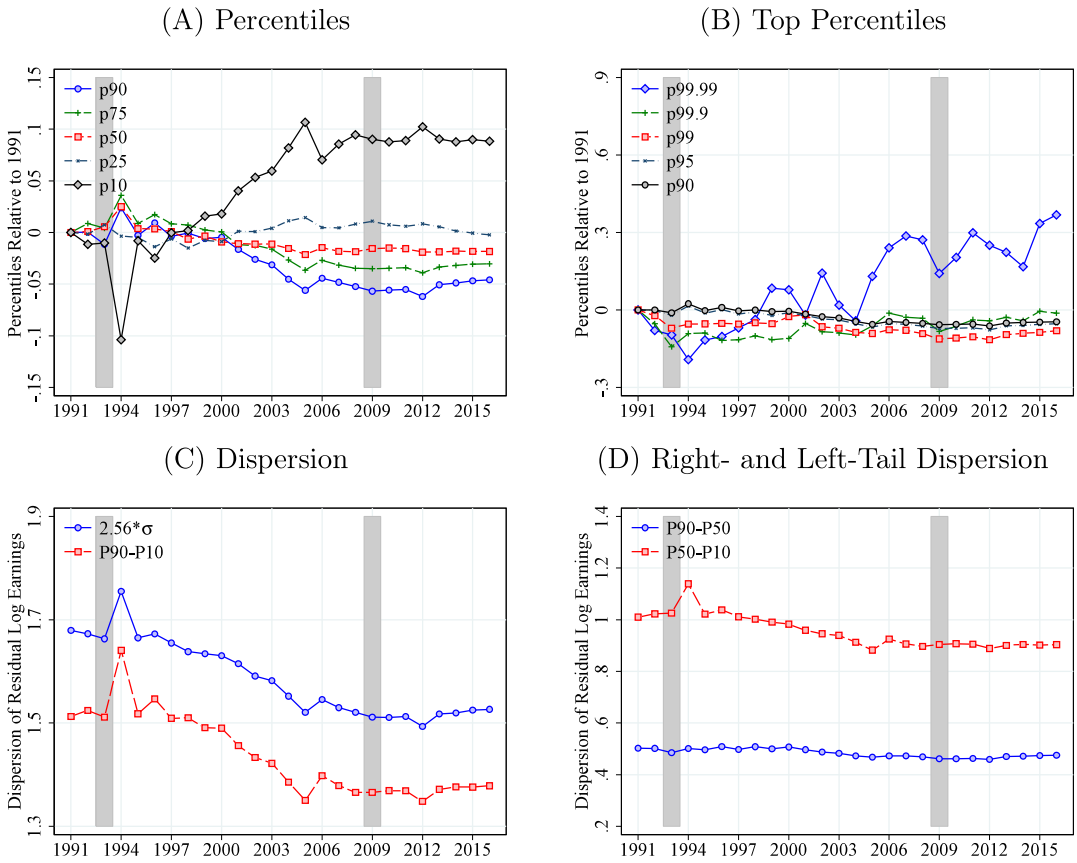
Note: Using raw real log earnings and the CS+TMax sample, Figure C.2 plots against time the difference between men and women mean (respectively median) earnings. Dataset: Panel DADS. Go back to main text

Figure C.3 – Distribution of Residual Earnings in the Population After Controlling for Age



Note: Using residual earnings (controlling for age) and the CS+TMax sample, Figure C.3 plots against time the following variables: (a) Men and women: P10, P25, P50, P75, P90 (b) Men and women: P90, P95, P99, P99.9, P99.99, (c) Men and women: P90-10 and 2,56*SD of log income, (d) Men and women: P90-50 and P50-10. All percentiles are normalized to 0 in the first available year. 2.56*SD corresponds to P90-10 differential for a Gaussian distribution. Shaded areas represent recession years. Dataset: Panel DADS. Go back to main text

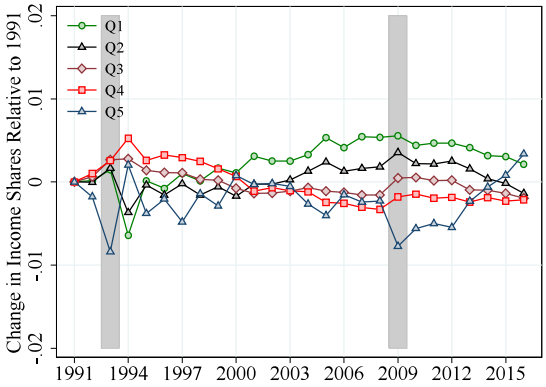
Figure C.4 – Distribution of Residual Earnings in the Population After Controlling for Age and Education



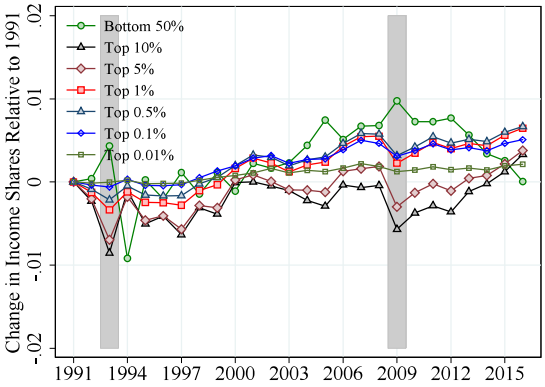
Note: Using residual earnings (controlling for age and education) and the CS+TMax sample, Figure C.4 plots against time the following variables: (a) Men and women: P10, P25, P50, P75, P90 (b) Men and women: P90, P95, P99, P99.9, P99.99, (c) Men and women: P90-10 and 2,56*SD of log income, (d) Men and women: P90-50 and P50-10. All percentiles are normalized to 0 in the first available year. 2.56*SD corresponds to P90-10 differential for a Gaussian distribution. Shaded areas represent recession years. Dataset: Panel DADS. Go back to main text

Figure C.5 – Changes in Income Shares

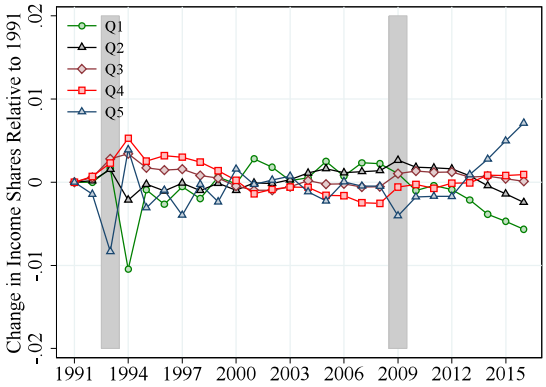
(A) Income Shares of Quintiles (All)



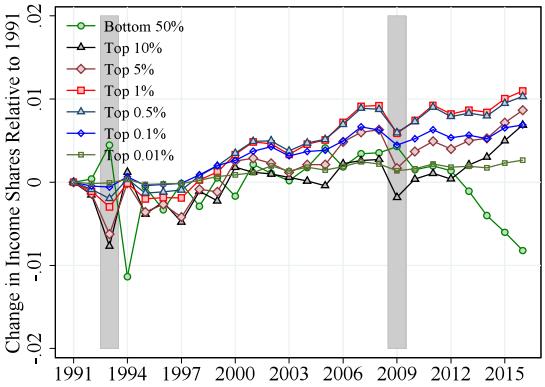
(B) Selected Income Shares (All)



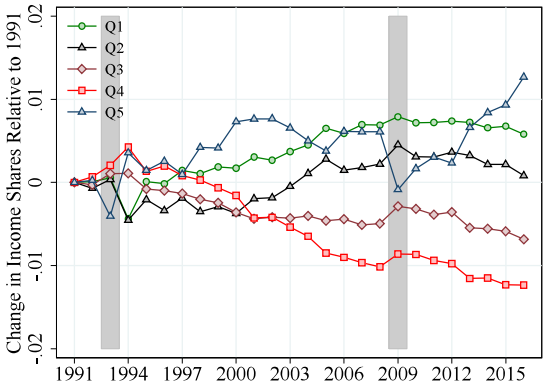
(C) Income Shares of Quintiles (Men)



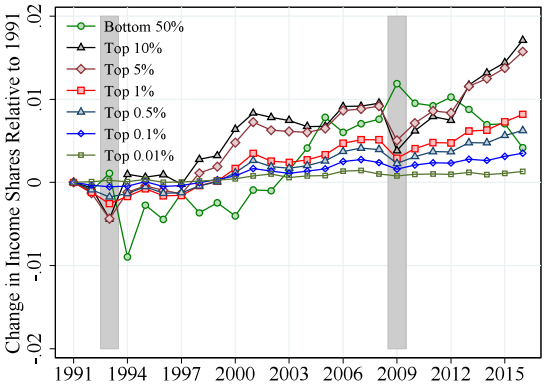
(D) Selected Income Shares (Men)



(E) Income Shares of Quintiles (Women)



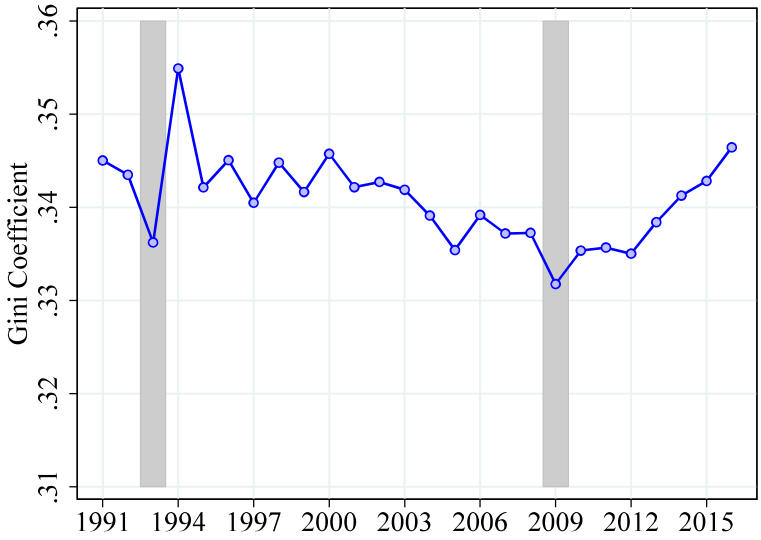
(F) Selected Income Shares (Women)



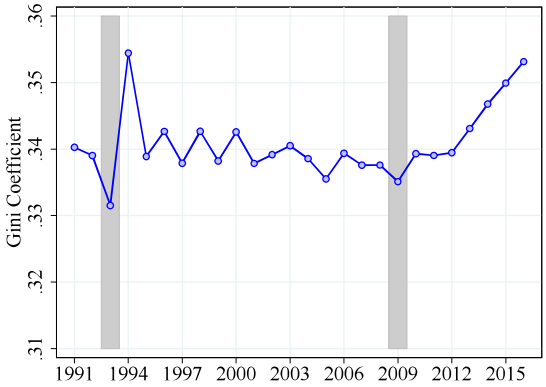
Note: Using real raw log earnings and the CS+TMax sample, Figure C.5 plots against time the income shares by quintiles and the income shares for some selected percentiles, normalized to 0 in 1991, for: (a-b) Men and women, (c-d) Men and, (e-f) Women. Shaded areas represent recession years. Dataset: Panel DADS. Go back to main text

Figure C.6 – Gini Coefficient

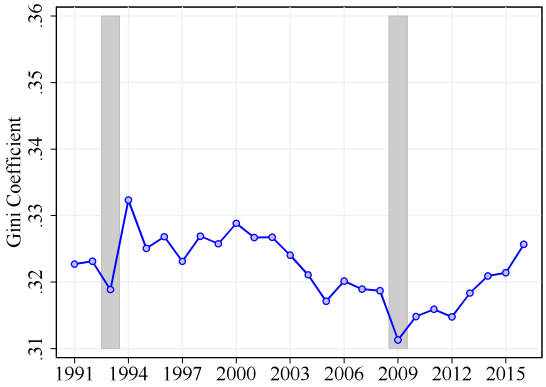
(A) All



(B) Men



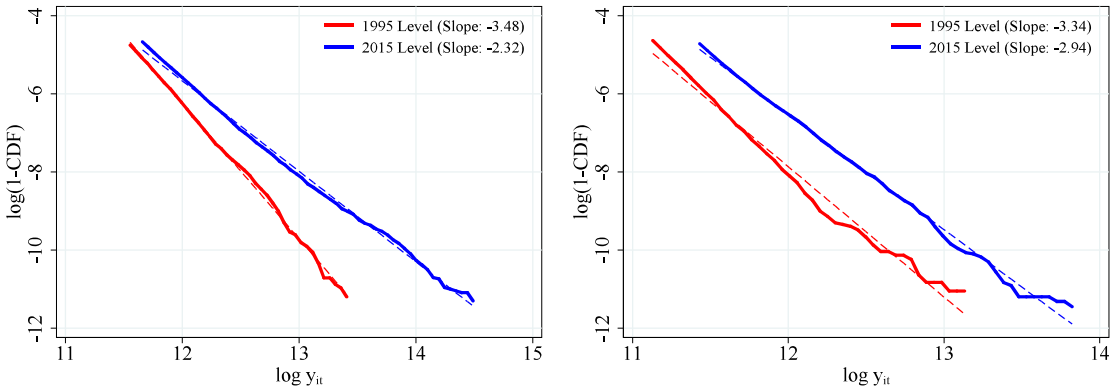
(C) Women



Note: Figure C.6 plots the Gini coefficient for (a) both men and women, (b) men and (c) women, using the CS+TMax sample. Shaded areas represent recession years. Dataset: Panel DADS. Go back to main text

Figure C.7 – Top Income Inequality: Pareto Tail at top 1%

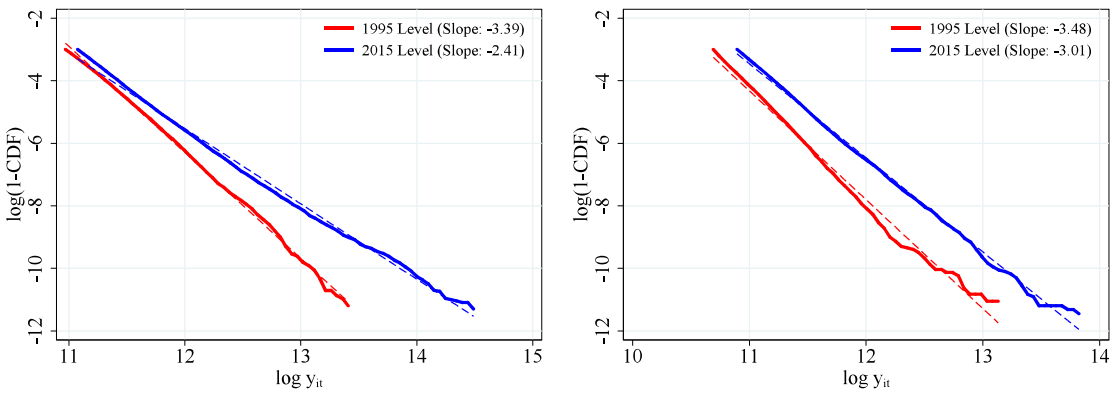
(A) Men (B) Women



Note: Using real raw log earnings above the 99th percentile and the CS+TMax sample, Figure C.7 plots separately for men and women the log of the counter cumulative distribution function against log earnings in 1995 and 2015. The slope coefficients are estimated using linear regressions. Dataset: Panel DADS. Go back to main text

Figure C.8 – Top Income Inequality: Pareto Tail at top 5%

(A) Men (B) Women

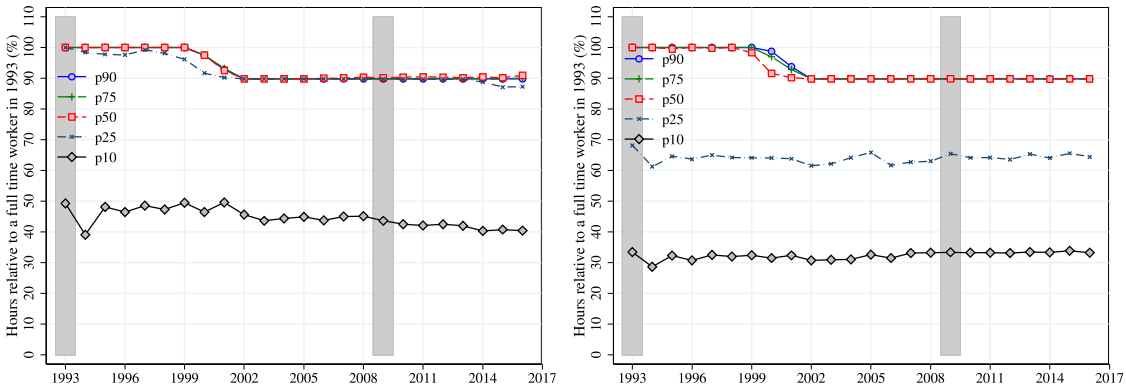


Note: Using real raw log earnings above the 95th percentile and the CS+TMax sample, Figure C.7 plots separately for men and women the log of the counter cumulative distribution function against log earnings in 1995 and 2015. The slope coefficients are estimated using linear regressions. Dataset: Panel DADS. Go back to main text

D The Reduction of the Working Week

Figure D.1 – Annual Working Time By Earning Percentile

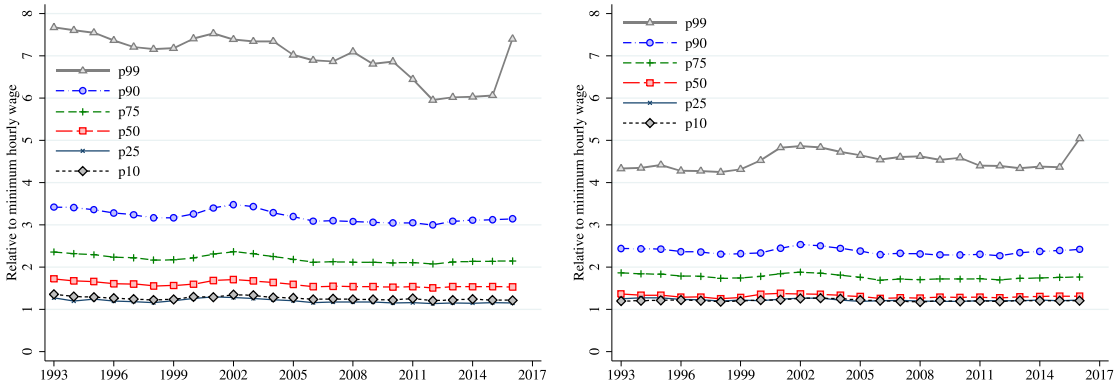
(A) Men (B) Women



Note: Figure D.1 plots against time, for 5 percentiles of the real raw earnings distribution, the following variables: (a) Men: median annual number of hours worked, (b) Women: median annual number of hours worked. For each of the 5 percentiles, we compute and plot the median number of hours worked as a share of a full time job in 1993. Dataset: Panel DADS. Go back to main text

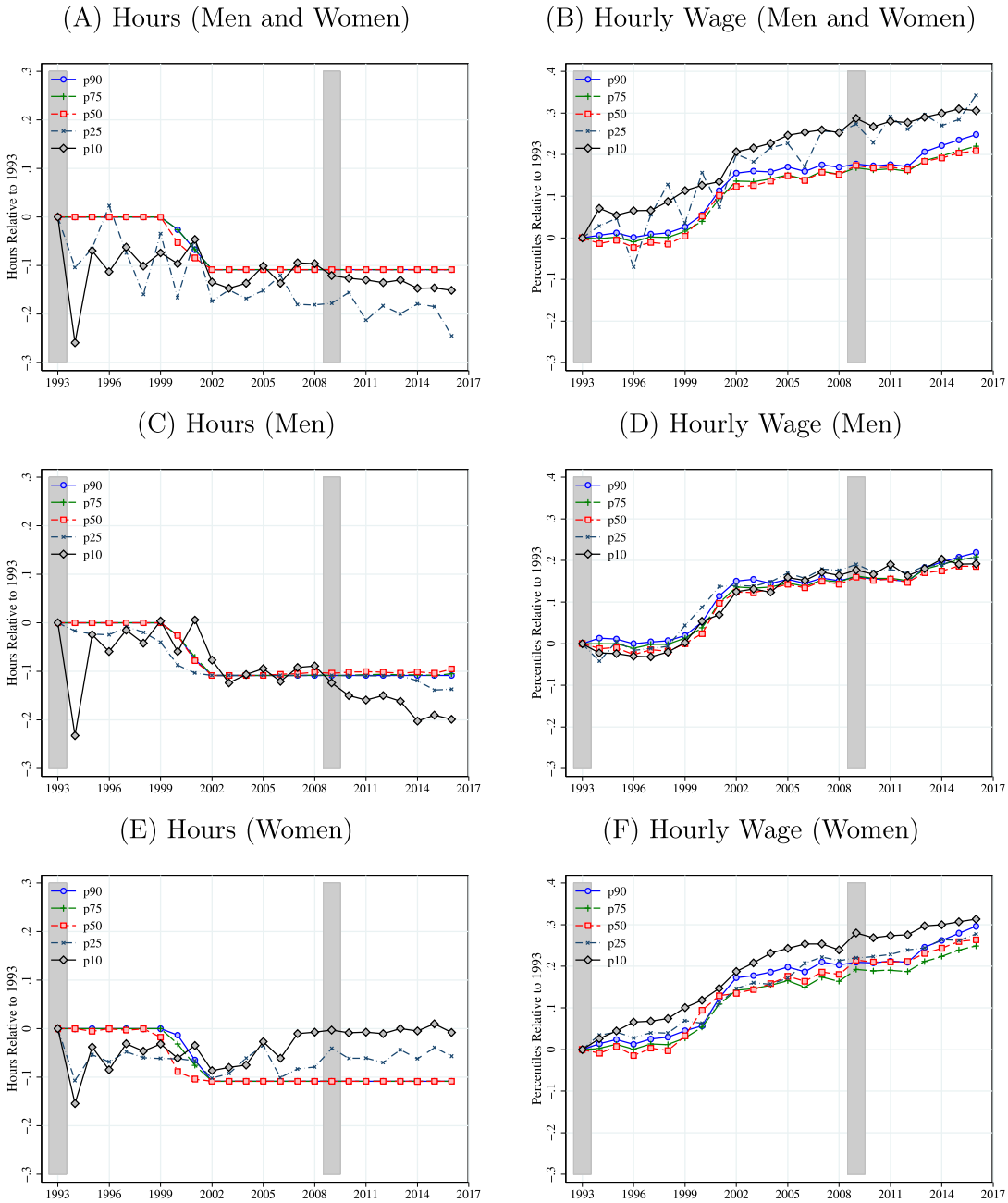
Figure D.2 – Hourly Wage By Earning Percentile

(A) Men (B) Women



Note: Figure D.2 plots against time, for 5 percentiles of the real raw earnings distribution, the following variables: (a) Men: median hourly wage relative to the French minimum wage, (b) Women: median hourly wage relative to the French minimum wage. For each of the 5 percentiles, we compute and plot the median hourly wage divided by the national minimum wage. Dataset: Panel DADS. Go back to main text

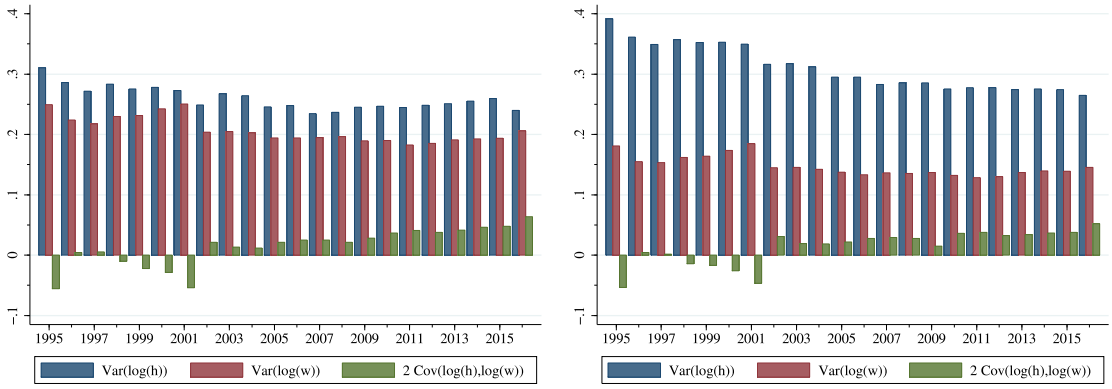
Figure D.3 – Evolution of hours and hourly wages by earning percentiles



Using real raw log earnings and the CS+TMax sample, Figure D.3 plots against time the following variables: (a) Men and Women: median number of hours worked for the P5, P10, P25, P50, P75, P90, P99 of the earnings distribution, (b) Men and Women: the median hourly wage for the P5 to P99 of the earnings distribution, (c) Men: median number of hours worked for the P5 to P99 of the earnings distribution, (d) Men: the median hourly wage for the P5 to P99 of the earnings distribution, (e) Women: median number of hours worked for the P5 to P99 of the earnings distribution, (f) Women: the median hourly wage for the P5 to P99 of the earnings distribution. All variables are normalized to 0 in 1993. Dataset: Panel DADS. Go back to main text

Figure D.4 – Decomposition of the Variance of Log-Earnings

(A) Men (B) Women

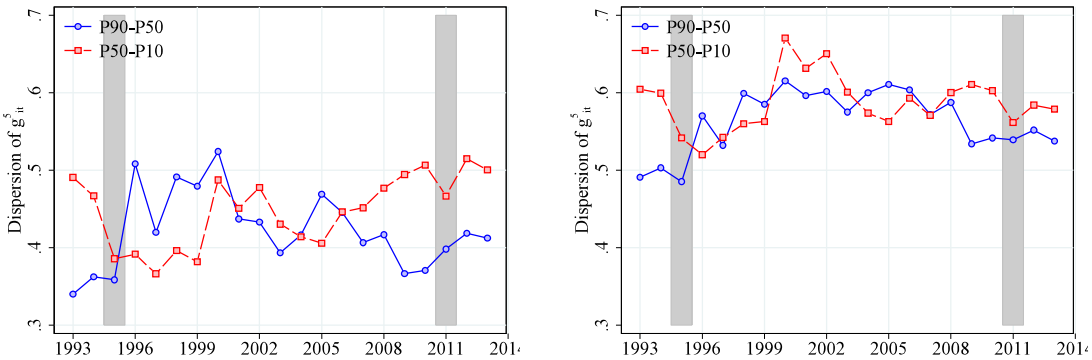


Note: Figure D.4 plots against time, the decomposition of the variance of the real raw log earnings into the variance of the log-hours, the log-hourly wage and the covariance between the two. Dataset: Panel DADS. Go back to main text

E Earnings Change

Figure E.1 – Dispersion of Five-Years Earnings Change

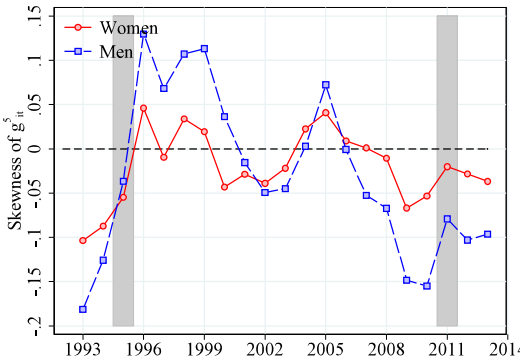
(A) Men (B) Women



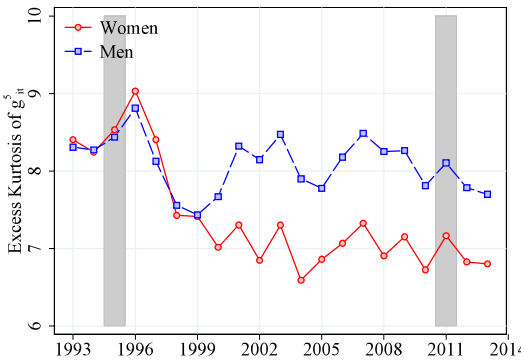
Note: Using residual five-year earnings changes and the LX sample, Figure E.1 plots against time the following variables: (a) Men: P90-10 differential, (b) Women: P90-10 differential. Shaded areas represent recession years. Dataset: Panel DADS. Go back to main text

Figure E.2 – Skewness and Kurtosis of Five-Years Earnings Changes

(A) Kelley Skewness

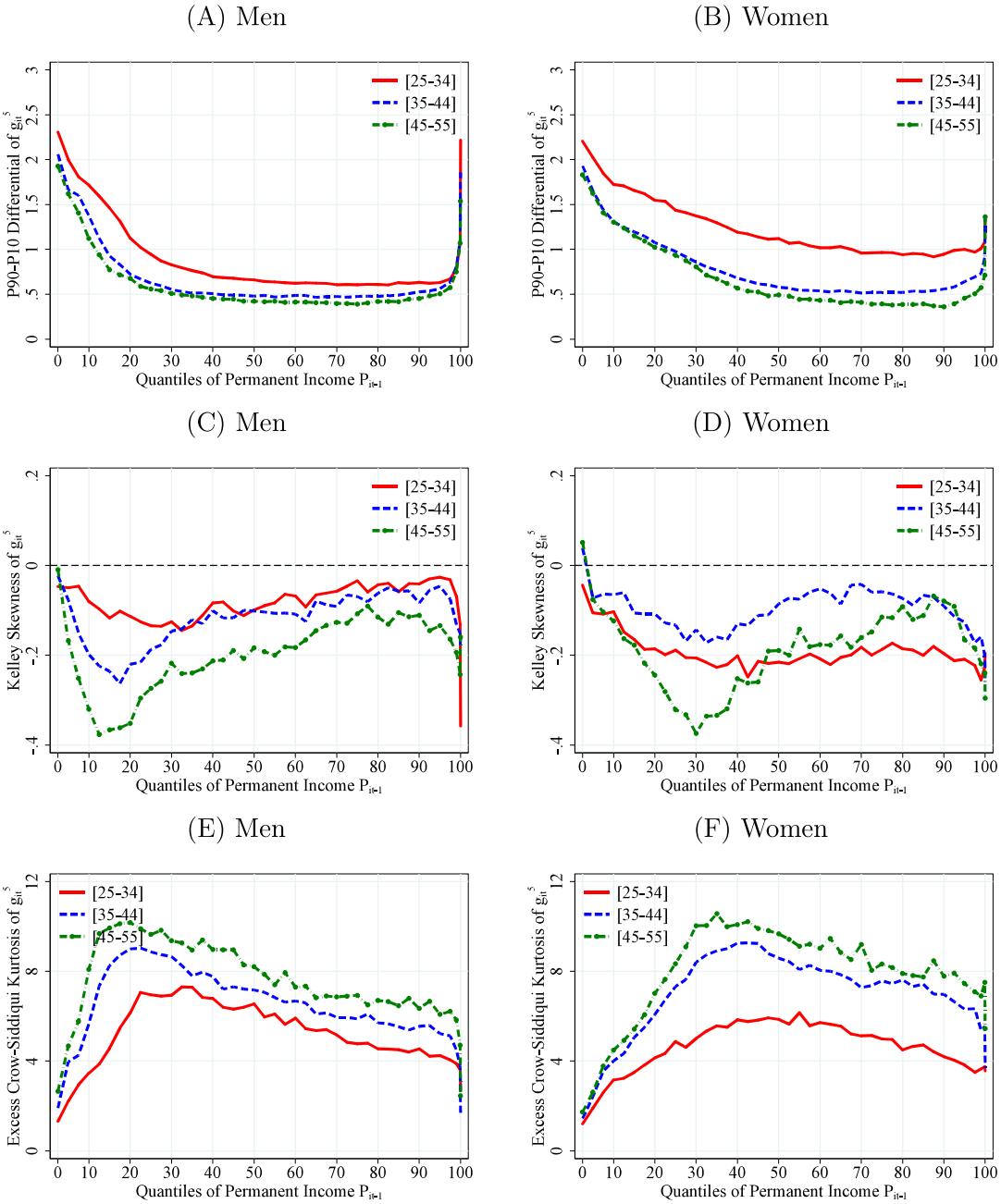


(B) Excess Crow-Siddiqui Kurtosis



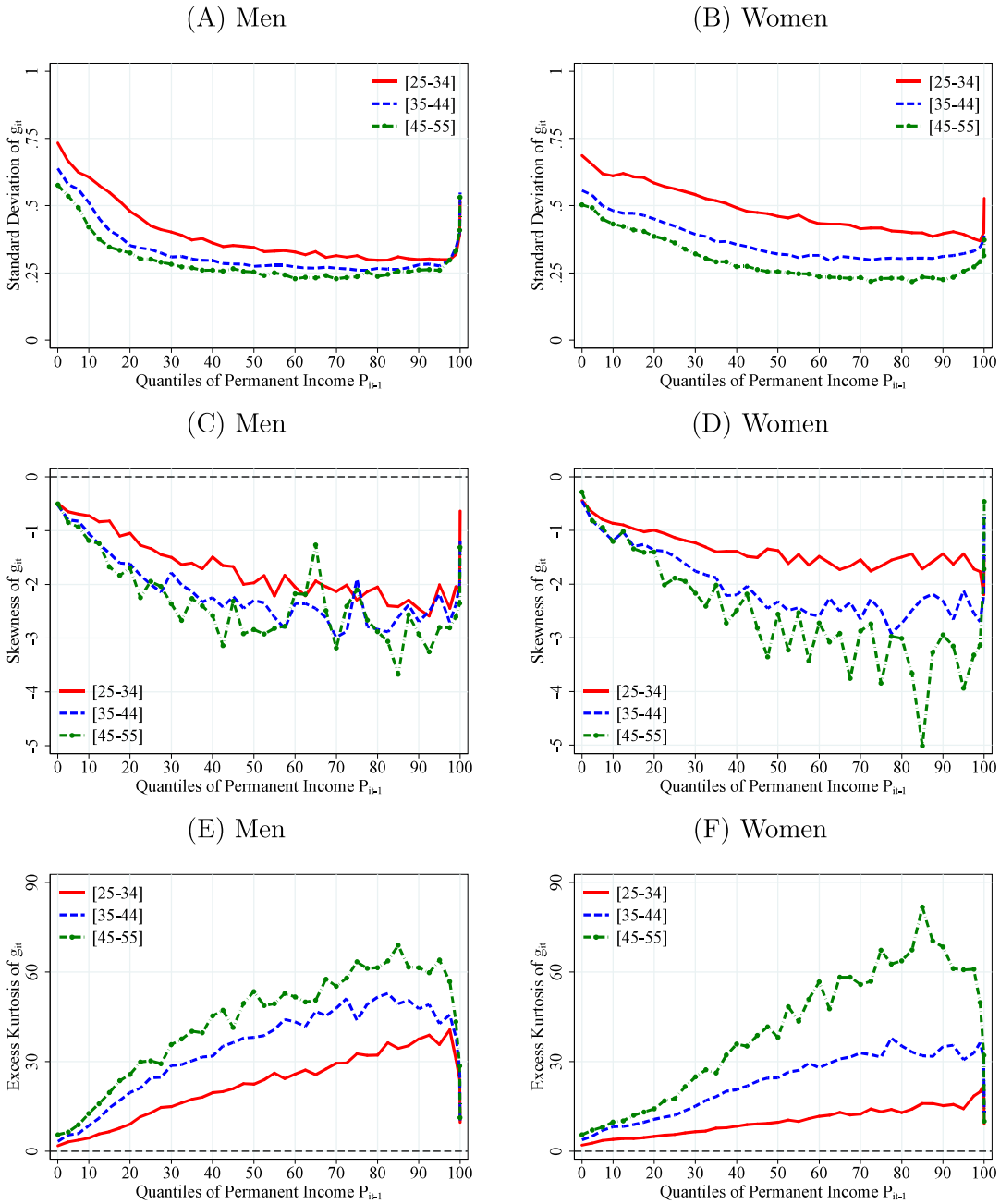
Note: Using residual five-year earnings changes and the LX sample, Figure E.2 plots against time the following variables: (a) Men and Women: Kelley skewness, (b) Men and Women: Excess Crow-Siddiqui kurtosis calculated as $\frac{P97.5-P2.5}{P75-P25} - 2.91$ where the first term is the Crow-Siddiqui measure of Kurtosis and 2.91 corresponds to the value of this measure for Normal distribution. Shaded areas represent recession years. Dataset: Panel DADS. Go back to main text

Figure E.3 – Dispersion, Kelley Skewness and Excess Crow-Siddiqui Kurtosis of Five-Years Earnings Changes



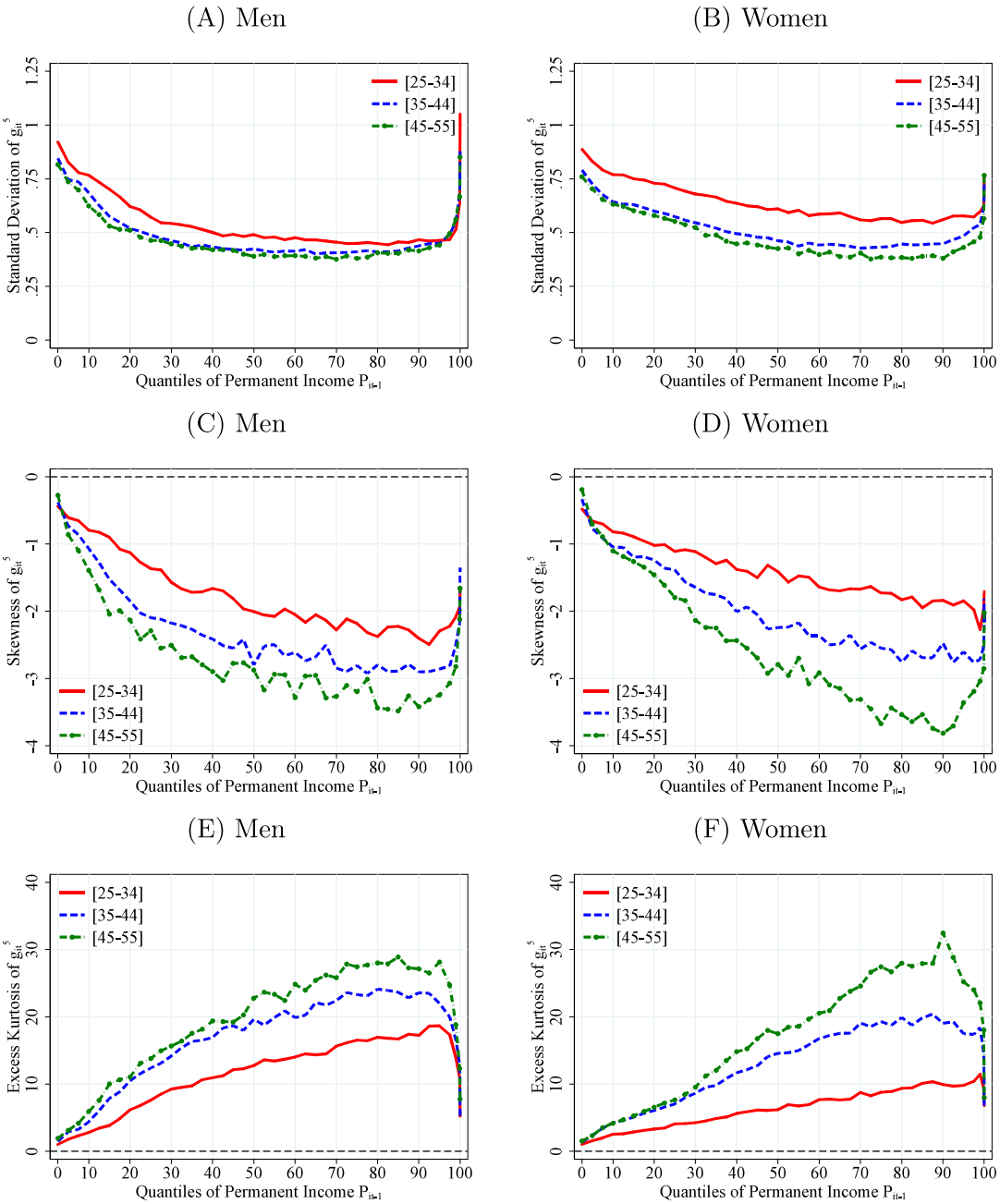
Note: Using residual five-year earnings changes and the H sample over the period 1994-2011, Figure E.3 plots against permanent income quantile groups the following variables for the 3 age groups: (a) Men: P90-10, (b) Women: P90-10, (c) Men: Kelley Skewness, (d) Women: Kelley Skewness, (e) Men: Excess Crow-Siddiqui kurtosis, (f) Women: Excess Crow-Siddiqui kurtosis. Excess Crow-Siddiqui kurtosis calculated as $\frac{P97.5-P2.5}{P75-P25} - 2.91$ where the first term is the Crow-Siddiqui measure of Kurtosis and 2.91 corresponds to the value of this measure for Normal distribution. Dataset: Panel DADS. Go back to main text

Figure E.4 – Standardized Moments of One-Year Earnings Changes



Note: Using residual one-year earnings changes and the H sample over the period 1994-2015, Figure E.4 plot against permanent income quantile groups the following variables for the 3 age groups: (a) Men: Standard deviation, (b) Women: Standard deviation, (c) Men: Skewness, (d) Women: Skewness, (e) Men: Excess kurtosis, (f) Women: Excess kurtosis. Excess kurtosis is defined as the value of kurtosis minus 3 which is the corresponding value for a Normal distribution. Dataset: Panel DADS. Go back to main text

Figure E.5 – Standardized Moments of Five-Years Earnings Changes

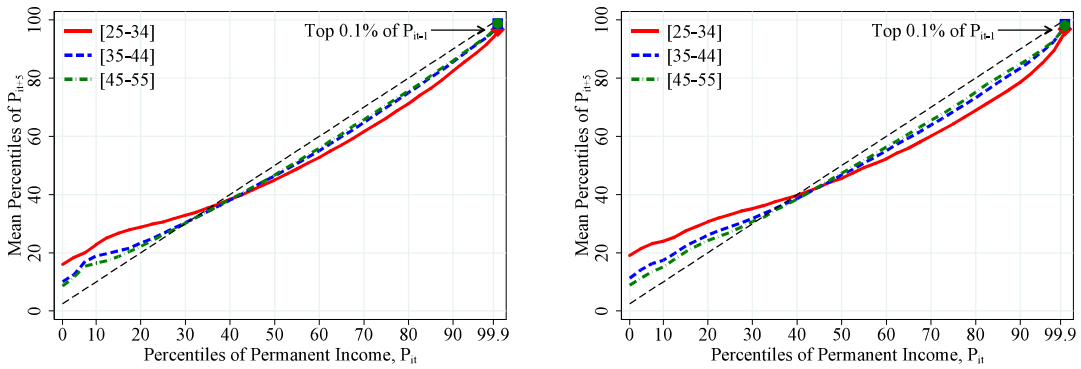


Note: Using residual five-year earnings changes and the H sample over the period 1994-2011, Figure E.5 plot against permanent income quantile groups the following variables for the 3 age groups: (a) Men: Standard deviation, (b) Women: Standard deviation, (c) Men: Skewness, (d) Women: Skewness, (e) Men: Excess kurtosis, (f) Women: Excess kurtosis. Excess kurtosis is defined as the value of kurtosis minus 3 which is the corresponding value for a Normal distribution. Dataset: Panel DADS. Go back to main text

F Earnings Mobility

Figure F.1 – Evolution of 5-Year Mobility Over the Life Cycle

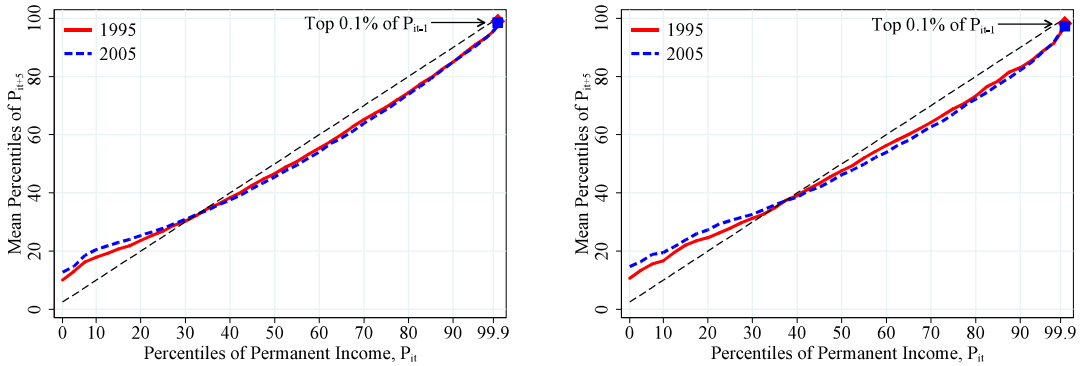
(A) Men (B) Women



Note: Figure F.1 shows average rank-rank mobility for different age groups over the period 1993-2011 using the H sample. The 45-degree (dashed black) line corresponds to the case of perfect immobility: workers stay on average at the same percentile after 5 years. Dataset: Panel DADS. Go back to main text

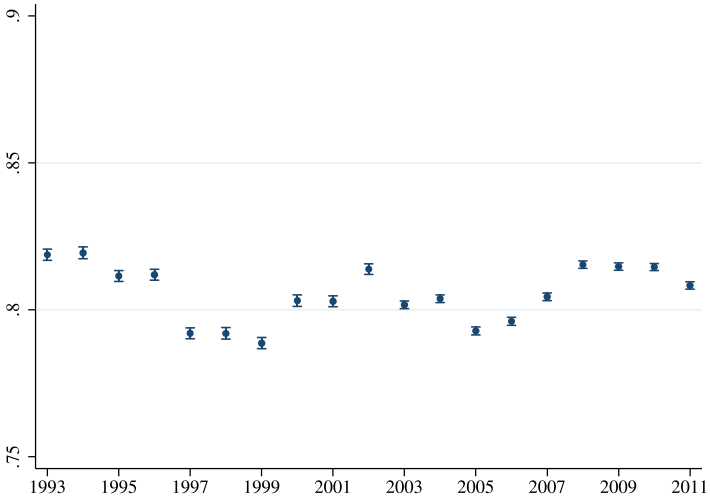
Figure F.2 – Evolution of 5-Year Mobility Over Time

(A) Men (B) Women



Note: Figure F.2 shows average rank-rank mobility using the H sample over the period 1993-2011. The 45-degree (dashed black) line corresponds to the case of perfect immobility: workers stay on average at the same percentile after 5 years. Dataset: Panel DADS. Go back to main text

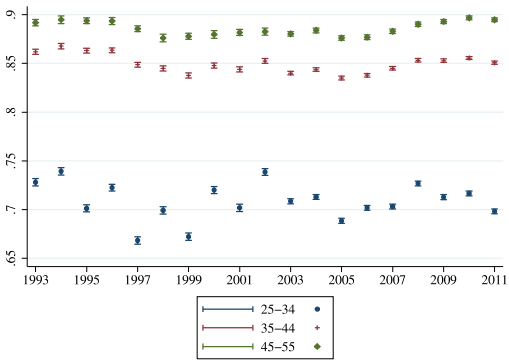
Figure F.3 – Evolution of the 5-Year Rank-Rank Correlation Over Time



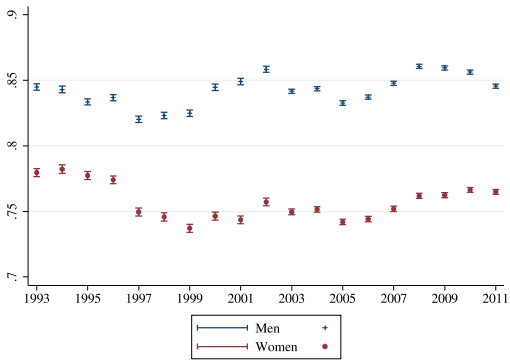
Note: F.3 shows the evolution over time of the permanent earnings five-year rank-rank correlation coefficient. Dataset: Panel DADS. Go back to main text

Figure F.4 – Evolution of the 5-Year Rank-Rank Correlation By Demographic Group

(A) Age

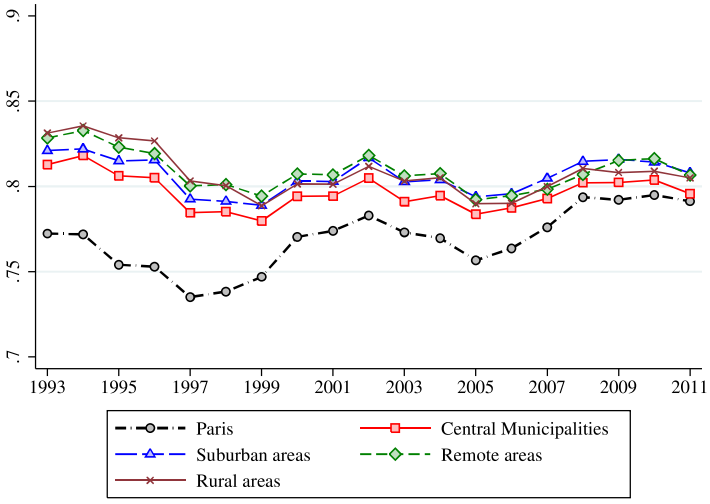


(B) Gender



Note: Figure F.4 shows the evolution over time of the permanent earnings five-year rank-rank correlation coefficient by age group and gender. Dataset: Panel DADS. Go back to main text

Figure F.5 – Evolution of the 5-Year Rank-Rank Correlation By Territory

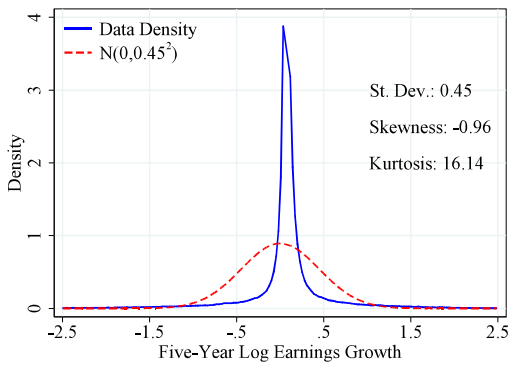


Note: Figure F.5 shows the evolution over time of the five-year permanent earnings rank-rank correlation coefficient by territory based on the place of residence during the initial year. Dataset: Panel DADS. Go back to main text

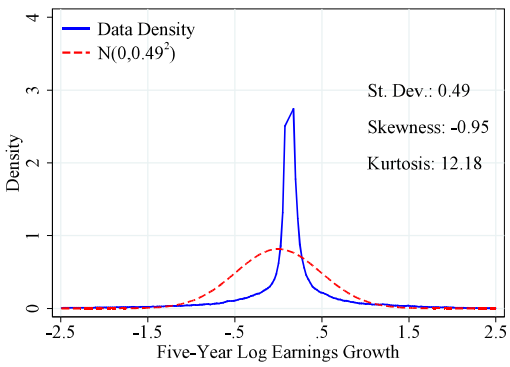
G Densities of Earnings Growth

Figure G.1 – Empirical Densities of One-Year Earnings Growth

(A) Men



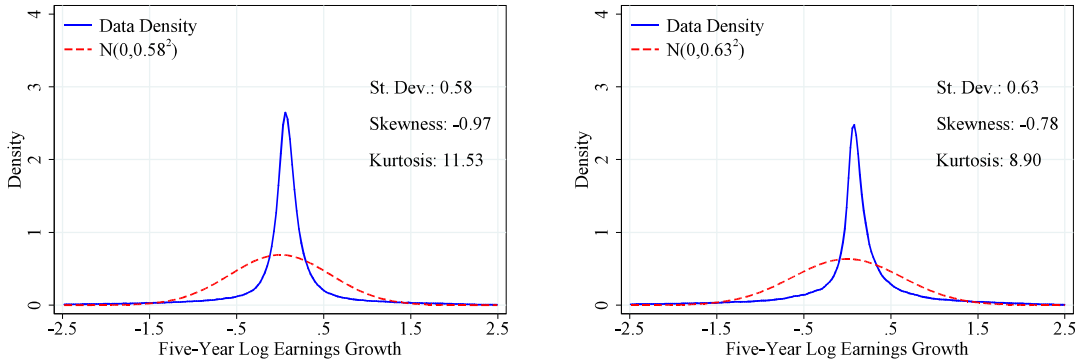
(B) Women



Note: Figure G.1 shows the density of one-year log residual earnings growth for men and women for 2005. Dataset: Panel DADS. Go back to main text

Figure G.2 – Empirical Densities of Five-Year Earnings Growth

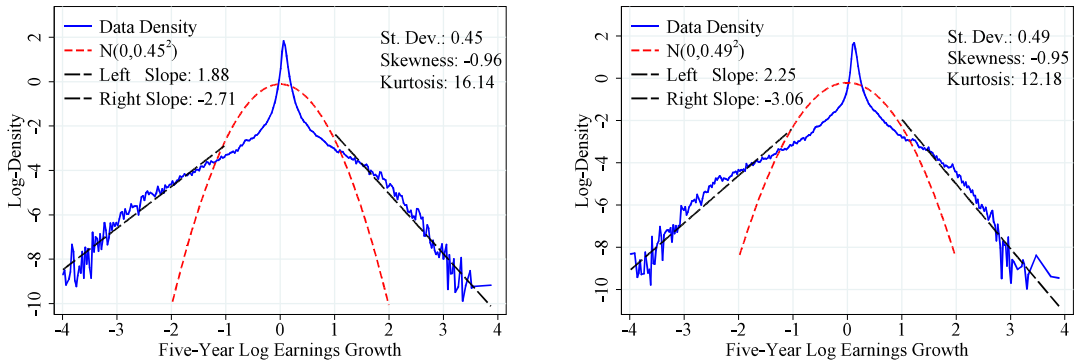
(A) Men (B) Women



Note: Figure G.2 shows the density of five-year log residual earnings growth for men and women for 2005. Dataset: Panel DADS. Go back to main text

Figure G.3 – Empirical Log-Densities of One-Year Earnings Growth

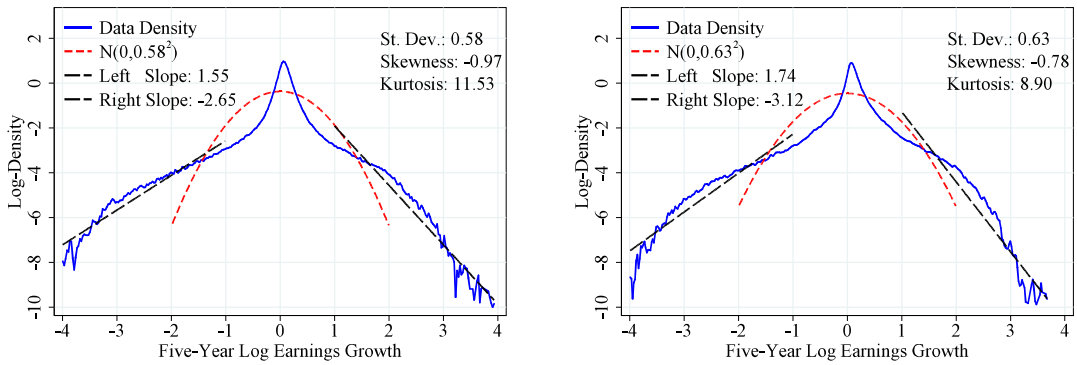
(A) Men (B) Women



Note: Figure G.3 shows the log-density of one-year log residual earnings growth for men and women for 2005. Dataset: Panel DADS. Go back to main text

Figure G.4 – Empirical Log-Densities of Five-Year Earnings Growth

(A) Men (B) Women



Note: Figure G.4 shows the log-density of five-year log residual earnings growth for men and women for 2005. Dataset: Panel DADS. Go back to main text

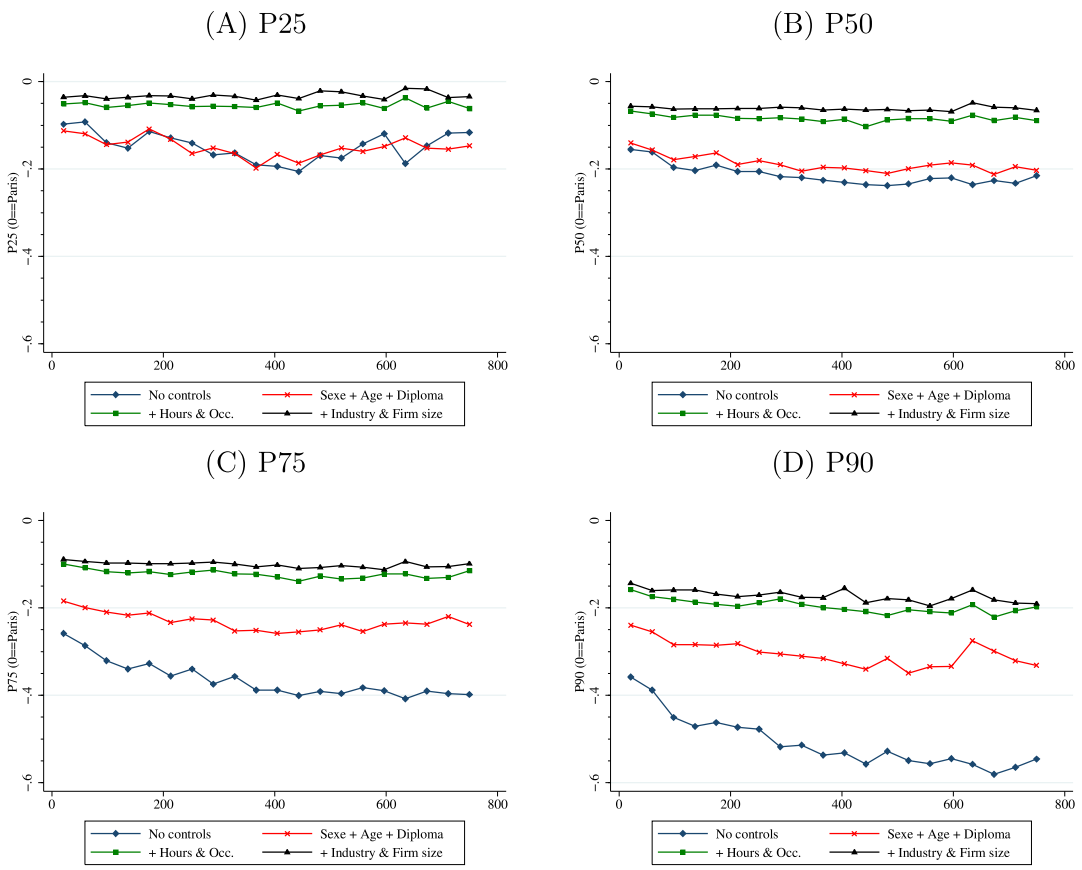
Table G.1 – Empirical Log-Densities of Five-Year Earnings Growth

	One-year growth of residualised earnings				Five-year growth of residualised earnings			
	Left slope	Right slope	Skewness	Kurtosis	Left slope	Right slope	Skewness	Kurtosis
1991	1.57	-2.72	-1.35	15.3	1.37	-2.49	-1.09	11.2
1995	1.78	-2.75	-1.33	16.1	1.42	-2.66	-0.82	11.4
2000	2.05	-2.96	-0.89	13.6	1.49	-2.79	-0.96	10.0
2005	2.01	-3.02	-0.94	14.1	1.61	-2.86	-0.91	10.4
2010	2.32	-3.34	-0.98	13.1	1.63	-3.09	-1.03	9.8
2015	2.09	-3.45	-1.04	13.1				

Note: Table G.1 shows the left and right slope coefficients, as well as the skewness and kurtosis coefficients, of the log-density of one and five-year log residual earnings growth for the wole population. Dataset: Panel DADS. Go back to main text

H Geographic Inequality

Figure H.1 – Between-Urban Areas Inequality After Controlling for Observable Characteristics



Note: Using residual log earnings for men and women, Figure H.1 plots against city rank (a) P25, (b) P50, (c) P75, (d) P90 for the period 2014-2016. City rank is based on 2015 census population. Controls include age dummies, four education dummies, the total number of hours worked, 2-digit occupation dummies, 4-digit industry dummies, and the size of the firm in head count. Observations are the 759 urban areas. They are displayed using a bin-scatter. Dataset: Panel DADS matched with EDP. Go back to main text

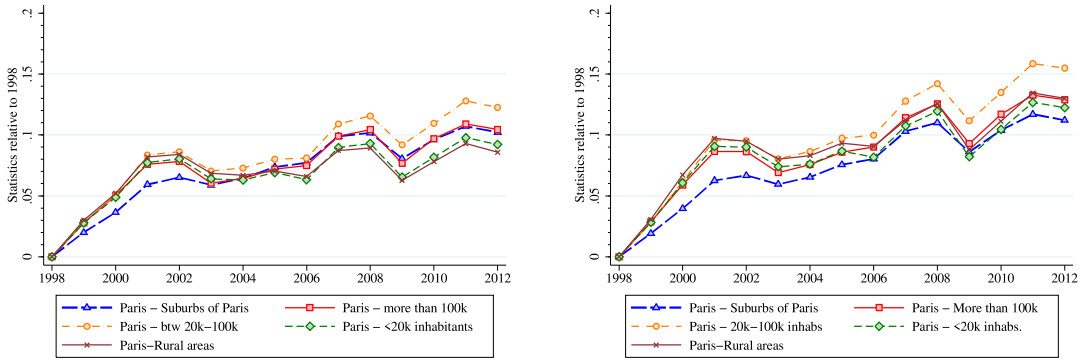
Table H.1 – Squared Deviation from Paris

Percentiles	10th	25th	50th	75th	90th	95th	99th
2001	25.28	47.20	52.68	115.26	208.07	266.23	361.71
2015	17.38	33.72	37.16	103.97	205.27	283.75	500.76

Note: Table H.1 shows the sum across urban areas of the squared difference in earnings w.r.t. Paris for various percentiles of the earnings distribution. Dataset: panel DADS. Go back to main text

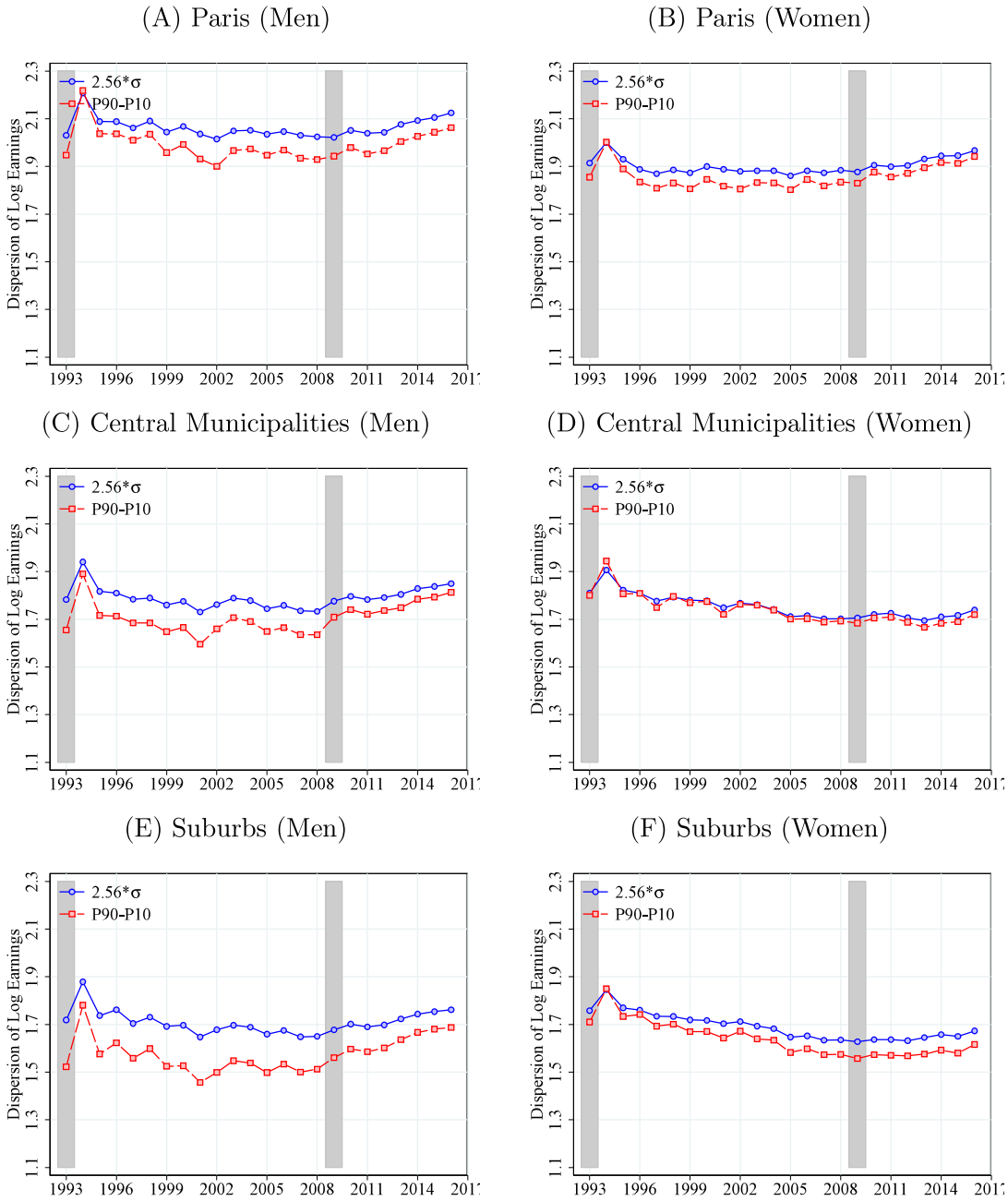
Figure H.2 – Mean Earnings with Local vs. National CPI

(A) National CPI (B) Local CPI



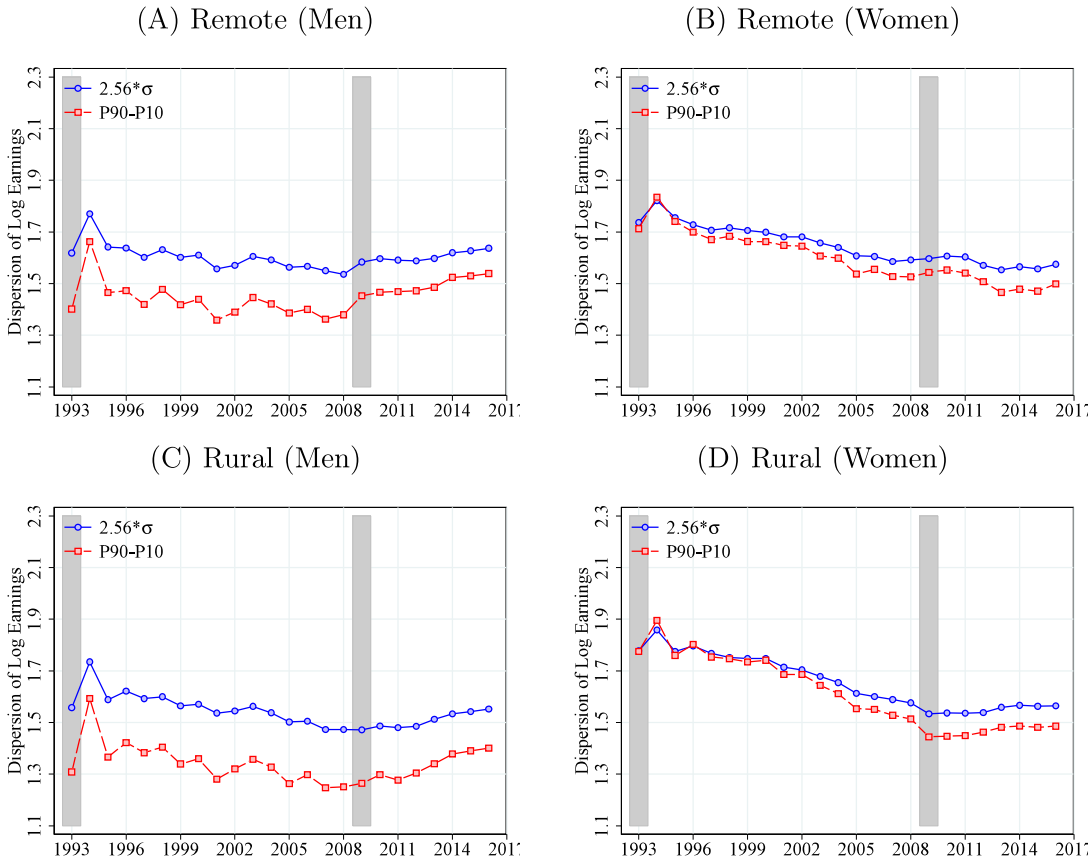
Note: Using the real raw log labor earnings of both men and women, Figure H.2 plots against time the differential between mean labor earnings in the municipality of Paris and in groups of urban units based on their size using (a) labor earnings deflated by the national price index, (b) labor earnings deflated by local price indexes. The suburbs of Paris are defined as the urban unit of Paris without the municipality of Paris. Dataset: Panel DADS. Go back to main text

Figure H.3 – Earnings Inequality by Territory



Note: Using real raw log earnings separately for men and women, Figure H.3 plots against time the P90-10 and 2.56*SD of log earnings for: (a-b) the urban unit of Paris, (c-d) central municipalities and (e-f) the suburbs. Territories and Paris are defined using urban units. Shaded areas represent recession years. 2.56*SD corresponds to P90-10 differential for a Gaussian distribution. Dataset: Panel DADS. Go back to main text

Figure H.4 – Earnings Inequality by Territory (continuation)



Note: Using real raw log earnings separately for men and women, Figure H.4 plots against time the P90-10 and 2.56*SD of log earnings for: (a-b) remote municipalities, (c-d) rural municipalities. Territories and Paris are defined using urban units. Shaded areas represent recession years. 2.56*SD corresponds to P90-10 differential for a Gaussian distribution. Dataset: Panel DADS. Go back to main text