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

Francis Kramarz∗ Elio Nimier-David† Thomas Delemotte‡

March 2021

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.

∗Email: francis.kramarz@ensae.fr CREST-ENSAE, Institut Polytechnique de Paris
†Email: elio.nimier-david@ensae.fr CREST-ENSAE, Institut Polytechnique de Paris
‡Email: thomas.delemotte@ensae.fr CREST-ENSAE, Institut Polytechnique de Paris
§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 their tremendous work on harmonizing the core statistics, as well as Pauline Carry, Bertrand Garbinti and seminar participants at the Global Income Dynamics Conferences at Stanford SITE in 2019 and held virtually in 2020 for helpful comments and suggestions. This paper has been conducted in collaboration with the CASD (Secure Data Access Center). We thank Kamel Gadouche, Marie Vidal and Raphaëlle Fleureux for their help and support. 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. 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, insisting on the differences between men and women as well as on the differences between the national and the local levels. Indeed, this paper is part of the Global Income Dynamics project, which has at least two objectives: (i) produce harmonized statistics to compare inequality and earnings dynamics between countries and over time (ii) 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

---

1Charles 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 imply 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 37% decrease in the (unconditional) gender pay gap.

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 change 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)). However, wage mobility is pretty low in France, in particular when compared to Scandinavian countries, especially at the top of the distribution (see other articles of this issue). Earnings mobility is also very stable over the sample period. 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, and the industry structure. However, these differences have been reduced over the period of interest. 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, using multiple data sources including one that we also use in what follows (the DADS panel). His study focuses mainly on men employed full-time full-year. No data on the self-employed or the public sector are used. Results clearly show increases in inequality between 1950 and 1965 both at the bottom and at the top of the earnings distribution. Then, inequality tended to decrease. At the bottom, the decrease was likely initiated in 1968 by the massive increases in the minimum wages of the time. At the top of the earnings distribution, this decrease started in the nineties. A massive increase in those years of the supply of educated individuals clearly is a potential explanation for these changes at the top. Charnoz et al. (2014) studies a shorter period, 1967 to 2009, but uses the same data source (the Panel-DADS). The paper again concentrates on full-time private sector male workers. It assesses the respective roles of skill-supply and skill-demand (potentially biased) in the transformations of the French wage structure. The strong increase in the supply of educated workers that started in the 1990s clearly induces a strong decrease in the returns to skills. The associated decrease in inequality measured by P90-10 is mainly driven by the P50-10 differential, even controlling for education and experience. Indeed, if we believe that skilled biased technical change exists, it was partly hidden in France by the late increase of educated workers (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 2010 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. Finally, Godechot (2012) examines the 1975-2007 period using similar data. The paper 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.
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. 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.

As will appear rapidly, the present article does not examine the role of transfers on earnings inequality and its changes. However, Bozio et al. (2020) studies the impact of redistribution policies on income inequality in France and in the US over the period 1900-2018. Their article finds that most of the long-term decline in inequality in France is due to the fall in pretax inequality. In addition, inequality is much smaller in France than in the US because of differences in pretax inequality. As a result, focusing on gross earnings, as we do in this paper, is relevant to study inequality in France.

We turn now to earnings mobility. As Pareto (1916) said, social mobility is a matter of both social justice and efficiency. “The circulation of elites” has two components, one between generations and one within a generation. Our data will only allow us to study within generation mobility. Hence, in this literature review we restrict attention to studies on this latter component: earnings mobility over the life-cycle. Buchinsky et al. (2003) use various measures of mobility based either on

---

"Hence, before all taxes and transfers, except pensions and unemployment insurance."
ranks in the income distribution or on Francs for periods of 3 years. They use similar data as ours (Panel DADS with the EDP) over the period 1967 to 1999. Among the six concepts used, five of them suggest a decrease in mobility over time. The diagnostic is however quite sensitive to the measurement used, in particular when assessing results by sex or education groups.

Using Panel data allowing to track the tax returns of all French tax residents from year to year, Aghion et al. (2019) find a rank-rank correlation of total income of .83 between 2011 and 2015. 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 and presents the (local) social movements that took place in France over the last two decades. In Section 3, we describe the data and provide some descriptive statistics. We then present our main results on earnings inequality and dynamics in Section 4. Finally, Section 5 provides complementary statistics on earnings inequality between and within various French territories. Section 6 concludes.

2 The French Labor Market

2.1 The 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: BLS and INSEE for the unemployment rates. The World Bank for the GDP.

The inability to decrease the unemployment rate in good times to, say, 4 or 5% 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 start with a brief description of the main institutional features of the French labor market. First, as in multiple other European countries with dysfunctional labor markets, there are two main types of labor contracts: permanent and temporary. Most hires are made under the latter when most positions are held under the former. 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\textsuperscript{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 Figure 2. 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.

Figure 2 – Participation Rate

(A) People Aged 25-64

(B) People Aged 55-64

(C) Men

(D) Women

Note: Figure 2 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.

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 is the total labor cost i.e. the wage plus the payroll taxes. These payroll taxes comprise two components, one paid by the worker and one paid by the firm.

Until the beginning of the 1990s, France was characterized by both a very high 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 3 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 4, 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 4.1 that this strong increase in the minimum wage, especially since the middle of the 2000’s, had a big impact on earnings inequality.

Figure 3 – Nominal and Real Minimum Wage Over Time

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

Note: Figure 3 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.

4In 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.
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. 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 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 5, 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.

Figure 5 – Average Annual Working Time

![Figure 5](image_url)

**Note:** Figure 5 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 Social Movements across French Territories

France has had high unemployment rates for the last 40 years. This unemployment rate displays considerable variation across space and time: Paris was and still is a relatively low-unemployment city, Brittany was a high and is now a low-unemployment region, when some eastern or northern departments went the opposite. However, most labor market policies were national in nature, providing ad-hoc responses to specific and even local shocks. For instance, to address local educational problems (mostly in junior-high and high schools), the central Ministry of Education created the “Zones d’Education Prioritaires” (ZEP, see Bénabou et al. (2009)). To combat the lack of jobs creation in difficult suburban areas, the “Zones Urbaines Sensibles” (ZUS) and the “Zones Franches Urbaines” (ZFU) were created to help foster firms’ locations there (see Givord et al. (2018)).

Not surprisingly, this one-size-fits-all attitude led from “Paris”, with no leeway for the local authorities or local initiatives, has been regularly resented. And, following a well-established tradition (that even preceded the French revolution), social movements have sprung up over the centuries and have continued over our sample period. We describe three of them and try to show their “local territory” component. Endowed with this view, we compute in Section 5 statistics on inequality and public employment, using a nomenclature of these territories that captures the distance to the center ... Paris.

In 2005, what was deemed “Most Important Riot in the History of French Contemporary Society” (see Mucchielli (2009)) took place. Over a period of three weeks, the rioters destroyed more than 10,000 cars and rubbish containers by burning them. These destructions took place mainly in Paris suburbs, but also in some large cities. Rioters also burnt or ransacked public buildings, in particular schools, sports facilities, IRS buildings, police stations, etc. Buses, police and firemen vehicles were stoned. These riots started in the aftermath of the death of two young men of Northern African descent, in Clichy-sous-Bois, who were trying to escape a police operation which was not directed against them. Riots started there and extended

---

5Clichy-sous-Bois is one of the most economically disadvantaged and isolated suburbs of Paris. It is located in the North-East of the Parisian region in the départment of Seine-Saint-Denis.
mostly to the whole département of Seine-Saint-Denis, especially in municipalities labelled ZUS. After some days of riots, and a geographic extension to the west of the Parisian region, in the Yvelines’s poor neighborhoods, and to other French ZUS, a state of emergency was declared, resulting in a curfew.

This movement was clearly a direct reaction to what was perceived, not unjustly, as widespread police violence directly targeted to the young in a context of mass youth (low-skill) unemployment and massive discrimination both at school and on the job market, within some of these poorest neighborhoods. Mucchielli (2009) uses the word of “Ghettoization” to characterize the process that led to these riots.

As already mentioned, the political response was not extremely new and imaginative, with targeted measures for the poor neighborhoods (subsidized jobs for people living in ZUS, positive discrimination for High-School students coming from ZUS into higher education, and urban renewal instigated by the newly created Agence Nationale de Rénovation Urbaine (ANRU) with both demolitions and new constructions in impoverished zones). This urban renewal effort, albeit limited in scope, was considered a success.

In 2013, the “Red caps” movement (les Bonnets Rouges) started in Brittany. This social protest was clearly and explicitly intended to fight against the newly decided (October 2013) carbon tax explicitly targeted at transport trucks. The name was a clear reference to the Phrygian cap, also called “Liberty Cap”, used by both French and American Revolutionaries, but also to the great peasant revolt of 1675 (see Le Coadic (2015) for an insightful article on this episode).

This carbon tax was supposedly automated, using gantries equipped to detect vehicles carrying heavy loads. The protests resulted in demonstrations as well as the destruction of some these gantries.

Until the second half of the 20th century, Brittany was an extremely isolated region, with strong local traditions. To foster its development, the government decided at the end of the 1960’s to construct (free) highways to connect it to the rest of France. This clearly helped agriculture to shift from traditional farming to its intensive equivalent, one that relies heavily on trucks transportation to sell its production all over France and Europe. This carbon tax was clearly considered a
threat to the local economy. It was far from the only one: competition from low-wage countries, a decrease in EU subsidies, pollution directly resulting from intensive farming. Indeed, unemployment zoomed up in 2012.

Hence, in the face of this sudden new tax, huge demonstrations took place in west Brittany, in particular in Quimper and Carhaix, at the end of 2013. Unions, political parties, from the left to the extreme-right, including some favoring Brittany’s independence, were united in opposition to the policy.

The tax was temporarily suspended in 2014, and then definitely cancelled. The cost – billions in fact – was not only coming from the protests and the associated destruction, but mostly from the need to compensate the company EcoMouv’ which implemented the automated component of the system for its losses, as well as from the loss of income collected through taxation (one billion a year).

More recently, the Yellow Vests movement has directed international attention to France and much puzzlement. Again, we intend to describe the events associated to this social movement and highlight the local components that define it.

The Yellow Vests movement started at the end of October 2018. This wave of protests was organized locally, at the multiple roundabouts that characterize the French (road) landscape. Having such a yellow vest has become mandatory for every car and every driver since 2008, allowing some visibility even at night in case of a car breakdown. The actions were triggered by the tightening of speed limits (from 90 to 80 km per hour, effective July 1st, 2018) on local roads outside highways and main roads, in a context of rising fuel prices, induced by an increase of already high taxes.

Indeed, the success of the movement appears related to converging claims in the face of increased fuel prices (motorists), an increase in taxes on pensions (retirees), and “high taxes” with apparently decreasing public services (working and middle class). As often happens in France, this type of complaints was supported by the extreme-right, the extreme-left, as well as abstainers. Boyer et al. [2020] provides a thorough analysis of the characteristics of the localities where the Yellow Vests where successful in mobilizing supporters (both physically on roundabouts and online, on Facebook) using data on “départements” and employment zones, together with a
simple yet convincing econometric analysis. Their results clearly show that those living in isolated, remote zones who have to drive long distances to go to work were actively supporting the cause (i.e. being on roundabouts or present on Facebook Yellow Vests’ groups). The econometric analysis singles out the share of roads affected by the changes in the speed limit regulation as a very strongly contributing factor (when local inequality does not seem to have a robust role).

On top of gathering at roundabouts, the Yellow Vests blocked fuel repositories, organized massive demonstrations in Paris as well as in other major French cities.

The political response was swift. A plan was announced by President Macron (10 billions euros, December 2018). However, protests continued after New Year’s eve. After roughly one year, decisions were taken by the Government: (i) the additional tax on fuel was cancelled (ii) a massive increase in the “Prime d’activité” for low-wage workers (iii) a decrease of the income tax in 2020, mostly for low-income households (iv) a tax exemption for overtime hours (v) the additional tax on pensions was cancelled (vi) the employers were allowed to pay a bonus (up to 1,000 euros) to their employees exempt of payroll and income taxes. The total cost of these decisions was estimated to be 17 billions euros. Essential to our perspective, all centrally-taken decisions were cancelled. President Macron’s started to rebuild some relationships with mayors and local authorities, a policy largely supported by a majority of French citizens. The right balance in French governance between “Paris” and the “Territories” seems still a work in progress.

3 Data and Descriptive Statistics

3.1 The French Employer-Employee Data

In what follows, we use the DADS, 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 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\(^6\). In addition, the panel can be matched to the EDP (“Echantillon Démographique Permanent”) 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\(^7\). In addition, the self-employed are not covered when, for the unemployed, unemployment benefits are not available. According to the French Statistical Office (INSEE), wage employment represented 89.25% of total employment in 2019\(^8\). Finally, data availability precludes access to employees working outside of metropolitan France (e.g. overseas territories), employees working in the agricultural sector, or for private individuals. We also exclude apprentices, interns, and people working for the clergy.

The data available to researchers is 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 (net labor earnings inclusive of workers’ mandatory social contributions at the exclusion of employers payroll taxes). 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. 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

---

\(^6\)The sample size was multiplied by two in 2002 by including individuals born in October of an odd year.

\(^7\)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 section 5.5 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.

\(^8\)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.
French minimum wage. Appendix Table B.1 depicts the annual minimum earning threshold for the period of interest and Figure B.1 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. This suggests that the decrease in inequality observed in Section 4.1 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 low annual earnings. It is likely to explain the peculiar patterns observed at the bottom of the distribution for this year.

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) separately for men and women. We also construct a measure of permanent earnings defined as the average earnings of a worker over a period of 3 years. Permanent earnings in year \( t \) is defined only for workers with earnings above the minimum threshold in year \( t \) and at least one additional year. We then residualize the log of this measure using the same procedure as for residualized earnings. 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 two samples: the cross-sectional (CS) and the longitudinal (LX) 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 are included in the longitudinal sample.

---

9It corresponds approximately to a part-time job for one quarter.
10We divide education into four groups: no diploma, less than high-school, high school, and some college. Education is only available for workers in the Panel DADS merged with the EDP.
11Permanent earnings is computed backward: it is the average of labor earnings between \( t \) and \( t - 2 \).
12In what follows, permanent earnings is computed using only age dummies.
ple who have a permanent earnings measure, as well as one and five-year residual earnings changes. We denote the full time period available for the analysis (i.e. 1991-2016) by $T_{\text{max}}$.

We present elements on the earnings distribution in Table B.2 for the Panel DADS and Table B.3 for the comprehensive DADS. Descriptive statistics on the number of observations, the age distribution and the level of education are shown in Table B.4. To better understand to what these percentiles refer to, Figures B.2 and B.3 plot 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. It is also interesting to note that they experienced different trends over the period of interest.\footnote{Hours are available since 1993 so we focus 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.} Men at the bottom of the earnings distribution 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 in Section 4.1.2. 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.

### 3.2 French Cities and Territories

As we saw in the previous Section, social movements that took place in France over the last 20 years appear to have a local origin. 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 spacial dispersion. In particular, we will use repeatedly categories

\footnotetext{13}{Hours are available since 1993 so we focus 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.}
that should help us approximate cities or territories. Indeed, the empirical analyses of Section 5 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 an out-sized city, Paris, 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. 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 around 85% of the population. Their size ranged from 2,500 inhabitants in 2015 to 11M 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.

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

14 See Tricaud (2020).
15 We exclude areas “000”, “997” and “998” which include municipalities that do not belong to urban areas.
16 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.\textsuperscript{17} 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.\textsuperscript{18} An \textit{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.\textsuperscript{19}

\textsuperscript{17}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.

\textsuperscript{18}As a result, Paris refers to the urban unit of Paris when considered for across-territories comparisons.

\textsuperscript{19}For this specific Section, we exclude people living in Corsica because the necessary variable is not available every year. Hence, our across cities and across territories statistics will restrict to continental France.
4 Earnings Inequality and Dynamics

4.1 Inequality

4.1.1 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 6 presents the various percentiles of the distribution of earnings. The first four figures (6A-6D) use the sample whereas the last two figures (6E and 6F) use the exhaustive data to present top percentiles. Although comprehensive data are only available since 2001, it allows to eliminate fluctuations due to insufficient sample size.

First, we see little wage growth for men, except for the very top percentiles (P99.9 and P99.99, see 6C and 6E). 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, we saw in Section 2.1 that women at the 10\textsuperscript{th} and 25\textsuperscript{th} percentiles of the earnings distribution had hourly wages close to the minimum wage. In the following Section, we decompose labor earnings into hours and hourly wage to assess the contribution of these two factors. Finally, we observe that the growth at very top percentiles is also slightly higher for women than for men. Between 1991 and 2016, the top 0.1\% increased by 57\% for women (45\% for men) compared to 41\% (respectively 2\%) for the 10\textsuperscript{th} percentile.

\textsuperscript{20}The worker’s identifier used to aggregate all jobs within a year is available only since 2001 in the comprehensive data. As a result, we cannot compute total earnings before this date.

\textsuperscript{21}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.
Figure 6 – Change of Percentiles of the Log Real Earnings Distribution

Note: Using real raw log earnings and the CS+TMax sample, Figure 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. Using real raw log earnings and comprehensive data for the period 2001-2017, Figure plots against time: (e) Men: P90, P95, P99, P99.9, P99.99, (f) Women: P90, P95, P99, P99.9, P99.99. All percentiles are normalized to 0 in the first available year. Shaded areas are recessions. Dataset: Panel DADS (a-d) and comprehensive DADS (e-f).

The consequences of these trends in the various percentiles can be seen on Figure 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 growth, for women, of the 10th percentile since 2009.

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

Note: Using real raw log earnings and the CS+TMax sample, Figure 7 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 are recessions. 2.56*SD corresponds to P90-10 differential for a Gaussian distribution. Dataset: Panel DADS.

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.

Results for the combined sample of men and women are displayed in the Appendix Figure C.1.
Norway (see other papers in this issue). It also appears to be close to that prevailing in a Gaussian distribution, especially for women (the P90-10 is close to 2.56 SD). 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).

Previous measures focus 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 6.

Using residual earnings yields essentially identical results, when controlling either for age or age and education (see Appendix Figures C.3 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 population and of educational attainment.

Other measures of inequality yield very similar conclusions. In Figure C.5, the first quintile increases until 2009 before decreasing while the top quintile declines just before the financial crisis and increases since then. The Gini coefficient is almost stable until 2006. It then decreases between 2006 and 2009 before increasing continuously until 2016 (see Figure C.6).

Finally, the distribution of earnings is (unsurprisingly) fat-tailed as we see from Appendix Figures C.7 and C.8. The linear relationship suggests that the right-tail of the distribution has a Pareto shape. The strong increase in very top percentiles over time, depicted in Figure 6 translates into a thickening of the right-tail (associated with a decrease in the slope coefficient in absolute value). 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.

4.1.2 Inequality and the Reduction of the Working Week

We now discuss the impact of the reduction of the working week on labor earnings. To do so, we decompose labor earnings into the number of hours worked and the hourly earnings for the period 1993-2016. Appendix Figure D.1 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 Figure D.1A 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

---

23 Hours are only available since 1993. We focus on workers with non-missing hours for all job spells.
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.

4.1.3 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 8 plots the P90-50 and the P50-10 every year for workers who turn 25. Figures 8A and 8B show that the distributions are very similar for men and women at age 25, contrary to what we found in Figure 6. Hence, this means that the distribution for women becomes asymmetric as they age. As in Section 4.1.1, 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 8 – Initial Earnings Inequality (at age 25)**

(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: P90-50 and P50-10 at age 25, (b) Women: P90-50 and P50-10 at age 25. Shaded areas are recessions.

Dataset: Panel DADS.

Figure 9 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. Furthermore, the life-cycle inequality of cohorts is decreasing for women
and U-shaped for men. Similar to what found previously, within cohorts inequality has decreased until the financial crisis and increased since then for male workers (respectively stagnate for female workers).

**Figure 9 – Life-Cycle Inequality Over Cohorts**

(A) Men

(B) Women

Note: Using real raw log earnings and the CS+TMax sample, Figure 9 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 dash grey lines plot for each year the P90-10 for people aged 25, 30 and 35. The four remaining lines plot the evolution of the P90-10 over time for specific cohorts. Dataset: Panel DADS.

4.2 Earnings Change

4.2.1 The Distribution of Earnings Change 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 10 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.

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. 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.

Figure 10 – Dispersion of One-Year Log Earnings Changes

(A) Men

(B) Women

![Figure 10](image)

Note: Using residual one-year earnings changes (controlling for age) and the LS+TMax sample, Figure 10 plots against time the following variables: (a) Men: P90-50 and P50-10, (b) Women: P90-50 and P50-10. Shaded areas are recessions. Dataset: Panel DADS.

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 earnings changes are very far from a normal distribution. The distribution is negatively skewed: the left tail of the distribution is longer than the right tail. As a results, the bad shocks (below median) 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, there appears to be more dispersion for women but a higher kurtosis for men. Very similar

\footnote{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.}

\footnote{The red dotted line plots the density of a normal distribution with similar variance as in our data.
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. This distance to normality, this Pareto shape, with clear and strong skewness and large kurtosis, are all elements that confirm that idiosyncratic shocks have large welfare costs, much larger at least than in a (log-)normal world.

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 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. This thinning implies that the potential costs of idiosyncratic shocks might be attenuating through time.

4.2.2 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 11 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 procyclical: 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.

In Figure 12, we condition our various statistics using a measure of “permanent earnings.” We look at the P90-10 differential in the first panel, at Kelley skewness in the second, and at Crow-Siddiqui kurtosis in the third. Each time results

\footnote{Results for the five-year growth rate are displayed in Appendix Figure E.2}

\footnote{Permanent earnings are defined as the average of non-missing earnings between t and t-2 net of age and year effects.}
for men are presented in the left column when those for women in the right one. Hence, Figure 12 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, our measure of 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 90-10 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.
Figure 11 – 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 LS+TMax sample, Figure 11 plots against time the following variables: (a) Men and Women: Kelley skewness, (b) Men and Women: Excess Crow-Siddiqui kurtosis calculated as $P_{97.5} - P_{2.5} - 2.91$ 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 are recessions. Dataset: Panel DADS.
Figure 12 – Dispersion, Skewness and Kurtosis of One-Year Log Earnings Changes by Age Group

(A) Men

(B) Women

(C) Men

(D) Women

(E) Men

(F) Women

Note: Using residual one-year earnings changes and the H+TMax sample, Figure 12 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 \( \frac{P_{97.5} - P_{2.5} - 2P_{25}}{2.91} \) 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.3 and E.4 we present (standardized) measures of the moments of the earnings change using its standard deviation, its skewness, and its 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.

Fortunately, 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).

4.3 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 13. 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. 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 grey (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.
Figure 13 – Evolution of 10-Year Mobility Over the Life Cycle

(A) Men

(B) Women

Note: Using permanent income, Figure 13 plots the average rank-rank mobility for two age groups separately for men and women. Dataset: Panel DADS.

Figure 14 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, except at the very top of the distribution (top .1%) which experienced an increase, especially for men. The Appendix Figure F.2 shows a small increase in 5-year mobility for both men and women, including at the very top.

Figure 14 – Evolution of 10-Year Mobility Over Time

(A) Men

(B) Women

Note: Using permanent income, Figure 14 plots the average rank-rank mobility in 1995 and 2005 separately for men and women. Dataset: Panel DADS.

5 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 de-
5.1 Inequality Between Urban Areas

Figure 15 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. However, we see a strong discontinuity between Paris and other cities for percentiles strictly above this first decile. This gap is clearly increasing when city size decreases (on the right of each Figure). However, because Paris’s urban area also includes poor areas, the gap between Paris and other cities is a lower bound for each percentile shown on Figure 15. We will come back to this point in Section 5.4 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 much larger in 2016 than in 2001. On the other hand, the gap at the bottom of the distribution is closing over the period. 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).

In Appendix Figure H.1, we examine the same question but controlling for age, 2-digit industry code, and workers’ education level. Results are qualitatively unchanged. Adding controls decreases the gaps between percentiles as well as the slopes across cities, making these lines flatter. Unsurprisingly, 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.
These results are reminiscent of Combes et al. (2012) who focus on full-time employees in the private sector over the 1993-2007 period (using also the DADS Panel). Indeed, their results, based on employment zones, show that both particularly high and low skills workers are over-represented in denser areas.

Figure 15 – Between-Urban Areas Inequality

(A) 2001

(B) 2016

Note: Using raw log earnings for men and women, Figure 15 plots against city rank the 10th, 25th, 50th, 75th, 90th, 99th percentiles in: (a) 2001, (b) 2016. City rank is based on 2015 census population. Observations are the 759 French urban areas. Data are displayed using a bin-scatter. Dataset: comprehensive DADS.

5.2 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 16 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 16 – 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 16 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.

We then turn to inequality between Territories, including both urban and rural areas. In Figure 17, we plot the log difference in (A) median, (C) mean earnings, between Paris and the other territories. Figures 17B and 17D plot the evolution of these log differences normalized to 0 in 1993. 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).

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.

---

28 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.

29 The place of residence is only available in the data since 1993. As a result, we focus on the period 1993-2016 thereafter.
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 17B and 17D 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 17 – The Urban Unit of Paris vs. the Rest

(A) Median Labor Earnings
(B) Median Labor Earnings (Normalized)
(C) Mean Labor Earnings
(D) Mean Labor Earnings (Normalized)

Note: Using the real raw log labor earnings of both men and women, Figure 17 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. 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 Paris municipality. Appendix Figure 1.A replicates Figure 17.D 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. 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 (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.

---

30Similar conclusions can be drawn when using median earnings rather than mean earnings.
To further compare these territories, we present two sets of statistics and their evolution over the sample period. In Figure 18 we present 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 also observe a convergence in the share of minimum wage workers between the five Territories, especially since the mid-2000’s.

![Figure 18 – Share of Minimum Wage Workers by Territory](image)

Note: Using the real raw log labor earnings of both men and women, Figure 18 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 the hourly minimum wage. Territories and Paris are defined using urban units. Dataset: Panel DADS.

Finally, Figure 19 presents job-to-job mobility statistics by territory between 1993 and 2015. As expected in a dense territory with more jobs and firms, mobility is highest in Paris’s urban unit. It is lowest in rural areas, again an unsurprising result in the less dense territory. For all territories though, the evolution is strictly parallel and pro-cyclical (with a maximum in 2000). Again, 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 the following Section.

Figure 19 – Job to Job Mobility by Territory

Note: Figure 19 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.

5.3 The Decrease in Within Territories Inequality

In this section, we study how inequality evolved within the six territories considered. Figures 20 and 21 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 percentile. 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).

**Figure 20 – Change of Percentiles of the Log Real Earnings Distributions by Territory**

(A) Paris (Men)  
(B) Paris (Women)  
(C) Central Municipalities (Men)  
(D) Central Municipalities (Women)  
(E) Suburbs (Men)  
(F) Suburbs (Women)

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) 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 are recessions. Dataset: Panel DADS.
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.
5.4 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 22 with the dark blue showing the municipality of Paris, in medium blue Paris’s urban unit (as defined in Section 3), a unit that includes 408 municipalities, and in light blue the rest of Paris’s urban area, which includes 1,342 municipalities.

Figure 22 – Paris and its Surroundings

Note: Figure 22 plots Paris and its suburbs. Numbers in parenthesis correspond to the number of municipalities.

Figure 23 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 munic-
ipality 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 23 – Paris center vs. its surroundings

(A) Median

(B) Mean

Note: Using raw log earnings for men and women, Figure 23 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.

5.5 Evolution of Public Employment

Recent political events in France have placed the spotlight on employment and its evolution in the public sector. In particular, one of the demands associated to the recent protests was to increase public services in remote and rural areas. A complain was the perceived lack and decrease in services provided by the State in these territories. In this Section, we provide 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.

Figure 24 presents (A) the National changes and (B) the local changes for our five categories of territories, relative to 2002. First, public employment strongly decreases between 2002 and 2003 but then re-increases until 2008 and decreases af-
The analysis by territories shows that most territories display a similar evolution except suburbs where employment seems to stabilize at a higher level than that of 2002 (+8%), rural territories with strong fluctuations between 2007 and 2009, and Paris which looses public jobs in 2016 when compared to 2002 (-7%).

![Figure 24 - Public Employment](image)

**Note:** Figure 24 plots against time the number of workers in the public sector (a) at the national level (b) in the territories. Employment is computed using full time workers working the whole year. All statistics are normalized to 0 in the first available year. Territories and Paris are defined using urban units. Dataset: Panel DADS.

Figure 25 shows the evolution of public employment by category of civil service (State, local, hospital) both in levels (left panel) and relative to 2002 (right panel).

The number of State civil servants decreases almost continuously with an acceleration between 2009 and 2011 and a stabilization afterwards. By contrast, employment of local civil servants and employment in public hospitals increases until 2010 for the first, until 2006 for the second. Both stabilize afterwards (see Figure 25B).

31 We suspect that the decrease observed in 2003 is due to data quality issues and does not reflect the evolution of public employment. Statistics produced by the French statistical office suggest much smaller variations between 2002 and 2003.
These changes are the outcome of several waves of decentralization that took place between 2006 and 2011. The structure of public employment was modified by having transfers from State to Local civil service (around 5-6% of State civil servants).\(^{32}\)

Notice though that these Figures do not include the strong reduction in the military and related employees over the last two decades. Indeed, between 2005 and 2015, employment decreases by approximately 14%. The closure of many military bases might have affected negatively remote and rural areas, something we cannot measure.

Figure 25 – Public Employment by Category in France

![Public Employment by Category in France](image)

Note: Figure 25 plots against time (a) the number of observations in the public sector by type of public employment (b) the number of observations in the public sector by type of public employment normalized to 0 in the first available year. Employment is computed using full time workers working full year. Territories and Paris are defined using urban units. Dataset: Panel DADS.

Finally, Figure 26 plots the evolution of employment for the three types of public jobs, relative to 2002, by type of territory. Because some jobs were transferred from the State civil service to the local civil service, we see on all figures that the decrease in the first one is associated to an increase in the second one, essentially between 2005 and 2010. Because employment in hospitals was often pretty low in most territories, the relative change seems huge. Still, Paris clearly lost State jobs which were not compensated by an increase in hospitals or local civil service, in contrast to other territories. Interestingly, and in contrast with public perception, employment in the hospital civil service has increased steadily everywhere but in Paris. More generally, these numbers do not support the idea – often invoked when

\(^{32}\)It is worth noting that more than one half of local civil servants are employed by municipalities.
attempting to make sense of the Yellow Vests movement – that public employment has left the remote and rural territories, quite the contrary.

Figure 26 – Public Employment by Category in the Territories

(A) Paris

(B) Central Municipalities

(C) Suburban Areas

(D) Remote Municipalities

(E) Rural Areas

Note: Figure 26 plots against time the number of workers in the public sector by type of public employment normalized to 0 in the first available year. Employment is computed using full time workers working full year. Territories and Paris are defined using urban units. Dataset: Panel DADS.
6 Conclusion

The French 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, potentially since they are decided at the central State level, in Paris as locals would say there.

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 Tri-caud (2020)). Were the Yellow Vests protests an echo from the populist movements that emerged in many other countries, in particular the United States?
References


51


Appendices

A The French Labor Market Institutions

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

**Table B.1 – Minimum Earnings Threshold**

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Threshold</td>
<td>1850</td>
<td>1913</td>
<td>1909</td>
<td>1941</td>
<td>1964</td>
<td>1992</td>
<td>2024</td>
<td>2077</td>
<td>2100</td>
<td>2111</td>
<td>2153</td>
<td>2182</td>
<td>2220</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Threshold</td>
<td>2295</td>
<td>2385</td>
<td>2444</td>
<td>2468</td>
<td>2505</td>
<td>2506</td>
<td>2498</td>
<td>2529</td>
<td>2539</td>
<td>2553</td>
<td>2574</td>
<td>2585</td>
<td></td>
</tr>
</tbody>
</table>

*Note: Table B.1 displays for each year the minimum labor earnings threshold in euros 2018.*

**Figure B.1 – Share of Observations Below the Minimum Earnings Threshold**

*Note: Figure B.1 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.*
Table B.2 – Earnings Distribution in France (Panel DADS)

(a) Total Population

<table>
<thead>
<tr>
<th>Year</th>
<th>P1</th>
<th>P5</th>
<th>P10</th>
<th>P25</th>
<th>P50</th>
<th>P75</th>
<th>P90</th>
<th>P95</th>
<th>P99</th>
<th>P99.9</th>
</tr>
</thead>
<tbody>
<tr>
<td>2005</td>
<td>2,874</td>
<td>5,067</td>
<td>8,332</td>
<td>17,094</td>
<td>24,122</td>
<td>32,863</td>
<td>46,521</td>
<td>60,114</td>
<td>106,274</td>
<td>243,560</td>
</tr>
<tr>
<td>2015</td>
<td>3,122</td>
<td>5,546</td>
<td>8,829</td>
<td>17,811</td>
<td>25,615</td>
<td>34,973</td>
<td>49,885</td>
<td>64,264</td>
<td>113,347</td>
<td>270,955</td>
</tr>
</tbody>
</table>

(b) Men

<table>
<thead>
<tr>
<th>Year</th>
<th>P1</th>
<th>P5</th>
<th>P10</th>
<th>P25</th>
<th>P50</th>
<th>P75</th>
<th>P90</th>
<th>P95</th>
<th>P99</th>
<th>P99.9</th>
</tr>
</thead>
<tbody>
<tr>
<td>1995</td>
<td>2,511</td>
<td>5,171</td>
<td>9,098</td>
<td>18,373</td>
<td>25,225</td>
<td>34,873</td>
<td>51,158</td>
<td>67,447</td>
<td>115,424</td>
<td>227,547</td>
</tr>
<tr>
<td>2015</td>
<td>3,208</td>
<td>6,000</td>
<td>9,757</td>
<td>20,079</td>
<td>27,745</td>
<td>38,345</td>
<td>55,990</td>
<td>72,719</td>
<td>132,730</td>
<td>332,115</td>
</tr>
</tbody>
</table>

(c) Women

<table>
<thead>
<tr>
<th>Year</th>
<th>P1</th>
<th>P5</th>
<th>P10</th>
<th>P25</th>
<th>P50</th>
<th>P75</th>
<th>P90</th>
<th>P95</th>
<th>P99</th>
<th>P99.9</th>
</tr>
</thead>
<tbody>
<tr>
<td>1995</td>
<td>2,271</td>
<td>3,668</td>
<td>5,841</td>
<td>12,335</td>
<td>20,247</td>
<td>28,025</td>
<td>37,057</td>
<td>43,846</td>
<td>67,395</td>
<td>119,759</td>
</tr>
<tr>
<td>2005</td>
<td>2,761</td>
<td>4,425</td>
<td>6,923</td>
<td>14,064</td>
<td>21,516</td>
<td>29,157</td>
<td>39,465</td>
<td>48,055</td>
<td>77,505</td>
<td>150,145</td>
</tr>
<tr>
<td>2015</td>
<td>3,055</td>
<td>5,170</td>
<td>8,012</td>
<td>15,714</td>
<td>23,556</td>
<td>31,525</td>
<td>42,884</td>
<td>53,644</td>
<td>89,075</td>
<td>186,786</td>
</tr>
</tbody>
</table>

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 – Earnings Distribution in France (Comprehensive DADS)

<table>
<thead>
<tr>
<th>Year</th>
<th>P1</th>
<th>P5</th>
<th>P10</th>
<th>P25</th>
<th>P50</th>
<th>P75</th>
<th>P90</th>
<th>P95</th>
<th>P99</th>
<th>P99.9</th>
</tr>
</thead>
<tbody>
<tr>
<td>2005</td>
<td>2,781</td>
<td>4,586</td>
<td>7,354</td>
<td>16,114</td>
<td>24,081</td>
<td>33,315</td>
<td>48,097</td>
<td>62,684</td>
<td>111,156</td>
<td>250,488</td>
</tr>
</tbody>
</table>

Note: Table B.3 shows summary statistics for CS sample. Dataset: comprehensive DADS. Go back to main text

Table B.4 – Descriptive Statistics

<table>
<thead>
<tr>
<th>Year</th>
<th>Obs. (Mill)</th>
<th>Mean Income Men</th>
<th>Women</th>
<th>Age Shares %</th>
<th>Education Shares %</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>[25,35]</td>
<td>[36,45]</td>
</tr>
<tr>
<td>1995</td>
<td>.58</td>
<td>29,829</td>
<td>21,732</td>
<td>43.2</td>
<td>37.7</td>
</tr>
<tr>
<td>2015</td>
<td>1.34</td>
<td>33,013</td>
<td>25,924</td>
<td>47.8</td>
<td>34.9</td>
</tr>
</tbody>
</table>

Note: Table B.4 shows descriptive statistics for CS sample. Dataset: panel DADS. Go back to main text
Figure B.2 – Annual Working Time By Earning Percentile

(A) Men

(B) Women

Note: Figure B.2 plots against time, for 5 percentiles of the 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 B.3 – Hourly Wage By Earning Percentile

(A) Men

(B) Women

Note: Figure B.3 plots against time, for 5 percentiles of the 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
C Inequality

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

(A) Percentiles

(B) Top Percentiles

(C) Dispersion

(D) Right- and Left-Tail Dispersion

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 are recessions. Dataset: Panel DADS. Go back to main text
Figure C.2 – Unconditional Gender Pay Gap

[Graph showing the difference between men and women mean earnings over time, with data points for 1991 to 2015.]

Note: Using raw real log earnings, 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

(A) Percentiles

(B) Top Percentiles

(C) Dispersion

(D) Right- and Left-Tail Dispersion

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 are recessions. Dataset: Panel DADS. Go back to main text.
Figure C.4 – Distribution of Residual Earnings in the Population After Controlling for age and education

(A) Percentiles

(B) Top Percentiles

(C) Dispersion

(D) Right- and Left-Tail Dispersion

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 are recessions. Dataset: Panel DADS. Go back to main text

Figure C.5 – Changes in Income Shares

(A) Income Shares of Quintiles

(B) Selected Income Shares

Note: Shaded areas are recessions. Dataset: Panel DADS. Go back to main text
Figure C.6 – Gini Coefficient

Note: Figure C.6 plots the Gini coefficient for both men and women. Shaded areas are recessions. 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, 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 95\textsuperscript{th} percentile, 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.
D The Reduction of the Working Week

Figure D.1 – Evolution of hours and hourly wages by earning percentiles

(A) Hours (Men and Women)  
(B) Hourly Wage (Men and Women)

(C) Hours (Men)  
(D) Hourly Wage (Men)

(E) Hours (Women)  
(F) Hourly Wage (Women)

Using raw log earnings and the CS+TMax sample, Figure D.1 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. Dataset: Panel DADS. Go back to main text
Earnings Change

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

(A) Men

(B) Women

Note: Using residual five-year earnings changes and the LS+TMax sample, Figure plots against time the following variables: (a) Men: P90-10 differential, (b) Women: P90-10 differential. Shaded areas are recessions. Dataset: Panel DADS.

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 LS+TMax sample, Figure plots against time the following variables: (a) Men and Women: Kelley skewness, (b) Men and Women: Excess Crow-Siddiqui kurtosis calculated as \( \frac{\text{P}_{97.5} - \text{P}_{50}}{\text{P}_{75} - \text{P}_{25}} - 2.91 \) 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 are recessions. Dataset: Panel DADS.
Figure E.3 – Dispersion, Skewness and Kurtosis of Five-Years Earnings Changes

(A) Men

(B) Women

(C) Men

(D) Women

(E) Men

(F) Women

Note: Using residual five-year earnings changes and the H+TMax sample, 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 
\[ \frac{P_{97.5} - P_{2.5}}{2.91} \]
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

(A) Men

(B) Women

(C) Men

(D) Women

(E) Men

(F) Women

Note: Using residual one-year earnings changes and the H+TMax sample, Figure E.4 plots 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: Kurtosis, (f) Women: Kurtosis. Dataset: Panel DADS. Go back to main text

65
Figure E.5 – Standardized Moments of Five-Years Earnings Changes

(A) Men

(B) Women

(C) Men

(D) Women

(E) Men

(F) Women

Note: Using residual five-year earnings changes and the H+TMax sample, 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: Kurtosis, (f) Women: Kurtosis. Dataset: Panel DADS. Go back to main text
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. Dataset: Panel DADS.

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

(A) Men

(B) Women

Note: Figure F.2 shows average rank-rank mobility. Dataset: Panel DADS.
G Densities of Earnings Growth

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

(A) Men

- St. Dev.: 0.45
- Skewness: -0.97
- Kurtosis: 16.27

(B) Women

- St. Dev.: 0.49
- Skewness: -0.95
- Kurtosis: 12.46

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

- St. Dev.: 0.58
- Skewness: -1.03
- Kurtosis: 11.90

(B) Women

- St. Dev.: 0.63
- Skewness: -0.80
- Kurtosis: 8.97

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

- St. Dev.: 0.45
- Left Slope: 1.84
- Right Slope: -2.60
- Log-Density
- Skewness: -0.97
- Kurtosis: 16.27

(B) Women

- St. Dev.: 0.49
- Left Slope: 2.04
- Right Slope: -2.98
- Log-Density
- Skewness: -0.95
- Kurtosis: 12.46

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

St. Dev.: 0.58
Skewness: -1.03
Kurtosis: 11.90

(B) Women

St. Dev.: 0.63
Skewness: -0.80
Kurtosis: 8.97

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

<table>
<thead>
<tr>
<th>Year</th>
<th>Left Slope</th>
<th>Right Slope</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>Left Slope</th>
<th>Right Slope</th>
<th>Skewness</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>1991</td>
<td>1.57</td>
<td>-2.72</td>
<td>-1.35</td>
<td>15.3</td>
<td>1.37</td>
<td>-2.49</td>
<td>-1.09</td>
<td>11.2</td>
</tr>
<tr>
<td>1995</td>
<td>1.78</td>
<td>-2.75</td>
<td>-1.33</td>
<td>16.1</td>
<td>1.42</td>
<td>-2.66</td>
<td>-0.82</td>
<td>11.4</td>
</tr>
<tr>
<td>2000</td>
<td>2.05</td>
<td>-2.96</td>
<td>-0.89</td>
<td>13.6</td>
<td>1.49</td>
<td>-2.79</td>
<td>-0.96</td>
<td>10.0</td>
</tr>
<tr>
<td>2005</td>
<td>2.01</td>
<td>-3.02</td>
<td>-0.94</td>
<td>14.1</td>
<td>1.61</td>
<td>-2.86</td>
<td>-0.91</td>
<td>10.4</td>
</tr>
<tr>
<td>2010</td>
<td>2.32</td>
<td>-3.34</td>
<td>-0.98</td>
<td>13.1</td>
<td>1.63</td>
<td>-3.09</td>
<td>-1.03</td>
<td>9.8</td>
</tr>
<tr>
<td>2015</td>
<td>2.09</td>
<td>-3.45</td>
<td>-1.04</td>
<td>13.1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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 whole population. Dataset: Panel DADS. Go back to main text.
H Geographic Inequality

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

(A) P25

(B) P50

(C) P75

(D) P90

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, 2-digit industry code, and four education dummies. Observations are the 759 urban areas. They are displayed using a bin-scatter. Dataset: Panel DADS matched with EDP.

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.
Figure H.3 – Earnings Inequality by Territory

(A) Paris (Men)

(B) Paris (Women)

(C) Central Municipalities (Men)

(D) Central Municipalities (Women)

(E) Suburbs (Men)

(F) Suburbs (Women)

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 are recessions. 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)

(A) Remote (Men)  
(B) Remote (Women)  
(C) Rural (Men)  
(D) Rural (Women)

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 are recessions. 2.56*SD corresponds to P90-10 differential for a Gaussian distribution. Dataset: Panel DADS. Go back to main text