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A decomposition of labor earnings growth: Recovering Gaussianity?[☆]

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ABSTRACT

Recent works have concluded that labor earnings dynamics exhibit non-Gaussian and nonlinear features. We argue in this paper that this finding is mainly due to volatility in working time. Using a non-parametric approach, we find from French data that changes in labor earnings exhibit strong asymmetry and high peakedness. However, after decomposing labor earnings growth into growth in wages and working time, deviations from Gaussianity stem from changes in working time. The nonlinearity of earnings dynamics is also mostly driven by working time dynamics at the extensive margin.

1. Introduction

The canonical model of earnings assumes log-normal shocks and linear dynamics, although both assumptions have been challenged based on the data. Relaxing these assumptions matters for at least three reasons. First, deviations of labor earnings shocks from log-normality lead to the overestimation of upward earnings mobility. Models based on normal processes are known to overestimate the probability of an individual with low earnings having high earnings in the future (Horowitz and Markatou, 1996; Lillard and Willis, 1978). Hence, a diagnosis of labor market inequalities along the lifecycle based on Gaussianity assumptions suffers from excessive optimism that is likely to be detrimental to the workers in question, who are possibly trapped at the bottom of the distribution. Second, knowledge about the distributional properties of hourly wage growth and earnings is crucial for quantifying precautionary savings and labor supply (Jessen et al., 2018) and other reactions to fluctuations as a first step. Third, welfare costs associated with fluctuations in labor earnings (quantified for instance by Pijoan-Mas, 2006, under incomplete markets) are likely to be underestimated under log-normality on wage growth combined with linearity assumptions on earnings dynamics. In addition to deviations from Gaussianity, nonlinear dynamics of labor income have a first-order impact on consumption and saving behavior; a better understanding of income processes helps fill the gap between income and consumption inequalities. Taking both the nonlinearity and the non-Gaussianity of income dynamics into account is therefore essential when designing optimal social insurance and direct taxation. Arellano et al. (2017) show, for instance, that nonlinearity and non-Gaussianity generate heterogeneous consumption responses and that assuming linearity instead is misleading when assessing the impact of earnings shocks. Large, negative income shocks are responsible for relatively small consumption drops at the bottom of the distribution but have sizable effects at the top. By contrast, large, positive shocks seem more profitable in the short run at the bottom of the distribution, but this effect vanishes in the long run. Under the canonical model, the effect of earnings shocks on consumption is assumed to be homogeneous regardless of the location in the distribution.

This paper investigates the channels through which deviations from normality and nonlinear dynamics occur by relying on an accounting decomposition of labor earnings into hourly wages and working time at both the extensive and intensive margins; the infra-annual extensive margin upon which we focus in this paper refers to participation in the labor market, captured by the annual number of days worked, while the intensive margin designates the daily number of hours worked, i.e., the annual number of hours worked divided by the annual number of workdays. We build in particular on recent works (Guvenen et al., 2016) that quantify the importance of deviations from Gaussianity. We adopt an agnostic perspective on French labor earnings data and character-

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ize the distribution of earnings changes conditional on recent earnings history. The novelty of our approach consists in decomposing earnings into several components (wage, days worked, number of hours worked per day) thanks to available information on working time. When assessing the importance of the deviation from log-normality, we are able to disentangle what is due to hourly wages from what is related to working time at both margins. We rely on the DADS (*Déclaration Annuelle de Données Sociales*) panel, a longitudinal administrative database, the completion of which is mandatory for payroll taxes and that contains information on individuals' labor earnings. We focus on men working in the private sector from 1995 to 2015. As in the US, we find that log-earnings changes are not Gaussian, that their distribution is leptokurtic and negatively skewed, and that individual labor earnings dynamics are both nonlinear and heterogeneous. More precisely, we find that (i) large labor earnings changes that drive the negative skewness and the fat tail are primarily working time changes, especially at the extensive margin; (ii) although we reject the log-normality assumption in the data for wage growth, this deviation from Gaussianity is much smaller than it is for working time; (iii) much of the nonlinearity[1] and heterogeneity[2] in earnings dynamics is driven by working time dynamics at the extensive margin; and (iv) finally, the choice between moment-based and quantile-based measures of higher-order moments of the distribution of changes in labor outcomes matters, which stresses the role played by methodological issues.

Overall, deviations from normality are primarily the result of unemployment risk: it follows that the welfare cost of non-Gaussian earnings fluctuations depends mainly on the level of insurance provided by unemployment benefits. This work sheds light on the relative importance of the extensive margin, and this empirical finding has two implications. First, for policy makers, the appropriate solutions to labor market inequalities are highly dependent on the relative importance of each channel. It turns out that in France, the extensive margin plays a larger role, which calls for a careful examination of the design of the unemployment insurance scheme.[3] Most of the recent policy debate has focused on enhancing both flexibility and security: on the one hand, by improving coverage after layoffs and by providing workers with unemployment insurance; on the other hand, by lowering labor costs, either thanks to social contribution exemptions at the bottom of the distribution or by diminishing firing costs and capping the maximal amount granted by labor courts to workers in case of disputes. Second, in the same vein but from a more academic perspective, addressing the problem of "zeroes", i.e., career gaps or incomplete labor market sequences, is a first-order issue; although this topic is relatively well known, few papers take this concern seriously (see for instance Biewen et al., 2018; Magnac and Roux, 2009). Censored models, microsimulation and supplementary data (e.g. on non-labor earned income) would definitely be needed to further pursue this topic.

Literature

Numerous papers in the literature are devoted to earnings dynamics model volatility while relying on parametric assumptions: Moffitt and Gottschalk (2002, 2011), Baker and Solon (2003), Low et al. (2010), Altonji et al. (2013) as well as Magnac et al. (2018). Most papers assume Gaussian shocks, although Lillard and Willis (1978) noted that "the actual distribution of log earnings is leptokurtic and slightly negatively skewed with respect to [the corresponding normal distribution]" and Horowitz and Markatou (1996) further argued that in such models, the transitory error component exhibits fatter tails than a normal distribution and that misspecification, including Gaussian shocks, could overestimate the probability of upward earnings mobility. Other papers consider mixtures of normals, including Geweke and Keane (2000) and Bonhomme and Robin (2009).

Recent works have suggested an agnostic, non-parametric perspective on log-earnings changes in the data to document the validity of parametric assumptions used by researchers when estimating dynamic models of earnings. Using individual-level earnings data, namely, W-2 forms[4] obtained from the US Social Security Administration (SSA) over the 1978-2011 period, Guvenen et al. (2016) documented first that labor earnings *changes* are not log-normal. In another contemporaneous project, Busch et al. (2018) propose decomposing labor earnings into the product of hourly wages and annual hours worked. However, there is a methodological issue related to the measure of higher-order moments of the distribution of shocks. Based on Italian data, Hoffmann and Malacrino (2019) use *moment-based* measures of dispersion, asymmetry and heaviness of tails. They show that both the negative skewness of annual labor earnings growth and its fluctuations over the business cycle are driven by employment time changes, i.e., changes in the number of weeks an individual works during a year. The distribution of weekly earnings growth is instead symmetric and stable over the business cycle. By contrast, Busch et al. (2018a) resort to *quantile-based* measures to characterize the distribution of hourly wage shocks in German data, and they find that Kelley's skewness is negative, therefore concluding that hourly wage changes in the country exhibit an asymmetric distribution.

Finally, a vast strand of literature relates labor earnings changes to consumption and saving behavior: see, e.g., Blundell and Preston (1998), Parker and Preston (2005), Blundell et al. (2008) as well as Pistolesi (2014) who focus on income and consumption inequalities. Under tight borrowing constraints, higher volatility of labor income might prevent individuals from smoothing their consumption; incomplete markets combined with inequality may result in inefficiency. In such situations, precautionary motives arise as a way for agents to insure themselves against earnings fluctuations, either by saving more (precautionary saving) or by working longer hours (precautionary labor supply). According to Pijoan-Mas (2006), the relative importance of the two motives depends on the persistence of the non-deterministic component of the wage process,[5] and the inability of markets to insure against fluctuations could be responsible for large welfare losses. According to Jessen et al. (2018), precautionary labor supply would amount to 2.8% of hours worked in Germany.

The remainder of the paper is organized as follows. The next section is devoted to a brief description of the institutional setting that prevails in the French labor market. Section 3 presents our data. In Section 4, we describe our empirical approach to disentangle wages from working time changes in labor earnings growth. Section 5 presents our main results, while Section 6 is devoted to some extensions, and Section 7 concludes the paper.

2. Institutional setting

In contrast with most developed countries which have experienced increasing wage inequality in recent decades, the latter being mainly attributed to skill-biased technological change (Katz and Murphy, 1992), wage inequality remains extremely stable in France, if not decreasing in the long run (Verdugo, 2014). A variety of institutional features may well account for this specific national trajectory: (i) a relatively high minimum wage,[6] which by law increases at least as fast as inflation (as

[1] The serial dependence between earnings changes is poorly approximated by linear assumptions.

[2] Earnings dynamics differ regarding the location in the distribution of recent hourly wages.

[3] At the time of this writing, reforms of unemployment benefits are possible in France.

[4] This form is officially called the "Wage and Tax Statement"; it is an Internal Revenue Service (IRS) tax form used in the United States to report wages paid to employees and the taxes withheld from them. Employers must complete a W-2 form for each employee to whom they pay a salary, wage, or other compensation as part of the employment relationship.

[5] In a standard permanent-transitory model, the permanent component is often assumed to be a random walk while the transitory component follows some MA process.

[6] In 2015, the minimum wage amounted to 63% of the median wage.

measured in the lowest quintile of the income distribution), plus half of the increase of a wage index (essentially measured for blue collar workers), plus a discretionary increase determined by the government;[7] (ii) employers' social security contributions (SSC) became increasingly redistributive over the last decades, which is believed to explain to a large extent the overall stability of wage inequality (Bozio et al., 2016); (iii) French wages depend tightly on a set of agreements between unions and employer representatives, either at the industry or at the firm level (Fougère et al., 2018); specifically, at the industry level, agreements set wage floors that are occupation-specific, and such wage floors are automatically extended to all firms that belong to the industry once an agreement is reached between unions and employer representatives.

An additional feature of the French institutional setting is the legal duration of work for full-time workers that changed over our period of interest. Namely, the legal weekly duration of work was moved from 39 hours to 35 hours in a law passed in 2000. This law was progressively enforced between 2000 and 2002, with some heterogeneity among firms. This legal duration is not a maximum: full-time workers may work overtime, and in 2015, the average number of hours per week for full-time workers as measured by the LFS was 41.5. The French version of the Structure of Earnings Survey shows 38.7% of male full-time workers in firms larger than 10 employees to have been subject to overtime in 2014. Relatedly, workers may also work less than this duration by working part-time. However, part-time work remains marginal among male workers on whom we focus in this paper: the share of part-time workers among male employees rose from 4.6 to 7.3% of workers between 1995 and 2015.

3. Data

3.1. The DADS panel

Our analysis is based on a large panel of French salaried employees working in the private sector, the longitudinal version of the *Declaration Annuelle de Données Sociales* (DADS).

By law,[8] French firms have to complete the DADS – an annual form that is the analogue of the W-2 form in the US – for every employee subject to payroll taxes. This panel contains information about individuals born in October of even-numbered years; it is therefore a representative sample of the French salaried population at a rate of 1/24. Since filling in the form is mandatory and because of the comprehensiveness of the panel with respect to individuals' careers, the data are of exceptional quality. It has one main desirable feature, namely, low measurement error, in addition to its large sample size and lack of top-coding.

The database contains detailed information about gross and net wages, work days, working hours,[9] other job characteristics (the beginning and the end of an employment spell, seniority, a dummy for part-time employment), firm characteristics (industry, size, region) and individual characteristics (age, gender). Our variables of interest are (i) real annual earnings defined as the sum of all salaried earnings, (ii) days worked, ranging between 0 and 360, (iii) working time measured in hours, and (iv) hourly wages computed as the ratio of annual earnings over working time. We decompose working time into its extensive and intensive margins by considering working time measured in hours as the product of days worked (extensive margin) and hours worked per day (intensive margin).

Our measure of labor earnings relies on net annual earnings.[10] This measure aggregates all wages paid to an individual, including performance pay and bonuses, paid vacations, in-kind benefits, the share of severance payments that exceeds the legal minimum, sick leave allowances, and early retirement benefits (to the extent that these benefits exceed an amount that is roughly equal to the minimum wage) but excludes stock options. In our dataset, hours worked refer to hours for which the worker is paid according to his or her labor contract. In Appendix A, we provide additional information on the quality of the data with respect to the measure of earnings and hours and on the few corrections implemented by Insee.

The most salient issue regarding the data is that a small subset of workers, who tend to concentrate in the upper part of the wage distribution, are not paid by the hour. As a result, employers do not directly report hours worked in the DADS. Instead, Insee ascribes hours worked to these observations based on days worked, provided that the implied hourly wages are consistent with those of otherwise comparable workers. This would tend to lead us to understate flexibility in hours worked and overstate flexibility in hourly wages at the top of the distribution; however, this issue is innocuous with respect to earnings changes and working time changes at the extensive margin.

From 2008 onwards, the DADS panel provides information about unemployment benefits issued by the national unemployment agency (*Pôle Emploi*) that has to complete DADS records for all individuals who earn unemployment benefits. Social security contributions are paid on these benefits. Nevertheless, this information is available at t only for individuals who have held at least some salaried employment during year t or $t-1$. Additionally, we know the amount of unemployment benefits that was granted to individuals, but we ignore the exact duration of unemployment spells.

3.2. Sample selection

Our working sample is composed of male salaried employees working in the private sector in metropolitan France between 1995 and 2015, aged 20 to 60, at the exclusion of agricultural workers and household employees.

The empirical analysis described in Section 4 requires the selection of individuals with a strong attachment to the labor market. We rely on "relatively stable" workers to describe changes in earnings between year t and year $t+5$. We impose in particular that these individuals are present in at least two years between $t-5$ and $t-2$, in addition to being present in $t-1$ and in t. To avoid very low working time or very low hourly wages, we restrict our attention to individuals whose number of workdays exceeds 45 days per year, hours worked per day exceed 1/8 of the annual legal duration of work divided by 360 and whose hourly wages exceed 90% of the minimum hourly wage. Our results are nevertheless robust to different choices of censoring thresholds.

Table 1 provides descriptive statistics on the selection of "relatively stable" workers.[11] First, we address the censoring related to working time and to hourly wages. Second, we impose that individuals be present in at least two years between $t-5$ and $t-2$, in addition to being present in $t-1$ and in t. The first step leaves us with a larger share of workers in the manufacturing industry and slightly modifies the age distribution of the sample by selecting out some young workers. The second step implements the employment stability criterion, which slightly amplifies the previous distortion of the age distribution.

4. Empirical analysis

4.1. Methodology

We follow the approach introduced by Guvenen et al. (2016). Thanks to the information on the duration of employment spells and on working time, we do not restrict our attention to the dynamics of labor earnings.

[7] The last discretionary increase dates back to 2012.

[8] The absence of a DADS form or incorrect or missing answers is punished with fines.

[9] This information has been available since 1995 only.

[10] In Online Appendix B.2, we also use gross earnings and find very few differences in our results.

[11] Additional summary statistics including earnings and its component profiles along the lifecycle are available upon request.

Table 1
Descriptive statistics on the selection process

	Base sample		Censoring		Final sample	
N	8 218 738		7 594 734		5 388 366	
	Frequency (in %)	Average earnings (2015 €)	Frequency (in %)	Average earnings (2015 €)	Frequency (in %)	Average earnings (2015 €)
Industry						
Manuf.	25,1	25 500	26,6	26 400	29,2	28 000
Constr.	11,4	19 800	12	20 600	12,3	22 900
Trade	15,4	21 600	15,8	22 800	15,9	25 600
Services	48,1	20 200	45,7	23 100	42,7	27 700
Age						
23-24	6,3	10 600	5,6	12 300	2,9	14 900
25-29	16,2	15 800	15,9	17 200	13,7	19 000
30-34	15,5	20 300	15,6	21 500	15,8	23 100
35-39	15,1	23 300	15,3	24 700	15,7	26 300
40-44	14	25 700	14,3	27 100	15,3	28 700
45-49	13,3	27 500	13,5	29 000	14,3	30 400
50-54	11,4	29 000	11,6	30 500	13	31 800
55-59	8,2	29 300	8,2	31 300	9,3	32 900

The base sample includes all individuals with positive employment in the private sector for a given year t. Censoring excludes observations for which annuals days of work are below 45, working hours per day are below 1/8 of the legal full-time duration of work and hourly wages are below 90% of the minimum wage. The final sample includes only observations that pass this thresholds for year t, $t-1$ and at least twice between $t-3$ and $t-5$. *Note.* Manuf. manufacturing industries. Constr. construction industry. *Source.* DADS panel, Insee.

More precisely, we decompose earnings into three components: hourly wages and working time at both the intensive and extensive margins of employment. We therefore rely on nonparametric estimations of the distribution of individual labor earnings growth and of each of its three components, which enables us not to make any parametric assumption on the distribution of changes, in contrast to many papers in the literature devoted to earnings dynamics.

Another difference with Guvenen et al. (2016) is that we rank individuals according to their recent hourly wages rather than according to their recent labor earnings. This choice emphasizes the role played by the heterogeneity along the hourly wage (the usual proxy for productivity) distribution.

Let us denote the logarithm of labor earnings for individual i in year $t = 1, \dots, T$ by $\tilde{e}_{it}$. We consider the following accounting decomposition:

$$\tilde{e}_{it} = \tilde{w}_{it} + \tilde{d}_{it} + \tilde{h}_{it}, \quad (1)$$

where $\tilde{w}_{it}$ is the logarithm of hourly wages, $\tilde{d}_{it}$ accounts for the logarithm of the total duration of employment spells (ranging between 1 and 360) and $\tilde{h}_{it}$ is the logarithm of hours worked per day. Hence, $\tilde{d}_{it}$ represents the extensive margin of employment,[12] whereas $\tilde{h}_{it}$ is related to the intensive margin of employment (how many hours individuals work provided that we observe them during an employment spell).

Our aim is to measure changes at the individual level and over a 5-year horizon, which Guvenen et al. (2016) call "permanent changes". We consider a normalized version of log earnings (resp. hourly wages, within-year employment or hours per day), net of age effects. Let $\tilde{y}_{it}$ generically denote a labor outcome, either earnings or any of its three components. We begin by regressing $\tilde{y}_{it}$ on a set of age, period and cohort dummies and by considering the residuals:[13]

$$\tilde{y}_{it} = y_0 + \sum_c \alpha_c \mathbb{1}_{cohort_i = c} + \sum_a \beta_a \mathbb{1}_{age_{it} = a} + \sum_j \gamma_j \mathbb{1}_{t=j} + \epsilon_{it}. \quad (2)$$

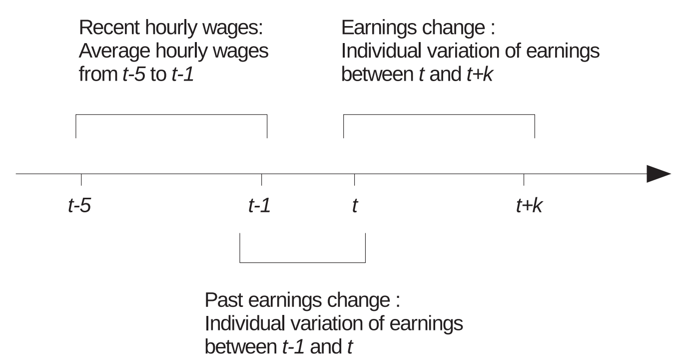

Fig. 1. Labor earnings changes

The inclusion of year dummies is another slight difference with Guvenen et al. (2016). Sampling issues lead us to introduce them: (i) we want to control for any disruption caused by minor, methodological changes in the production of the DADS panel that occurred in 2002, 2009 and 2013, and (ii) our sample includes individuals born in even years only: even (odd) ages are thus observed in even (odd) years. Including these year dummies does not influence our results on labor earnings growth and dynamics.

We estimate these four models (one for labor earnings and one for each component) independently. Accounting decomposition (1) ensures that $\alpha^e = \alpha^w + \alpha^d + \alpha^h$; similar equalities hold for β and γ.

As far as annual earnings are concerned, our variable of interest is $e_{it} = \tilde{e}_{it} - \widehat{\alpha}_{cohort_i} - \widehat{\beta}_{age_{it}} - \widehat{\gamma}_t$, which can be interpreted as residual log-labor earnings (net of age, period and cohort effects). We do the same for each component of labor earnings: Equation (1) guarantees that $e_{it} = w_{it} + d_{it} + h_{it}$. The 5-year change in normalized log-earnings $\delta^5 e_{it} = e_{i,t+5} - e_{it}$ accounts for the relative change in individual i's earnings between t and $t+5$ with respect to his or her counterparts in the same age and cohort; the overall value is again decomposed into hourly wages and working time at both the intensive and extensive margins of employment.

Fig. 1 provides a synthetic view of the current approach. We use hourly wages between $t-5$ and $t-1$ to depict heterogeneity along the hourly wage distribution, while focusing specifically on the distribution

[12] e.g., individuals leaving and returning to salaried employment with at least one hour of work in the year. This definition also includes the following: the choice not to be in the labor force for at most 360 days, maternity/sick leaves, sabbaticals, long-term unemployment spells, switching to self-employment, working in a foreign country and retiring.

[13] The identification of age-period-cohort (APC) models can be achieved at the cost of some normalization. We refer to Online Appendix A for further details on the topic.

of changes between t and $t+5$ and its relationship to past changes, i.e., changes between $t-1$ and t.

In the rest of the paper, we distinguish labor earnings *growth*, which corresponds to individual earnings changes, from earnings *dynamics*, which refers to the more general relationship between past and future earnings changes. These two definitions are conditional on recent hourly wages. Measures of serial dependence turn out to be an useful tool to describe the latter.

4.2. Distribution of labor earnings growth

Our aim is to compare workers with similar histories in terms of hourly wages. We therefore introduce a measure of recent hourly wages $W_{i,t-1}$ similar to that used by Guvenen et al. (2016) with respect to recent earnings. This measure of recent hourly wages approximates average hourly wages between $t-5$ and $t-1$, net of age, period and cohort effects:

$$W_{i,t-1} = \frac{\sum_{\tau=t-5}^{t-1} \exp(\tilde{w}_{i\tau})}{\sum_{\tau=t-5}^{t-1} \exp(\hat{\alpha}^{w}_{cohort_i} + \hat{\beta}^{w}_{age_{i\tau}} + \hat{\gamma}^{w}_{\tau})} \tag{3}$$

We divide workers into 8 age groups: 23-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54 and 55-59. For each year t and each age group, we rank workers according to their recent hourly wages $W_{i,t-1}$ and consider 100 percentile groups.

We resort to local statistical indicators to describe the heterogeneity of annual individual changes in normalized labor earnings and in any of its three components.

The variance, i.e., the second moment of the standardized variable, describes the dispersion of 5-year changes.[14] An alternative, quantile-based measure of dispersion is the difference between the 90th and 10th percentiles ($P90$ and $P10$) of 5-year changes.

The skewness, i.e., the third moment of the standardized variable, accounts for the degree of asymmetry. A related, quantile-based measure is Kelley's measure of skewness (Kelley, 1947), defined as the relative share of P90-P10 that can be explained by P90-P50 and P50-P10:

$$\text{Kelley's Skewness} = \frac{(P90 - P50) - (P50 - P10)}{P90 - P10} \tag{4}$$

It is constant and equal to 0 for Gaussian distributions.

The kurtosis, i.e., the fourth moment of the standardized variable, measures the peakedness of the tails of the distribution of those changes. We consider the normalized kurtosis, which is constant and equal to 0 for Gaussian distributions. A quantile-based measure of the heaviness of tails is Crow-Siddiqui's measure of kurtosis (Crow and Siddiqui, 1967). It is defined as:

$$\text{Crow-Siddiqui's kurtosis} = \frac{P97.5 - P2.5}{P75 - P25} \tag{5}$$

It is constant and equal to roughly 2.91 for Gaussian distributions.

The methodological choice between moment-based and quantile-based measures of dispersion, asymmetry and heaviness of tails will be discussed in Section 6.3. For now, we prefer the latter because they are more robust to the presence of outliers. Such measures are also used by Arellano (2014), who refers to Kim and White (2004).

4.3. Measures of serial dependence

Dynamics is described here thanks to measures of serial dependence that relate future to past changes. From this point of view, labor earnings, hourly wages or working time dynamics can again be described in a similar fashion.

We measure serial dependence non-parametrically to allow for *nonlinearities* in labor earnings dynamics. To account for further heterogeneity across the wage distribution, we compute separate measures of serial dependence for 21 subgroups (P0-P5, P5-P10, P10-P15,..., P90-P95, P95-P99 and P99-P100) of the distribution of recent wages.[15] We compute labor earnings, hourly wages, and working time changes at both the intensive and extensive margins between $t-1$ and t as $\delta^1 y_{i,t-1} = y_t - y_{t-1}$.

Within each subgroup, we rank workers according to $\delta^1 y_{i,t-1}$ and create 20 past change groups of the same size ($P0^\delta - P5^\delta$, $P5^\delta - P10^\delta$,..., $P90^\delta - P95^\delta$, $P95^\delta - P100^\delta$).[16] This gives us $21 \times 20 = 420$ recent earnings $\times$ past change groups denoted as g_{mn} with $(m,n) \in \{P0 - P5, \dots, P95 - P99, P99 - P100\} \times \{P0^\delta - P5^\delta, \dots, P95^\delta - P100^\delta\}$.

For each of these groups, we estimate the average past change $(\mathbb{E})[\delta^1 y_{i,t-1} \mid g_{mn}]$ and the average future change $(\mathbb{E})[\delta^k y_{i,t} \mid g_{mn}]$, with $k = 1, \dots, 5$. To the extent that within each of these recent earnings $\times$ past change groups, workers have similar recent earnings and experience similar past changes, $(\mathbb{E})[\delta^k y_{i,t} \mid g_{mn}]$ approximates a nonparametric estimation of $(\mathbb{E})[\delta^k y_{it} \mid \delta^1 y_{i,t-1}, Y_{it}]$. Hence, plotting $(\mathbb{E})[\delta^k y_{i,t} \mid g_{mn}]$ against $\mathbb{E}[\delta^1 y_{i,t-1} \mid g_{mn}]$ for various percentile groups corresponds to a serial dependence that may be nonlinear and heterogeneous across the distribution of earnings and that exhibits some asymmetry between positive and negative changes.

5. Results

5.1. Earnings growth dispersion

The dispersion of growth rates is depicted in Fig. 2, which plots the P90-P10 difference of 5-year earnings, wages, hours changes and within-year employment against recent hourly wages. The volatility of future labor earnings is U-shaped along the distribution of recent hourly wages. In addition, individuals with low hourly wages are much more exposed to earnings volatility. However, the main lesson of the decomposition of labor earnings growth into growth in hourly wages and working time is that much of its dispersion stems from the volatility of working time, except perhaps for top earners, who are subject to significant volatility in their hourly wage rate.[17] While the dispersion in hourly wage changes increases along the distribution, especially at the top, the dispersion of working time changes at both margins decreases when moving to better paid workers, with the exception of top earners, for whom the dispersion of changes in hours per day increases once again.

5.2. Asymmetry of changes

Fig. 3 displays Kelley's measure of skewness of 5-year earnings, wages, within-year employment and hours changes along the distribution of recent hourly wages. The Kelley skewness of earnings measure varies between -.20 and -.05: earnings changes are negatively skewed, which means that large downward changes are more frequent than large upward changes. As a result, the log-normality assumption is not likely to hold since a skewness of zero would be expected in that case: in this respect, this result is rather consistent with previous findings by Guvenen et al. (2016) for the US.

For the sake of the comparison with other national settings, for the US, Guvenen et al. (2016) display estimates of Kelley's skewness of 5-

[14] One could also think of *volatility*. By contrast, in standard lifecycle models, *wage risk*, or *wage uncertainty*, refers to the conditional distribution of future wages given the agent's current information set.

[15] This ranking is also conditional on year and age to control for possible life-cycle and business cycle effects.

[16] Within each recent wages subgroup, cells are defined by the rank in the distribution of past change conditional on age group (25-34 and 35-50) and year t.

[17] In Appendix C, we contrast volatility in hours worked within and between jobs. There is much more flexibility at the intensive margin between jobs than within jobs, which may reflect that workers are constrained in their hours worked for several years when they begin a job spell.

Fig. 2. P90-P10 of 5-year earnings, hourly wages and working time changes. Estimates of P90-P10 of 5-year (year t to $t+5$) normalized log-earnings changes and their components against the rank in the recent hourly wage distribution (time $t-5$ to $t-1$).

Note. The sample covers male workers with more that 45 workdays per year, working hours per day over 1/8 of the legal full-time duration of work and hourly wages over 90% of the minimum wage at time $t+5$, t, and $t-1$ and at least twice between $t-5$ and $t-2$.

Source. DADS panel, Insee.

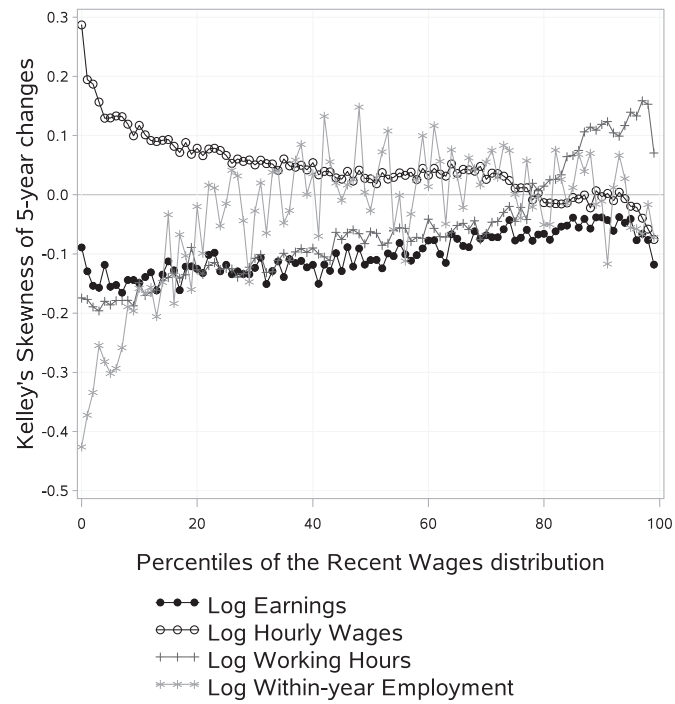

Fig. 3. Kelley's measure of skewness of 5-year earnings, hourly wages and working time changes. Estimates of Kelley's skewness of 5-year (year t to $t+5$) normalized log-earnings changes and their components against the rank in the recent hourly wage distribution (time $t-5$ to $t-1$).

Note. The sample covers male workers with more than 45 workdays per year, working hours per day over 1/8 of the legal full-time duration of work and hourly wages over 90% of the minimum wage at time $t+5$, t, and $t-1$ and at least twice between $t-5$ and $t-2$.

Source. DADS panel, Insee.

year earnings changes that range from -.45 to .05. In Italy, the estimates of Hoffmann and Malacrino (2019) imply a Kelley's skewness of yearly earnings growth of -.09, which seems close to our own findings. The French and Italian labor markets therefore appear quite comparable in this respect, whereas the downward asymmetry of labor earnings changes is stronger in the US.

Importantly, most of the asymmetry stems from working time at both the intensive and the extensive margins. First, with the exception of the highest quintile of recent hourly wages, changes in hours worked display negative asymmetry, which follows quite closely the results for labor earnings changes. Second, in the lowest part of the hourly wage distribution, within-year employment changes appear highly asymmetric, particularly at the bottom of the distribution, where large, negative changes are more frequent, with Kelley's skewness being less than -.1 in the lowest quintile.

Furthermore, hourly wage changes exhibit a positive asymmetry at the bottom of the distribution but almost no asymmetry elsewhere. In the first quintile, wage decreases are constrained by the minimum wage, while wage increases remain unbounded, which helps explain the positive asymmetry there and, more generally, the downward-sloping pattern of wage skewness. An important exception concerns the top 3% of earners, who are the only ones to more frequently experience large negative changes than large positive changes. Mechanically, there is more room to fall at these compensation levels. Moreover, these wages are likely to include both fixed and variable components, with the latter being more dependent on aggregate fluctuations and possibly subject to downward movements. These workers are also more stable: the growth of their annual earnings closely follows the growth of their wages.

In addition, Kelley's skewness is not additive. However, a decomposition based on the third moment is possible and confirms that the asymmetry of labor earnings changes is mainly driven by changes in employment at both margins. This decomposition is available upon request.

Lastly, we compute confidence intervals for our asymmetry measures. Our bootstrap estimates are displayed in Appendix B.

5.3. *Peakedness of the distribution and heaviness of tails*

Fig. 4 displays Crow-Siddiqui's measure of kurtosis of earnings, wages and hours changes. Since Gaussian distributions have a constant Crow-Siddiqui of roughly 2.91 and because we focus on deviations from normal distributions, we plot the normalized Crow-Siddiqui defined as the Crow-Siddiqui minus 2.91. Earnings exhibit a higher peakedness than the Gaussian reference, but this peakedness is rather homogeneous along the recent hourly wage distribution. Moreover, hourly wages have a normalized Crow-Siddiqui of slightly less than 2 and are completely homogeneous along the hourly wage distribution, which makes them even closer to a normal distribution. On the whole, fat tails arise in earnings growth because of working time changes.

Working time changes at the intensive margin display substantial peakedness. This may particularly be the case if workers are restricted in their choice set with respect to hours.[18] In that case, many workers work the exact same number of hours several years in a row, instead of slightly changing their hours depending on the shocks they experience. This might be especially true for contracted hours upon which we rely because actual hours might be more flexible, and thus, the distribution might be less peaked.

[18] In Appendix C, we further investigate this question by contrasting working hours changes within and between jobs.

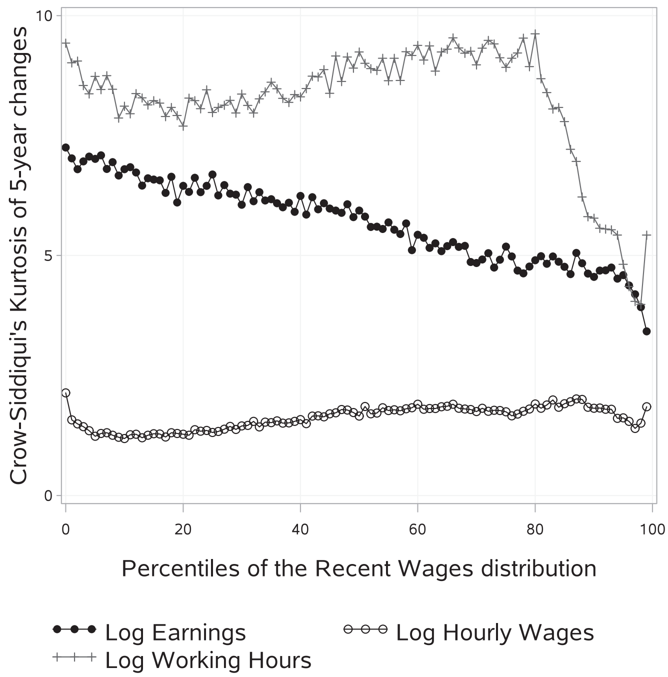

Fig. 4. Crow-Siddiqui's measure of kurtosis of 5-year earnings, hourly wages and working time changes. Estimates of Crow-Siddiqui's kurtosis of 5-year (year t to $t+5$) normalized log-earnings changes and their components against the rank in the recent hourly wage distribution (time $t-5$ to $t-1$).
Note. The sample covers male workers with more that 45 workdays per year, working hours per day over 1/8 of the legal full-time duration of work and hourly wages over 90% of the minimum wage at time $t+5$, t, and $t-1$ and at least twice between $t-5$ and $t-2$.
Source. DADS panel, Insee.

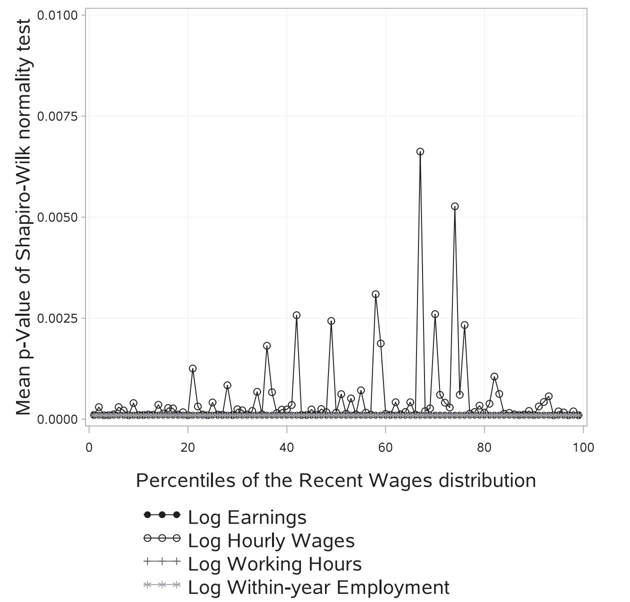

Fig. 5. Shapiro-Wilk test of Gaussianity (distribution of 5-year changes in labor earnings and their components). Estimates of p-values of Shapiro-Wilk test of normality for 5-year (year t to $t+5$) normalized log-earnings changes and their components against the rank in the recent hourly wage distribution (time $t-5$ to $t-1$).
Note. The sample covers male workers with more than 45 workdays per year, working hours per day over 1/8 of the legal full-time duration of work and hourly wages over 90% of the minimum wage at time $t+5$, t, and $t-1$ and at least twice between $t-5$ and $t-2$.
Source. DADS panel, Insee.

Crow-Siddiqui's kurtosis of within-year employment is not displayed in Fig. 4 because its values are mechanically far higher than those related to the other labor outcomes: most workers' within-year employment remains stable at 360 days; hence, the denominator of (5) can be very low.

We now provide with more formal tests of the Gaussianity assumption for labor earnings and for their components. Namely, we rely on two usual normality tests: the Shapiro-Wilk test (Shapiro and Wilk, 1965), which relies on a rank statistic, and the Jarque-Bera test (Jarque and Bera, 1987), which is precisely based on both skewness and kurtosis.[19] For each component of labor earnings, we perform these tests within each recent wage × year × age cell and recover the corresponding p-value. To ensure readability, we report the average p-value over all year × age groups for each rank in the distribution of recent wages (see Figs. 5 and 6).

Both tests clearly reject the null hypothesis that the distributions of 5-year changes in labor earnings are Gaussian. This empirical result also holds for 5-year changes in labor supply, at both the extensive and intensive margins. Although the Gaussianity of the distribution of hourly wage changes is rejected based on the data at usual levels of significance, these results are less clear-cut than they are for the other components.

The main results presented in the previous subsections are robust to several alternative methodological approaches. First, we rely on moments of the distribution of changes in labor outcomes (standard deviation, skewness and kurtosis) instead of quantile-based indicators. Although this methodological choice has a certain quantitative impact (see Section 6.3), it does not affect our findings from a qualitative point of

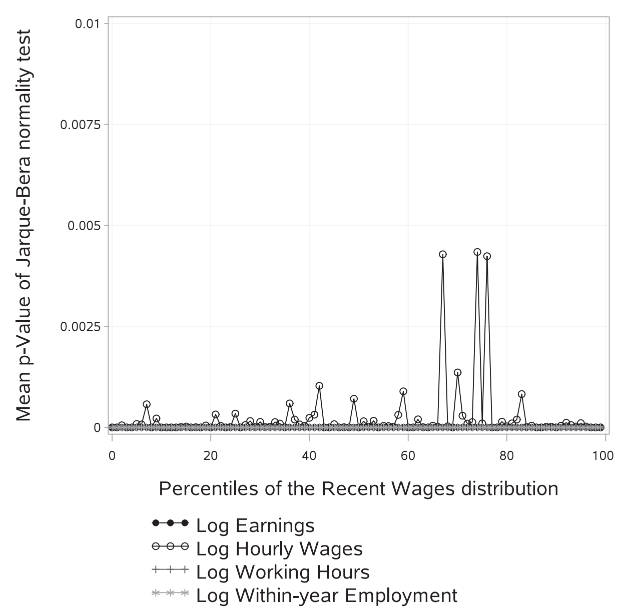

Fig. 6. Robust Jarque-Bera test of Gaussianity (distribution of 5-year changes in labor earnings and their components). Estimates of p-values of the outlier-robust version (Gel and Gastwirth, 2008) of Jarque-Bera's test of normality for 5-year (year t to $t+5$) normalized log-earnings changes and their components against the rank in the recent hourly wage distribution (time $t-5$ to $t-1$).
Note. The sample covers male workers with more than 45 workdays per year, working hours per day over 1/8 of the legal full-time duration of work and hourly wages over 90% of the minimum wage at time $t+5$, t, and $t-1$ and at least twice between $t-5$ and $t-2$.
Source. DADS panel, Insee.

[19] Specifically, we resort to the modification proposed by Gel and Gastwirth (2008), which is more robust to outliers than the canonical Jarque-Bera test.

view (see Online Appendix C.1). Second, we perform the entire analysis conditional on the ranking in the distribution of annual earnings, rather than the distribution of hourly wages. The main advantage of the former relies on a better approximation of productivity, but it is perhaps more dependent on the quality of the "hours worked" variable. Once again, qualitatively speaking, our results are robust to this change (see Online Appendix C.2). Third, from an econometric perspective, we remove period effects from Eq. (2). Although this yields different lifecycle profiles, with regard to earnings changes, our results hardly vary from a qualitative perspective (see Online Appendix C.3). Fourth, we decompose our analysis by age groups as Guvenen et al. (2016) do. Most stylized facts documented in the US are also observed in France. However, for the sake of clarity, since our goal here is to carefully disentangle hourly wages from working time effects, we present results obtained by pooling over these age groups (see Online Appendix C.4).

5.4. Nonlinearity of labor earnings dynamics

We now report our measure of serial dependence. Fig. 7 displays the growth of earnings, wages, hours worked and within-year employment for various time horizons $\delta^k y_{it} = y_{i,t+k} - y_{it},\ k = 1, \dots, 5$ and for various values of corresponding past changes $y_{it} - y_{i,t-1}$. Hence, this figure is not conditional on recent hourly wages.

First, labor earnings changes display some mean reversion: the higher the past, the lower the future change. Downward past changes tend to be accompanied by positive future changes, while upward past changes are associated with negative future changes. Furthermore, the higher the magnitude of past changes is, the higher the magnitude of future changes: workers who experience large changes between $t-1$ and t tend to experience larger changes between t and $t+k$ than those who were subject to smaller changes.

Second, serial dependence tells us about the persistence of changes: past changes are all the more transitory when $\delta^k y_{it} \approx -(y_{it} - y_{i,t-1})$, i.e., when their effect has vanished after k years. Conversely, when $\delta^k y_{it} = 0$, past changes are more persistent. As far as annual earnings are concerned, large, negative past changes tend to be transitory, while large, positive ones are more persistent. For instance, individuals who experienced a 60 log-points loss between $t-1$ and t with respect to the age trend recover more than half of this loss within 5 years.

Third, the serial dependence related to within-year employment unambiguously shows that negative shocks are transitory, while positive shocks are strikingly permanent, which is empirical evidence in favor of nonlinear dynamics. In contrast, hourly wages' serial dependence is almost linear with a negative slope, which is consistent with some mean reversion (up to some pass-through). The same holds, more or less, for working hours. Finally, annual earnings' serial dependence resembles a combination of these three functions, but its shape is qualitatively similar to that of within-year employment. This empirical finding again emphasizes the role played by labor supply at the extensive margin: much of the nonlinearity in annual earnings seems to be driven by that of within-year employment.

Fig. 8 plots the 5-year growth of earnings, wages, hours and within-year employment against past changes in earnings, wages, hours and within-year employment for various locations in the distribution of recent hourly wages. As in Guvenen et al. (2016), labor earnings changes exhibit a "butterfly" pattern: highly negative (positive) changes are more transitory (persistent) for individuals who earned low hourly wages but less so for their better paid counterparts. The "butterfly" pattern for earnings contrasts with the patterns corresponding to each of the three earnings components, for which heterogeneity in the dynamics is much more limited. This latter finding suggests that heterogeneity in labor earnings dynamics is not driven by any of its components displaying substantial heterogeneity in its dynamics along the wage distribution, but rather from each component explaining a different share of labor earnings changes along the wage distribution.

5.4.1. Decomposition of labor earnings changes

We decompose labor earnings changes into their simultaneous wage, working hours and within-year employment components:

$$\begin{aligned} e_{i,t} - e_{i,t-1} =& (\mathbb{E})[w_{i,t} - w_{i,t-1} \mid e_{i,t} - e_{i,t-1}] \\ &+ (\mathbb{E})[h_{i,t} - h_{i,t-1} \mid e_{i,t} - e_{i,t-1}] \\ &+ (\mathbb{E})[d_{i,t} - d_{i,t-1} \mid e_{i,t} - e_{i,t-1}] \end{aligned} \tag{6}$$

The non-parametric estimations of the conditional expectations of each component $(\mathbb{E})[w_{i,t} - w_{i,t-1} \mid e_{i,t} - e_{i,t-1}] = e_w(e_{i,t} - e_{i,t-1})$, $(\mathbb{E})[h_{i,t} - h_{i,t-1} \mid e_{i,t} - e_{i,t-1}] = e_h(e_{i,t} - e_{i,t-1})$ and $(\mathbb{E})[d_{i,t} - d_{i,t-1} \mid e_{i,t} - e_{i,t-1}] = e_d(e_{i,t} - e_{i,t-1})$ as a function of earnings differences yield an exact decomposition of labor earnings changes. Fig. 9 plots our estimates for various positions in the distribution of recent hourly wages. The figures display the estimated functions $\hat{e}_w$, $\hat{e}_h$ and $\hat{e}_d$ given that $e_w(x) + e_h(x) + e_d(x) = x$ against labor earnings changes. By construction, due to accounting decomposition (6), the patterns are upward-sloping, either S-curved or horizontal; what is interesting here is the contrast between different components and heterogeneity across wage groups.

Earnings, wages, working hours and within-year employment are net of the systematic age component, so these changes represent deviations from the average earnings, wages, working hours and within-year employment lifecycle profiles.

At the very bottom of the distribution, labor earnings changes are roughly pure changes in working time: they are hardly related to hourly wage changes. As one moves up in the distribution, the share of labor earnings changes that stems from wage changes increases; the slope of $\hat{e}_w$ is steeper for high earnings. However, even among the highest earnings group (P99-P100), working time changes still explain one half of the 60 log-points in labor earnings changes. Moreover, for these individuals, the slope of $\hat{e}_w$ is steeper for earnings changes smaller than 20 log-points, regardless of their sign: large (small) annual earnings changes correspond to substantial working time changes (wage changes).

These stylized facts are consistent with an increasing share of labor earnings volatility due to wage volatility along the wage distribution. Additionally, we show large labor earnings changes to be primarily driven by working time changes at the extensive margin, rather than by hourly wage changes, even at the top of the wage distribution. As a consequence, wage changes are unlikely to generate non-Gaussian features that relate to large earnings changes (such as downward asymmetry and fatness of the tails), even among top earners.

Finally, all the findings presented in this section are robust to numerous aspects related to sample composition and data issues such as the left-censoring and right-censoring (winsorization) of annual earnings, imputation, definition of working time and hourly wages. Changing the censoring threshold from 45 days per year to 30 days per year, from 1/8 to 1/12 of the annual legal duration of work and from 90% to 60% of the minimum hourly wage does not impact our findings (see Online Appendix C.5), neither does trimming very high annual earnings. Defining working time in full-time units (FTU) instead of hours also has a very minor impact on results.[20]

6. Extensions

6.1. Long-term employment changes

Our focus on the extensive margin of employment has been based thus far only on individuals who have a strong relationship to the labor market, which mechanically excludes decisions that lead to longer periods spent outside the workforce. We compute the probability of being

[20] We also replicated our approach on a sample of women working in the private sector. The main stylized facts documented here still hold. However, labor supply decisions may be more difficult to disentangle from hourly wage growth in that case.

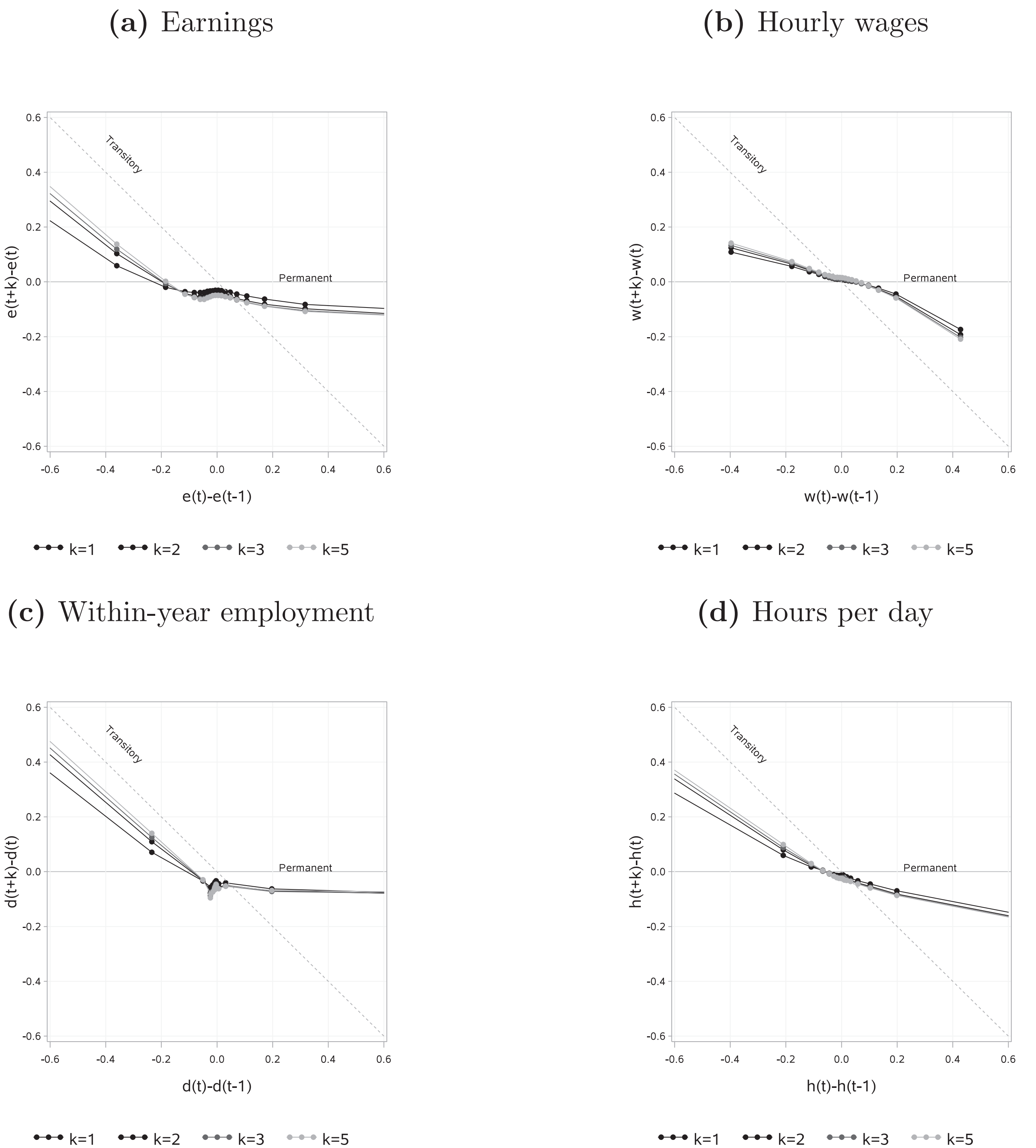

Fig. 7. Serial dependence measures of earnings, hourly wages and working time. Estimates of $\log(y_{i,t+k}) - \log(y_{i,t}) = f(\log(y_{i,t}) - \log(y_{i,t-1}))$ for normalized earnings and its components (d: within-year employment; h: hours per day; w: hourly wages).
Note. The sample covers male workers with more than 45 work days per year, working hours per day over 1/8 of the legal full-time duration of work and hourly wages over 90% of the minimum wage at time $t+k$, t, and $t-1$ and at least twice between $t-5$ and $t-2$.
Source. DADS panel, Insee.

out of employment at time $t+k$ as a function of past within-employment changes $d_{i,t} - d_{i,t-1}$.[21] Fig. 10 displays our estimates. We find that after a

[21] Because we do not observe whether individuals are unemployed (although we know whether they receive some unemployment benefits for a given period), we infer from the data that they are (or not) salaried employees in the private sector for some amount of time. Hence, the probability computed here corresponds simply to the empirical frequency of individuals who are not found in the data in year $t+k$.

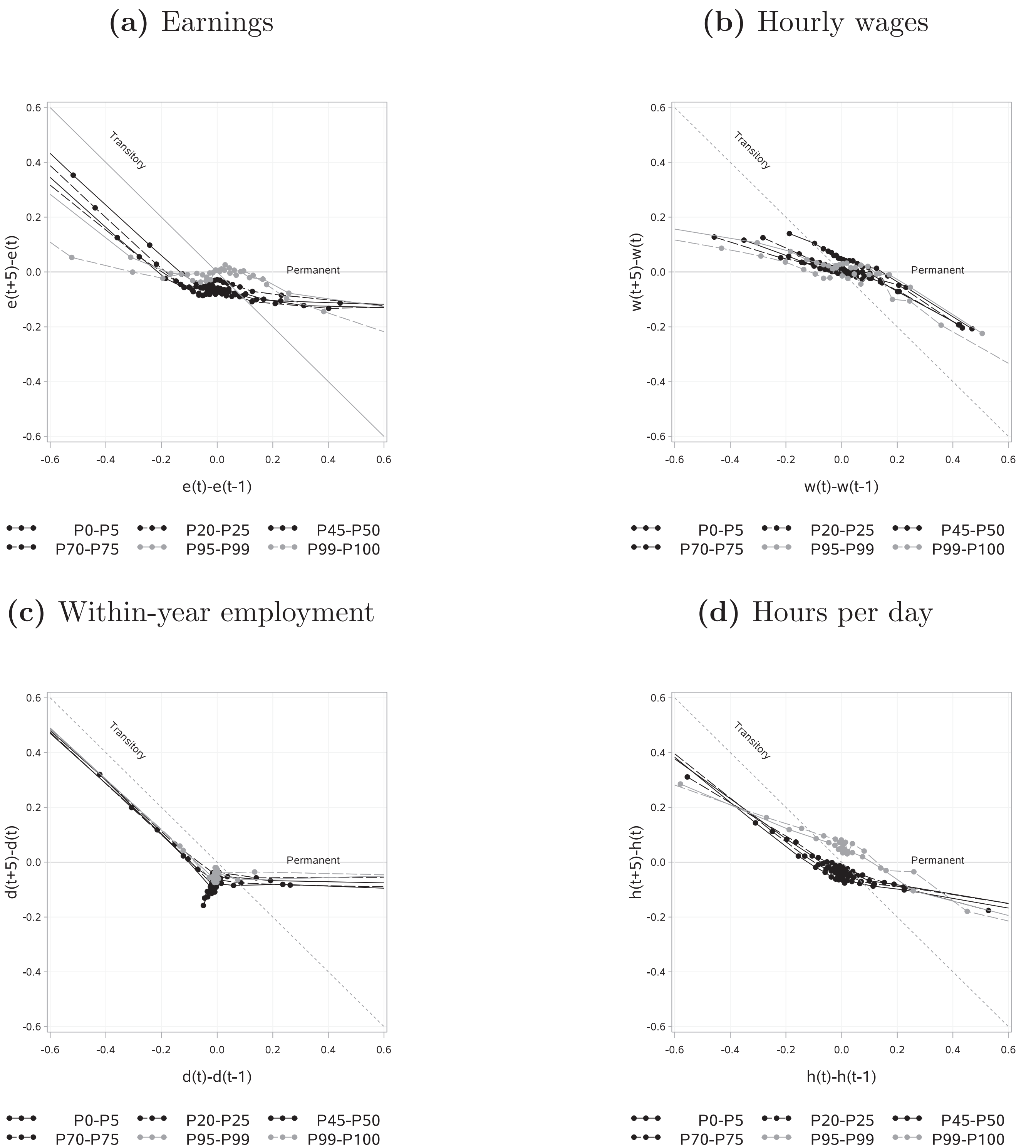

Fig. 8. Serial dependence measures of earnings, hourly wage and working time changes at a 5-year horizon. Estimates of $\log(y_{i,t+5}) - \log(y_{i,t}) = f(\log(y_{i,t}) - \log(y_{i,t-1}))$ for normalized earnings and its components (d: within-year employment; h: hours per day; w: hourly wages) against the rank in the recent hourly wage distribution (time $t-5$ to $t-1$).
Note. The sample covers male workers with more than 45 workdays per year, working hours per day over 1/8 of the legal full-time duration of work and hourly wages over 90% of the minimum wage at time $t+5$, t, and $t-1$ and at least twice between $t-5$ and $t-2$.
Source. DADS panel, Insee.

large, negative working time change at the extensive margin, a substantial share of individuals are no longer private-sector salaried employees. This proportion amounts to more than one-third of individuals over the five following years among those who experienced the largest negative shocks. By contrast, among those whose within-year employment did not vary between $t-1$ and t, the share of individuals without a job in the private sector grew from approximately 5% at time $t+1$ to 15% at time $t+5$.[22]

[22] A comparison may be provided by Nolan and Voitchovsky (2016), who compute the probability that an individual is employed at the end of a 12-month period as a function of the individual's wages at the beginning of the period. They

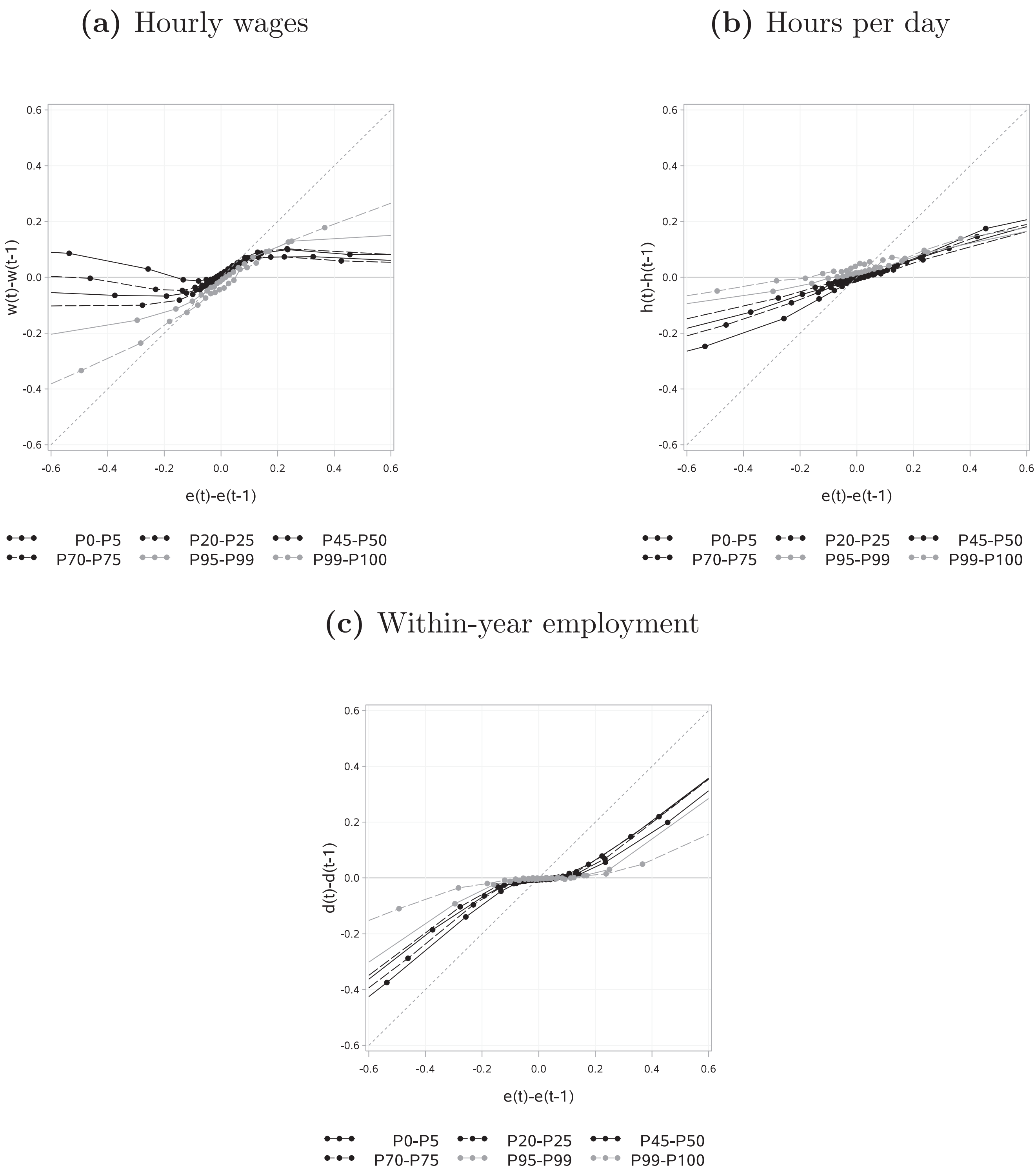

Fig. 9. Earnings change decomposition. Estimates of the accounting decomposition of 1-year normalized log-earnings changes (year $t-1$ to t) along the recent hourly wage distribution (time $t-5$ to $t-1$).
Note. The sample covers male workers with more than 45 workdays per year, working hours per day over 1/8 of the legal full-time duration of work and hourly wages over 90% of the minimum wage at time t and $t-1$ and at least twice between $t-5$ and $t-2$.
Source. DADS panel, Insee.

These results suggest that a substantial amount of negative changes at the extensive margin correspond to transitions toward long periods spent outside employment in the private sector. As a result, assessing the dynamics of labor earnings while relying only on individuals with uninterrupted labor market histories understates the persistence of large,

find that this probability varies between 83 and 97% before the Great Recession and 78 and 95% during the Great Recession. This kind of value is not inconsistent with our estimates, which suggest that the nonemployment probability in $t+1$ is approximately 5 to 10%.

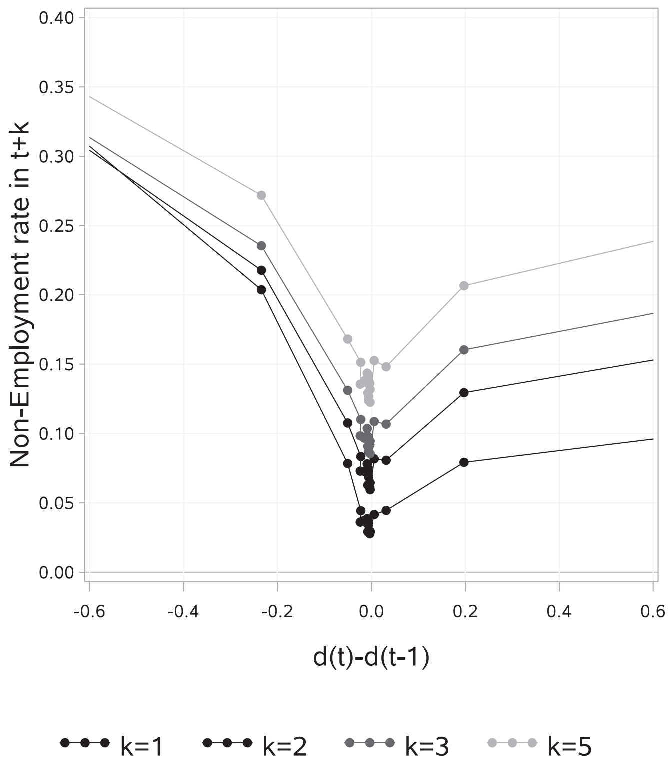

Fig. 10. Probability of spending a full year outside employment after a within-year employment change. Estimates of the probability of being jobless during year $t+k$ against 1-year normalized log-within year employment changes (year $t-1$ to t).
Note. The sample covers male workers with more than 45 workdays per year, working hours per day over 1/8 of the legal full-time duration of work and hourly wages over 90% of the minimum wage at time t and $t-1$ and at least twice between $t-5$ and $t-2$.
Source. DADS panel, Insee.

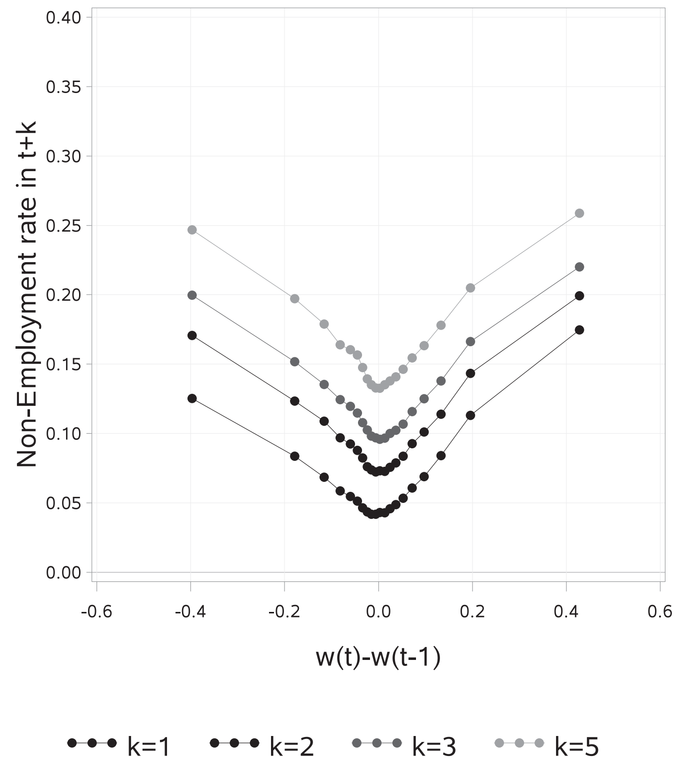

Fig. 11. Non-employment response to hourly wage changes. Estimates of the probability to be jobless during year $t+k$ against 1-year normalized log-hourly wage changes (year $t-1$ to t).
Note. The sample covers male workers with more than 45 workdays, working hours per day over 1/8 of the legal full-time duration of work and hourly wages over 90% of the minimum wage at time t and $t-1$ and at least twice between $t-5$ and $t-2$.
Source. DADS panel, Insee.

negative labor earnings changes, which we showed to be driven by working time changes at the extensive margin. Hence, the welfare consequences of labor earnings fluctuations cannot be evaluated without (i) appropriate modeling of long-term unemployment, and (ii) carefully accounting for unemployment insurance and welfare benefits.

Our results also suggest that after a large, positive change in within-year employment, the unemployment probability increases. This pattern could depend on occupation (e.g. managers, craftsmen, operatives, etc): some of these jobs may be performed under flexible contracts, which may enable workers to adjust their labor supply in anticipation of a higher unemployment risk. By contrast, rigid contractual hours might be more common in other jobs, which could lead workers to drop out early when they anticipate a higher unemployment risk.

6.2. *Wage growth and probability of employment*

We relate hourly wage growth to these transitions towards long-term nonemployment. We investigate how past hourly wage changes depend on subsequent labor supply decisions at the extensive margin by estimating the probability of being out of employment at time $t+k$ as a function of past hourly wage changes $w_{i,t} - w_{i,t-1}$ (see Fig. 11).[23]

We find that the probability of being out of employment at time $t+k$ has a U-shaped relationship to past hourly wage changes: workers who experienced large hourly wage changes between $t-1$ and t, both positive and negative, are less likely to remain in employment in the future. The difference with respect to past wage growth can be quite large: workers who experience 40 log-points (resp. −40 log-points) hourly wage changes between $t-1$ and t are 12 (resp. 8) percentage points more likely to be without employment in $t+1$.

The interpretation of this pattern is difficult because causality flows both ways. Namely, changes in the wage rate are likely to trigger working time responses on both demand and supply sides. Conversely, changes in the wage rate may depend on future employment through the institutional setting, in particular because our measure of earnings incorporates part of severance payments.[24] Disentangling these channels is a challenging task that is beyond the scope of this paper. However, that workers are more likely to leave employment after they experience massive, positive hourly wage growth is puzzling and suggests severance payments to be at play here. As a consequence, non-Gaussian features that are related to the tails of the hourly wage growth distribution are likely due to employment decisions at the extensive margin.

6.3. *Cyclicality*

We document here how the distribution of earnings changes depends on the business cycle. This issue echoes numerous concerns in the design of social insurance schemes and, more generally, of government tax and transfer programs. Do they succeed in insuring individuals against idiosyncratic earnings shocks? In a recent work, Guvenen et al. (2014) show that the variance of income changes is acycli-

[23] We also investigate how current changes in labor supply correlate with future hourly wage growth (see Online Appendix B.1).

[24] Changes in the wage rate may also reflect anticipations of future employment, in the case where agents are forward-looking.

Table 2
Replication of Busch et al. (2018a)

	Quantile-based skewness	Moment-based skewness
Earnings	3.46***	17.1***
	(0.472)	(3.01)
Wages	0.920***	6.87**
	(0.262)	(2.81)
Employment	0.266	23.1***
	(1.73)	(4.22)
Hours	1.57***	3.39**
	(0.492)	(1.47)

Dependent variable. Annual asymmetry measure of the distribution of changes in each component of labor earnings. *Note.* Reported figures correspond to log GDP growth coefficients in a regression that further includes an intercept and a linear time trend. Standard errors are computed using Newey-West estimator with two lags.

cal, while the skewness is procyclical. In such a context, government-provided insurance should reduce the cyclicality of such fluctuations. When decomposing labor earnings growth into one component related to hours and another related to wages, it is therefore natural to address the respective roles of unemployment insurance and wage insurance policies.

To address this question, we tackle a methodological issue, the choice between moment-based and quantile-based measures of asymmetry.[25] Both Busch et al. (2018a) and Hoffmann and Malacrino (2019) rely on German and Italian data that also allow them to disentangle the contribution of both working time and the wage rate to the cyclicality of that asymmetry. While the former find a strong cyclical component in the asymmetry of full-time wage changes, Hoffmann and Malacrino (2019) provide evidence that this pattern is driven by working time (more precisely by changes in the number of weeks an individual works during a year). In addition to institutional differences between Germany and Italy, the two approaches differ in methodological choices. Busch et al. (2018a) rely on quantile-based measures of the asymmetry, i.e., on Kelley's skewness.[26] By contrast, Hoffmann and Malacrino (2019) rely on a moment-based measure of asymmetry, the 3rd moment, i.e., skewness, multiplied by standard deviation to the power of three.[27]

To neutralize institution-specific factors and hence identify the impact of methodological choices, we replicate both approaches using French data. Table 2 reports our findings when using the method used by Busch et al. (2018a). Both quantile-based and moment-based measures display substantial cyclicality: they yield estimated coefficients of log GDP growth that are positive and significantly different from zero. However, which component of earnings is the main driver of this cyclicality remains unclear. On the one hand, resorting to the quantile-based measure, i.e., Kelley's skewness, suggests significant cyclicality in the asymmetry of hourly wage changes,[28] whereas other components would not display any cyclical asymmetry. On the other hand, using a moment-based measure suggests that this cyclical asymmetry is driven by within-year employment changes rather than by hourly wages.

[25] The extension to measures of dispersion and to heaviness of the tails is straightforward and available upon request.

[26] They regress annual Kelley's measures of skewness on log GDP growth, a constant and a linear time trend; the coefficient related to log GDP growth captures the cyclicality of each component.

[27] They regress a detrended, normalized version of the 3rd moment of annual earnings growth on detrended, normalized log GPD growth; adding up the detrended, normalized 3rd moment of working time changes as an explanatory variable does capture the cyclicality of the asymmetry of earnings changes.

[28] This is the case both for the full sample and when restricting the analysis to individuals who do not change employers. The latter estimates are available upon request.

Table 3
Replication of Hoffmann and Malacrino (2019)

	(1)	(2)	(3)	(4)
Quantile-based skewness				
log GDP growth	1.52***	1.51***	1.26***	0.841*
	(0.198)	(0.235)	(0.270)	(0.468)
Employment		0.122***	0.157*	0.160**
		(0.030)	(0.086)	(0.64)
Wages			0.406**	0.755**
			(0.144)	(0.305)
Hours				0.311
				(0.228)
R^2	0.474	0.512	0.580	0.626
Third moment				
log GDP growth	0.744***	0.118***	0.107**	0.029
	(0.116)	(0.042)	(0.036)	(0.035)
Employment		1.08***	1.07***	0.998***
		(0.068)	(0.077)	(0.053)
Wages			0.127	0.471***
			(0.128)	(0.111)
Hours				0.458***
				(0.092)
R^2	0.572	0.966	0.968	0.986

Dependent variable. Measure of asymmetry (top panel: quantile-based, bottom panel: moment-based) of annual labor earnings changes. *Explanatory variables.* log-GDP growth and the measure of asymmetry of the components of labor earnings. All time-series are detrended and standardized. Standard errors are computed using Newey-West estimator with two lags.

Table 3 replicates the approach used by Hoffmann and Malacrino (2019) and matches their results very closely (bottom panel). The asymmetry of the distribution of annual earnings changes is very cyclical. Within-employment changes are sufficient to account for this cyclicality; by contrast, the contribution of the asymmetry of hourly wage changes is negligible. However, when moving to a quantile-based measure (top panel), this result vanishes. While the quantile-based Kelley's skewness of the distribution of earnings changes is also cyclical, the contribution of the within-year employment margin is non-significant after all other margins are taken into account, which contrasts with the contribution of hourly wages. Note that, even so, we fail to capture the largest part of the cyclicality.

In summary, this replication exercise applied to the same French data suggests that the divergence between the results obtained by these two papers is very related to the chosen measure of asymmetry, either quantile-based or moment-based.[29]

6.4. Contribution of unemployment insurance

The previous results suggest that unemployment benefits could be instrumental in providing insurance against earnings shocks. We assess the plausibility of this hypothesis by contrasting the asymmetry of the annual earnings change distribution without accounting for these benefits and when taking them into account. Fig. 12 displays our estimates.

It turns out that for workers who belong to the lower part of the wage distribution, the distribution of earnings changes is substantially less asymmetric when unemployment benefits are taken into account. The Kelley's skewness of 1-year earnings changes remains negative but is substantially higher when unemployment insurance is taken into ac-

[29] By contrast, either regressing each measure on the business cycle as in Table 2 or regressing earnings change asymmetry on the business cycle while controlling for the different margins as in Table 3 yields qualitatively the same results.

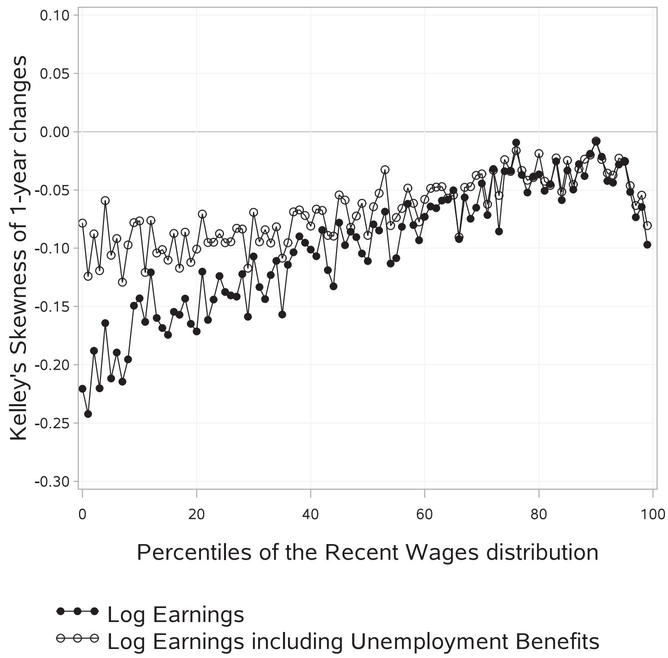

Fig. 12. Kelley's measure of skewness of 1-year earnings changes: with and without accounting for unemployment benefits. Estimates of Kelley's skewness of 1-year (year t to $t+1$) normalized log-earnings changes with and without taking into account unemployment benefits against the rank in the recent hourly wage distribution (time $t-5$ to $t-1$).
Note. The sample covers male workers with more than 45 workdays per year, working hours per day over 1/8 of the legal full-time duration of work and hourly wages over 90% of the minimum wage at time $t+1$, t, and $t-1$ and at least twice between $t-5$ and $t-2$. Time period t covers 2008-2014.
Source. DADS panel, Insee.

count (approximately -0.1 at the very bottom against -0.25 when unemployment benefits are not included). In contrast, the progressivity of payroll taxes does not mitigate the asymmetry of labor earnings changes (see Online Appendix B.2).

This empirical result provides additional support for the idea that the negative asymmetry of labor earnings changes is mainly driven by unemployment risk. Accounting for unemployment insurance, either thanks to data on unemployment benefits or to careful modeling, is hence useful to properly assess the welfare consequences of deviations from Gaussianity.

7. Conclusion

This investigation of labor earnings dynamics builds on a non-parametric estimation of individual earnings, wages and working time changes. We find the same striking results as in the US: labor earnings also exhibit several non-Gaussian features in France, including negative skewness and high kurtosis. More interesting, the availability of working hours and days worked in our dataset enables us to disentangle growth in hourly wages from growth in working time at both extensive and intensive margins.

Major deviations from normality stem rather from working time at both the extensive margin, i.e., within-year employment, and the intensive margin, i.e., hours worked per day. Importantly, taking unemployment benefits into account reduces the asymmetry, especially at the bottom of the wage distribution, which highlights the role played by unemployment insurance in smoothing earnings fluctuations. In addition, nonlinear dynamics in the labor earnings process arise essentially due to the extensive margin of working time. In summary, transitions to and from employment are key drivers of non-Gaussian, nonlinear labor earnings dynamics. The last methodological contribution of the paper is to shed light on the role played by the measure of higher-order moments of the distribution of changes in labor outcomes.

This descriptive framework has focused on cross-sectional distributions of labor earnings, hourly wages and working time changes, on the one hand, and on the correlation between two subsequent changes, on the other hand. However, from a truly dynamic perspective at the individual level, current changes are likely to be a response to previous changes: a more complete, possibly structural model of both hourly wages and working time is needed to better capture this phenomenon.

Given that individual earnings fluctuations are largely driven by working time changes at both margins, further exploring the question would likely require additional data. Indeed, resorting only to information on labor outcomes, conditional on positive employment, turns out to be insufficient, especially when unemployment is involved. To estimate to what extent workers are insured against idiosyncratic labor income risk, one would definitely need data including not only labor earnings and working time but also unemployment benefits and, more generally, all kinds of welfare benefits.

Finally, a challenging task consists in performing a welfare analysis that would quantify the loss related to earnings fluctuations, especially when they are driven by the extensive margin of employment. On the one hand, it is tempting to alleviate the labor cost by lowering social security contributions, hence increasing the incentives to hire workers. On the other hand, it is also necessary to insure people against the risk of job loss, which requires providing them with unemployment benefits. There is thus a trade-off that stems from the budget constraint of the social insurer; determining the optimal level of unemployment insurance is an empirical question. Recent papers that rely on a sufficient statistics approach, including Chetty (2008) and Landais et al. (2018), have addressed this issue. An overall structural analysis would probably require a model of job creation and destruction based on the labor cost that would be embedded within a matching process between firms and workers, as well as an intertemporal model of workers' consumption that takes the corresponding earnings process, including unemployment insurance, into account.

Appendix A. Additional details on the data

A1. Earnings

Our measure of labor earnings relies on net annual earnings. This measure aggregates all wages paid to an individual, including performance pay and bonuses, paid vacations, in-kind benefits, the share of severance payments that exceeds the legal minimum, sick leave allowances and early retirement benefits (to the extent that these benefits exceed an amount roughly equal to the minimum wage), but it excludes stock options. Social security contributions, public pension schemes, unemployment benefits and other contributions, including two flat taxes on labor income (CSG and CRDS), are subtracted from this amount to compute our measure of net annual earnings. In that sense, we measure earnings before income taxes but after some transfers.

In a restricted subset of industries, paid vacations are not compensated for by the employer itself but rather by distinct entities called "paid leave funds". In that case, Insee aggregates paid leave benefits with labor earnings depending on the industry: total labor earnings of an individual × employer × year observations are then the sum of labor earnings (paid directly by the employer) and paid leave benefits, in the case in which the employer belongs to an industry where paid leave benefits are granted by a paid leave fund.

A2. Hours

In our dataset, working hours refer to hours for which the worker is paid according to the labor contract. The information on hours is reported by employers when they fill in payroll tax forms. Before making the data available, Insee performs three checks:

- the total number of hours for a given individual × employer × year observation should not exceed an industry-specific threshold: 2,500 hours per year in a small subset of industries (mostly manufacturing industries, transportation, hotels and restaurants), and 2,200 hours per year in the rest of the private sector;
- the implied hourly wages should exceed 80% of the minimum wage; and
- the total number of hours should be positive with the exception of a narrow subset of occupations (mostly journalists and salespersons) working on a fixed-price basis.

If one of these conditions does not hold, then Insee ascribes hours to the observation to make the hourly wage consistent within narrow cells defined by 4-digit occupation, full-time or part-time status, age and gender.

Regarding workers whose compensation does not depend on their working time but who do not belong to one of the previously mentioned occupations, i.e., typically managers (”forfait-jour”), employers fill in the number of days only. A number of hours is ascribed to these observations based on the legal duration of work for full-time workers and the number of work days. If anything, this procedure should bias downward (resp. upward) the dispersion of working hours (resp. hourly wage) changes at the top of the distribution: for this group of workers, hours should be more flexible than a measure based on the legal duration of work. However, this issue affects neither the measurement of working days nor the measurement of earnings. As a result, it does not affect results regarding the dispersion or the asymmetry of the distributions of labor supply changes at the extensive margin or earnings growth (although this form of measurement error may affect the relative dispersion and asymmetry of the distributions of hourly wage and working hours growth).

In our dataset, working hours refer to hours for which the worker is paid according to the labor contract. This concept of working hours hence differs from the concept of working hours in terms of the time spent working. This second concept is typically the Labor Force Survey. Since the two concepts differ, the comparison between the DADS and the LFS is not meaningful. However, another survey, the ESS, which is the French version of the Structure of Earnings Survey, provides a comparable measure. In 2014, according to this survey, full-time (resp. part-time) male individuals employed in firms with more than 9 employees worked 160 (resp. 89) hours per month. In our dataset, the corresponding figures are 157 and 91, respectively; part of the difference is attributable to the inclusion of the public sector in the ESS.

Appendix B. Inference for asymmetry of 5-year changes

We compute confidence intervals for our measures of asymmetry and peakedness of tails of the distribution of 5-year earnings (resp. hourly wage and working time) changes. We bootstrap the whole procedure, starting from the estimation of age-period-cohort coefficients and the ranking of individuals along the recent hourly wage distribution.

It is important to account for any correlation between changes observed for the same individual over different years, given that these changes may overlap, for instance, if this individual is observed both at time t and for some time $t + k$ with $k < 5$. To address this issue, we cluster our bootstrap procedure at the individual level, i.e., we resample over individuals rather than over individual-year observations.

Figures B.13 and B.14 display the results for labor earnings changes and for hourly wage changes. They show that (i) the asymmetry of 5-year earnings changes is always significantly negative; (ii) the asymmetry of 5-year hourly wage changes is significantly positive in the lower half of the recent wage distribution.

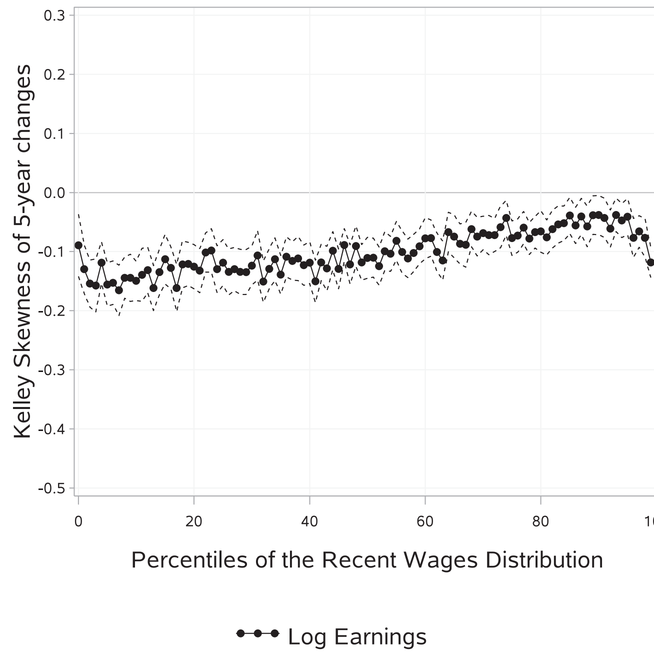

Fig. B.13. Testing the symmetry of annual earnings changes. Estimates of Kelley's skewness of 5-year (year t to $t + 5$) normalized log-earnings changes against the rank in the recent hourly wage distribution (time $t - 5$ to $t - 1$). Dashed lines display confidence intervals at the 95%-level.

Note. The sample covers male workers with more than 45 workdays per year, working hours per day over 1/8 of the legal full-time duration of work and hourly wages over 90% of the minimum wage at time $t + 5$, t, and $t - 1$ and at least twice between $t - 5$ and $t - 2$.

Source. DADS panel, Insee.

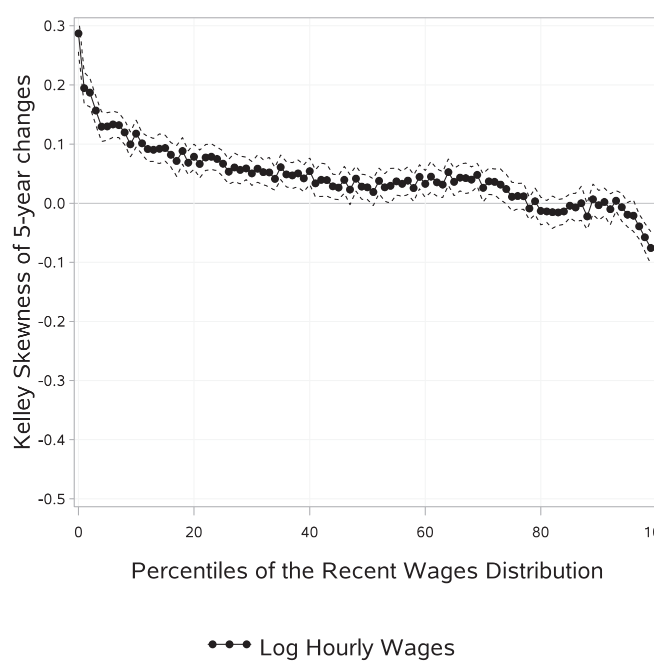

Fig. B.14. Testing the symmetry of hourly wage changes. Estimates of Kelley's skewness of 5-year (year t to $t + 5$) normalized log-hourly wage changes against rank in the recent hourly wage distribution (time $t - 5$ to $t - 1$). Dashed lines display confidence intervals at the 95%-level.

Note. The sample covers male workers with more than 45 days of work per year, working hours per day over 1/8 of the legal full-time duration of work and hourly wages over 90% of the minimum wage at time $t + 5$, t, and $t - 1$ and at least twice between $t - 5$ and $t - 2$.

Source. DADS panel, Insee.

Appendix C. Additional results: flexibility of hours

We delve further into the data to obtain a better sense of how flexible hours worked are. To do so, we compare the dispersion of k-year changes in hours worked for workers who did not change jobs between t and $t+k$ on the one hand and those who did on the other hand. We characterize workers thanks to the linked-employee-employer nature of our data: we define a worker's main employer for a given year as the firm (defined by the Siren, its legal identifier) that paid him the highest labor earnings. We then define job stayers as individuals who did not change their main employer between t and $t+k$ and job movers as those who did. Fig. C.15 displays our estimates.

For all ranks in the distribution of recent wages, the dispersion of working hours changes, as measured by the P90-P10, is 2 to 4 times as large for job movers as it is for job stayers. In other words, hours worked are much more flexible between jobs than they are within jobs. This empirical finding suggests that workers may be restricted in their choice set regarding hours within a firm, which is reminiscent of

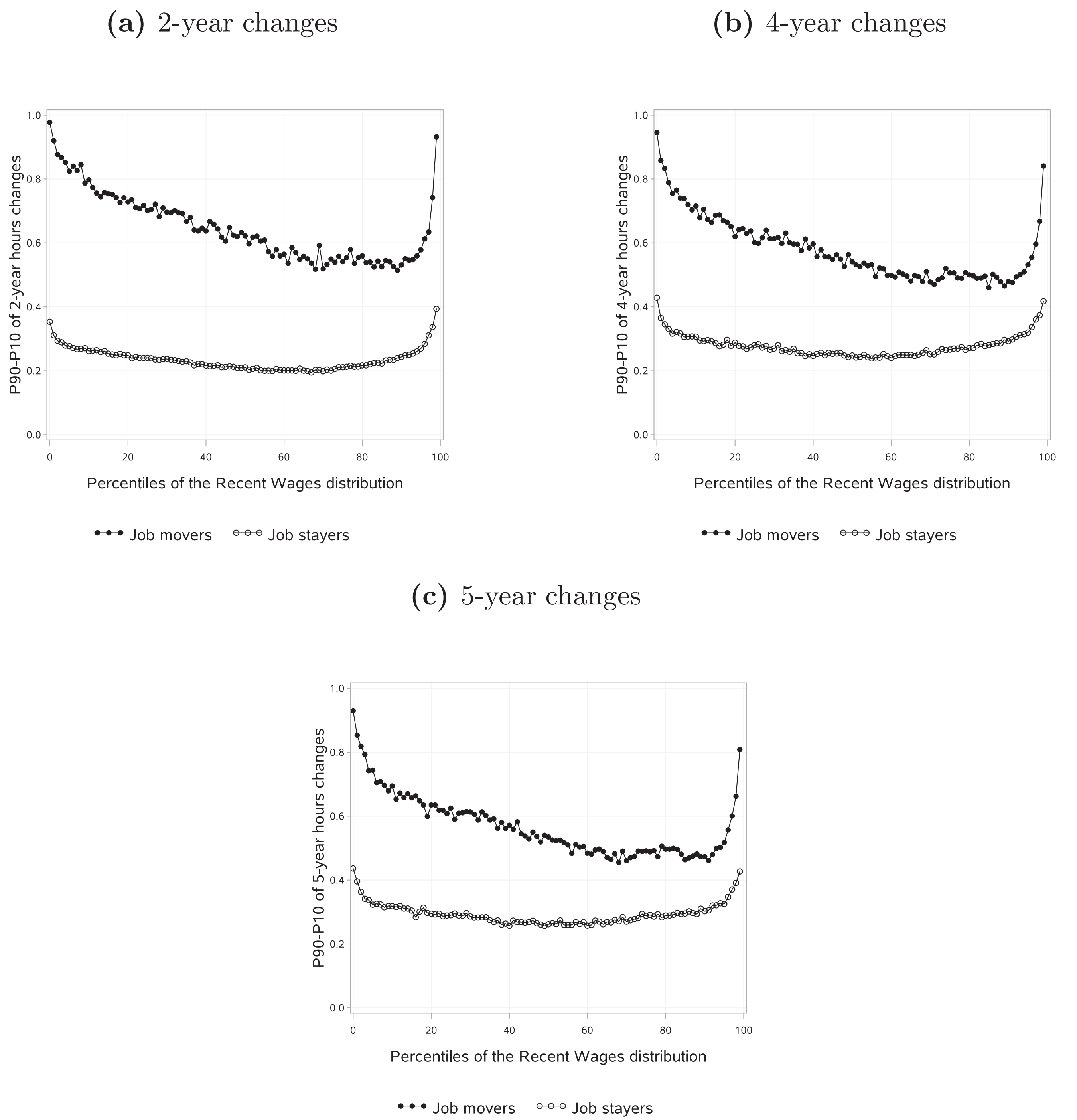

Fig. C.15. P90-P10 of 5-year working hours changes: by job mobility. Estimates of P90-P10 of 5-year (year t to $t+5$) normalized log-working hours changes against rank in the recent hourly wage distribution (time $t-5$ to $t-1$) by job mobility.
Note. The sample covers male workers with more than 45 workdays per year, working hours per day over 1/8 of the legal full-time duration of work and hourly wages over 90% of the minimum wage at time $t+k$, t, and $t-1$ and at least twice between $t-5$ and $t-2$.
Source. DADS panel, Insee.

Altonji and Paxson (1992). As a result, if (some) labor supply decisions at the intensive margin are impossible within firms, when hit by shocks to their preferences, some workers may (i) make labor supply decisions at the extensive margin, which is always possible, and thus leave the labor workforce; (ii) change jobs, which may force them to spend time out of employment, due to frictions in the labor market. As a result, a lack of hours flexibility within jobs is likely to generate changes at the extensive margin and thus additional downward asymmetry in the distribution of labor earnings changes.

When comparing different time horizons, we find that between-jobs dispersion tends to decrease over time, whereas within-jobs dispersion increases very slightly. Nevertheless, there is not much heterogeneity along the wage distribution in this pattern. It thus remains difficult to assess whether workers can adjust their working hours more or less rapidly depending on where they stand in the wage distribution.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.labeco.2020.101807

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