Follow the money ? Workers' mobility, wages and amenities

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L’appât du gain ? Mobilité des salariés, salaires et aménités

Nous utilisons une version chaînée des données d’emploi françaises (BTS-postes) pour analyser la dynamique salariale des personnes qui changent d'employeur au cours de la période 2005-2019. Tout d'abord, nous montrons que près de la moitié des mobilités que nous interprétons comme choisies s'accompagnent d'une baisse du salaire horaire. Pour comprendre pourquoi certains salariés quittent volontairement un emploi pour un autre moins bien rémunéré, nous appliquons la méthode de Sorkin (2018) pour mesurer les aménités non monétaires offertes par les entreprises en utilisant la structure des transitions d'employeur à employeur. Nous constatons que dans le contexte français, les caractéristiques non monétaires des emplois jouent un rôle similaire à celui des États-Unis, expliquant environ 10 % de la variance des (log)-salaires. En comparant les estimations basées sur les salaires annualisés et les salaires horaires, nous constatons que les salariés apprécient davantage les entreprises dans lesquelles ils peuvent travailler plus d’heures.

Mots-clés : Mobilité inter-entreprises, baisse de salaire, aménités non-monétaires

Codes JEL : J31, J63

Follow the money ? Workers’ mobility, wages and amenities

We use a chained version of the French matched employer-employee dataset (BTS-postes) to analyze the wage dynamics of people who change employers during the 2005-2019 period. First, we show that almost half of the moves that we interpret as being chosen are accompanied by a decrease in the hourly wage. To understand why workers might voluntarily quit a job for another one that pays less, we follow Sorkin (2018) to measure non-wage amenities offered by firms using the structure of employer-to-employer transitions. We find that in the French context, non-pay characteristics of jobs play a similar role than in the US, explaining about 10% of the variance of (log)-wages. By comparing estimates based on annualized and hourly wages, we see indications that workers value more firms in which they can work longer hours.

Keywords: Firm-to-firm mobility, wage gap, non-wage amenities

JEL Code : J31, J63

1 Introduction

This paper documents an apparently very surprising fact that has been little studied in the labor economics literature: when workers move from one firm to another, they experience an hourly wage cut in almost half of the cases.[1] This finding is not driven by workers facing involuntary moves (either because of the end of a fixed-term contract or because of a potential lay-off) but is instead very general. The magnitude of such wage cuts is often important, suggesting that this pattern is not due to small variations in the ways different firms report wages. Moreover, we show that experiencing a wage cut is very - though a bit less frequent - common when considering annualized wages instead of hourly wages. This calls for an explanation that could rationalize why workers would accept less-paid jobs while moving.

Economic theory has long considered labor has a source of disutility for workers, and wages as a compensation. If the disutility of labor varies across firms due to different working conditions, the wage that a worker will be willing to accept will also vary across firms. Consistently, recent survey evidence indicates that workers who express a desire to change jobs are equally motivated by the desire to increase their wages and to improve their working conditions (Bour et al., 2024). It can therefore be perfectly rational for a worker to experience a wage cut while moving from one firm to another, if the new firm has better non-wage amenities (e.g. working environment, accessibility, flexibility, ...). In this perspective, getting a higher wage in one firm is interpreted as a way to be compensated for having worst non-wage amenities than in another firm that pays less, so the difference between the two wages is called *compensating differentials* (Rosen, 1986). The objective of this paper is to quantify the importance of such compensating differentials - due to the existence of non-wage amenities - in the variance of wages in France during the last two decades.

To achieve this, we follow Sorkin (2018) and rank firms according to two dimensions: their attractiveness (hereafter called their "global value"), based on the observed mobility of workers across firms; their pay policy (hereafter called their "wage premium"), based on the observed wage that a given employee gets in different firms. Regarding the attractiveness dimension, we use the fact that workers' flows between firms contain information on workers' preferences: if there are more voluntary moves from firm A to firm B than from firm B to firm A, one can infer that firm B is on average preferred to firm A. Sorkin (2018) shows that this logic can be generalized to a large set of firms that are connected to each other by workers' flows. The application of a Pagerank-type algorithm aggregates the information revealed by workers' mobility in a unique value vector of firms. Regarding the pay policy dimension, we use an Abowd et al. (1999) (hereafter AKM) decomposition to estimate firm wage premiums, reflecting the fact that some firms pay higher wage than others for otherwise similar workers. These wage premiums are identified through the wage gaps of movers (workers who move from an employer to another). The existence of such wage premiums has long been debated in the literature, and there exists three main ways to rationalize it. First, wage premiums might stem only from model (mis)-specifications, an artefact of some kind of the AKM model. The most obvious idea is that there is a specific match value to each employee-employer pair, that the additive specification misinterprets as firm fixed effects because of some systematic variation in match values (Bonhomme et al., 2019). Second, wage premiums might reflect *rents* on the product markets that are partly redistributed to workers, and that survive competition because of frictions on the labor market, as is supposed in the literature on rent-sharing (Card et al., 2018).[2] Third and finally, wage premiums might reflect *compensating differentials* for systematic differences in job quality between firms, or "amenities" that workers value. There has been a substantial body of literature that explore the role played by non-wage characteristics in the variance of wages since the seminal paper of Rosen (1986), notably with hedonist estimation on cross-sectional or panel data, with estimates that have been small, unstable or even wrong-signed (Bonhomme and Jolivet, 2009). These difficulties might stem from three

[1] In this paper, a "firm" is defined as a legal unit (*SIREN*).

[2] The redistribution of rents to workers can result from bargaining or from an optimization of firms aiming at retaining workers to minimize turnover, as theorized in the "efficiency wage" literature.

main causes: unobserved heterogeneity (especially of workers, if it is correlated to working conditions), measurement errors (especially of amenities, when only some specific working conditions are measured and there are omitted variable biases) and job market frictions (where utility is not equal across jobs for identical workers, so that wage dispersion cannot be interpreted as compensating differentials). More recent literature use various methods to overcome these obstacles: surveys (Maestas et al., 2023, Hall and Mueller, 2018), experiments (Mas and Pallais, 2017, He et al., 2021), structural estimation (Lamadon et al., 2022, Taber and Vejlin, 2020), and revealed preferences induced from mobility flows in matched employee-employer data (Sorkin, 2018). All these papers conclude that compensating differentials are substantial or that amenities explain a large share of the dispersion of utility.

We take advantage of a new matching procedure for French data, first described in Godechot et al. (2020), to give new insights on this question. We use an almost exhaustive pseudo-panel of matched employer-employee data from 2005 to 2019, and then we estimate separately both firms' global values (using the structure of mobility across firms) and firms' wage premiums (with an AKM decomposition on the wages). AKM estimation power rests on the density of the network of movers among firms. Sample panels, like the "DADS panel" that is usually used to keep track of French workers' trajectories over time, induce important biases that are much alleviated with the use of exhaustive data. This is due to the fact that the so-called *limited mobility bias*, which leads to overestimate the role of firms in the variance of wages (Bonhomme et al., 2023), depends on the number of "movers" observed per firm. Because sample panels drastically decrease the number of observations per firm, they reduce the number of such movers that are observed and therefore give biased estimates of firm wage premiums. We overcome this issue by using our almost exhaustive panel of matched employer-employee data.

Once we get both rankings of firms according to their global value and their wage premium, we are able to identify the share of the variance of firm wage premiums that is due respectively to the existence of *rents* and to the existence of *compensating differentials*. To do this, we assume that the utility that employees get from working in a firm comes from two components: pay and non-pay characteristics. More formally, the global value V_j of firm j is assumed to be additively separable in these two components:

$$V_j = c(\psi_j + a_j)$$

ψ_j being the pay component (*i.e.* the wage premium of firm j, in log-euros), a_j being the average monetary valuation of the non-pay component (*i.e.* the level of amenities provided by firm j, in log-euros) and c being the (unknown) unit of conversion from log-euro to utility. Rent-sharing (and more generally labor market frictions explanations of wage premiums) implies correlation between global values and wage premiums, because higher wage premiums tend to attract workers. The part of the variance of wage premiums that is not explained by global value (*i.e.* the systematic variation of wages between firms to which workers appear indifferent) can thus be interpreted as compensating differentials in amenities. We cannot, however, reverse the logic and measure the relative role that amenities and wage premiums play in the attractiveness of a firm. The fundamental reason is that, contrary to wages, amenities are not directly observed and that we do not know the euro value of the utility value we estimate from revealed preferences. To better explain this limitation, Sorkin (2018) distinguishes between two dimensions of amenities dispersion : the "Mortensen" motive (from Mortensen, 2003), where differences in amenities cause firms to have different global values, and the "Rosen" motive (from Rosen, 1986) where firms offer exactly equal global value but differ in the provision of wages versus amenities, thus generating compensating differentials. The method identifies the pure "Rosen" motive but cannot identify the "Mortensen" motive, *i.e.* the importance (or presence) of augmenting amenities.

The main contribution of this paper is to extend Sorkin (2018)'s method to new data features. First, we provide estimates on the importance of compensating differentials in the variance of wages in France, which might differ from the US in several dimensions (labor market regulation, workers' mobility, ...). Moreover, compared to the original US data used in Sorkin (2018), our matched employer-employee data is richer in at least two ways: first, we are able to observe the number of hours worked, which is crucial to interpret the sign of the wage gap experienced by movers; second, because we observe the type of contract, we can identify voluntary move in a more precise way than Sorkin (2018), restricting them to moves from a permanent contract. Combined with the exclusion of moves that include a period of unemployment, this restriction allows to distinguish more clearly between voluntary moves and lay-offs. It also allows to test the robustness of the method to alternative definitions of mobility.

Turning to our main results, we find that compensating differentials explain about 10% of the total variance of (log) wages in the economy. Indeed, we find that (1) firm wage premiums explain 12% of the total variance of (log) wages, and that (2) compensating differentials explain 81% of the variance of firm wage premiums.[3] The intuition behind this result is that the heterogeneity of non-wage amenities across firms tend to increase the variance of wages in order to prevent workers from all moving in the firms with good amenities. Result (1) means that even if most of the variance of wages is due to personal characteristics of workers, there remains a significant share of the variance (12%) that is due to firm-specific pay policies. This estimate is very close to other studies that use bias-corrected methods to estimate the role of firms in the log-wage variance (Babet et al., 2022, Bonhomme et al., 2023), suggesting that the exhaustiveness of our dataset is very useful to overcome the *limited mobility bias*. We also show that the individual wage gaps that we observe when workers move from one firm to another are closely related to the firm wage premiums, suggesting that these wage gaps can be rationalized by different firm pay policies. Result (2) means that the primary explanation of the existence of wage premiums is the strong heterogeneity in the provision of non-wage amenities across firms (81%), rather than the presence of rents (19%). This estimate is similar to the one estimated on US data (72%). This similarity with the US is quite surprising given the differences that exist between the two countries, in terms of mobility and potentially of workers' preferences. Next, we exploit variation in the number of hours worked to show that workers seem to value more firms where they can work longer hours (either by avoiding part-time or by working extra-hours). Finally, we find the method to be quite robust to alternative definitions of job-to-job transitions.

The rest of this paper is organized as follows. Section 2 introduces our new quasi-exhaustive matched employer-employee data. Section 3 documents empirically the high frequency of negative wage gaps when workers move from one firm to another. Section 4 details the method used to estimate firms' global values and wage premiums. Section 5 shows our results on French data and describes the importance of the number of hours worked to interpret mobility. Section 6 assesses the robustness of our results to alternative definitions of voluntary moves and to noise. Finally, Section 7 concludes.

2 Data

We use the annual French "Base tous salariés" (BTS, "all employees file") from 2005 to 2019. The BTS are matched employer-employee yearly wage files built from administrative data, and are used for most public statistics on wages. They do not constitute a panel, the individual identification number changes every year. Panel studies on careers and wages are traditionally done on a smaller, 1/12th sample of the population. This "narrow panel" is however not sufficient when one wants to estimate individual parameters for each firm, as it is the case for the AKM wage premiums and the Sorkin (2018)'s global values.[4]

[3] So $0.12 \times 0.81 = 0.10$.

[4] The original 1999 AKM paper exploited the French narrow panel, unique at the time. But because of these limitations the subsequent literature has focused mostly on countries where exhaustive matched employer-employee data became available.

Fortunately, each yearly file contains variables both for the year t as well as for the year t−1. A direct use of this data as short, two years panel data is possible, but this overlap also allows for matching between yearly files, based on common information (establishment and firm IDs, gender, number of hours, job duration in days, start and end dates of the job, municipality of work and residence, earnings and age) between year t of yearfile y–1 and year t–1 of yearfile y. Following Godechot et al. (2020), we use the overlap between the successive short panels to match individuals from yearfile to yearfile, and build a quasi-exhaustive panel. We need this wide panel to accurately estimate the models used here. The matching procedure and performances are described in Babet et al. (2023).[5]

We consider only workers aged between 15 and 64. Moreover, we remove (i) "non-ordinary" jobs like internships and subsidized jobs, jobs where the employer is a private individual (*particuliers employeurs*) and temporary work (*intérim*) and (ii) very short contracts (less than 120 hours). We also restrict the sample to jobs with hourly wage greater than 0.8 minimum wage and smaller than 2,000 minimum wages. Finally, following similar studies on this type of data, we keep only one observation by person-year so we take the annual dominant employer of the worker (defined as the employer from which the worker earns the most during the year).[6] In the following and unless explicitly mentioned, we consider the real net hourly wage as our variable of interest.[7]

We define a move as a transition between two different firms (identified by their *SIREN* code), with the condition that less than 70% of the workers in the leaving firm move to the receiving firm (otherwise it is probably simply a relabelling or an acquisition). In order to rationalize the existence of wage gaps when people change employers, it is important to distinguish between different types of moves. Indeed, the economic interpretation differs if the wage gaps are mainly explained by suffered moves (e.g. lay-offs or ends of a fixed-term contract) or are also observed in moves that are more likely to be chosen. To distinguish between different types of moves, we make use of the richness of the BTS. First, information on the type of contract allows us to distinguish between fixed-term contracts (*CDD*) and permanent contracts (*CDI*). This distinction is very important in the French context because labor laws protect much more the workers that have a permanent contract rather than a fixed-term contract (where by definition, an employer is not obliged to renew the contract when it comes to an end). Therefore, we only consider moves from a permanent contract as a potential voluntary move. Second, we observe the amount of unemployment benefits received by the worker during the year. Because a lay-off is often followed by an unemployment spell, we only consider moves that do not include any significant unemployment spell as a potential voluntary move.[8] Finally, we consider a move as being a voluntary move if it satisfies the two previous conditions and concerns two consecutive years. We label these (likely) voluntary moves as employer-to-employer (EE) moves.
We also define employer-to-nonemployment-to-employer (ENE) moves as being moves from a permanent contract but that include a significant unemployment spell or that concern two years that are not consecutive. The last type of moves (labelled as "Other" moves) concerns all the moves from a fixed-term contract.

Finally, to reduce estimation biases caused by too few moves between firms, we impose size restrictions on the firms. We follow Sorkin (2018) and remove all firms that have less than 90 non-singleton person-years, with a non-singleton person-year being defined as an indicator variable equal to 1 when the worker appears a later year in the dataset.[9] Table 1 shows that this restriction leads to drop the vast majority

[5] The code for the matching is available at http://olivier.godechot.free.fr/hoprubrique.php?id_rub=97. The data used is confidential and can be accessed through the CASD.

[6] 87% of the workers have already only one employer per year.

[7] We get real wages by deflating nominal wages by the Price Consumer Index (*IPC*).

[8] A significant unemployment spell corresponds to a spell for which the amount of unemployment benefits received exceeds two weeks of earnings. This choice is driven by the fact that we consider an unemployment spell as significant if it exceeds a month, and we assume that the wage replacement rate in unemployment is approximately one half.

[9] For instance, none of the observations in 2019 are non-singleton person-years because it is the last year available in the data.

of firms (more than 90%) but only 16% of the person-year observations. We impose a further restriction related to the network structure of the firms. Indeed, in order to estimate firm fixed-effects, Abowd et al. (2002) showed that it is necessary to restrict the sample to the weakly connected set of firms, because wage premiums are only identified relatively to a given firm (whose premium is normalized to be null).[10] Our restriction is even more important because we consider only firms that belong to the strongly connected set, as explained in Section 4.2.2.[11] Our sample restrictions lead us to consider jobs that are slightly better paid and more skilled than in the whole sample (Tables 1 and A.1 in Appendix). Overall, even if these sample size restrictions lead us to drop a significant part of our observations (25%), they are necessary to estimate firms' wage premiums and global values that are not too biased. For the rest of the paper, unless otherwise specified, we thus use the sample described in column (3) of Table 1. It is made of 45.4 millions of employees working in 260,000 firms. The average hourly wage in these firms is slightly higher than in the global (+ 4%).

Table 1: Summary statistics

	All (1)	$\geq$ 90 person-years (2)	S.connected by EE (3)	Private sector (4)
Sample size				
Person-year	339,894,000	284,746,000	253,865,000	208,256,000
Matches	99,923,000	76,906,000	67,337,000	56,715,000
Persons	61,955,000	50,752,000	45,387,000	38,247,000
Employers	3,402,000	323,000	260,000	249,000
Hourly wage				
Mean	14.11 €	14.59 €	14.69 €	14.76 €
Std. deviation	13.41 €	13.74 €	14.26 €	15.34 €
1^{st} quartile	9.21 €	9.52 €	9.52 €	9.34 €
Median	11.51 €	11.97 €	11.98 €	11.81 €
3^{rd} quartile	15.67 €	16.24 €	16.32 €	16.36 €

Note : "S. connected by EE" refers to the set of firms that are strongly connected by employer-to-employer (EE) transitions and that hire at least one person from an employment-nonemployment-employment (ENE) or an other transition. The private sector includes all firms belonging to this strongly connected set and that are not part of the public administration (so it includes state-owned companies).
Sample : French firms, 2005-2019.

3 Stylised fact: half of the moves come with a wage cut

3.1 Wage changes of stayers and movers

We start by providing a first illustration of the importance of wage cuts when people change employers, considering all types of moves together. To do this, we look at the proportion of real hourly wage cuts and the magnitude of wage gaps between two adjacent years among stayers and movers for the 2005-2019 period.

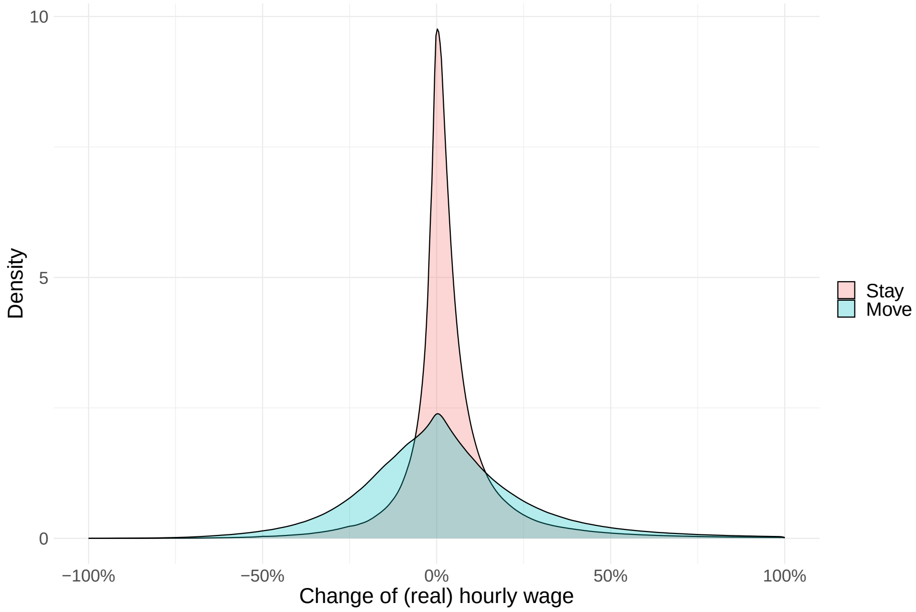
Figure 1 shows that the distribution of the "stay" observations is very tightly concentrated around zero, contrary to the distribution of the "move" observations which is much more dispersed. Table 2 provides more details on how the distributions of "stay" and "move" observations differ. First, it confirms that wage cuts are much more frequent when people change firm than when people stay at their firm (0.49 vs. 0.37). Moreover, the difference between the proportion of wage cuts when the wage is computed in real or nominal terms is much more important for the "stay" observations (difference of 8 p.p., *i.e.*

[10] A weakly connected set of firms is defined as a set of firms that have at least one employee who is observed in another firm belonging to the set.

[11] A strongly connected set is defined as a set of firms that hires at least one employee from another firm of the set and that has at least one employee who is hired by another firm of the set.

22%) than for the “move” observations (difference of 4 p.p., *i.e.* 8%), an indication that stayers’ nominal wage variations are sticky, whereas movers’ wage gaps are driven by more significant changes. In order to remove small variations around zero that could reflect measurement errors, we also look at the proportion of significant wage cuts (defined as a wage cut of more than 5%). The difference between the “stay” and the “move” observations is here even more striking: movers experience a significant wage cut in 38% of the cases, whereas stayers only in 15% of the cases. We show in Figure B.1 in Appendix that this difference is almost constant across years of observations. However, as shown in Figure B.3 in Appendix, the magnitude of wage gaps varies across years.[12] Movers also experience more frequent significant wage rises (defined symmetrically as a wage rise of more than 5%), but the difference with stayers (40% vs. 32%) is much smaller.

Figure 1: Wage changes according to the type of observation



Note: “Stay” includes 187.6 millions couples of observations in the same firm. “Move” includes 20.3 millions couples of observations in two different firms.
Scope: All sectors.

[12] The spike in 2009 is concomitant to a large increase of unemployment following the economic crisis, which has mostly affected low-wage earners, leading to selection effects in the measurement of the median hourly wage gap. The annualized wage encompasses part of the variations in the number of hours worked and decreases sharply in 2009, as shown in Figure B.4 in Appendix.

Table 2: Wage gaps among movers and stayers

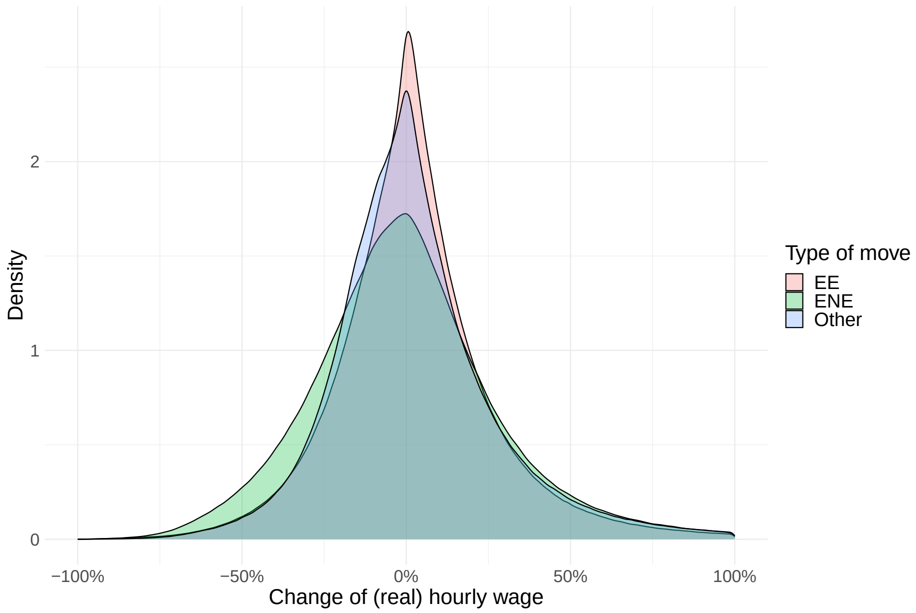
	Stay	Move
Hourly wage (w)		
Average wage gap	+4.8%	+4.0%
Median wage gap	+1.7%	+0.5%
Proba w $\downarrow$ (real)	0.37	0.49
Proba w $\downarrow$ (nominal)	0.29	0.45
Proba w $\downarrow < -5$ % (real)	0.15	0.38
Proba w $\uparrow > +5$ % (real)	0.32	0.40
Annualized wage (y)		
Average wage gap	+6.4%	+17.8%
Median wage gap	+2.9%	+4.1%
Proba y $\downarrow$ (real)	0.30	0.43
Proba y $\downarrow$ (nominal)	0.25	0.41
Proba y $\downarrow < -5$ % (real)	0.15	0.36
Proba y $\uparrow > +5$ % (real)	0.38	0.49

Note: "Stay" includes 187.6 millions couples of observations in the same firm. "Move" includes 20.3 millions couples of observations in two different firms.

3.2 Wage changes for voluntary moves

We now show that these results also hold in the specific case of voluntary moves (EE transitions), suggesting that looking for better paid jobs does not seem to be the unique motivation of workers' mobility. Figure 2 shows the distribution of the wage gaps according to the type of move. It appears that even for the EE moves, wage cuts are very common. As expected, the probability of experiencing a negative wage change is more frequent for potential unvoluntary moves (either ENE or "Other" moves). The ENE left-tail is especially fat, suggesting that a significant part of ENE moves comes with difficulties to find a new job that pays as well as the last, which can explain part of the wage cuts that are observed when people change employers. However, there is still an important part of EE moves that come with wage cuts, and the EE distribution shows a relative high variance compared to the "stay" distribution.

Figure 2: Distribution of wage changes according to the type of move



Note: "EE" (employer-to-employer) includes 7.8 millions of moves. "ENE" (employer-to-nonemployment-to-employer) includes 3.4 millions of moves. "Other" (moves from a fixed-term contract) includes 9.1 millions of moves.
Scope: All sectors.

Table 3 details these results. On average, workers who experience an EE transition have their hourly wage that increases by 4.1%. Reassuringly for our definitions, the probability of experiencing a wage cut is the lowest for the EE transitions (that we interpret as chosen). Nevertheless, in almost half of the cases (47%), an EE transition comes with a wage cut.[13] Table 3 also shows that there is little difference between males and females and that young people tend to experience less frequent wage cuts than people aged over 30. Low-paid workers are also less likely to experience a wage cut than high-paid workers, possibly because of the existence of a minimum wage. Finally, geography seems to be an important predictor of wage cuts: it is much more likely to experience a wage cut when moving out of the Paris area (proba = 0.58 for EE transitions) than when entering the Paris area (proba = 0.39 for EE transitions). However, simply changing of municipality is not associated with a particular pattern of wage change.[14]

[13]Similar evidence on a much more restricted sample has been provided long ago by Postel–Vinay and Robin (2002), using a non-exhaustive 3-year panel in the Paris area.
[14]Such changes concern 25% of the EE transitions.

Table 3: Wage gaps according to the type of move

	All	EE	ENE	Other
Hourly wage (w)				
Average wage gap	+4.1%	+4.1%	+1.7%	+4.9%
Median wage gap	+0.5%	+1.2%	−1.2%	+0.3%
Proba(w ↓)				
All	0.49	0.47	0.52	0.49
All (nominal)	0.45	0.44	0.48	0.46
Male	0.49	0.47	0.53	0.48
Female	0.49	0.46	0.50	0.50
Age < 30	0.46	0.43	0.44	0.47
$30 \leq$ Age < 50	0.51	0.48	0.55	0.52
Age ≥ 50	0.54	0.51	0.61	0.54
1^{st} quartile (wage)	0.23	0.25	0.20	0.23
4^{th} quartile (wage)	0.62	0.56	0.78	0.66
Changing municipality (32% of moves)	0.48	0.48	0.50	0.48
Entering Paris area (4% of moves)	0.38	0.39	0.42	0.35
Leaving Paris area (5% of moves)	0.59	0.58	0.63	0.57
Annualized wage (y)				
Average wage gap	+17.8%	+12.8%	+24.8%	+19.4%
Median wage gap	+4.1%	+3.9%	+6.7%	+3.7%
Proba(y ↓)				
All	0.43	0.42	0.43	0.44
All (nominal)	0.41	0.39	0.40	0.42

Note: "All" includes 20.3 millions of moves. "EE" (employer-to-employer) includes 7.8 millions of moves. "ENE" (employer-to-nonemployment-to-employer) includes 3.4 millions of moves. "Other" (moves from a fixed-term contract) includes 9.1 millions of moves. All wages are in real terms, unless otherwise specified.

Instead of reasoning at the firm level, it is also interesting to compare regions using geographical moves. We simply report here the ranking of geographical moves by the proportion of wage cuts, with the intuition that regions to which people move while accepting frequent wage cuts may have other desirable characteristics. The five "worst" of these moves in terms of wage cuts in Table 4 seem to confirm the attractiveness of the Atlantic and Southern regions. At the opposite, the cost of living in the Paris area should explain why there are fewer people who accept a wage cut when moving there.[15]

[15] We do not have regional price indexes: the real wage is computed by deflating the nominal wage by the national consumer price index, ignoring price differences across regions. This implies that what we label as a wage increase can reflect a wage decrease when these price differences across regions are taken into account.

Table 4: Wage cuts and geography

	Nb. moves	Proba(w ↓)
5 "best" moves		
Nouvelle Aquitaine - Paris	24,070	0.37
Bretagne - Paris	14,783	0.37
Pays de la Loire - Paris	21,211	0.37
Grand Est - Paris	26,189	0.38
Occitanie - Paris	26,748	0.38
5 "worst" moves		
Paris - Bretagne	22,167	0.65
Paris - Pays de la Loire	30,155	0.62
Paris - Nouvelle Aquitaine	37,528	0.62
Paris - Corse	1,112	0.61
Paris - Occitanie	36,866	0.59

Note: "Proba(w ↓)" shows the probability of experiencing a (real) hourly wage cut when moving from one region to another. This table is about EE transitions only. Moreover, only moves that represent more than 1,000 EE transitions are taken into account.

3.3 Hourly wage vs. annualized wage

One concern about our measure of wage cuts could be that it relies on an hourly measure of the wage. There are two potential reasons why it may be more relevant to focus on variations in daily wage rather than in hourly wage. First, the number of hours worked can be misreported more often than the period of employment. However, it is not clear why potential measurement errors on the hours would tend to overestimate the share of wage cuts. For this to be true, the number of hours worked in the new firm should be systematically overestimated compared to the number of hours worked in the leaving firm. It seems unlikely to us that this type of systematic measurement error will occur. Second, people might be more concerned by their total earnings rather than their hourly wage. To see whether people accept more hourly wage cuts or annualized wage cuts, we reconstruct an annualized wage in a method similar to Sorkin (2018). However, because we have the total duration (in days) of the period of employment at the firm, we are able to get a more precise annualized wage than in the US data. To construct the annualized wage, we simply take the ratio between total earnings (net salary) and the number of days of employment at the firm, and we multiply by 365. This is actually equivalent to calculating a daily wage, so the variations we capture between the hourly wage and the annualized wage are the variations of the number of hours worked per day (either due to part-time or overtime).[16] If this is true that people are primarily concerned by their annualized wage rather than their hourly wage, we would count as a wage cut something that is not perceived as such by people.

Table 2 suggests that this concern is partially verified: only 43% of the moves come with an annualized wage cut (vs. 49% for hourly wages). The average annualized wage gap of the moves is also much higher than the average hourly wage gap (+17.8% vs. +4.1%), suggesting that some adjustment occurs in the number of hours worked. Similarly, the proportion of EE moves that come with an annualized wage cut is significantly lower than those accompanied by a hourly wage cut (0.42 vs. 0.47, see Table 3). People seem therefore more reluctant to experience a decrease in their annualized wage than in their hourly wage. This is confirmed by other descriptive evidence suggesting that people value more jobs where they can work longer hours. To see this, we compare the number of transitions accompanied by an increase in the number of hours worked with those that come with a decrease of hours. Table E.4 in Appendix shows that 45% of the EE transitions are accompanied by a decrease of hours. In order to disentangle what comes from small variations in hours and what is due to more profound change in the status of the

[16] We call it "annualized wage" in the rest of the paper to be consistent with the literature.

job (part-time vs. full-time jobs), we define a part-time job as a job with less than 30 hours per week.[17] We then compare the shares of EE transitions from part-time to full-time with those from full-time to part-time and find that the first are nearly twice more frequent than the second (0.13 vs. 0.07, see Table E.5 in Appendix). This is especially true for women and young people, suggesting that these demographic groups are more likely to be constrained into working part-time than to choose it. Recent survey evidence confirm that women and young workers are much more likely to face underemployment than the rest of the population: in 2023, 6.7% of the employed women (7.2% of the 15-24) declared that they would be willing to work more hours (vs. 2.7% for men and 3.9% for the 25-49).[18]

These results suggest that people might be more concerned about their annualized wage than their hourly wage. Table 5 confirms this idea by showing that there might be a trade-off between the number of hours worked and the hourly wage. Indeed, we see that EE moves that are accompanied by an increase of the number of hours are much more likely to come with an hourly wage cut than those that are accompanied by a decrease in the number of hours (0.54 vs. 0.38). We see a similar pattern between part-time to full-time and full-time to part-time transitions (0.58 vs. 0.34). Note that this finding is not mechanical since the difference is much less pronounced for the moves that we do not interpret as chosen. We discuss in more details how we can interpret the differences between hourly wage and annualized wage changes in our framework in Section 5.2.3.

Table 5: Hourly wage cuts and number of hours

	All	EE	ENE	Other
Proba(w ↓)				
When number of hours				
...increases	0.53	0.54	0.55	0.51
...decreases	0.44	0.38	0.48	0.47
When transitioning				
...part-time to full-time	0.54	0.58	0.53	0.53
...full-time to part-time	0.44	0.34	0.48	0.48

Note : "All" includes 20.3 millions of moves. "EE" (employer-to-employer) includes 7.8 millions of moves. "ENE" (employer-to-nonemployment-to-employer) includes 3.4 millions of moves. "Other" (moves from a fixed-term contract) includes 9.1 millions of moves. The number of hours refers to the number of hours per day. Part-time is defined as working less than 30 hours/week.

However, even if there are less negative moves with the annualized wage than the hourly wage, there are still more than 40% of voluntary moves that experience an annualized wage cut. Moreover, as shown in Figures B.5 and B.6 in Appendix, the comparison of distributions between "stay", "move" and the different types of moves for the annualized wage is very similar to what we discussed so far with the hourly wage.

[17] We do not use the French traditional threshold of 35 hours/week to avoid accounting for small variations around this threshold. To make sure that our definition is relevant, we compare the observed proportion of part-time jobs implied by our definition with data collected in the *Enquête Emploi* and find very similar results (the share of part-time jobs is 19% with our definition and 18% in the *Enquête Emploi* (see Insee, 2020). Similarly, a recent study about working conditions when working part-time (Beatriz and Erb, 2024) uses a threshold at 28 hours per week in order to disentangle between contracts that are similar to full-time jobs (*i.e.* contracts of more than 28 hours per week) and contracts that reflect more accurately the experience of working part-time (*i.e.* contracts of less than 28 hours per week).

[18] See https://www.insee.fr/fr/statistiques/2432294#figure1_radio1.

3.4 Measurement issue: last and first years

Another concern about our measure of wage cuts is that we defined them using only the last year in the leaving firm and the first year in the new firm. It may be the case that the revenues of the last year in a firm are overstated by some compensations that are granted when the employee leaves. Symmetrically, the revenues of the first year in a firm might be understated because some bonuses or other compensations granted in the first year could be delayed to the next year. By overestimating the wage in the leaving firm and underestimating the wage in the new firm, we would overestimate the share of wage cuts.

To assess the importance of this measurement issue in the last and new years at the firm, we consider the sub-sample of EE moves for which we have at least two observations before and after the move. This allows us to find abnormal variations of wage around the move that could reflect extra or missing compensations. Table 6 suggests that this measurement issue around the move is not negligible. Indeed, compared with the average wage growth of people who do not experience any move (the "stayers"), the average growth rate of the wage between the second to last ($t-2$) and the last ($t-1$) year in the leaving firm is three times bigger. The difference is less pronounced between the first (t) and second ($t+1$) year at the new firm, but the wage of the movers still grows two time faster than the one of the stayers. We can note that these differences are likely to be due to administrative discrepancies for years around moves because for other years before and after the move, the wage growth is very similar between movers and stayers (see the comparison between column (1) and (2) for the first and last row of Table 6).

Table 6: Measurement errors in the years around the move

	Movers (1)	Stayers (2)
Annual wage growth		
Before $t-2$	+3.9%	+3.3%
Btw. $t-2$ and $t-1$	+9.1%	+3.1%
Btw. t and $t+1$	+7.9%	+3.7%
After $t+1$	+4.9%	+5.1%

Note: The t of movers is defined as the year of the move, *i.e.* the first year in the new firm. The t of stayers is defined as the middle observation in the firm. The growth rates reported in the first and last rows are calculated using the sub-sample of people who are observed at least 3 years at the leaving firm and 3 years at the new firm. The growth rates reported in the second and third rows are calculated using the sub-sample of people that are observed at least 2 years at the leaving firm and 2 years at the new firm. Only EE moves are taken into account.

In order to isolate the specific effect of this measurement issue in the proportion of wage cuts, we impute the wages of the last (first) year at the leaving (new) firm by using the corresponding wage growth of the stayers. Indeed, this wage growth is not subject to doubts about extra or loss of compensations the years around the move. We reconstruct the wage of the last (first) year in the leaving (new) firm as the wage obtained by applying these growth rates to the second to last (second) wage in the leaving (new) firm. We redefine a wage cut as a loss between these two wages imputed from their previous and next counterparts. Using this technique, we find that the proportion of wage cuts for voluntary moves decreases, but is still 44% (meaning only 10% lower than without the correction).

Overall, it suggests that simply defining a wage cut by comparing only the two adjacent years is likely to overestimate the proportion of the phenomenon, but this bias seems moderate and does not question the fact that wage cuts are common in the data. More importantly, it does not affect much the estimation of firm wage premiums because the premiums are estimated using the full period of a worker/firm match and not only the first or last observation, and because moves between firms can go both ways. It does not affect either the estimation of firm global values because they are estimated using the structure of mobility only (and not using the wages).

This section has highlighted the stylised fact that wage cuts are very common and sometimes large, even for the moves that are most likely to be chosen by the employees. The objective of the rest of the paper is to rationalize this stylised fact by showing that (1) the wage gaps we observe do not reflect only idiosyncratic shocks at the worker level but reflect heterogeneous pay policies at the firm level, and that (2) firms' pay policies cannot explain alone the attractiveness of a firm, suggesting that non-wage amenities are also an important driver of mobility.

4 Estimation strategy

The high frequency of wage cuts when people move from one firm to another does not necessarily reflect systematic differences in wage policies across firms, but could instead reflect only idiosyncratic differences across workers. The objective of this section is to describe the method used by Sorkin (2018) to isolate the variations in wage and non-wage characteristics that are due to firm-specific policies. This method allows us to estimate the relative share of rents and compensating differentials in the variance of firm wage premiums. To achieve this, we use two sources of identification (mobility and wages) to estimate separately two outcomes (firms' global values and wage premiums). This makes it possible to estimate two rankings of firms, and to compare them in order to identify the relative share of rents and compensating differentials in amenities. Section 4.1 starts by illustrating this idea, then sections 4.2 and 4.3 recall the method used to estimate respectively firms' global values and firms' wage premiums.

4.1 Identification of compensating differentials

Suppose we have two rankings of firms: one based on workers' revealed preferences through their firm-to-firm mobility (ranking of firms' global values), the other one based on wage differences across firms (ranking of firms' wage premiums). The intuition is that if these two rankings are very close, we conclude that the difference in firms' wage policies translate into a difference of firms' attractiveness : it reflects the existence of "rents". Conversely, if these two rankings are very different, the difference in firms' wage policies can be interpreted as a way to compensate workers for other non-pay characteristics : it reflects the existence of "compensating differentials". Formally, let V_j and ψ_j be respectively the global value (*i.e.* degree of attractiveness) and the wage premium (*i.e.* the part of the wage that depends on the specific firm wage policy, and not on worker specific characteristics) of firm j. In order to see how these two outcomes are related, we compute the R^2 of the simple linear regression of the ranking of V_j on the ranking of ψ_j. We therefore decompose the variance of the wage premiums in two components:

$$Var(\psi) = \underbrace{R^2 Var(\psi)}_{\text{rents}} + \underbrace{(1 - R^2)Var(\psi)}_{\text{compensating differentials}} \tag{1}$$

Note that the identification of the relative share of compensating differentials in the variance of wage premiums is not equivalent to the identification (in monetary terms) of the entire distribution of amenities across firms. More precisely, Sorkin (2018) shows that the compensating differentials component of the variance of wage premiums is the part of the variance of amenities that corresponds to the "pure" Rosen motive, *i.e.* the part that equalizes the global value of firms (the "compensating" part). However, the part of amenities imputable to the Mortensen motive, *i.e.* the part that contributes to the dispersion of firms' global values (the "augmenting" part), is not identifiable because we do not know the unit of conversion from utility to log-euro so we cannot quantify what a given dispersion of values means in terms of monetary dispersion.

The goal of the next two sections is to explain how the firms' global values and wage premiums are estimated.

4.2 Estimation of firms' global values

The originality of Sorkin (2018)'s framework consists in applying an algorithm very close to Google's PageRank algorithm to a matched employer-employee dataset. The goal of this section is to briefly recall the method and underlying assumptions needed to rank firms using the observed moves of workers.

4.2.1 Model

The model is a partial equilibrium, on-the-job search model with job posting, no directed search, exogenous search effort (*i.e.* arrival rate of offers is independent of the worker's firm) and homogeneous workers (*i.e.* all workers search from the same distribution and agree on a common ranking of firms). This type of model is inspired by Burdett and Mortensen (1998).

In this model, a firm j employs a certain share of the workers (g_j) and posts a certain share of the job offers (f_j). Moreover, a firm is characterized by a certain global value that aggregates pay (wage premium) and non-pay (amenities) characteristics. The first important assumption specific to our model is that these characteristics are additively separable so that we can write:

$$V_j = c(\psi_j + a_j) \tag{2}$$

ψ_j being the firm wage premium (in log-euro), a_j being the amount (in log-euro) of non-pecuniary amenities provided at the firm-level and c being the (unknown) unit of conversion from log-euro to utility. The second assumption is that this global value is firm-specific, meaning that there exists a common valuation of firms that is accepted and known by all workers. This can be interpreted for example as the average valuation of the firm. The assumption of the existence of a common firm ladder is also found for example in Haltiwanger et al. (2018), Moscarini and Postel-Vinay (2018) and Bagger and Lentz (2018). It might be violated if there exists systematic differences of valuation across groups of people, as discussed in Section 5.2.2. However, this assumption does not mean that all workers value all firms the same, but that this heterogeneity of valuation is assumed to be independent and identically distributed across workers. With these assumptions, we can write the value function of working at the firm j as:

$$V_j = \underbrace{v_j}_{\text{payoff}} + \beta\ E\{\underbrace{\lambda_1}_{\text{offer}} \sum_k \underbrace{f_k \int_{\iota_3}\int_{\iota_4} max(V_k + \iota_3, V_j + \iota_4) dI dI}_{\text{offer from firm } k} + \underbrace{(1-\lambda_1)}_{\text{no offer}} \underbrace{\int_{\iota_5} (V_j + \iota_5) dI}_{\text{stay at firm } j}\ \} \tag{3}$$

λ_1 denotes the probability of receiving any offer and f_k denotes the probability of receiving an offer from firm k. The individual-specific utility draw is denoted by ι and, as mentioned before, it is identically distributed (from dI) across workers.

This value function is identical as the one in Sorkin (2018), except that we do not allow workers to choose to quit their jobs to enter non-employment. The reason why we make this restrictive hypothesis is that it is very difficult to empirically identify a chosen move toward non-employment and it is likely that what we would consider as a chosen move will instead be a lay-off in the vast majority of the cases. Since the value can only be estimated when we are able to identify chosen moves from and toward the firm (we will explicit this point in the next subsection), this implies that, contrary to Sorkin (2018), we do not estimate the value of non-employment.

4.2.2 From worker flows to PageRank

The goal of this subsection is to detail how it is possible to infer a ranking of firms from the information on worker flows. Because we want to interpret the flows between firms as revealing preferences about the common ranking of firms, we focus on the chosen moves, *i.e.* the EE moves that we defined in Section 2. Following the model presented above and denoting W the total number of employed workers in the economy, the amount of chosen moves from firm k to firm j (M_{jk}) can be expressed as follow:

$$M_{jk} = \underbrace{g_k W}_{\text{Nb. of workers at firm k}} \times \underbrace{\lambda_1 f_j}_{\text{Proba. get an offer from firm j}} \times \underbrace{P(V_{ij} > V_{ik})}_{\text{Proba. accept offer}} \tag{4}$$

We introduce here a new notation V_{ij} that corresponds to the global value of the firm j for a given worker i.[19] This value is individual-specific and therefore is not equal to the common global value V_j we are interested in. The crucial assumption needed to get a relation between these two values is that the individual-specific valuation of the firm can be written as the sum of the common valuation and an *i.i.d.* idiosyncratic term that follows a type I extreme value distribution :

$$V_{ij} = V_j + \iota_{ij}$$

The distributional assumption for ι_{ij} allows to get a direct relation between $P(V_{ij} > V_{ik})$ and V_j :

$$\begin{aligned} P(V_{ij} > V_{ik}) &= P(V_j + \iota_{ij} > V_k + \iota_{ik}) \\ &= P(\iota_{ij} - \iota_{ik} > V_k - V_j) \\ &= \frac{exp(V_j)}{exp(V_j) + exp(V_k)} \end{aligned}$$

Therefore we can rewrite M_{jk} as follow:

$$M_{jk} = g_k W \ \lambda_1 f_j \ \frac{exp(V_j)}{exp(V_j) + exp(V_k)} \tag{5}$$

Our objective is to get $\{V_j\}_{j\in\mathcal{E}}$, *i.e.* the common ranking of firms ($\mathcal{E}$ being the set of employers), from the observed $\{M_{jk}\}_{j\in\mathcal{E},k\in\mathcal{E}}$ flows. To get this, let us first write the relative flows between firm j and firm k to simplify the expression:

$$\underbrace{\frac{M_{jk}}{M_{kj}}}_{\text{relative flows}} = \underbrace{\frac{g_k}{g_j}}_{\text{relative sizes}} \underbrace{\frac{f_j}{f_k}}_{\text{relative offers}} \underbrace{\frac{exp(V_j)}{exp(V_k)}}_{\text{relative values}} \tag{6}$$

The relative flows between firm j and firm k depend first on their relative sizes: if firm k is bigger than firm j, the probability that one of their workers has an idiosyncratic draw that makes her willing to move from k to j independently of the relative values of the firms will be higher.
The relative flows between firm j and firm k depend also on their relative offer rates: if firm j makes much more offers than firm k, more workers of firm k will consider moving to firm j than the reverse so again the probability that an idiosyncratic draw makes them prefer j to k independently of the relative values of the firms will be higher.
Finally, the relative flows between both firms depend on their relative (common) values.

[19] This notation was implicit in the "max" terms of the value function in Section 4.2.1.

Now let us define the "flow-relevant" value of firm j as:

$$exp(\tilde{V}_j) \equiv \frac{f_j exp(V_j)}{g_j} \tag{7}$$

The term "flow-relevant" means that this is the value of the firm that we would infer if we only took into account the relative flows between firms without controlling for their sizes and offer rates. Indeed, combining equation (6) and (7) gives:

$$\frac{M_{jk}}{M_{kj}} = \frac{exp(\tilde{V}_j)}{exp(\tilde{V}_k)} \tag{8}$$

Now the objective is to get $\{exp(\tilde{V}_j)\}_{j\in\mathcal{E}}$ using all the observed relative flows. The reason why we do not estimate the relative value of two firms only from their relative flows is that (1) most pairs of firms do not have direct relative flows between them ; (2) because of the Condorcet paradox, a comparison between firm j and firm k using the flows between them can lead to different results than the same comparison using also flows with an intermediate firm l. This suggests that the rank of a firm must be determined simultaneously with the rank of all other firms to avoid such inconsistency.
Cross-multiplying equation (8) and considering all the possible firms that exchange workers with firm j gives:

$$\forall k \in \mathcal{E}, M_{jk} exp(\tilde{V}_k) = M_{kj} exp(\tilde{V}_j) \tag{9}$$

$$\Longrightarrow \underbrace{\sum_{k\in\mathcal{E}} M_{jk}}_{\text{Nb. entries to firm j}} exp(\tilde{V}_k) = \underbrace{\sum_{k\in\mathcal{E}} M_{kj}}_{\text{Nb. exits from firm j}} exp(\tilde{V}_j) \tag{10}$$

$$\Longrightarrow \frac{\sum_{k\in\mathcal{E}} M_{jk} exp(\tilde{V}_k)}{\sum_{k\in\mathcal{E}} M_{kj}} = exp(\tilde{V}_j) \tag{11}$$

As emphasized by Sorkin (2018), this expression is very close to the recursion underlying Google's PageRank algorithm: the value of firm j depends on the value of the firms from which it recruits, as the popularity of a webpage depends on the popularity of the webpages that link to it.
In matrix form, denoting S the diagonal matrix with the sum of exits in the kth diagonal entry, M the matrix of flows (with the leaving firm in column and the receiving firm in row) and $exp(\tilde{V})$ the vector of the firm ("flow-relevant") values, we can rewrite equation (11) as:

$$S^{-1} M exp(\tilde{V}) = exp(\tilde{V}) \tag{12}$$

Then, Sorkin (2018) uses graph theory to show that if the firms are strongly connected by chosen moves, then there is a unique solution of this equation.[20] He then uses the power iteration method to solve for $exp(\tilde{V})$. We briefly recall the steps of the reasoning but we do not reproduce the proofs (those proofs are available in the online appendix of Sorkin's paper).
First, theory on non-negative matrices ensures that $S^{-1}M$ has a unique eigenvector (denoted $exp(\tilde{V})$) with all elements of the same sign and with associated eigenvalue λ, so that we can write $S^{-1}Mexp(\tilde{V}) = \lambda exp(\tilde{V})$.
Second, Sorkin (2018) shows that this eigenvalue (λ) is actually equal to 1, which guarantees the existence and the uniqueness of a solution $exp(\tilde{V})$ in equation (12).
Third, the use of the power iteration algorithm allows to get the solution of equation (12). Given an initial guess for $exp(\tilde{V})$ that must not be a null vector (we take a random guess), this algorithm consists in repeatedly applying the matrix multiplication of the left-hand side of equation (12) to the value of

[20] Firms are strongly connected by chosen moves if for all couple of firms j and k there exists a path of chosen moves to go from j to k and from k to j.

$exp(\tilde{V})$ obtained in the previous iteration, and it converges reasonably fast (in about 5 min in our sample of 260,000 firms).

Once we get the vector of "flow-relevant" values $\{exp(\tilde{V_j})\}_{j\in\mathcal{E}}$, we can infer the vector of common values $\{V_j\}_{j\in\mathcal{E}}$ from equation (7). First, g_j is simply the relative size of firm j and is observed from the data.[21] Second, f_j can be recovered under an assumption about the recruiting behavior of firms. We observe in our data not only direct employer-to-employer moves but also indirect moves that are not accounted as chosen moves (these are the moves that include a spell of non-employment or that follow a fixed-term contract).[22] We assume that firms recruit indistinctly from already employed people with a permanent contract (our population of interest *i.e.* the one that is included in the matrix of transitions M) and non-employed people or people with a fixed-term contract. Formally, it means that we assume that the offer rate f_j is the same for these two populations. We can therefore identify the vector of offer rates $\{f_j\}_{j\in\mathcal{E}}$ independently from the EE transitions (which are already used to infer the value of the firm), using the observed employer-to-nonemployment-to-employer transitions ("ENE" moves) and the transitions from fixed-term contracts ("Other" moves).[23]

4.3 Estimation of firms' wage premiums

Now that we got the vector of firms' global values, it remains to get the vector of firms' wage premiums in order to compare them and get an estimate of the relative share of compensating differentials in the variance of wages. In order to estimate wage premiums, we use an Abowd et al. (1999) decomposition, as in Babet et al. (2023). The AKM model is a model of log-wages with additive worker and firm fixed effets:

$$w_{it} = \phi_i + \psi_{j(i,t)} + X_{it}\beta + u_{it} \tag{13}$$

with w_{it} the logarithm of the hourly wage of worker i in year t. ϕ_i is the fixed effect of worker i, and ψ_j is the fixed effect of firm j (or the "wage premium" of firm j), firm $j(i,t)$ being the employer of worker i during year t. ψ_j is a measure of the firm wage premium, *i.e.* a part of the wage that is not due to a specific worker-firm match but that captures the general pay policy of the firm. The effects are supposed to remain constant during the period. Time-varying covariates X_{it} are limited to fixed effects for years and age as a cubic polynomial to avoid colinearity with years and generation effects (captured in individual fixed effects), following Card et al. (2013) and Sorkin (2018)[24]. u_{it} is the idiosyncratic error term. The interpretation of the estimated model rests on classic hypothesis that this residual has null expectation conditional on the explanatory variables, but also conditional on the design matrix (specifically the matrix of movements of individuals between jobs). This hypothesis is known as the "exogenous mobility assumption": wages idiosyncratic shocks are supposed to be independent of moves, or moves independent of wages shocks. The exogenous mobility assumption was not necessary to estimate the global value of firms, because the model presented in Section 4.2 allows mobility to depend on idiosyncratic shocks on utility (potentially driven by idiosyncratic shocks on the wage). This assumption might seem more credible for moves that are not chosen by workers (either because of an economic lay-off or the end of a fixed-term contract), *i.e.* mostly our ENE and "Other" moves. However, we decided to keep EE moves in the estimation of wage premiums in order to have enough moves to overcome the limited mobility bias.[25] Section 6.1.2 provides suggestive evidence that the exogenous mobility assumption is reasonable even for

[21] Because in our setting only workers with a permanent contract can experience an EE move, the size g_j is defined as the number of permanent contracts at firm j.

[22] We detailed our definitions of the moves in Section 2.

[23] Note that this identification assumption implies that we can only recover the value of firms that hire at least one worker from unemployment or from a fixed-term contract.

[24] It is not possible to separately identify the linear trends in year effects, age effects and generations of individual effects, so one has to constrain one of the three. Card et al. (2013)'s solution, that we replicate here, is to constrain the linear trend in age by using the $P = a(x-40)^2 + b(x-40)^3$ polynomial in age, based on the assumption that the age profile of wages is approximately flat at 40.

[25] EE moves represent 36% of the moves, so the network of mobility would be very affected if they were not included in the sample used to estimate the AKM decomposition.

EE moves, so that keeping them in the estimation of firm wage premiums is unlikely to bias significantly our results.

One can use the model to decompose the variance of log-wages into several components in order to interpret the dispersion of wages. Following Card et al. (2018) and Sorkin (2018), we consider an "ensemble" decomposition of the following form :

$$\underbrace{Var(w_{it})}_{\text{Variance of wages}} = \underbrace{Cov(\phi_i, w_{it})}_{\text{person effect}} + \underbrace{Cov(\psi_{j(i,t)}, w_{it})}_{\text{firm effect}} + \underbrace{Cov(X_{it}\beta, w_{it})}_{\text{covariates}} + \underbrace{Cov(u_{it}, w_{it})}_{\text{residual}} \tag{14}$$

The "ensemble" decomposition allows us to interpret the relative importance of person, firm and covariates effects in the variance of wages. In particular, the term corresponding to firms aggregates two ways by which firm-specific characteristics contribute to the variance of wages. Indeed, we have:

$$Cov(\psi_{j(i,t)}, w_{it}) = Cov(\psi_{j(i,t)}, \phi_i + \psi_{j(i,t)} + X_{it}\beta + u_{it}) \tag{15}$$

$$= \underbrace{Var(\psi_{j(i,t)})}_{\text{premiums}} + \underbrace{Cov(\psi_{j(i,t)}, \phi_i + X_{it}\beta)}_{\text{sorting}} \tag{16}$$

According to this simple decomposition, we see that firm-specific wage policies impact the distribution of wages in two ways: first, firms can pay premiums; second, firms can recruit specific types of workers, and the relation between the premiums and the types of workers recruited (the "sorting") impacts the distribution of the wages.

In order to dig into the "ensemble" decomposition and disaggregate the effects, we also consider a "variance" decomposition of the following form:

$$Var(w_{it}) = Var(\phi_i) + Var(\psi_{j(i,t)}) + Var(X_{it}\beta) + 2Cov(\phi_i, \psi_{j(i,t)}) + 2Cov(\phi_i + \psi_{j(i,t)}, X_{it}\beta) + Var(u_{it}) \tag{17}$$

In the next section we present the results of the estimation of firms' wage premiums and global values and how the two are related.

5 Results

5.1 Firms' wage premiums

We now present the results of the AKM decomposition to see how firms impact the dispersion of wages. Table 7 shows that the variance of the firm-effects accounts for 6% of the variance of log-wages. This result is very similar to the one found by Babet et al. (2023), with a share varying between 5.8% to 6.8% according to the period they consider (see Table 2 in Babet et al., 2023).[26] Overall, if we decompose the variance of log-wages according to the "ensemble" decomposition, we find that the heterogeneity between firms explains 12% of the variance of log-wages (13% if we restrict to the private sector), the 6 extra percentage points being due to sorting. Sorting means that workers that have more desirable characteristics on the labor market tend to work in firms that pay higher wages. Our results suggest that there is a strong positive sorting between high-paying firms and high-wage workers (the correlation between both effects is 0.26). Overall, the variance due to heterogeneous pay policies across firms is much smaller than the one due to heterogeneous types of workers but it is still significant. If we look at the

[26] Note that our results are not directly comparable to the ones presented in Babet et al. (2023) because in our study the sample of firms is more restricted (we focus on the strongly connected set of firms by EE moves). Moreover, Babet et al. (2023) focus on the evolution of the AKM decomposition over time, whereas we consider the 2005-2019 period as a whole.

same decomposition but estimated on the log annualized wages instead of on the log hourly wages, we find that firms explain a larger part of the variance (0.16 vs. 0.12). This result implies that the average number of hours worked per day is, at least partially, a firm characteristic (see Section E in Appendix for a proof). It can reflect for example a different use of part-time employment or overtime across firms. We discuss all the implications of this result in a specific section (see Section 5.2.3).

Table 7: AKM decomposition

	Hourly wages, all sectors (1)	Hourly wages, private sector (2)	Annualized wages, all sectors (3)
Ensemble decomposition (share)			
Firms	0.12	0.13	0.16
Persons	0.73	0.72	0.65
Xβ	0.04	0.05	0.07
Residuals	0.11	0.10	0.12
Variance components (share)			
Var. firm effect	0.06	0.06	0.10
Var. person effect	0.68	0.66	0.60
Var. Xβ	0.05	0.05	0.07
Var. residuals	0.11	0.10	0.12
2Cov(person, firm)	0.11	0.13	0.12
2Cov(Xβ, person+firm)	0	0	
Correlation person and firm effects			
Corr(person, firm)	0.26	0.32	0.24
Overall fit			
Adjusted R^2	0.87	0.87	0.85

Note : The private sector includes all firms that are not part of the public administration (so it includes state-owned companies). Columns (1) and (2) show the results of the AKM decomposition on the log-hourly wage. Column (3) shows the results of the AKM decomposition on the log-annualized wages (on all sectors).

5.2 Global values and wage premiums

5.2.1 Main results

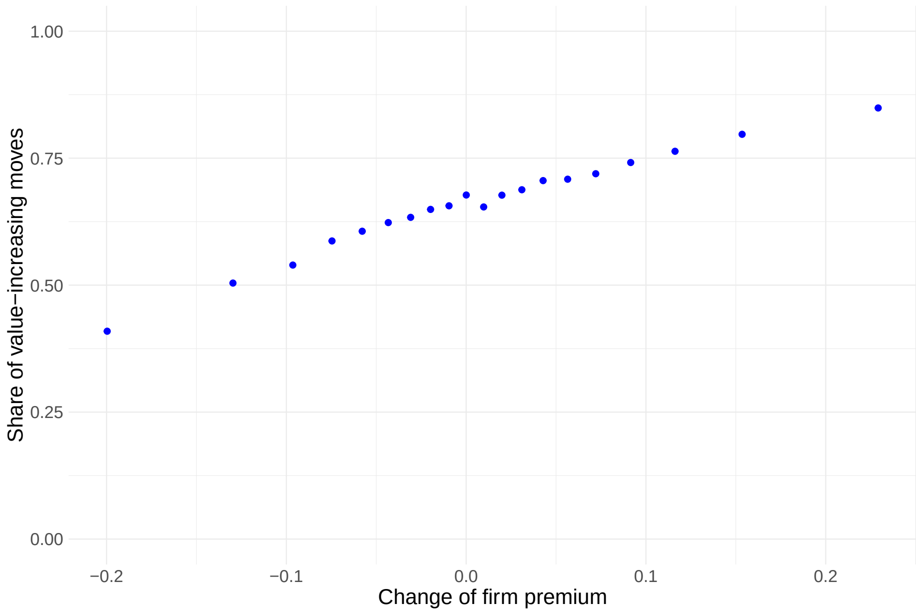
We now turn to the main empirical results of this paper. First, we find that wage premiums (pay) are approximately as much related to global values in France as in the US. The novelty of Sorkin's results was already to show that pay and value were not so much correlated (in the US, the correlation between the two rankings was 0.54, leading to a R^2 of 0.29). Table 8 shows that in France, this relation is even smaller (correlation is 0.44, leading to a R^2 of 0.19). Figure 3 illustrates this correlation, which is still effective: the probability of moving to a higher-value firm is much lower when there is an important negative change of wage premium than when there is an important positive change of wage premium. The first part of Table 8 shows that overall, the probability of ending in a better value firm when moving to a better-paying firm is 15 p.p higher than when moving to a lower-paying firm (0.66 vs. 0.51). This means that workers do value pay, but that pay is far from being the only determinant of mobility.

Table 8: Patterns of mobility and correlation between pay and value

	All sectors				*Private sector*			
	All	EE	ENE	Other	All	EE	ENE	Other
Proba(value ↑)								
Unconditional	0.59	0.66	0.59	0.52	0.60	0.67	0.59	0.52
When moving to a								
...higher-paying firm	0.66	0.73	0.68	0.60	0.67	0.73	0.68	0.60
...lower-paying firm	0.51	0.58	0.49	0.45	0.52	0.61	0.51	0.44
Correlations	Spearman (rank)	R^2	Comp. diff. share		Spearman (rank)	R^2	Comp. diff. share	
Value and premium	0.44	0.19	0.10		0.43	0.19	0.11	
Value and size	0.16				0.21			
Premium and size	0.26				0.36			

Note : **All sectors :** "All" includes 20.3 millions of moves. "EE" (employer-to-employer) includes 7.8 millions of moves. "ENE" (employer-to-nonemployment-to-employer) includes 3.4 millions of moves. "Other" (moves from a fixed-term contract) includes 9.1 millions of moves. **Private sector :** "All" includes 16.6 millions of moves. "EE" (employer-to-employer) includes 7.3 millions of moves. "ENE" (employer-to-nonemployment-to-employer) includes 3.1 millions of moves. "Other" (moves from a fixed-term contract) includes 6.2 millions of moves. The R^2 between the ranks of global values and wage premiums is obtained by taking the square of the Spearman correlation between these two ranks. The compensating differentials share is obtained by multiplying $1 - R^2$ by the share of the variance of the log-wage that is imputable to firms in the AKM ensemble decomposition (0.12 for all sectors and 0.13 for the private sector).

Figure 3: Proportion of value-increasing move according to the change of wage premium



Note: Only employer-to-employer (EE) transitions are taken into account. The transitions are sorted according to the change of wage premiums in 20 bins of equal number of transitions.
Reading note: When a worker moves to a firm paying a wage premium lower by 0.1 log-€ compared to her original firm, the probability that the new firm will have a higher global value than the original one is 54%.
Scope: All sectors.

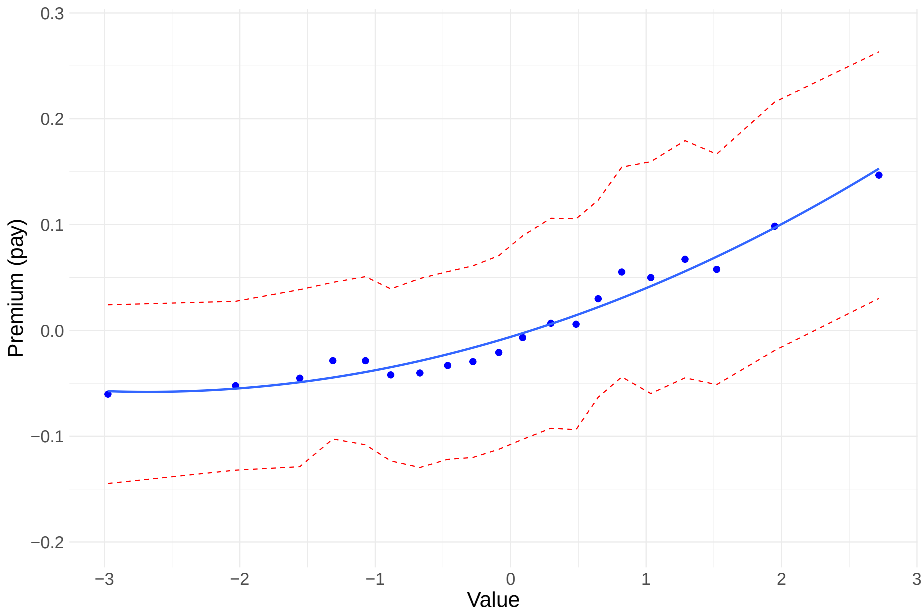
In order to assess the sensitivity of the results to the type of jobs taken into account, we repeat the whole method excluding jobs from the public administration.[27] We find that focusing on the private sector gives very similar results: the R^2 between wage premiums and global values' ranks is even exactly the same (0.19).

We directly illustrate the relation between pay and value in Figure 4. We sort the firm global values in 20 groups of equal size of workers and we compute for each group the median wage premium. The global

[27]We exclude all the jobs where the variable "employment domain" (*DOMEMPL*) corresponds to either central administration, local administration or hospital administration.

value of the firm is represented in the x-axis and has been normalized such that the median firm value is equal to 0. We also represent the standard errors of the wage premiums in each bin. We see a clear positive relation between value and pay, especially for the half of firms that are the most attractive.

Figure 4: Relation between pay and value



Note: The global value is normalized such that the median firm value is equal to 0. The firm global values are sorted in 20 bins of equal number of observations. For each bin we report the median wage premium. The solid line plots a quadratic fit. The red dashed lines correspond to +/- 1 standard deviation of wage premium in each value bin.
Reading note: Firms that are in the top vingtile of attractiveness pay on average a wage premium of 0.15 log-€, whereas firms that are in the bottom vingtile of attractiveness pay on average a wage premium of −0.05 log-€.
Scope: All sectors.

We now look at Figure 5 and Table 9 to relate the pay/value relationship to observables. These figure and table allow us to visualize the differences of pay and value across sectors.[28] They also allow to deduce easily which sectors offer good non-wage amenities (the sectors that pay little compared to their values, *i.e.* the sectors *below* the regression line in Figure 5 and in the last column of panel "best sectors" in Table 9) and which sectors offer compensating differentials (the sectors that pay a lot compared to their values, *i.e.* the sectors *above* the regression line in Figure 5 and in the last column of panel "worst sectors" in Table 9). For a given global value (*x-axis*), the amount of non-wage amenities that firms provide to equalize their value (Rosen motive, or *compensating differentials*) is identified by the variations of wage premiums (*y-axis*). For example, because the sectors of teaching and retail have similar global values, the difference between the wage premiums of these sectors corresponds to the monetary value of the difference of non-wage amenities between these two sectors. However, we cannot identify the amount of non-wage amenities that firms provide to augment their global value (Mortensen motive, or *augmenting differentials*). To see this, let us fix the firm wage premium (*y-axis*) and look at the variations of global value (*x-axis*). For example, let us look at the hotel/restaurant and the public administration sectors. These two sectors have similar wage premiums but very different global values, so there must exist important non-wage amenities in the public administration that explain this difference. However, we cannot infer the monetary value of the difference of non-wage amenities between the two sectors because we do not know the unit of conversion from global value to log-euro. This is why it is hard to quantify the amount of non-wage amenities in absolute terms: it is only possible to get the relative amount of non-wage amenities provided by firms that have a similar global value. For example, it is difficult to know the amount of non-wage amenities provided by the "Electricity and gas" sector because there is

[28] For both wage premiums and global values, the between-sector variance represents about 1/3 of the total variance across firms.

no sector that has a similar global value. Because this sector is far above the regression line, one might think that it offers poor non-wage amenities and compensate for this, but since it is also the most valued sector there can be an (undetermined) amount of non-wage amenities that are augmenting. Overall, this graph shows that the relation between attractiveness and pay is somewhat close to what we expect. For instance, sectors where jobs have a civic dimension and where employment is more protected (e.g. teaching and health) are sectors that pay little relative to their value. On the contrary, sectors where working conditions are likely to be difficult (e.g. manufacturing industry and construction) or where the intensity of work can be important (e.g. finance/insurance and information/communication) pay more relative to their value.[29]

The ranking of sectors in Table 9 also shows interesting results. First, it appears that the global value is related to pay: two of the five best paid sectors are also in the top-five values ("Electricity and gas" and "Coking and refining"), and one of the five worst paid sectors is also in the bottom-five values ("Private security").[30] However, this relation is only partial and attractiveness seems also related to other aspects of the jobs, as suggested by the presence of air transports in top-value sectors and hotel/restaurant and retail in bottom-value sectors. These other aspects are underlined when we look at the "Non-wage amenities" column, which has been obtained by first rescaling global values and wage premiums such that they have the same variance. The "best sectors" of this column correspond to sectors that are much more valued than expected given their pay (so they provide good non-wage amenities). They correspond to sectors with a high level of *savoir-faire* (leather and wood sectors) or with an important social commitment (social action). The "worst sectors" of this column correspond to sectors that pay much more than they are valued (so they provide lots of compensating differentials). They correspond to sectors where competition is important (movies and TV), or where working conditions are known to be difficult (restaurant).[31]

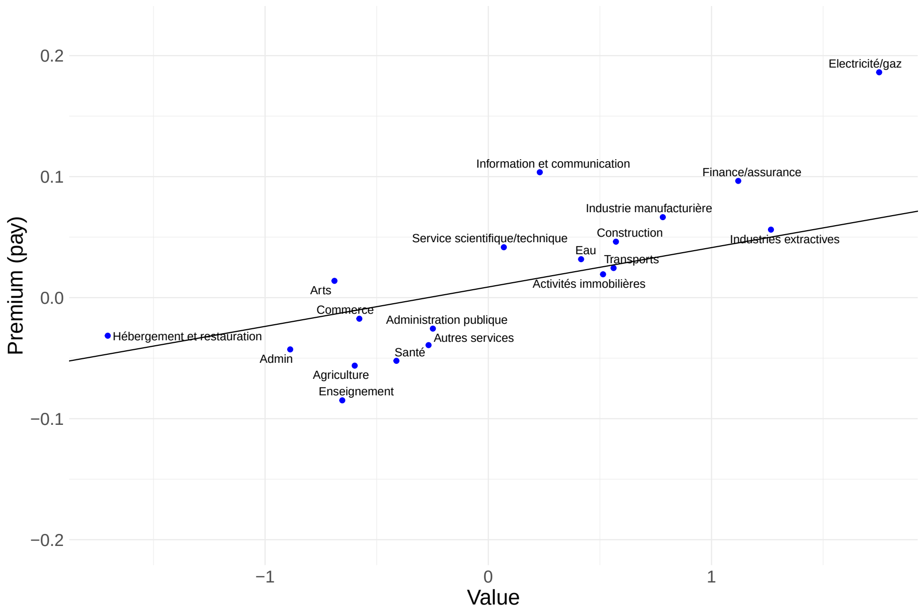
Another interesting result is the role of size as an indicator of quality. We find that the relation between pay and size (measured as the number of employees in the firm over the whole period) is much stronger in France than in the US (correlation = 0.26 vs. 0.07, see Table 8), and this relation is even stronger when we restrict to the private sector (0.36) because large public entities have low wage premiums. If we now look at the relation between global value and size, we find a much smaller relation (correlation = 0.16 in the whole economy and 0.21 in the private sector). The fact that the relation between value and size is smaller than the relation between pay and size suggests that bigger firms tend to compensate workers for working for them. In this perspective, part of the wage premiums of big firms that are often interpreted as rents (e.g. obtained because of market power) would correspond instead to compensating differentials.

[29] According to recent surveys on working conditions, the finance/insurance and information/communication sectors are those where workers most frequently report working more than 40 hours per week (42% vs. 31% on average) and not being compensated for overtime (74% in finance/insurance and 65% in information/communication, vs. 44% on average). The finance/insurance sector also has the highest percentage of workers reporting that they work under pressure (48% vs. 34% on average) and is second in the percentage of workers who must reach precise quantified goals (60% vs. 31% on average). However, other characteristics can also be more valued in these sectors, such as the opportunity to learn new things, for which the information/communication sector ranks first (92% vs. 78% on average). For more details, see https://dares.travail-emploi.gouv.fr/donnees/35-ans-devolutions-des-conditions-de-travail.

[30] The aggregation level of Table 9 is a 2-digits level, so it is formed of 77 sectors.

[31] For the sectors "Production de films, musique, TV" and "Arts", the global value might be downweighted by the fact that in these sectors the offer rate is very high because there are a lot of short-term contracts in exemption to ordinary job market regulations, stemming from the "intermittent du spectacle" status. The ratio between offer rates and size ($\frac{f}{g}$) is indeed high in this sector. For the other sectors presented in Table 9, we do not find any extreme link with $\frac{f}{g}$, suggesting that the rank is not driven by sectoral specific features in the recruiting or size structures.

Figure 5: Pay and value by sector



Note: The global value is normalized such that the median firm value is equal to 0. Wage premiums and global values are size-weighted averages by sector. The line plots the (size-weighted) linear fit obtained on firm-level data. Sectors are at the most aggregated level of *NAF rev.2* (1-letter level).
Reading note: The retail sector ("Commerce") has an attractiveness similar to the agricultural sector ("Agriculture") but pays around 0.05 log-€ more. This means that the compensating differentials in the retail sector compared to the agricultural sector amounts to 0.05 log-€.
Scope: All sectors.

Note:

Table 9: Ranking of sectors

	Global value	Wage premium (pay)	Non-wage amenities
Best sectors			
1	Transports aériens	Cokéfaction et raffinage	Industrie du cuir
2	Cokéfaction et raffinage	Programmation et diffusion	Action sociale
3	Fabrication de matériel de transport	Industrie pharmaceutique	Travail du bois
4	Électricité et gaz	Électricité et gaz	Transports aériens
5	Industrie automobile	Production de films, musique, TV	Transports terrestres
Worst sectors			
1	Restauration	Action sociale	Production de films, musique, TV
2	Production de films, musique, TV	Enseignement	Programmation et diffusion
3	Hébergement	Services personnels	Arts
4	Sécurité privée	Sécurité privée	Industrie pharmaceutique
5	Commerce de détail	Nettoyage	Restauration

Note : The column "Non-wage amenities" is obtained by first normalizing the wage premiums and the global values such that they have the same variance and then by taking the difference between these two normalized variables. The five "best" sectors of this column are those that offer the most non-wage amenities. The five "worst" sectors of this column are those that compensate workers (with pay) the most.
The sector "Services personnels" includes laundry, hairdresser, beauty care and funeral service. Sectors are at the second most aggregated level of *NAF rev.2* (2-digits level). Only sectors with more than 100,000 person-years are represented.

Finally, what are the implications of theses results in terms of wage inequalities? First, note that taking into account the existence of compensating differentials in the wage does not imply *a priori* that (unobserved) utility inequality is lower than wage inequality. To see this, suppose that those who earn more are also those who benefit from the best non-wage amenities. If we take into account the non-wage amenities in the computation of their utility, we will find that inequalities are higher than when only wages are considered. To see what is the effect of taking into account compensating differentials in wage inequalities, we compute for each firm the Rosen amount of amenities (as explained above, we cannot estimate the total amount of amenities provided by the firm because we cannot identify the Mortensen part). The Rosen amount of amenities is equal to the difference between the wage premium and the predicted premium given the global value of the firm (graphically, for a firm of a given value in the *x-axis* of Figure 5, the Rosen amount of amenities is equal to the vertical distance between the wage premium of the firm and the regression line, so it can be either positive or negative). We then add this monetary-valued amount of amenities to the log-wage and see how the variance evolve. The variance of log-wages is 0.18 without adjusting for non-wage amenities and 0.16 when making this adjustment, suggesting that compensated wage inequalities are actually 11% percent lower. Again, this result is limited by the fact that augmenting amenities cannot be measured here, even though they might tend on the opposite to increase utility inequalities. Recent evidence from the US using a series of stated-preference experiments (Maestas et al., 2023) show for instance that taking into account non-wage amenities leads actually to increase the measure of wage inequality.

5.2.2 Heterogeneity among types of workers

So far we have assumed that workers differ in their valuation of firms only due to idiosyncratic shocks. However, this hypothesis is unlikely to hold in practice. Recent work on the importance of non-wage amenities show that people have heterogeneous preferences across different socio-demographic groups (see e.g. Mas and Pallais, 2017, Maestas et al., 2023, Rousille and Scuderi, 2021, and Coudin et al., 2018 or Le Barbanchon et al., 2020 for France). In order to see how the relation between attractiveness and pay differs across groups, we split our sample accordingly and run the whole model (*i.e.* both AKM and the PageRank) separately for each group. Note that this leads to more biased estimates because the estimation bias decreases with the sample size. However, it is possible to get an order of magnitude of how the sample size impacts our results by splitting randomly our sample (see Section 6.3). We can therefore use this as a benchmark to better interpret heterogeneity across groups. We look at the heterogeneity across four dimensions: gender, age, skills and period.

Our results are summarized in Table 10. First, the results confirm that socio-demographic groups are heterogeneous in the way they value firms. For example, the correlation between the ranking of firms established according to the flows of younger workers (below 35) only vs. older workers (above 35) only is 0.72. Similarly, global value evolves with time and differs also with gender and other unobserved individual characteristics. Second, the heterogeneity of firm wage premiums between sub-groups is less pronounced than the heterogeneity of firm global values. We also find that firms' wage premiums are quite persistent over time (the correlation between periods is 0.80), consistently with Lachowska et al. (2022). Third, the relation between wage premiums and global values also varies across subgroups, suggesting that all workers do not value non-wage amenities in the same proportion. Interestingly, we find that women value much more non-wage characteristics of the jobs ($R^2 = 0.15$ for women vs. 0.22 for men). Note that this is not due to sample noise being more important in the "women" sub-sample because the ratio between the number of moves and the number of firms is similar in the two sub-samples.[32] This finding is consistent with studies that account for gender-specific preferences for non-wage amenities in the explanation of the gender-pay gap and show that women tend to value more flexibility (Goldin, 2014, Wiswall and Zafar, 2017, Xiao, 2021) and child-friendly environments (Kleven et al., 2019). In France, Coudin et al. (2018) show that 11% of the gender wage gap can be explained by the fact that women tend to work in firms with lower wage premiums and better non-wage amenities (flexibility and accessibility). Similarly, Le Barbanchon et al. (2020) show that women tend to value short commute more than men. When we look at the heterogeneity between age groups, we find that older workers tend to value more non-wage amenities than young workers. Again, this is not due to different levels of precision during

[32]Section 6.3 shows that the heterogeneity revealed by comparing sub-samples is not a pure artefact due to the presence of noise, even if noise explains part of the differences. Indeed, when splitting the data randomly instead of according to socio-demographic groups, we find a much closer relationship between ranks of both sub-samples.

the estimation because we chose age 35 such that the dataset is separated in two sub-samples of equal number of moves. We also find that non-wage amenities matter a bit more for workers whose personal characteristics are less valued in the labor market (defined as workers with a small estimated AKM individual-effect). Finally, we do not observe an increasing importance of non-wage amenities during the period of study. The results stating that young people do not exhibit higher preferences for non-wage amenities and that there is no apparent increasing trend in the importance of non-paid dimensions of the jobs may seem surprising given the context of "vocational crisis", recently documented by a serie of surveys.[33] We posit that such evolution, partly related to the Covid-19 pandemic crisis, is too recent to be observed in our data, but relating the evolution of the ranking of firms with this social phenomenon will be a promising avenue for future research.

Table 10: Heterogeneity of the relation between pay and value

	R^2(value, premium)	$\frac{\text{Nb.moves}}{\text{Nb.firms}}$
All	0.19	30.4
Gender		
Men	0.22	21.4
Women	0.15	19.2
Age		
Young $(15-35)$	0.24	18.4
Old $(36-64)$	0.18	19.9
Worker effect		
Low	0.10	17.9
High	0.14	22.1
Period		
Before 2012	0.15	19
After 2012	0.19	21.8
	Corr. premiums	Corr. values
Men and women	0.88	0.81
Young and old	0.83	0.72
Low and high worker effect	0.78	0.66
Before and after 2012	0.80	0.69

Note : "Low" (resp. "High") refers to workers whose AKM individual fixed-effect ($\hat{\phi}$) is below (resp. above) the median AKM individual fixed-effect.
The correlations reported at the bottom of the table are calculated on the sub-sample of firms that are common to the two groups in the corresponding row.

5.2.3 Role of hours worked

So far we have presented results obtained on the hourly wage in order to rule-out potential changes in the number of hours worked when people experience an EE move. Therefore our results are not directly comparable to Sorkin (2018) because we do not calculate wage premiums on the same variable. According to Sorkin (2018), taking into account the number of hours worked (as we did so far) should lead to find a closer relationship between attractiveness and pay, by correcting for one source of compensating differentials.[34] The reasoning behind this suggestion is that firms that are identified as lower-paying firms on the annualized wage also tend to be firms where people work less (because working less means being

[33] See e.g. https://www.lemonde.fr/economie/article/2022/07/12/penurie-de-main-d-uvre-demissions-a-la-chaine-ou-sont-passes-les-salaries_6134394_3234.html.

[34] Sorkin (2018) (p.1381): "I observe earnings and not hours, and so a low-earnings job might just be a low-hours job. [...] I conclude that while some of the compensating differential is variation in hours, it is unlikely to be the main compensating differential."

paid less if one looks at the annualized wage rather than the hourly wage). Therefore, part of the EE moves that are toward lower-paying firms in annualized wage are not necessarily toward lower-paying firms in hourly wage, which can lead to underestimate the relation between wage premiums (pay) and global values. But what Sorkin (2018) does not mention is that the reverse is also true: if part of the EE moves that are toward lower-paying firms in hourly wage but not in annualized wage, reasoning with the hourly wage can lead to underestimate the relation between pay and value. Determining what variable leads to a closer alignment between pay and value is an empirical question and only depends on whether people move more frequently toward firms that pay smaller hourly wages (in this case pay and value will be less related when taking the hourly wage rather than the annualized wage) or toward firms that pay smaller annualized wage (in this case pay and value will be more related when taking the hourly wage rather than the annualized wage). Section 3.3 already showed that the former is true, *i.e.* that people are less likely to experience an annualized wage cut than an hourly wage cut. To assess its implication on the relative share of compensating differentials in the variance of wages, we simply recalculate firms' wage premiums on the annualized wage and we compare them with the firms' global values obtained previously.[35]

First, as mentioned in Section 5.1, taking the annualized wage rather than the hourly wage leads to estimate a higher share attributed to firms in the variance of wage premiums (column (3) of Table 7). This suggests that the number of hours worked per day is not uniformly distributed among firms. Indeed, we show in Section E of Appendix that if the number of hours worked were uniformly distributed among firms and workers, changing from hourly wage to annualized wage would lead to the same AKM estimation. We also show that if the number of hours worked was only worker-specific, we would see an increase of the share attributed to the firms under the very implausible case where workers who work long hours receive a much lower hourly wage than workers who work few hours (e.g. part-time). Therefore, the number of hours worked is likely to be - at least partially - a firm characteristic (e.g. through the propensity to use part-time employment, to propose overtime to the workers, ...). This implies that estimating wage premiums on annualized wage instead of hourly wage leads to count as a pay characteristic what is actually a non-pay one, as Sorkin (2018) suggested.

To confirm that the number of hours worked is indeed a firm-characteristic, we run an AKM-style model on the log of the number of hours worked. This model is subject to the same limitations as a traditional AKM decomposition. For instance, it is likely that worker-effects on the number of hours are not time-invariant but depend on the life-cycle (e.g. by looking for part-time only when having young children). Nevertheless, because age is included as a covariate, we expect that this concern is of limited importance. Table E.3 in Appendix shows that 15% of the variance of the (log) number of hours worked can be attributed to firms. Note that the overall fit of this AKM-style decomposition is much smaller than for the log hourly wage or the log annualized wage ($R^2 = 0.57$ vs. 0.87), so this share should be more taken as an indicator that firms play a significant role in determining the number of hours worked than as a perfect estimation of this role.

We now show how the relation between wage premiums (pay) and global values is affected by considering annualized wages rather than hourly wages. Table 11 shows that the relation between pay and value is stronger than when the pay was measured in hourly wage: the probability to move to a more attractive firm differs more between moves to higher-paying firm and lower-paying firms than when pay was measured in hourly wage (difference $= 0.68 - 0.48 = 0.20$ with annualized wage vs. $0.66 - 0.51 = 0.15$ with hourly wage). Moreover, the correlation between wage premiums and global values rises to 0.52 when pay is measured by the annualized wage (vs. 0.44 when pay is measured by the hourly wage, see Table 8), lowering the relative share of compensating differentials (that include now variations of hours worked)

[35]Note that it is not necessary to repeat the value estimation step because value only depends on the moves, which are not affected by the change of variable for the wage.

in the variance of wage premiums (and symmetrically increasing the relative share of rents). However, because the share attributed to firms in the total variance of wages is estimated to be higher with the annualized wage than the hourly wage, the share of compensating differentials in the variance of wages is finally higher when taking this variable (12% vs. 10% with the hourly wage).

How can we interpret these results? The fact that pay and attractiveness are more closely aligned when taking the annualized wage suggests that workers value more full-time jobs and/or overtime, as already suggested in Section 3.3. This result contradicts Sorkin's intuition that the possibility of working less being perceived as a positive amenity would lead to overestimate the relative share of compensating differentials when taking the annualized wage rather than the hourly wage. This might be due to the fact that when people work part-time, it is often suffered and so it could actually be that it is the possibility of working *more* that is perceived as a positive amenity.[36] Consistently, recent survey in France show that in 2022, 26% of part-time workers reported being in their position primarily because they could not find full-time employment (see Insee, 2023). This preference for full-time jobs has also recently been documented in the US in a stated-preference approach (see Mas and Pallais, 2017).

Finally, we look directly at the correlation between the number of hours worked, the proportion of part-time and the global value of a firm to confirm this interpretation. Table 11 shows that there is a strong correlation between the global value and these observables, in a direction that is very consistent with our previous interpretation. The correlation between the ranks of the global value and the number of hours worked per day is 0.37. It is even more clear when we look at the correlation between the ranks of the global value and the propensity to have part-time jobs (−0.41). Finally, to be consistent with our measure of the correlation between value and pay, we evaluate the correlation between the global value and the firm fixed-effect obtained in the AKM-style decomposition on the log of the number of hours worked per day (see above). Here again we find a positive correlation of 0.31.

Table 11: Patterns of mobility and correlation between pay and value (annualized wage)

	All sectors			
	All	EE	ENE	Other
Proba(value ↑)				
Unconditional	0.59	0.66	0.59	0.52
When moving to a				
...higher-paying firm	0.68	0.73	0.70	0.61
...lower-paying firm	0.48	0.57	0.45	0.43
Correlations	Spearman (rank)	R^2	Comp. diff. share	
Value and premium	0.52	0.27	0.12	
Premium and size	0.19			
Value and *nb. hours*	0.37			
Value and *% part-time*	−0.41			
Value and ψ_{hours}	0.31			

Note : "All" includes 20.3 millions of moves. "EE" (employer-to-employer) includes 7.8 millions of moves. "ENE" (employer-to-nonemployment-to-employer) includes 3.4 millions of moves. "Other" (moves from a fixed-term contract) includes 9.1 millions of moves.
The compensating differentials share is obtained by multiplying $1 - R^2$ by the share of the variance of the log annualized wage that is imputable to firms in the AKM ensemble decomposition (0.16).
The number of hours refers to the number of hours per day. Part-time is defined as working less than 30 hours/week.
ψ_{hours} is the firm fixed-effect obtained by an AKM decomposition of the log of the number of hours worked per day.

[36] Interestingly, this is also what Sorkin (2018) mentions when citing Smith in footnote 36 of p.1381, but he considers that this explanation is less credible than the other.

6 Robustness

6.1 Are firms' wage premiums well estimated?

Our results assume that the AKM decomposition is effective to identify heterogeneous wage policies across firms. We now discuss three main limitations of the AKM model (limited mobility bias, exogenous mobility assumption and model specification) and how we try to overcome them.

6.1.1 Limited mobility bias is reduced by sample size and connectivity

The limited mobility bias has been proved to be a very important issue when estimating AKM-style models. Bonhomme et al. (2023) showed that many studies strongly overestimate the role of firms and underestimate the role of sorting in the variance of wages (some studies even find wrong-signed estimates for the covariance between worker and firm effects). The origin of this bias is known and is due to too little mobility between employers. To illustrate this, Bonhomme et al. (2023) plot the bias according to the number of movers and find a strong negative relation. This is why the use of an exhaustive panel is so crucial to estimate an AKM decomposition. The gains made possible by this exhaustive panel compared to the "small panel" that was used in the seminal paper of Abowd et al. (1999) have already been described by Babet et al. (2022) and are impressive.[37] We show that imposing additional restrictions on the size of the firms and on their connectivity allows to further reduce the bias. Table C.2 in Appendix reports results without imposing these restrictions and shows that, compared to our preferred estimates in column (1) of Table 7, the share of the variance attributed to firms is 50% higher. The downward bias for sorting is more limited (less than 10%), but overall the share attributed to employers is overestimated by 17%. The reason why we are confident that our preferred results have little bias is that they are very close to AKM estimations that directly correct for the limited mobility bias. First, Babet et al. (2022) apply a split-sampling method and find that the sorting accounts for about 12% of the variance of wages (we find 11%). We also directly correct for noise ourselves by using also a split-sampling method and find that the results are unchanged.[38] We also estimate shrunken estimates (which separate the variance due to noise from the true variance) and impose further sample size restriction and find in both cases that the share attributed to firms is left unchanged (see Section 6.3). Finally, our estimates are very close to other bias-corrected estimates on similar countries and data. Using several correction methods, Bonhomme et al. (2023) find that for European countries, the share of wage premiums in the variance of earnings ranges between 5-15% (we find 6%) and the correlation between worker and firm effects ranges between 0.24-0.34 (we find a correlation of 0.26 with all sectors and 0.32 with only the private sector). The reason why our results are close to bias-corrected estimates even when we do not correct for the bias is that this bias is mainly due to small and poorly connected firms, that we excluded from our sample. In our final sample, we have on average 51 movers per firm, which is huge compared to other studies and explains why our results are likely to be unbiased.[39]

Finally, the impact of the limited mobility on our main results is channeled by adding noise to the measure of wage premiums, thus decreasing the share of wage premiums' variance that is explained by firms' global values. We directly control for this effect in Section 6.3.

[37] Until very recently this "small panel" was the only available French matched employer-employee dataset that allowed to follow workers through time.

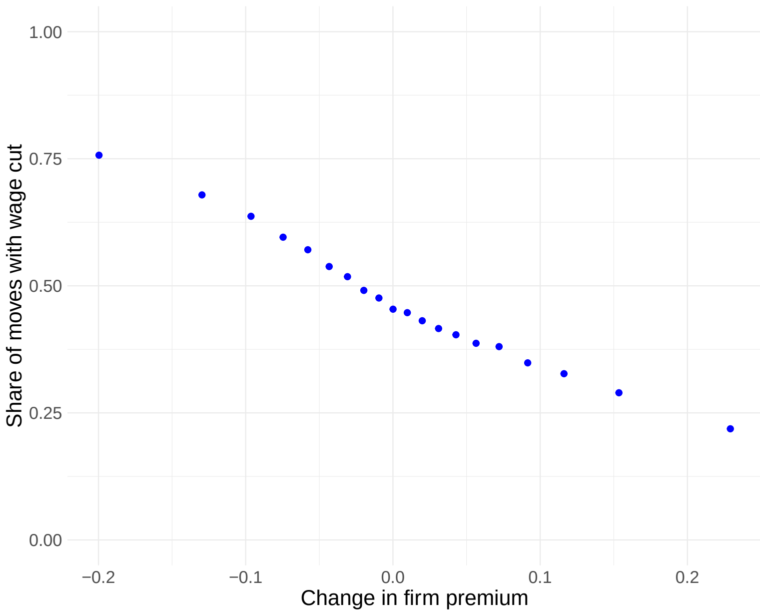
[38] In Babet et al. (2023), the split-sampling method does change the results because their sample include much smaller firms than ours, since we impose stronger restrictions on the size and connectivity of the firms.

[39] For instance, Bonhomme et al. (2023) find that bias-corrected methods give only small gains of precision in a subset of firms that have more than 15 movers; Lachowska et al. (2022) find that in their sample, the bias becomes relatively small (around 10%) when there are more than 11 movers per firm on average.

6.1.2 Exogenous mobility assumption : some reassuring evidence

Even if the fact that we find a modest role of the firm in the variance of log-wages is reassuring about the validity of our AKM estimation, it could also suggest that firms' wage premiums play a negligible role in the determination of wages and that they are not related to the individual wage dynamics that movers experience. Figure 6 suggests that the opposite is true: the probability of experiencing a wage cut when moving to a lower-paying firm (*i.e.* a firm with a lower wage premium ψ) is much higher than when moving to a higher-paying firm. For instance, the probability of experiencing a wage cut in the 5% lowest negative change of wage premium is 0.75, whereas the same probability in the 5% highest positive change of wage premium is only 0.22 (Figure 6). Table 12 also illustrates that the probability of experiencing a wage cut is closely related to the change of wage premium. This close relationship between individual wage gaps and firms' wage premiums is not mechanical and directly supports the validity of the exogenous mobility assumption, as explained by Card et al. (2013) and Sorkin (2018). Indeed, if the residual component of the wage was driving mobility, wage cuts should be much less frequent (including when the moves are toward lower-paying firms).

Figure 6: Proportion of wage cuts according to the change of wage premium



Note: Only employer-to-employer (EE) transitions are taken into account. The transitions are sorted according to the change in firm wage premium in 20 bins of equal number of transitions.
Reading note: When a worker moves to a firm paying a wage premium lower by 0.1 log-€ compared to her original firm, the probability that she experiences a wage cut is 63%.
Scope: All sectors.

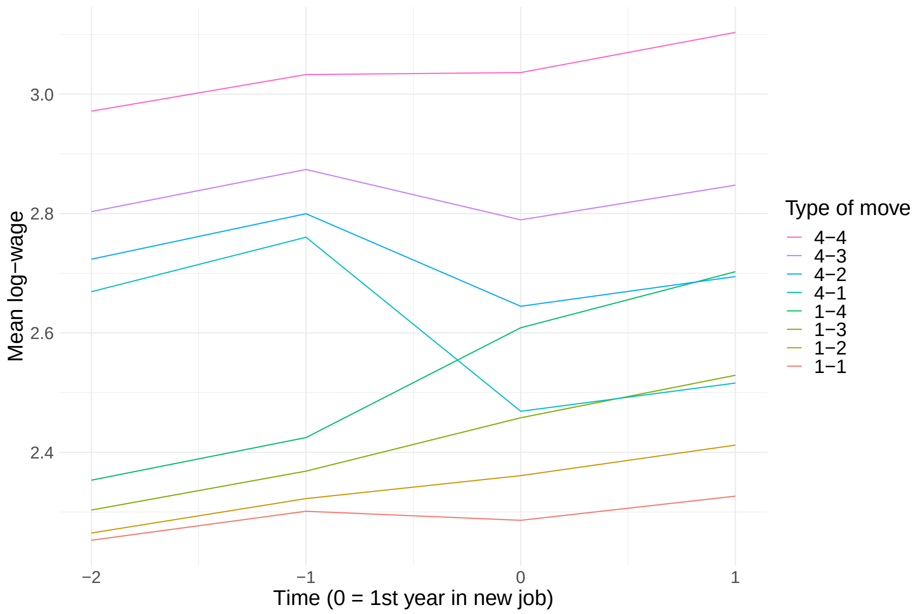
Table 12: Wage gaps and firm wage premiums

	All	EE	ENE	Other
Proba(premium $\uparrow$)				
Unconditional	0.51	0.53	0.51	0.49
Proba(w $\downarrow$)				
When moving to a				
...higher-paying firm	0.37	0.37	0.39	0.37
...lower-paying firm	0.61	0.58	0.65	0.61

Note : "All" includes 20.3 millions of moves. "EE" (employer-to-employer) includes 7.8 millions of moves. "ENE" (employer-to-nonemployment-to-employer) includes 3.4 millions of moves. "Other" (moves from a fixed-term contract) includes 9.1 millions of moves.

Figure 7 also suggests that the exogenous mobility assumption seems to be satisfactory. This figure plots the average log-wage around the year of a change of employer for eight types of moves, combining the wage premium quartile of the original firm with the quartile of the arrival firm: for instance, the "4-4" type gathers the moves going from a firm belonging to the top-quartile of wage premiums to another firm belonging to this quartile; whereas the "4-1" gathers the moves going from a firm belonging to the top-quartile of wage premiums to a firm belonging to the bottom-quartile of wage premiums. We see that workers who move to lower and higher-paying firms have similar pre-trends and post-trends, so different types of mobility do not seem to be driven by different quality of matches before the move. The fact that we observe important wage growth rates before and after the move is therefore more likely due to the measurement issue we discussed in Section 3.4 than to the quality of the matches.[40]

Figure 7: Event study of wage changes



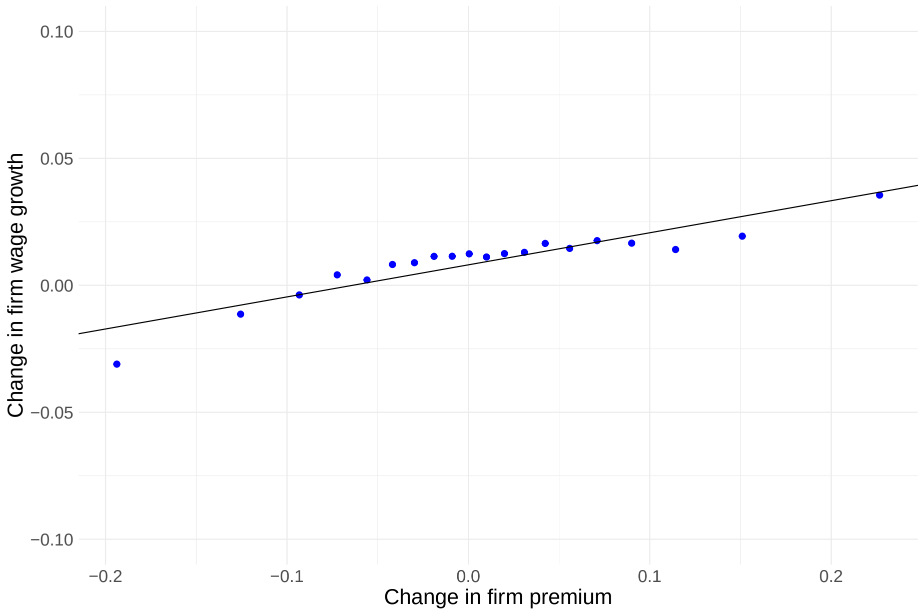
Note: Only employer-to-employer (EE) transitions where the worker is observed at least two years before and after the move are taken into account.
Reading note: When a worker moves from a firm in the top quartile of wage premiums to a firm in the bottome quartile of wage premiums, her wage falls on average by approximately 0.27 log-€.
Scope: All sectors.

Finally, we show that moves toward lower-paying firms are not driven by expectation of a higher wage in the future. To show this, we plot the change in the growth rate of the wage - for workers who are observed at least two years before and after an EE transition - with respect to the change of wage premium. Figure 8 shows that the relation between the change of wage growth and the change of wage premium is actually positive.

Overall, these results suggest that firms' wage premiums do play a role in the wage change of people who voluntarily move, and that this role cannot be rationalized by the future path of the wage.

[40] Indeed, models that allow for endogenous mobility explain moves by *negative* idiosyncratic shocks on the wage preceding the moves, but we saw in Section 3.4 that movers experience *positive* shocks on their wages just before they move.

Figure 8: Change of wage growth according to the change of firm-effect



Note: Only employer-to-employer (EE) transitions where the worker is observed at least two years before and after the move are taken into account. The transitions are sorted according to the change of wage premium in 20 bins of equal number of transitions. For each of these bins we plot the average change of wage growth experienced by the movers. The line plots the linear fit obtained on individual-level data.
Reading note: When a worker moves to a firm paying a wage premium lower by 0.1 log-€ compared to her original firm, her wage growth in the new firm will be similar to her wage growth in the original firm.
Scope: All sectors.

6.1.3 Model specification: discussion

The first characteristic of AKM is that worker and firm effects are additively separable. However, there is *a priori* no reason to think that firms pay similar wage premiums to all their employees, and it could be the case that specific workers receive a bigger/smaller wage premium than others. To see how reasonable is the assumption of additive separability, Bonhomme et al. (2019) estimate a model with non-linear interaction terms between worker and firm effects and find similar results. This suggests that additive separability is a reasonable assumption.

A second important concern that arises when we look at the specification of the model is that it assumes that worker and firm effects are time-invariant. Again, this assumption has been found to be reasonable in a recent study of Lachowska et al. (2022). By analyzing a long panel of 13 years in the Washington state, the authors show that firm fixed-effects are remarkably persistent over time. Because our panel is of similar length (15 years), we are confident about the validity of the time-invariant assumption in our setting. As mentioned in 5.2.2, we check ourselves the persistence of wage premiums over time by splitting the period in two (before/after 2012) and show that wage premiums are highly correlated between the two periods (correlation = 0.80, see Table 10). It suggests that firms' wage premiums, though not time-invariant, are persistent enough to pool all the years together.

6.2 Do unobserved lay-offs explain why the correlation between global values and wage premiums is so weak?

Our estimation strategy of firm global values relies on the crucial assumption that EE moves are really chosen. However, some of the EE moves are in fact lay-offs, simply because some lay-offs from permanent contract are not followed by an unemployment spell. In order to assess how unobserved lay-offs might overestimate the estimated share of compensating differentials in the variance of wages, we follow Sorkin (2018) in using firm size variations across years to identify lay-offs. More precisely, we assume that part of the EE moves coming from a firm j are not due to its relative value or to individual-specific shocks (e.g. lay-offs for individual motive, that are captured by the idiosyncratic term ι), but to its economic performance.[41] We assume that this type of lay-offs occurs only during the years when the firm is contracting. To determine the magnitude of these lay-offs in the observed exit flows of a firm, we compare the separation rate when the firm is expanding to the separation rate when the firm is contracting. The difference between these two rates is not interpreted as chosen moves but as lay-offs. Formally, we just downweight the outflows of the firms that are contracting by a factor proportional to this difference (more details are provided in Section D in Appendix). In this way, a move occurring during years when the firm is contracting will count less in the estimation of the firm global value, because in those years some of the moves are probably lay-offs. Table 13 shows that accounting for lay-offs in this way ("method 1") does yield higher correlation between global values and wage premiums (0.47 vs. 0.44), but the results remain very similar.

An alternative way of dealing with unobserved lay-offs would consist simply in removing from the data the outflows of firms that are contracting by too much. However, this procedure would yield two problems: first, it is not easy to define a threshold from which we ignore the observations (negative growth rate? -10 %? ...); second, simply removing the observations has an impact on the whole network structure and leads to estimate the ranking on a smaller sample, which increases noise. For sake of completeness, we still compute the ranking of firms with this method ("method 2") and show that it does not fundamentally affect our results (see Table 13).

Table 13: Correlation between global values and wage premiums when accounting for lay-offs

	Spearman corr. (rank)	Comp. diff. share
Values and premiums		
Baseline	0.44	0.10
Method 1: downweighting flows	0.47	0.09
Method 2: restricting flows $[-10\%, +20\%]$	0.50	0.09

Note : Baseline recalls the results presented in Section 4.2.
Method 1 computes the global value of the firm adjusting for potential lay-offs as explained in Section D in Appendix.
Method 2 computes the global value of the firm estimated only in years when the firm growth of the leaving firm is larger than -10% and the one of the receiving firm is smaller than $+20\%$.
The compensating differentials share is obtained by multiplying $1 - R^2$ by the share of the variance of the log hourly wage that is imputable to the firm-effect in the AKM ensemble decomposition (0.12).

Overall, we conclude from these two alternative methods that ignoring potential lay-offs do lead to underestimate the relation between attractiveness and wages (*i.e.* to overestimate the role of compensating differentials in the variance of wages), but this bias is small: compensating differentials explain 9% of the total variance of wages vs. 10% without correcting for potential lay-offs.

6.3 Does estimation noise explain why the correlation between global values and wage premiums is so weak?

As emphasized by Sorkin himself, noise mechanically leads to overestimate the role of compensating differentials compared to rents.[42] This is because noise in the estimation of wage premiums and global values leads to an attenuation bias when one is regressed on the other. Because the amount of compensating

[41] The types of lay-offs we have in mind in the French context are the lay-offs for economic motive or the *ruptures conventionnelles* when these are a way for the firm to reduce its labor demand in order to face a negative shock.

[42] Sorkin (2018) (p.1369): "[...] the empirical exercise in this article reduces to computing the R^2 between the values and earnings, so noise in either term biases me toward finding a larger role for compensating differentials."

differentials is higher when the correlation is lower, noise mechanically leads to overestimate the role of compensating differentials. To adress this issue, Sorkin proposes three methods that allow to account for noise and show that his results are robust to this concern. However, it is possible that our estimations of wage premiums and global values are more noisy than in Sorkin (2018) because worker mobility is more important in the US than in France (the share of people with more than a single employer during the period is 37% in our data, and 50% in Sorkin's data). To assess the importance of noise in the French data, we reproduce the three correction-methods proposed in Sorkin (2018). All these methods aim at reducing the variance of the quantities estimated (both for wage premiums and global values) and then compute a new correlation between these quantities using the corrected variances in the denominator.[43] In order to get an upper bound of the R^2 between global values and wage premiums (*i.e.* a lower bound of the share of compensating differentials in the variance of wages), we also correct for noise due to unobserved lay-offs ("method 1" presented above and in Section D in Appendix).

The first method consists to shrink the estimates of wage premiums and global values, following the method first proposed by Morris (1983). The idea of this method is to separate the part of the variance that is due to noise from the "true" variance. To do this, we first estimate the variance due to noise by bootstrap.[44] Then we estimate the "true" variance of the estimates by downweighting the noiser observations and removing the part of the variance attributed to noise. Finally we re-estimate the correlation coefficient with these adjusted variances. Table 14 shows that the R^2 do increase when we correct for noise ($R^2 = 0.27$ vs. 0.22 without adjustment), but the order of magnitude is unchanged. Note also that the share attributed to firms in the variance of wages is left unchanged by the correction.

The second method randomly splits the sample in two sub-samples with mutually exclusive workers. We then estimate AKM and the PageRank on both sub-samples and we compare the respective rankings. In the absence of noise, we expect that the rankings estimated in both sub-samples are perfectly similar because workers have been allocated randomly in the two sub-samples. Therefore, the discrepancy between the two rankings gives us an estimation of the amount of noise. We thus adjust the variance of the wage premium and global value rankings by the respective correlation coefficients between the two sub-samples. We find that the R^2 between wage premiums and global values increases by 3 percentage points when applying this method ($R^2 = 0.25$ vs. 0.22 without adjustment). Again, the share attributed to firms in the variance of wages is left unchanged by the correction. The split-sampling method also allows to make sure that the heterogeneity discussed in Section 5.2.2 is not a pure artefact due to the presence of noise. For example, the correlation between the rankings of global values between men and women is only 0.81, whereas we would expect it to be 0.86 if there was no heterogeneity. The presence of heterogeneity is even more obvious among the other groups.

The third method consists in re-estimating AKM and the PageRank on a subset of very large firms, that are less likely to be affected by noise. Instead of selecting firms that have more than 90 non-singleton person-years, we restrict to firms that have more than 1,000 non-singleton person-years (the sample falls to 27,000 firms). We find that the share attributed to firms in the variance of wages is slightly smaller (0.10 vs. 0.12) and that the relation between wage premiums and global values is larger ($R^2 = 0.31$ vs. 0.22).[45]

Overall, the maximum correlation we get when adjusting for noise (and potential lay-offs) implies a decomposition of the variance of wage premiums that attributes 69% to compensating differentials and 31% to rents (instead of 81% and 19% without any adjustment), and an overall share of compensating

[43] Because the correlation decreases with the variance, these methods lead to re-estimate upwards the correlation.

[44] Because of computational costs, we only draw 40 replications.

[45] Note that comparisons on different samples of firms are not perfectly suitable to infer the amount of noise: here, part of the explanation of the decrease of the importance of compensating differentials when considering very large firms could be that working in a smaller firm is seen as a positive non-wage amenitie, as suggested in Section 5.2.1. This R^2 of 0.31 is therefore likely to capture different effects, and should be seen as an implausible higher bound.

differentials in the total variance of wages of 7%. Our conclusion that compensating differentials account for a significant part of the variance of wages is therefore left unchanged by these adjustments.

Table 14: Adjusting for noise

	$\frac{Cov(w,\psi)}{Var(w)}$	$R^2(\psi, V^e)$	Comp. diff. share
No adjustment	0.12	0.22	0.09
Shrinkage	0.12	0.27	0.09
Split-sampling	0.12	0.25	0.09
Large firms (>1,000 obs.)	0.10	0.31	0.07
	$Corr(\psi)$	$Corr(V^e)$	
Split-sampling	0.94	0.86	

Note : V^e corresponds to the global value of the firm when we adjust for its relevant size, its offer rate and for the potential lay-offs, as explained in sections 6.2 and D. ψ corresponds to the firm-effect obtained in the AKM decomposition. The compensating differentials share is obtained by multiplying column (1) by $1-$ column (2).
The correlations reported at the bottom of the table are calculated on the subsample of firms that are common to the two groups obtained with the split-sampling.

6.4 Is the method sensitive to the definition of the transitions?

So far we have focused only on a strict definition of EE moves, which implies in particular that a worker has to have a permanent contract to be considered as a potential mover. We believe that this restriction is relevant in order to identify plausible voluntary moves. However, it might be interesting to see how the results are sensitive to this definition. Indeed, it could be the case that such information is missing in other datasets, and in this case it is important to know whether the application of the method is still relevant or not.[46] To see how the type of transition considered affects the ranking of firms and the conclusions about the importance of compensating differentials in the variance of wages, we add to the EE moves all the moves with a non-permanent contracts that are not followed by a period of non-employment. Then, we re-estimate the global value of firms with this new transition matrix.[47] Note that because more moves are taken into account, the identifiable set of firms is bigger than previously. To ensure comparability between the two sets of firms, we look at the correlation between wage premiums and global values on our original sample of firms. We also restrict to the private sector because permanent contracts are not coded the same in the public sector so the effect of pooling all the contracts is less straightforward. The results of this exercise are presented in Table 15 (see row "EE + fixed-term contracts (2)"). We see that the conclusions are unchanged when we consider all the job-to-job transitions instead of only the job-to-job transitions with a permanent contract. Moreover, the rankings obtained with or without this restriction are very similar (correlation = 0.93). This suggests that it might not be necessary to have complete information on the type of contracts. We believe however that it might still be relevant to include this variable in the definition of the EE transitions because we got the same results with much more moves per firm (on average there are 45 moves per firm vs. 30 with the restriction to permanent contracts). This implies that the ranking of firms obtained with the whole set of job-to-job transitions is estimated with much less noise than the one with the restricted job-to-job transitions, and still lead to estimate the same relation between wage premiums and global values. Since correcting for noise increases the R^2 by approximately 5 p.p., these results suggest that there still might be some differences between the estimates obtained with the two methods.

[46] This type of information is not available in Sorkin (2018), but it is less problematic in the US context where job contracts are not as constraining as in the European context.

[47] Note that it is not necessary to re-estimate wage premiums since we already use all the moves to estimate them (see 4.3 for a discussion on this point).

While it might seem reassuring that the method leads to results that are quite robust to a change of definition of the voluntary moves, it could on the contrary reveal a weakness of the method. Indeed, we know that the type of transition considered has an economic meaning, so it is problematic to interpret economically the results of a method that leads to the same results whether the transitions taken into account in the estimation are relevant or not. In order to rule out the concern that the method is completely insensitive to the type of moves consider, we calculate both firms' global values and wage premiums uniquely on ENE moves instead of EE moves, and look how it changes the conclusions regarding the relation between wage premiums and global values.[48] Reassuringly, we find that the results change dramatically when calculated on ENE transitions. The R^2 obtained with this method is only 0.07. Moreover, the correlation between the original ranking and the ranking obtained with ENE transitions is only 0.60. Note that the fact that we still find a positive R^2 between wage premiums and global values when looking at ENE transitions instead of EE transitions is logical: it seems likely that the moves following an unemployment spell still convey some information about the preferences of workers. For the same reason we are not surprised to find a clear positive correlation between the rankings obtained when considering EE moves or ENE moves as revealing preferences. However, it is reassuring to see that this correlation is far from being perfect.

Table 15: Robustness to different types of transitions

Moves considered	R^2(value, premium)	$\frac{\text{Nb.moves}}{\text{Nb.firms}}$
EE (1)	0.18	30.4
EE + fixed-term contracts (2)	0.19	45.3
ENE (3)	0.07	31.6
	Corr. values	
(1) and (2)	0.93	
(1) and (3)	0.60	

Note : To ensure comparability between estimates we consider the same sample of firms in the three cases. Only the private sector is considered here.

7 Conclusion

In this paper, we exploit a new matched employer-employee dataset - first described in Godechot et al. (2020) - to estimate how the existence of non-wage amenities impact the dispersion of wages in France during the 2005-2019 period. To do this, we replicate the method first proposed by Sorkin (2018) to estimate a decomposition of firm wage premiums between rents and compensating differentials. We find that compensating differentials explain about 10% of the total variance of (log) wages in the economy. This result comes from the fact that (1) firms explain a non-negligible part of the variance of log-wages (about 12%), and that (2) similarly to the US, the major part of firm wage premiums (about 80%) seems to reflect compensating differentials. It is consistent with the fact that, perhaps surprisingly, nearly half of the job-to-job transitions that are likely to be chosen are accompanied by a wage cut. When looking at differences between hourly wages and annualized wages, we find clear indications that people care more about their annualized wage than their hourly wage. This implies that firms where it is possible to work longer hours (either because of less part-time or more overtime) are more valued.

There are potentially many limitations to the method proposed by Sorkin (2018) to decompose wage premiums into rents and compensating differentials. The most obvious one is that it assumes a unique

[48]Because there is much less ENE transitions than EE transitions with our original definitions, we run this exercise without looking at the type of contract, just as previously. This allows to have quite balanced EE and ENE transitions (because now transitions toward non-employment from any type of contracts are accounted as ENE transitions) and ensures comparability with our original results without restricting too much the identifiable set of firms.

ranking of firms shared by all the workers. Note however that this common ranking of firms is compatible with individual-specific preferences because the method allows for idiosyncratic shocks. In the end, a lot of voluntary moves (34%) occur to a firm that is ranked lower, leaving place to unobserved motivations of the movers. One concern is that these idiosyncratic shocks are assumed to be *i.i.d.*, whereas they are likely to be differently distributed among groups of workers. However, when looking at heterogeneity according to observed characteristics (gender, age, ...), we always find that compensating differentials explain a large part of the variance of wage premiums, even if there exists differences across groups. Beyond dealing with these limitations, we believe that one possible avenue for future research would be to relate the ranking of the firms that we infer from workers' mobility to rankings coming from survey data in which workers are directly asked about the quality of working conditions and other amenities.

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Appendix

A Sample description

Table A.1: Socio-demographic statistics

	All (1)	S.connected by EE (3)
Gender		
Male	52%	52%
Female	48%	48%
Age		
Age $<$ 30	22%	21%
30 $\leq$ Age $<$ 50	52%	53%
Age $\geq$ 50	26%	26%
Profession		
Company director	1%	0%
Executives	17%	18%
Intermediate occupation	22%	24%
White-collar workers	34%	32%
Blue-collar workers	26%	25%

Note : "S. connected by EE" refers to the set of firms that are strongly connected by employer-to-employer (EE) transitions and that hire at least one person from an employment-nonemployment-employment (ENE) or an other transition. It is the main sample used in this study, and "(3)" refers to the corresponding column in Table 1.
The professions are translated from the five French *catégories socio-professionnelles*: *Chefs d'entreprise*, *Cadres*, *Professions intermédiaires*, *Employés* and *Ouvriers*.
Sample : French firms, 2005-2019.

B Additional descriptive evidence about wage cuts

B.1 Wage cuts per year

Figure B.1: Proportion of significant hourly wage cuts per year according to the type of observation

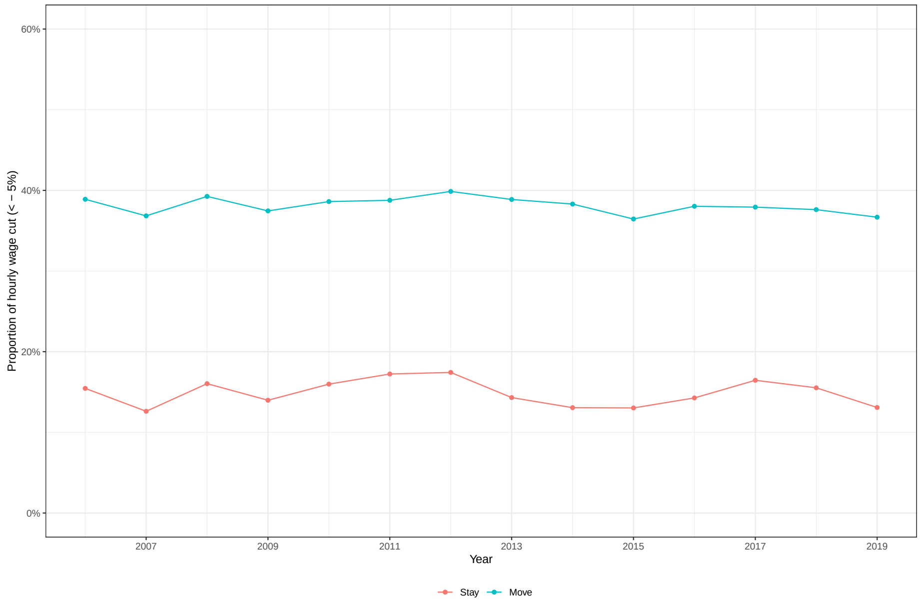
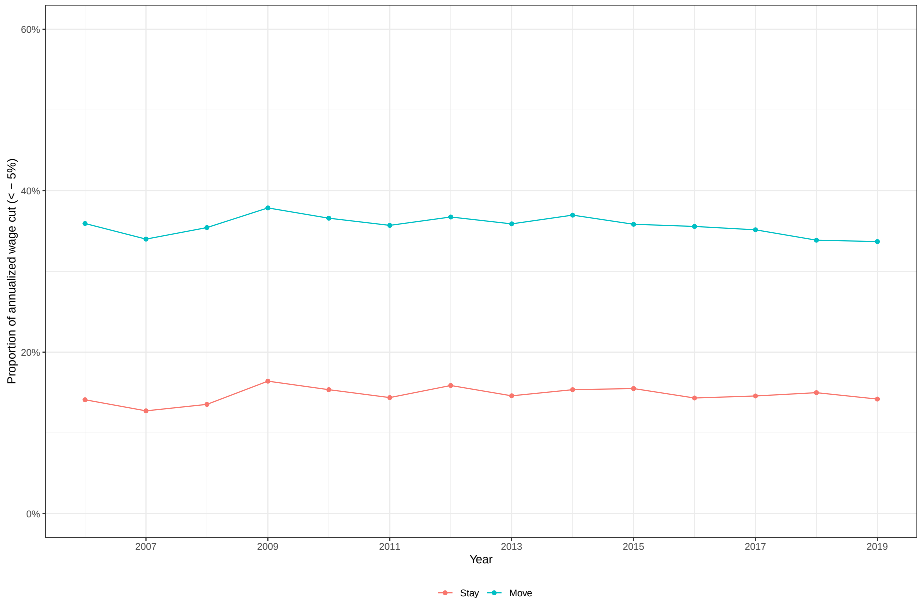


Figure B.2: Proportion of significant annualized wage cuts per year according to the type of observation



B.2 Wage gaps per year

Figure B.3: Median hourly wage gap per year according to the type of observation

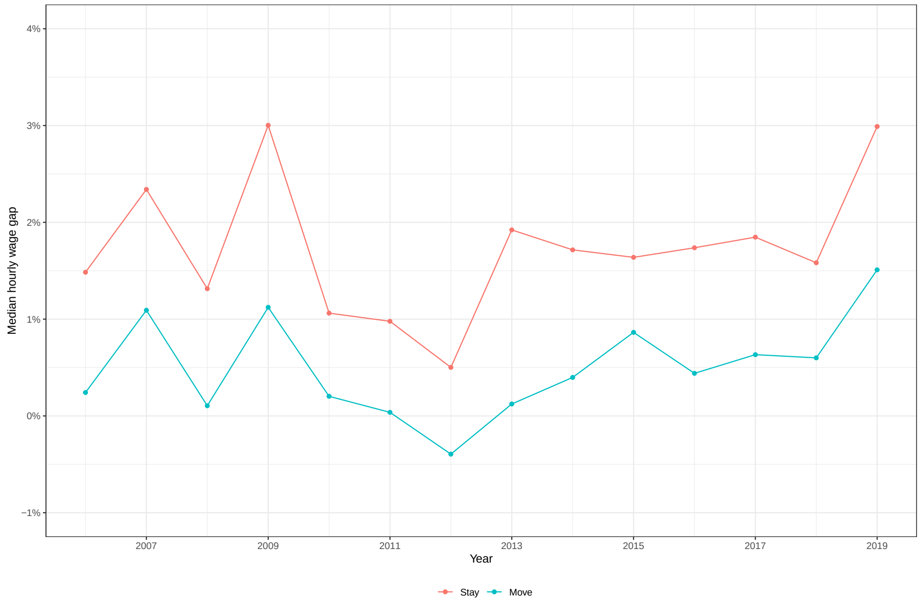
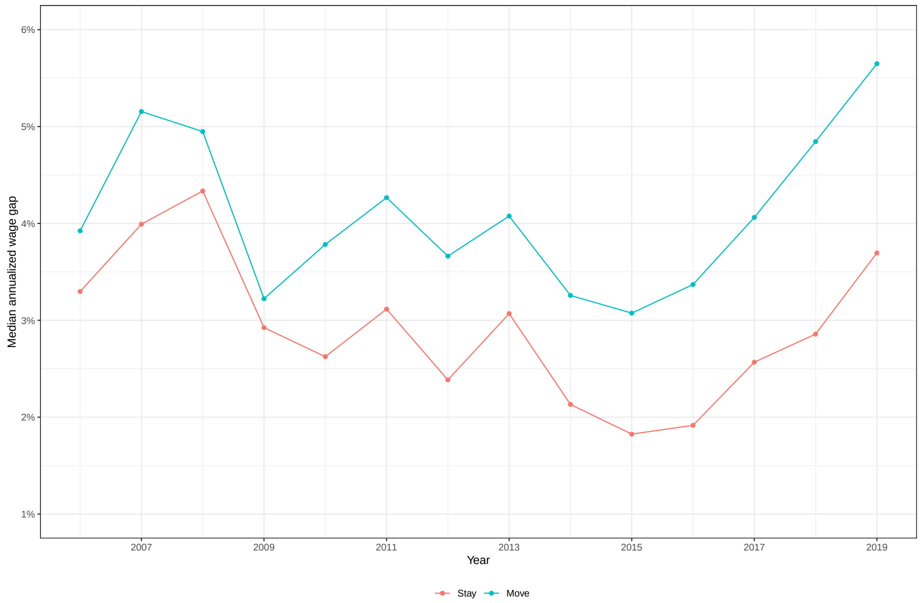


Figure B.4: Median annualized wage gap per year according to the type of observation



B.3 Distribution of annualized wage gaps

Figure B.5: Distribution of annualized wage changes according to the type of observation

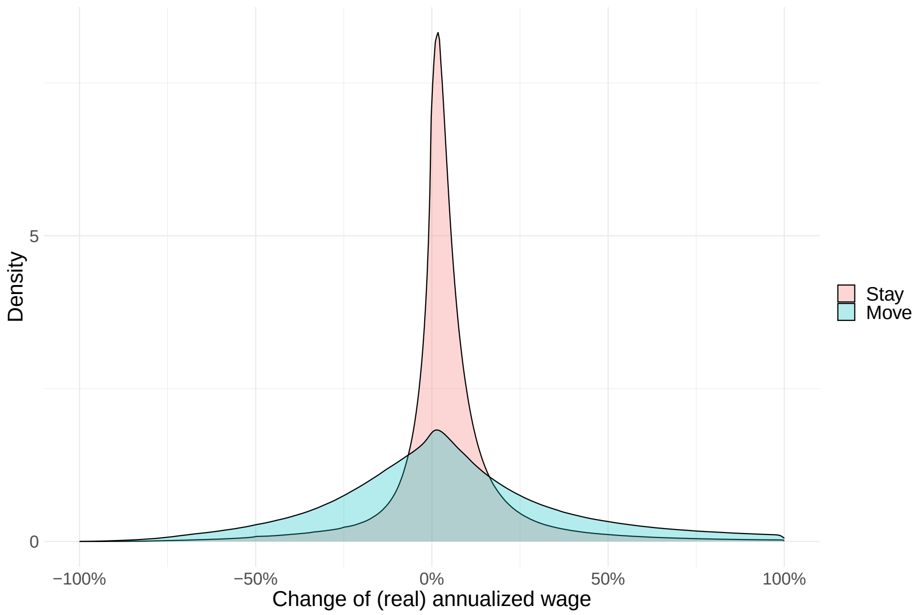
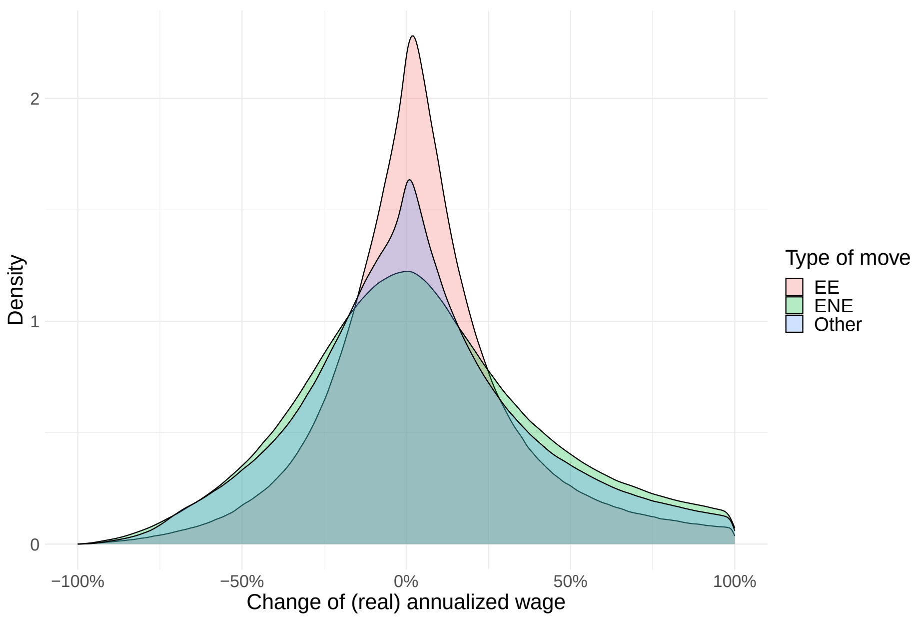


Figure B.6: Distribution of annualized wage changes according to the type of move



Note: "EE" moves are employment-to-employment moves. "ENE" moves are employment-nonemployment-employment moves. "Other" moves include all the moves from a fixed-term contract.

C AKM in full sample

Table C.2: AKM decomposition in weakly connected set of firms

	All sectors
Ensemble decomposition (share)	
Firms	0.14
Persons	0.71
Xb	0.04
Residuals	0.11
Variance components (share)	
Var. firm effect	0.09
Var. person effect	0.67
Var. Xb	0.05
Var. residuals	0.11
2Cov(person, firm)	0.10
2Cov(Xb, person+firm)	0
Correlation person and firm effects	
Corr(person, firm)	0.22
Overall fit	
Adjusted R^2	0.87

Note : The weakly connected set of firms represents 2,472,000 firms, 60,403,000 of workers and 335,080,000 of person-years.

D Accounting for potential lay-offs: details on the method

This section details the method used to account for potential lay-offs in the estimation of firms' global values.

Starting from the simple model presented in Section 4.2.1, we allow firms to be also characterized by their propensity to lay-off workers. These lay-offs can take two forms: a forced move toward non-employment or a forced move toward another firm. The probability of being affected by one of these two forced moves are respectively δ_j (move toward non-employment) and ρ_j (move toward another firm). We can then rewrite the value function of working at the firm j as:

$$V_j^e = \underbrace{v_j}_{\text{payoff}} + \beta\ E\{ \quad \underbrace{\delta_j \int_{\iota_1} (V^n + \iota_1) dI}_{\text{forced move to non-employment}} \quad + \underbrace{(1-\delta_j)\rho_j \sum_k \int_{\iota_2} (V_k^e + \iota_2) dI \tilde{f}_k}_{\text{forced move to other employer}}$$

$$+ \underbrace{(1-\delta_j)(1-\rho_j)}_{\text{not forced}} [\underbrace{\lambda_1}_{\text{offer}} \underbrace{\sum_k \int_{\iota_3} \int_{\iota_4} max(V_k^e + \iota_3, V_j^e + \iota_4) dI dI f_k}_{\text{employer-to-employer move}} + \underbrace{(1-\lambda_1)}_{\text{no offer}} \underbrace{\int_{\iota_5} (V_j^e + \iota_5) dI}_{\text{stay}}] \}$$

Similarly, equation 4 becomes :

$$\begin{aligned} M_{jk} &= \underbrace{g_k W}_{\text{Nb. of workers at firm k}} \underbrace{(1-\delta_k)(1-\rho_k)}_{\text{Proba. no forced move}} \underbrace{\lambda_1 f_j}_{\text{Proba. get an offer from firm j}} \underbrace{P(V_{ij} > V_{ik})}_{\text{Proba. accept offer}} \\ &= g_k W\ (1-\delta_k)(1-\rho_k)\ \lambda_1 f_j\ \frac{exp(V_j^e)}{exp(V_j^e) + exp(V_k^e)} \end{aligned}$$

The relative flows between firm j and firm k becomes:

$$\underbrace{\frac{M_{jk}}{M_{kj}}}_{\text{relative flows}} = \underbrace{\frac{g_k(1-\delta_k)(1-\rho_k)}{g_j(1-\delta_j)(1-\rho_j)}}_{\text{relative relevant sizes}} \underbrace{\frac{f_j}{f_k}}_{\text{relative offers}} \underbrace{\frac{exp(V_j^e)}{exp(V_k^e)}}_{\text{relative values}} \tag{18}$$

Finally, the "flow-relevant" value of firm j becomes:

$$exp(\tilde{V}_j) \equiv \frac{f_j exp(V_j^e)}{g_j(1-\delta_j)(1-\rho_j)} \tag{19}$$

In order to recover the "lay-offs corrected value" of firm j, V_j^e, it is thus necessary to get δ_j and ρ_j. First, δ_j is observed as it is simply the share of employees in firm j that experience an employer-to-nonemployment transition. Second, ρ_j can be determined by comparing the rate of employer-to-employer transition from firm j when the firm is contracting and when the firm is expanding, under the assumption that the difference between these two types of years is imputable to lay-offs, as described next.

The central idea is that for each firm, there is a level of separation that is chosen *i.e.* due to the relative value of the firm and to the idiosyncratic shock (endogenous separations). Any excess separation from this level when the firm is contracting is considered as due to lay-offs (exogenous separations). Formally, we define:

- EE(j,t) is a binary random variable equal to 1 when a worker at firm j in time t separates in an employer-to-employer transition (either endogenous or exogenous). This variable is observable.
- EE(j,t)^{endog} is a binary random variable equal to 1 when a worker at firm j in time t separates in an endogenous employer-to-employer transition. Because we do not observe the lay-offs, this variable is unobservable. Note also that this variable is time-independent because endogenous separations do not depend on the firm-level shocks but only on the ranking of firms, which is assumed to be time-invariant. Therefore we remove the time subscript and note EE(j,t)^{endog} = EE(j)^{endog}. We symmetrically define EE(j,t)^{exog} as $EE(j,t)^{exog} = EE(j,t) - EE(j)^{endog}$. Note that contrary to EE(j)^{endog}, EE(j,t)^{exog} is time-dependant because it depends on the shocks the firm faces.
- C(t,j) is a binary random variable equal to 1 when the firm j is contracting at time t. This variable is observable.

Now the goal is to construct for each firm and period the probability that a separation was endogenous or exogenous so that we can re-weight the flows. We have:

$$P(EE(j,t)^{endog} = 1 \mid EE(j,t) = 1, C(t,j) = 1) = \frac{P(EE(j,t)^{endog} = 1, EE(j,t) = 1 \mid C(t,j) = 1)}{P(EE(j,t) = 1 \mid C(t,j) = 1)} \tag{20}$$

$$= \frac{P(EE(j)^{endog} = 1)}{P(EE(j,t) = 1 \mid C(t,j) = 1)} \qquad \text{b.c. } EE(j,t)^{endog} \perp\!\!\!\perp C(t,j) \tag{21}$$

The denominator of this expression is observable and simply corresponds to the separation rate of the firm in year t. The numerator is unobserved and depends on the parameters of the model:

$$P(EE(j)^{endog} = 1) = (1-\delta_j)(1-\rho_j) \times [\lambda_1 \sum_{k\in\mathcal{E}} f_k \frac{exp(V_k^e)}{exp(V_k^e) + exp(V_j^e)}] \tag{22}$$

We initialize this endogenous separation rate as the average separation rate of the firm sector during expanding years. Then, to make sure that we reweight the observed flows by a factor less or equal to 1, we compute the endogenous probability as follow:

$$P(EE(j,t)^{endog} = 1 \mid EE(j,t) = 1, C(t,j) = 1) = min(\frac{P(EE(j)^{endog} = 1}{P(EE(j,t) = 1 \mid C(t,j) = 1)}, 1) \tag{23}$$

The following remarks can be made from the above expression:

- The exogenous probability is simply equal to one minus the endogenous probability: $P(EE(j,t)^{exog} = 1 \mid EE(j,t) = 1, C(t,j) = 1) = 1 - P(EE(j,t)^{endog} = 1 \mid EE(j,t) = 1, C(t,j) = 1)$
- When the firm is expanding, the endogenous probability is automatically set to 1: $P(EE(j,t)^{endog} = 1 \mid EE(j,t) = 1, C(t,j) = 0) = 1$ (so $P(EE(j,t)^{exog} = 1 \mid EE(j,t) = 1, C(t,j) = 0) = 0$)

Now that we have these probabilities, we can compute the endogenous flows as the observed flows weighted by the probability that they are endogenous. We want to have a unique directed flow between firm j and firm k so we sum over all the periods. Formally, we then compute:

- Endogenous mobility matrix M: for all couple of firms (j,k), we compute the flows from firm j to firm k as:

$$\begin{aligned} M_{kj} &= \sum_t M^o_{kj,t} P(EE(j,t)^{endog} \mid EE(j,t) = 1) \qquad \text{where } ^o \text{ stands for "observed"} \\ &= \sum_t M^o_{kj,t}[\mathbb{1}(C(t,j) = 0) + \mathbb{1}(C(t,j) = 1) P(EE(j,t)^{endog} \mid EE(j,t) = 1, C(t,j) = 1) \end{aligned}$$

- ρ_j (parameter of forced EE move) is obtained by taking the share of exogenous EE moves among all the potential moves of the firm (*i.e.* the size of the firm):

$$\rho_j = \frac{\sum_t \sum_{k \in \mathcal{E} \setminus j} M^o_{kj,t} P(EE(j,t)^{exog} \mid EE(j,t) = 1)}{g_j W}$$

We now summarize the estimation steps detailed previously:

- Step 0: Get the relative size (g_j), the offer distribution (f_j) and the rate of forced moves toward non-employment (δ_j) of the firms from the data. Initialize EE endogenous probabilities using the average of EE probabilities during expanding years. To avoid too many 0, take the sector average (weighted by the size of firms). Initialize a random value for the (common) value of firms $\{V^e_j\}_{j \in \mathcal{E}}$.
- Step 1: Build the endogenous mobility matrix M and compute ρ.
- Step 2: Compute $exp(\tilde{V})$ by power iteration (apply the algorithm similar to PageRank)
- Step 3: Given g_j (size), f_j (offers distribution), δ_j (forced moves toward non-employment) and ρ_j (forced moves toward another employer)[49], deduce the (common) value of firms $\{V^e_j\}_{j \in \mathcal{E}}$
- Step 4: Given the new values of $\{V^e_j\}_{j \in \mathcal{E}}$, compute the new endogenous probabilities using equation (22).[50] If the size-weighted correlation between old and new $\{V_j\}_{j \in \mathcal{E}}$ is less than 0.999, return to step 1.

[49]These parameters are in theory firm-specific but we compute them at the sector level to avoid measurement errors and null values.

[50]To speed-up the process we group firms in 500 groups according to their values, calculate the ratio of $exp(V^e_j)$ at the group level and then get the expression of equation (22). To determine $\lambda 1$, we minimize the gap between the model-predicted probability of experiencing an EE transition and the observed rate of EE transition.

E Analysis of hours and part-time

Table E.3: AKM decomposition on the log of the number of hours worked

	Log hours
Ensemble decomposition (share)	
Firms	0.15
Persons	0.48
Xb	0.01
Residuals	0.35
Variance components (share)	
Var. firm effect	0.16
Var. person effect	0.50
Var. Xb	0.01
Var. residuals	0.35
2Cov(person, firm)	−0.02
2Cov(Xb, person+firm)	0
Correlation person and firm effects	
Corr(person, firm)	−0.04
Overall fit	
Adjusted R^2	0.57

Table E.4: Patterns of hours changes

	All	EE	ENE	Other
Proba(Nb. hours ↓)				
All	0.45	0.45	0.41	0.46
Male	0.45	0.47	0.42	0.45
Female	0.44	0.43	0.39	0.46
Age < 30	0.44	0.42	0.34	0.46
$30 \leq$ Age < 50	0.45	0.46	0.43	0.45
Age ≥ 50	0.47	0.48	0.48	0.46
1^{st} quartile (hour. wage)	0.45	0.44	0.38	0.48
4^{th} quartile (hour. wage)	0.43	0.45	0.43	0.40
1^{st} quartile (ann. wage)	0.24	0.27	0.19	0.24
4^{th} quartile (ann. wage)	0.52	0.51	0.55	0.52

Note : "All" includes 20.3 millions of moves. "EE" (employer-to-employer) includes 7.8 millions of moves. "ENE" (employer-to-nonemployment-to-employer) includes 3.4 millions of moves. "Other" (moves from a fixed-term contract) includes 9.1 millions of moves. The number of hours ("Nb. hours") refers to the number of hours worked per day.

Table E.5: Patterns of part-time transitions

	All	EE	ENE	Other
Proba transition				
All				
Part-time to full-time	0.17	0.13	0.23	0.18
Part-time to part-time	0.12	0.11	0.12	0.12
Full-time to full-time	0.61	0.69	0.55	0.56
Full-time to part-time	0.11	0.07	0.10	0.14
Male				
Part-time to full-time	0.14	0.10	0.20	0.17
Full-time to part-time	0.09	0.07	0.09	0.12
Female				
Part-time to full-time	0.20	0.17	0.28	0.19
Full-time to part-time	0.12	0.09	0.11	0.15
Age $<$ 30				
Part-time to full-time	0.22	0.19	0.32	0.20
Full-time to part-time	0.12	0.08	0.08	0.15
30 $\leq$ Age $<$ 50				
Part-time to full-time	0.14	0.10	0.19	0.16
Full-time to part-time	0.09	0.07	0.10	0.12
Age $\geq$ 50				
Part-time to full-time	0.11	0.08	0.15	0.13
Full-time to part-time	0.12	0.09	0.14	0.14

Note : "All" includes 20.3 millions of moves. "EE" (employer-to-employer) includes 7.8 millions of moves. "ENE" (employer-to-nonemployment-to-employer) includes 3.4 millions of moves. "Other" (moves from a fixed-term contract) includes 9.1 millions of moves. Part-time is defined as working less than 30 hours/week.

Table E.6: Ranking of sectors according to number of hours/day and use of part-time

	Nb hours/day	Proportion of full-time
Top sectors		
1	Transports par eau	Électricité et gaz
2	Transports terrestres	Extraction de pierres, minéraux, sel
3	Réparation et installation	Cokéfaction et raffinage
4	Extraction de pierres, minéraux, sel	Réparation et installation
5	Fabrication de matériel de transport	Industrie du papier
Bottom sectors		
1	Nettoyage	Nettoyage
2	Action sociale	Action sociale
3	Activités liées à l'emploi	Restauration
4	Restauration	Activités liées à l'emploi
5	Arts et spectacles	Arts et spectacles

Note : Sectors are at the second most aggregated level of *NAF rev.2* (2-digits level).

Proof that the increase share of firms AKM estimation for the annualized wage compared to the hourly wage implies that the number of hours worked is firm-specific

The goal here is to rationalize the fact that we find a greater role of firms when we consider the (log) annualized wage rather than the (log) hourly wages. Let us start from the AKM decomposition of the log hourly wage. Here we denote w_{ij} the hourly wage of worker i in firm j.[51] Following AKM, we have:

$$log(w_{ij}) = \alpha_i + \psi_j + X_{it}\beta + u_{ij} \tag{24}$$

Now let us compute the same decomposition but for the log-daily wage (*i.e.* the log-annualized wage because we compute the annualized wage as the daily wage multiplied by 365) y. instead of the log-hourly wage w. Because the daily wage (y) can be written as the product between the hourly wage (w) and the daily number of hours (h), we have:

$$\begin{aligned} log(y_{ij}) &= log(h_{ij}w_{ij}) && (25)\\ &= log(h_{ij}) + log(w_{ij}) && (26)\\ &= log(h_{ij}) + \alpha_i + \psi_j + X_{it}\beta + u_{ij} && (27) \end{aligned}$$

We are interested in the evolution of the share of firms in the variance of the log-wages (namely between the case where we look at the hourly wage and the case where we look at the daily wage. Let us prove that when we see an increase in the share of firms when moving from the hourly wage to the daily wage, it is very likely that the number of hours per day is, at least partly, a firm-characteristic.

To see this, let us first assume that the number of hours worked per day is neither an individual nor a firm characteristics but is the same for everyone. In this case, we have:

$$log(y_{ij}) = log(h) + \alpha_i + \psi_j + X_{it}\beta + u_{ij} \tag{28}$$

Because $Var(log(h)) = 0$, this leads to exactly the same AKM decomposition as with the hourly wage. Because this is not what we observe, we can safely reject the hypothesis that everyone work the same number of hours per day.

Now let us consider a second case in which the number of hours worked is only worker-specific. This would be the case for instance if firms have no specific preference over the number of hours worked by their employees but the workers have heterogeneous preferences over this variable. In this case, we have:

$$log(y_{ij}) = \underbrace{log(h_i) + \alpha_i}_{\tilde{\alpha_i}} + \psi_j + X_{it}\beta + u_{ij} \tag{29}$$

Only the worker-specific effect is changed compared to the decomposition with the hourly wage. However, it might still be the case that the share attributed to firms change because the total variance changes. Formally, we are interested in the relation between $\frac{Var(\psi_j)}{Var(log(y_{ij}))}$ and $\frac{Var(\psi_j)}{Var(log(w_{ij}))}$. Even if the numerator is left unchanged, the denominator can change. To get something consistent with what we observe in the data, we must have:

[51] In Section 4.3, w denoted the log-hourly wage.

$$\frac{Var(\psi_j)}{Var(log(y_{ij}))} > \frac{Var(\psi_j)}{Var(log(w_{ij}))} \tag{30}$$

$$\implies Var(log(y_{ij})) < Var(log(w_{ij})) \tag{31}$$

$$\implies Var(log(h_i) + log(w_{ij}) < Var(log(w_{ij}) \tag{32}$$

$$\implies Var(log(h_i)) < -2Cov(log(h_i), log(w_{ij}) \tag{33}$$

This would imply that the covariance between the individual propensity to work many hours and the hourly wage is strongly negative (the covariance term has to be greater than $-\frac{1}{2}Var(log(h_i)))$, *i.e.* the more an employee works the less she is paid. Because such strong negative relation is unlikely to hold in practice, we reject this second case.

We can therefore conclude that it is most likely that the number of hours worked is, at least partially, a firm-specific characteristic. This is confirmed when we run an AKM-style decomposition on the log-number of hours worked per day (see Section 5.2.3).

F Other sample description

Table F.7: Number of years per person

Nb. years	Nb. people	Share
1	18,505,000	0.287
2	7,646,000	0.119
3	5,857,000	0.091
4	4,411,000	0.068
5	3,107,000	0.048
6	3,133,000	0.049
7	2,232,000	0.035
8	1,963,000	0.030
9	2,322,000	0.036
10	1,671,000	0.026
11	2,714,000	0.042
12	1,604,000	0.025
13	1,504,000	0.023
14	1,626,000	0.025
15	6,173,000	0.096

Table F.8: Number of years per match

Nb. of years per match	Nb. of matches	Share of matches	Share of person-year
1	$49,630,000$	0.450	0.139
2	$19,456,000$	0.177	0.109
3	$10,682,000$	0.097	0.090
4	$6,627,000$	0.060	0.074
5	$4,473,000$	0.041	0.063
6	$3,692,000$	0.033	0.062
7	$2,723,000$	0.025	0.054
8	$2,230,000$	0.020	0.050
9	$2,075,000$	0.019	0.052
10	$1,472,000$	0.013	0.041
11	$1,711,000$	0.016	0.053
12	$1,141,000$	0.010	0.038
13	$926,000$	0.008	0.034
14	$811,000$	0.007	0.032
15	$2,565,000$	0.023	0.108

Table F.9: Number of dominant employers per person

Nb. of employers	Nb. of people	Share of people
1	$40,545,000$	0.629
2	$12,589,000$	0.195
3	$5,818,000$	0.090
4	$2,849,000$	0.044
5	$1,398,000$	0.022
6	$680,000$	0.011
7	$322,000$	0.005
8	$150,000$	0.002
9	$67,000$	0.001
10	$29,000$	0
11	$12,000$	0
12	$5,000$	0
13	$2,000$	0
14	$1,000$	0
15	0	0

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