Job-to-job flows and wage cyclicality in France and Italy [*]

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Abstract

Recent literature about the U.S. shows that wage dynamics covaries more with job-to-job flows than with unemployment-to-employment transitions. In this paper we try to address whether this explanation is valid also for other countries characterized by a different institutional setting and a different economic structure, namely France and Italy. Using comparable administrative data we find that in both France and Italy realized job-to-job transitions are pro-cyclical and positively contribute to explain wage growth. We also find that outside opportunities affect the wage growth of workers who remain in the same job. Differently from the U.S., however, unemployment still explains a sizable part of wage dynamics. job-to-job flows and gains from moving are more relevant for workers in high-skilled occupations, for permanent workers and in sectors with higher wage variability. We then conclude that the relevance of job-to-job flows for wage dynamics depends also by the structural characteristics of each economy.

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1 Introduction

Recent literature about the U.S. outlines the importance of job-to-job flows for wage cyclicality. Job-to-job flows are relevant not only to uncover the functioning of the reallocation process of workers in more productive firms, but also at the macro level, to explain aggregate wage dynamics and its recent subdued evolution (e.g. Moscarini and Postel-Vinay (2016c) and Hahn et al. (2018)). In particular, the findings of Moscarini and Postel-Vinay (2016a,b) (henceforth MPV) lead the authors to provocatively conclude that wage cyclicality depends greatly on job-to-job flows, whereas the correlation of wage dynamics to unemployment could be spurious. They also argue that recent subdued wage growth in the U.S. is better explained by the lack of job-to-job flows and that policy-makers and monetary authorities in particular should put more attention on the mechanisms behind workers' transitions from one firm to another. Karahan et al. (2017) confirm the MPV findings using a state-level panel data on wage growth and flows from unemployment and from other jobs and show that hires from employment (EE henceforth) win the "horse race" against flows from unemployment in empirical models. However, they admit that their results cannot be easily reconciled with the enormous literature about the relationship between unemployment and wage dynamics (the Phillips curve framework) and with the literature based on Pissarides (2009), according to which wage cyclicality is determined by new hires from unemployment (see also Shin and Solon (2007) and Carneiro et al. (2012), among others for empirical tests).

In this paper, by the use of comparable administrative data for France and Italy, we empirically test whether and to what extent job-to-job flows contribute to explain nominal wage dynamics in these two euro area countries.

On the one hand, EE flows may matter even more for these countries; MPV (2016a) argue that in a model with binding minimum wage (or binding reservation wage) the wage distribution is highly influenced by EE flows. This hypothesis can be easily tested, as the wage setting system in Italy and France is more centralized than in the US and minimum wages are more likely to be binding.[1] On the other hand, wage dynamics may instead depend less on EE flows in Italy and France. First, the labor market in these two countries is less dynamic; EE flows are smaller both in absolute term and as a share of total flows. Furthermore, given the sectorial structure of the economy and the presence of a dual labor market, flows are mostly characterized by lower skilled and temporary workers, with lower bargaining power and whose wages are likely to be affected more by flows into and out of unemployment (also Kosar and Smith (2018) find that in the US only wages of high educated workers comove with EE flows). Finally, the wage structure in Italy and France

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[1]In Italy, wages are mostly determined by nation-wide collective bargaining which set minimum wages at the sector level (with no opting out for firms). Wage bargaining is more decentralized in France (there exist around 700 industries in 2018; industries can be sector and/or region specific) however the national minimum wage reduces the negotiation possibility on low wages.

is more compress and more homogeneous across firms, maybe due to the wage bargaining system; this may modify the type of competition among employers and their ability to retain or attract workers.

We use two distinct panels of matched employer-employee datasets spanning from 1995 to 2015 for France and from 2000 to 2015 for Italy. First, we look at four types of worker flows: (i) workers who stay in the same firm for two consecutive years, labelled as *stayers*; (ii) workers who move from one job to another (*movers*), (iii) movements from non-employment into employment (*entrants*), and (iv) vice-versa (*exiters*). Then, we decompose aggregate wage dynamics by flow type to identify the contribution of hires/separations out of or into non-employment and job-to-job flows.

We show that in both countries aggregate nominal wage dynamics is mostly determined by stayers, because of their very large weight in total employment. Aggregate flows into and out of employment are larger than flows from one job to another and these movements tend to offset, as found by Hahn et al. (2018) for the U.S. Moreover, the contribution of EE flows is higher in Italy than in France, especially before the Great Recession.

To analyze more in detail the cyclical properties of job-to-job flows, as opposed to those of workers who do not change job, we focus on stayers' and movers' (log) nominal wages. In our simplest empirical model the cyclicality of wage changes is captured by variations in the unemployment rate of the region where the individual works.

We find that in both Italy and France movers gain on average an extra 3 per cent increase in nominal wage growth when they move. We also find that in both countries this wage gain is procyclical. Wage changes of stayers are instead less responsive to changes in the local unemployment rate. We also look at the probability to observe a job-to-job move and we find that it declines as the local unemployment rate increases, i.e. it is procyclical, consistently with the findings about Haltiwanger et al. (2018).

Then we try to separately account for what MPV (2016a) define as the "composition" effect and the "strategic" effect of EE flows on wage dynamics. The first is the most obvious one: workers quit their job only if they receive a better wage offer, there is therefore a direct positive link between the number of (voluntary) movers in the economy and aggregate wage dynamics. The second is an indirect channel, which arises when employers respond to an external job offer, by increasing the wage of stayers to retain them. The composition effect should not affect the wages of stayers, who do not change job. We find instead that EE flows affect wage dynamics of both stayers and movers, as in MPV (2016a); MPV (2017a). However, differently from these papers we find that also transitions from non-employment contribute to explain wage dynamics of stayers.

We also look at relevant dimensions of heterogeneity. Since minimum wages are particularly binding for positions at the bottom of the job ladder, wage dynamics of workers

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in high-skilled occupations should be more affected by EE flows than wages of low-skilled workers. Additionally, as shown in MPV (2018), in models with heterogeneous human capital and human capital depreciation during unemployment, firms prefer to hire employed workers instead of the unemployed and the impact of EE flows on wages should be larger for high-skilled workers. We explicitly test this hypothesis by looking at wage growth by type of occupation and we find supportive evidence. However, wages of both high and low skilled workers remain affected also by flows into and out of unemployment. Moreover, we study how different flows affect wage dynamics of temporary or permanent workers, showing that temporary workers wages are not correlated with EE flows, but only with flows into and out of unemployment. Finally, we look at sectors characterized by a more or less centralized wage structure, i.e. where wages have an higher or lower cross-sectional variability, conditional of differences in workers' composition. We find that flows into and out of non-employment matter exclusively in sectors with low wage variability, where centralized bargaining is probably stronger.

We then conclude that EE flows are an important determinant of wage cyclicality, but in both countries we cannot disregard the impact of flows into and out of unemployment. Our evidence suggests also that the relevance of EE flows in each country depends on the characteristics of firms, workers and of the institutional setting.

The paper is organized as follows. Section 2 describes the datasets and how we define labor market flows and workers' and firms' characteristics. Section 3 presents novel evidence on average wage growth and the contribution of job-to-job flows. In Section 4, we rely on microdata to analyze the probability to move to another job and the impact of external labor market conditions, as summarized by the local unemployment rate. Section 5 looks at the direct and strategic effects of job-to-job transitions. Sections 6 and 7 look at heterogeneity by type of occupation and firm size. Last, Section 8 briefly concludes.

2 The data

We use French and Italian administrative data, drawn from companies' wage declarations for the calculation of social security contributions. We first describe each dataset and then how we construct labor market flows.

2.1 French data

We use a sample of DADS data (Déclarations annuelles de données sociales) for the period 1995-2015. DADS data cover wages of all French employees and is used to compute social security contributions. They constitute the informative basis used by the Institut national de la statistique et des études économiques (INSEE) to produce some of the statistics of

French wages and employment in France. A panel version of this dataset has been made available for research purposes, covering all individuals born in October of each even-numbered years ($1/24^{th}$ of the working population) for data since 1995 to 2001 and all individuals born in October of each year ($1/12^{th}$ of the working population) for data from 2002 to 2015. To avoid over-weighting the most recent part of the sample period for both time intervals we keep only half of the available sample for years from 2002 to 2015 and, for comparability with the Italian data, we only keep the private-non agricultural sector.

Each year, for each employer-employee match, we observe the length of the employment spell in days, its beginning and end dates, the associated wage that is subject to social contributions (included variable part and bonuses), the type of contract (since 2005), occupation (blue collar, low-skilled white collar, intermediate profession and professional/manager) and working time (part time/full time). The declared working period includes non-working days. For each worker we observe age, gender and geographical location. For each firm, we are matching our dataset to the exhaustive data and the fiscal dataset FARE to obtain information on the average size of the firm, its age, its geographical location, and average wage paid to workers.[2]

2.2 Italian data

Data on employment and wages consist of social security payments made by all private-sector firms with at least one employee to the Italian National Social Security Institute (INPS). From this master data, INPS extracts employment histories of all workers born on the 1st or the 9_{th} day of each month (6.5% of total workforce in the Italian private sector). This extraction, updated to 2015, provides for each job match information on demographics, the annual gross wage (before social security contributions), the number of days worked in the year, the main characteristics of the contract and occupation, the beginnings and the end date of each job spell. As for French data, we know gender and age of workers and, for each firm, we know its geographical location (at the province level), its size, age and the average wage paid to workers.

2.3 Sample selection and definitions

Since the data report the annual value of wages and days worked, we do not observe intra-annual wage variation unless individuals change their job. Thus, we look at the employment status of individuals in December of each year.[3]

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[2]Margolis (2002) and Picart (2007) outline the presence of spurious changes in firm identifiers, which imply an overestimation of flows of workers between firms. We adopt their procedure to correct firm identifiers, according to which a change in firm identifier is considered as spurious if two firms have at least one half of workers in common between two consecutive years.

[3]When the worker has several employment relationships during the same time interval, we keep the one with the longest overall duration and the higher daily wage.

Given the panel structure implicit in our dataset we can identify four types of worker annual flows. The first is composed of individuals who are employed in December of year t and also in $t-1$. If they work for the same firm in both t and $t-1$ they are labelled as *stayers*; if they have changed firm they are labelled as *movers*. Second we call *exiter* workers who are working in December $t-1$ but not in t; a worker is instead an *entrant* if she is not working in December $t-1$ but works in t.

Some measurement issues can affect our data. First, in our data we do not observe a direct measure of non-employment. Individuals who are not recorded as a private-sector employee in a given year could be either non-employed, or employed in the public sector or working as self-employed. It is not possible for us to evaluate the size of this potential source of bias, but in both countries the flows of private sector employees from and to public or self-employment are rather small, especially in recent years.[4] Moreover, to avoid mis-measurement due to retirement or student jobs, we keep only workers between 25 and 50 years old.

Second, since we are looking at annual transitions, given our definitions, it is possible that we classify as movers also people who, within the same year, lose their job and then find a new one after a non-employment spell. To avoid these spurious job-to-job transitions, we exclude people with a non-employment spell longer than one quarter and classify them as entrants. In some robustness checks we also exclude people with non-employment spells shorter than one month finding similar results.

Finally, in order to have comparable data on wages for the two countries we look at daily wages net of employers' social contributions and before income taxes. The two measures of wages are quite comparable but non-identical, because wages refer to the part of workers' compensation for which firms have to pay social security contributions, with some different rules in the two countries. Since the differences are more pronounced for the variable part of the compensation, which typically is more reactive to the business cycle, we cannot precisely compare the elasticity of flows and wage changes to unemployment. These differences, however, do not impede us to shed some light on the mechanisms that influence wage cyclicality in the two countries.

Table 1 reports some statistics and shows different patterns in France and Italy. In Italy movers account for 10% of total employees, whereas in France they are around 9%. These shares are remarkably higher if we relate movers to total hires (42% in Italy and 27% in France). The table reports also daily wages of stayers and movers. First, daily wages are apparently higher in Italy than in France, but the difference depends only on the fact that French data refer to the whole period a worker is employed in a firm (including non-working days), whereas Italian data report the actual days worked. With this difference in mind, in both countries those who move have lower daily wages than those who work for the

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[4]Between 2009 and 2015, 7.7% of moves are between the public and the private sectors in France using the DADS panel.

same firm for two consecutive years, but higher wage growth rate. The last rows report the average characteristics of the firms where movers work before moving. In both countries movers typically come from younger, smaller firms, paying lower wages. Since we are using samples of workers born in a given date, our samples are representative of the all population of workers, but are automatically composed mainly of workers in larger firms. Table 1 shows this point. In Italy in out sample there are around 47% firms with at least 50 employees. In France their incidence is even larger (63 per cent). If we look at the population of firms we find that in Italy only 2.6 % firms are 50+. This share is 10 times larger in France. This characteristics of the samples imply that aggregate wage growth recorded by DADS and INPS samples is larger than the one observed in National accounts. Nevertheless, in both countries we are capturing a relevant portion of the aggregate wage bill, as around 50% workers in Italy and 70% workers in France are employed in large firms.

3 A look to aggregate data

To assess the relevance of job-to-job flows and other flows in the labor market, we consider the following decomposition of the average wage change between time t and time $t + 1$, $\Delta \overline{w_t}$. We define the group of stayers as S_t, movers as Q_t, exiters as R_t and entrants as N_t. The employment population is $D_t = S_t + Q_t + N_t$ at time t and $D_{t-1} = S_t + Q_t + R_t$ at time $t-1$.

$$\Delta \overline{w_t} = \underbrace{\frac{\Sigma_i s_{it} w_{it} + \Sigma_i q_{it} w_{it} + \Sigma_i n_{it} w_{it}}{D_t}}_{\text{earnings at time t}} - \underbrace{\frac{\Sigma_i s_{it} w_{it-1} + \Sigma_i q_{it} w_{it-1} + \Sigma_i r_{it} w_{it-1}}{D_{t-1}}}_{\text{earnings at time t-1}}$$

We can separate each part of the equation by transition type:

$$\Delta \overline{w_t} = \underbrace{\frac{\frac{S_t}{D_t} + \frac{S_t}{D_{t-1}}}{2} \frac{\Sigma_i s_{it} \Delta w_{it}}{S_t}}_{\text{job stayers}} + \underbrace{\frac{\frac{Q_t}{D_t} + \frac{Q_t}{D_{t-1}}}{2} \frac{\Sigma_i q_{it} \Delta w_{it}}{Q_t}}_{\text{emp-to-emp.}} +$$
$$\underbrace{\frac{N_t}{D_t} \left(\frac{\Sigma_i n_{it} w_{it}}{N_t} - \tilde{w}_t \right) - \frac{R_t}{D_t} \left(\frac{\Sigma_i r_{it} w_{it-1}}{R_t} - \tilde{w}_t \right)}_{\text{new hires and exiters}}$$

where, s_{it}, q_{it}, n_{it} and r_{it} are indicator variables that refer to stayers, movers, entrants and exiters, respectively, and $\tilde{w}_t$ is the weighted average wage level of stayers and movers. A similar decomposition is used by Hahn et al. (2018) for the U.S.

Figures 1 and 2 report the decomposition during the period 1999–2015 for Italy and 1996–2015 for France. Vertical lines in both countries represent the years immediately

before a recession.

First, nominal wage growth is always positive. This is not a surprising result as in both countries wages are determined by collective agreements which typically prevent nominal wage cuts, whereas firm level bargaining can only regulate additional pay components.[5] Aggregate data show some cyclicality, slightly more evident in Italy than in France.

Second, in both countries wage dynamics is largely influenced by people who stay in the same job. Net flows from and to non-employment tend to have a negative or null impact on wage growth suggesting that firms recompose their workforce in order to counterbalance the growth rate of nominal wages of stayers.

Last, movers contribute positively on wage growth, but their contribution is rather low, especially in France where it is almost null. In Italy the contribution of movers was around 40% of total wage growth before the Great Recession and remained close to zero during the prolonged recessionary period of 2009–2014.

Our results are indeed rather similar to Hahn et al. (2017, 2018) for the US. Nevertheless, as shown by MPV (2017b), job-to-job flows can impact wage growth not only because of the composition effect, i.e. the incidence of movers in total employment, but also because of the strategic effect, i.e. the pressure that higher EE flows can exert on stayers' wage growth because of the higher bargaining power they get as the opportunities to find a better paid job increase.

To investigate these issues in the next two sections we first compare the cyclicality of wages of stayers and movers. Afterwards, following MPV (2017b) and Karahan et al. (2017) we construct proxies for the opportunity of an EE transition by worker-type and we check whether and to what extent wage growth of stayers and movers is affected by the presence of possible strategic effects.

4   The cyclicality of realized job-to-job flows

The lack of long time series on job-to-job moves does not allow us to analyze the cyclicality of aggregate flows. Thus, in this section we rely on regional variation in cyclical conditions, as represented by the local unemployment rate. We check whether in both countries, wages of movers react more than those of stayers to the regional unemployment rate. We match our employer-employee data with the LFS regional unemployment rate (20 regions in Italy, 13 in France).

We focus on workers employed for two consecutive years and we calculate the difference in log wages. To avoid spurious transitions towards retirement or school we focus on people

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[5]Using the DADS, Audenaert et al. (2014) shows that among full time workers from the private sector working for the same firm two consecutive years, 26% are subject to a wage cut.

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aged between 25 and 50. The final sample consists of almost 8 millions observations in Italy and 6 in France.

We estimate the following two basic equations:

$$\Delta ln(w_{ijt}) = \beta_1 mover_{it} + \beta_2 U_{rt} + \beta_3 U_{rt} * mover_{it} + \beta_4 x_{ijt} + \delta_r + \nu_i + \zeta_t + \epsilon_{ijt} \quad (1)$$

$$mover_{ijt} = \gamma_1 U_{rt} + \gamma x_{ijt} + \delta_r + \nu_i + \zeta_t + \epsilon_{ijt} \quad (2)$$

In Equation 1 the dependent variable $\Delta ln(w_{ijt})$ is the difference between time t and time $t-1$ of log nominal wages of worker i employed in firm j at $t-1$. The variable $mover_{it}$ is a dummy equal to 1 if worker i changes firm between $t-1$ and t. The variable U_{rt} is the employment rate at time t of region r where firm j is located. The variable δ_r captures region fixed effects. Thus, the coefficient β_2 then is the elasticity of wage growth with respect to deviation of the regional unemployment rate from its long-term average. Last, x_{it} contains workers' and firms' time variant characteristics, like occupation, part time regime, firm j (log) average wage, (log) firm size, firm age and firm age square depending on the specification; ν_i and ζ_t are individual and time fixed effects, respectively. In the second equation, the dummy $mover_{ijt}$ is the dependent variable and the equation is estimated by a linear probability model. The other variables are defined as in Equation 1. Standard errors are clustered by region-year to control for correlation of workers subject to common local shocks.

Equation 1 captures the direct cyclicality of nominal daily wages and allows us to determine whether it is similar for both stayers and movers. Equation 2 instead looks at composition effects over the business cycle.

In these estimates we assume that cyclicality is captured by the local conditions, as measured by the regional unemployment rate. One could argue that in both countries administrative regions are too large to capture local labor market conditions, being travel-to-work areas typically smaller than administrative regions. Our choice is motivated by the lack of data on the unemployment rate for smaller geographical areas and for all the years here considered. Our estimates should then be interpreted as a lower bound for wage growth cyclicality.

Tables 2 and 3 report the estimates for Italy and France respectively. In both tables columns 1-6 refer to Equation 1, columns 7 and 8 to Equation 2. Column 1 and 2 of both Tables 2 and 3 (without and with individual fixed effects) show that wage growth of movers is higher, confirming the standard Burdett and Mortensen (1998) model. For all workers wage changes negatively react to the unemployment rate (col. 3 and 4), as in a standard Phillips curve setting. In both countries wages of movers are considerably more elastic than wages of stayers to the local labor market conditions. Last, in both countries

the probability of a job-to-job move is procyclical, as typically found in the literature (e.g. Karahan et al. (2017); Haltiwanger et al. (2018)).

5   Can job-to-job flows impact on stayers' wages?

As pointed out by MPV (2017b), EE flows can affect aggregate wages not only because of a composition effect, like the one described in the previous section, but also because of what they call a strategic effect. When labor demand increases, employed workers face more opportunities to change their job. As their outside option increases also their wage increases, because firms try to retain them.

MPV (2016a) make a step forward and present a model in which wages respond directly only to EE flows (when minimum wages or reservation wages are binding). Karahan et al. (2017) and MPV (2017b) test empirically this result by including proxies of EE flows and flows into and out of employment in a standard wage growth regression. They find that EE flows are the only variable affecting nominal wage growth whereas unemployment-related measures are not.

We adopt their strategy and carry out the same test for France and Italy. Following in particular MPV (2017b) we identify some types of workers, based on the intersection of the following characteristics: region where individuals work at time $t-1$, gender, age group (three brackets) and workers in low-skilled occupations. Thus, using the full sample (i.e. including also entrants and exiters) we estimate the probability of being mover, an exiter or entrant as a function of individual and firm characteristics in $t-1$ (sector, full time, occupation, log of the firm size and log of the average wage of the firm) and a worker-type fixed effect interacted with time dummies. The latter are used as proxies for the expected probability of a given transition.

We label fixed effects as following: (i) EE for job-to-job transitions; (ii) EN for flows towards non-employment and (iii) NE for flows from non-employment into employment. Then we assign each variables to stayers and movers according to their own type and we run the following regression:

$$\Delta ln(w_{iyt}) = \beta_1 mover_{it} + \beta_2 U_{yt} + \beta_3 EE_{yt} + \beta_4 EN_{yt} + \beta_5 NE_{yt} + \gamma_y + \zeta_t + \epsilon_{iyt} \qquad (3)$$

where y indicates the type of the workers.

Here, differently from Equation 1, U_{yt} is the worker-type y unemployment rate probability estimated using LFS, i.e. the unemployment rate for each type of worker in a given region. Comparable data for subgroups are available only for years after 2003. EE_{yt}, EN_{yt} and NE_{yt} are the time-varying fixed effects for each transition described above. Last, γ_y and ζ_t are type and time fixed effects. Differently from Equation 1, Equation 3 then in-

cludes not only the unemployment rate U_{yt} but also flows into and out of employment which obviously correlate with U_{yt}. In this case U_{yt} captures cyclical conditions different from the ones that determine flows into and out of employment.

The results of the estimates of Equation 3 are reported in Tables 4 and 5 for Italy and France respectively. Columns 1-4 refer to the whole sample of stayers and movers, column 5 to movers only whereas column 6 to stayers only.

As in Tables 2 and 3, we find that wage changes are larger for movers than for stayers. More importantly we find that EE flows are positively correlated to wage growth whereas EN flows have a negatively correlation. Last, NE flows, which capture an increase in opportunities for non-employed workers tend to be positively correlated to wage growth. The same conclusions holds for the sub-sample of movers and stayers. Interestingly, larger EE flows impact not only on wages of movers, but also on stayers' wages, albeit with a lower coefficient. These results are in line with the findings of MPV (2017b) for the US and outline the importance of EE flows in wage determination of stayers.

More importantly, in all the specifications the unemployment rate is not statistically different from zero, but flows into and out of employment are and their magnitude is not affected by the inclusion of EE flows (as shown by col. 4). This result differs from the one of MPV (2017b) and Karahan et al. (2017) suggesting that in France and Italy the risk of unemployment affects wage growth, in line with standard literature of the determinants of wage dynamics.

6 Heterogeneity by occupation

One of the results of the MPV model is that firms compete for workers and are available to increase their wages if they are at risk to move to another firm. Implicit in this model there is the idea that workers cannot be easily substituted at low costs. On a similar ground MPV (2018) show that in a model with on-the-job search, heterogeneous human capital and human capital depreciation during unemployment, firms tend to prefer to poach from other firms.

This result implies however that outside options may exert pressure on wages especially of those workers that are not easily substituted by other workers. Instead, it might not hold for those occupations for which no specific human capital is required. For low-skilled workers, instead, wage could be more influenced by external labor market conditions, i.e. by the type-specific unemployment rate. To test for this hypothesis we subdivide our samples into two groups, according to the skill-content of the occupation. One group is composed of blue-collar workers, clerks and other low-skilled occupations in the service sector. The other group is composed of high-skilled white collars and managers. Workers'

type of occupation is observed at time $t-1$.[6]

Figures 3a and 3b report the probability of a job-to-job move for both groups of workers here considered, in the left-hand panel, and the associated wage change, in Italy and France respectively. In Italy the probability of moving is higher for low-skill occupations, but the associated wage change is smaller than in high-skilled occupations. The cyclicality of wages seems instead rather similar among groups (if any, it appears stronger for high-skilled occupations in Italy). The higher probability to record a job-to-job transition for low-skill occupations, associated to lower wage increases, suggests that these flows are probably generated by a separation and a subsequent new job, instead of a genuine job-to-job transition.

We then run the same regression as in 3. The results are reported in Tables 6 and 7 for Italy and France respectively. Table 6 shows that EE flows affect both types of workers but more those in occupations with a higher-skill content that move to another job. For this subgroup, flows from employment to non-employment, associated to a rise in the job separation rate, do not significantly affect wage growth. The opposite occurs for workers in low-skill occupations. Evidence for France is instead rather mixed (Table 7).

This evidence from the one side suggests that the skill-content of occupations and the substitutability of workers are probably one of the explanations for understanding the impact of flows from and to unemployment on wage growth, at least in Italy. Nevertheless, looking also at Table 7 we cannot exclude that in both countries workers' competition from outside the labor market (as summarized by flows into and out of employment) affect nominal wage growth.

7 Heterogeneity by firm size

Cyclicality of wages can depend also on the cyclicality of reallocation of workers across firms of different productivity. We test this hypothesis by proxying productivity by firm size (as for instance in Haltiwanger et al. (2018) and MPV (2016a); MPV (2016b)). If workers move to high-paying firms and high-paying firms are typically the larger ones, then we should find differentiated effects also by firm size. On the other hand, poaching should be easier for larger firms than for smaller ones.

To test this assumption in Tables 10 and **??** we present estimates which relate EE flows to the size of the firm left by the worker (i.e. firm size is measured at time $t-1$). Columns 1 and 2 report the effect of the variable EE interacted with firm size and suggest that the gain from moving declines the larger is the firm where the worker was previously employed. The returns from moving increase, however, as the size of the hiring firm increases (cols.

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[6]Education or detailed occupations are not available.

3 and 4).

All in all this evidence confirms that the dynamics of wages depend also on the distribution of firm size in each country and ultimately on the intensity of workers' movements from small firms to large firms. For a comparison, here we just mention that in Italy the probability that a worker in a small firm (defined as below the 25þpercentile of the firm size distribution) move to a large firm (in the 75% percentile) is around 7%. In France is just around 1%. Thus, any factor that hinder reallocation impact directly on this component of wage growth.

8   Conclusion

In this paper we analyze how job-to-job flows impact the responsiveness of aggregate wage changes in Italy and France. We use administrative microdata and look at two channels: a composition effect due to the procyclicality of job-to-job flows and a strategic effect determined by the response of wages of stayers to the option to move. We detect the presence of these effects in both France and Italy.

Differently from the U.S., however, we find that in these euro area countries flows from and to employment still affect wage growth of stayers and movers. This result claims for further research on the competition of employed and unemployed workers for jobs, that in turn may depend on some structural characteristics of jobs and firms. In Italy, wages of workers in high-skilled occupations react more intensively to outside options, whereas wages of workers in low-skilled occupation depend only on flows into and out of employment.

All in all our results confirm that monetary policy should put more attention on the determinants of job-to-job flows. Nevertheless, what is needed is a more flexible approach that allows to take into account both EE flows and flows from/to unemployment and some structural characteristics of the labor market in each country.

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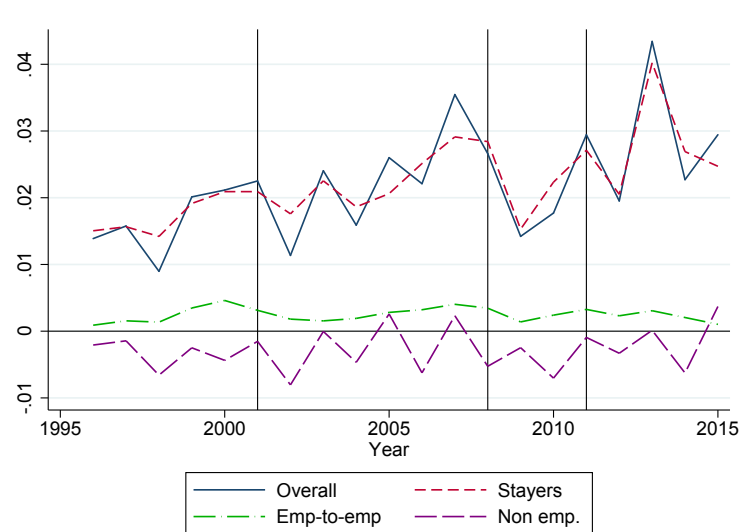
Figures

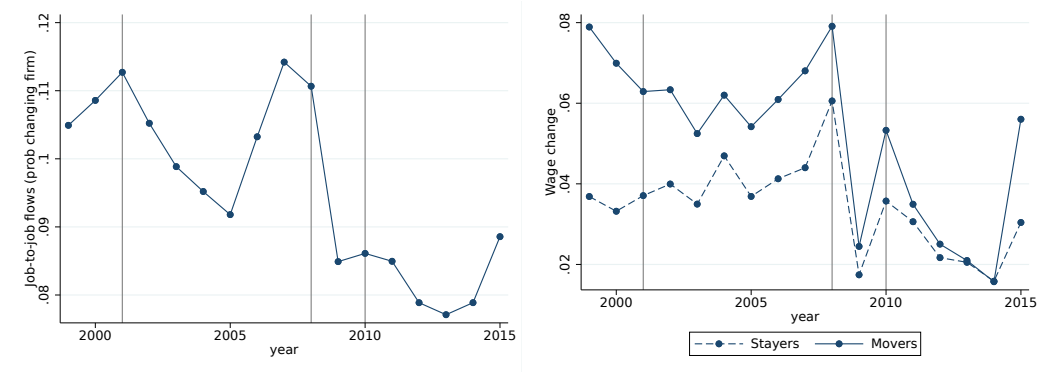Figure 1 – Italy: decomposition of wage growth by type of flow

Figure 2 – France: decomposition of wage growth by type of flow

Figure 3 – Italy: share of job-to-job movers and wage premium

Note: Source: INPS. The graph displays the share of job-to-job movers among employees in the private sector aged 25-50. Movers are computed as those who are employed in December each year, but in two different firms, with a non-employment spell within the year of less than one month. Wage change is the change in daily wage in two consecutive years for individuals who are employed both years, in the same firm (stayers) or in two different firms (movers). Grey lines refer to recessions.

Figure 4 – Italy: share of job-to-job movers and wage premium low and high skilled workers
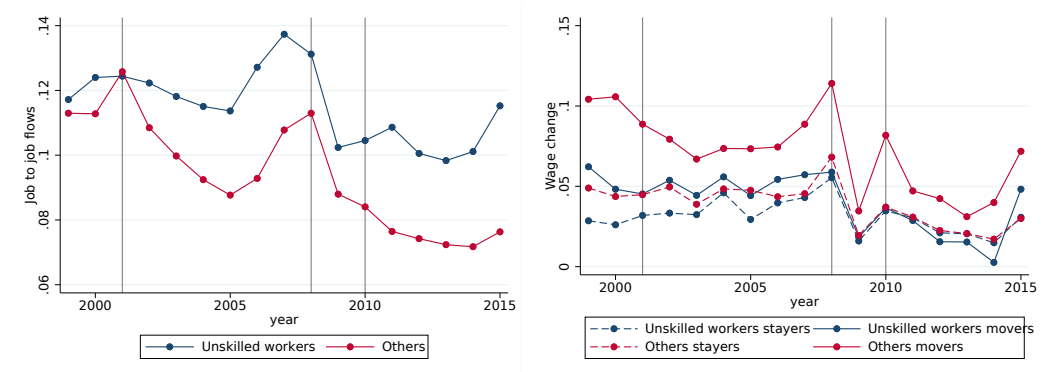
Note: Source: INPS. Unskilled workers are those classified by INPS as blue collars or apprentices. Grey lines refer to recessions.

Figure 5 – Italy: share of job-to-job movers and wage premium temporary and permanent workers

Note: Source: INPS. Grey lines refer to recessions.

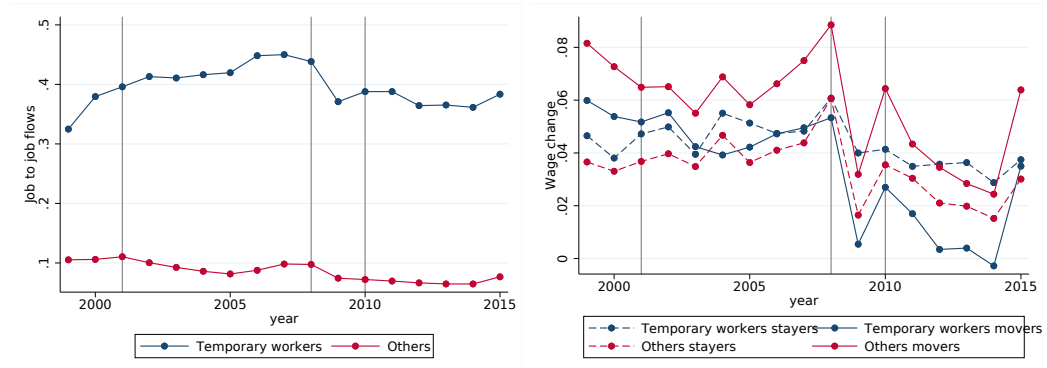Figure 6 – France: share of job-to-job movers and wage premium

Note: Source: DADS. The graph displays the share of job-to-job movers among employees in the private sector aged 25-50. Movers are computed as those who are employed in December each year, but in two different firms, with a non-employment spell within the year of less than one month. Wage change is the change in daily wage in two consecutive years for individuals who are employed both years, in the same firm (stayers) or in two different firms (movers). Grey lines refer to recessions.

Figure 7 – France: share of job-to-job movers and wage premium low and high skilled workers
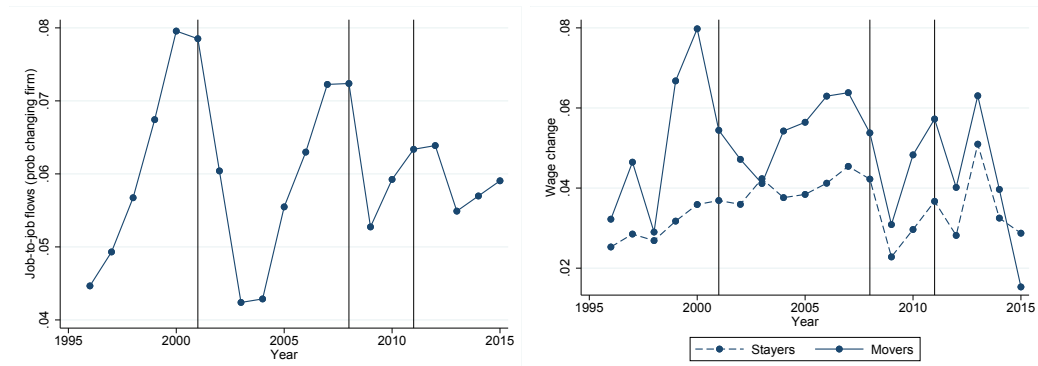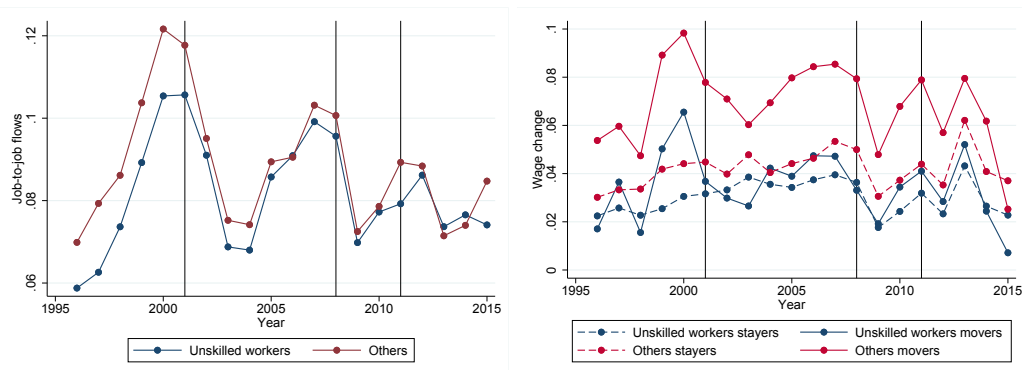

Source:DADS. Unskilled workers are those classified as drivers, unskilled workers, employees in trade or in services for the households. Grey lines refer to recessions.

Figure 8 – France: share of job-to-job movers and wage premium temporary and permanent workers
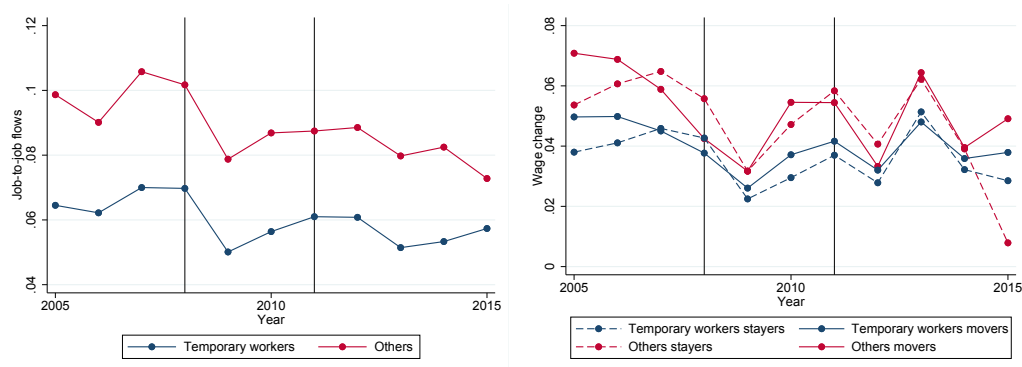
Note: Source: DADS. Grey lines refer to recessions. Labor contract is only available since 2005.

Figure 9 – France: share of job-to-job movers and wage premium temporary and permanent workers

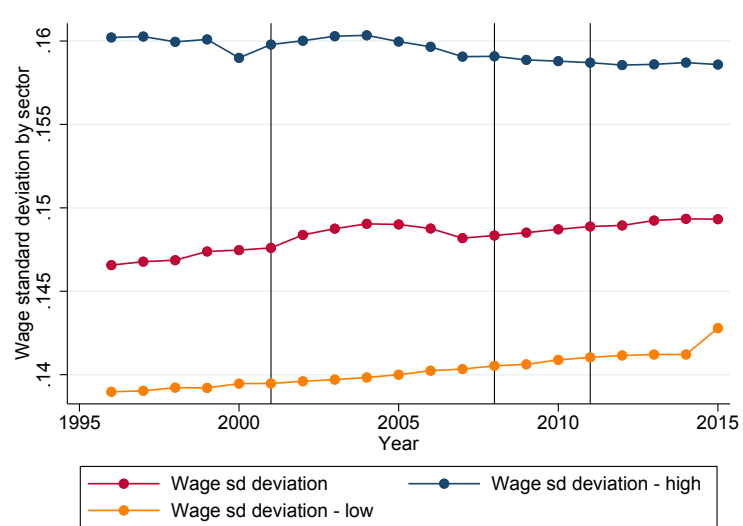**Note**: Source: DADS. Grey lines refer to recessions. Labor contract is only available since 2005.

Figure 10 – France: sector wage dispersion

Tables

Table 1 – Summary statistics Italy and France

	Italy			France		
	All	Stayers	Movers	All	Stayers	Movers
	(1)	(2)	(3)	(4)	(5)	(6)
Movers (as % of total empl.)	0.102			0.082		
Movers (as % of total hires)	0.426			0.280		
Daily wage	80.382	80.822	76.518	77.026	77.192	75.162
	(50.660)	(50.720)	(49.966)	(55.386)	(55.627)	(52.562)
Log wage evolution	0.036	0.034	0.054	0.037	0.036	0.050
	(0.149)	(0.134)	(0.240)	(0.176)	(0.162)	(0.287)
Days worked	272.770	284.865	166.592			
(current spell)	(73.451)	(59.578)	(95.075)			
Days paid				344.633	355.425	223.490
(current spell)				(58.909)	(32.819)	(119.801)
Female	0.349	0.352	0.319	0.413	0.417	0.375
Age	38.069	38.214	36.797	38.535	38.702	36.652
	(6.846)	(6.828)	(6.872)	(6.828)	(6.806)	(6.795)
Temporary contract				0.132	0.042	0.184
Full time	0.846	0.846	0.845	0.848	0.849	0.821
Unskilled workers	0.589	0.583	0.640	0.593	0.595	0.592
Firm average wage (log)	7.479	7.488	7.393	10.154	10.161	10.278
	(0.472)	(0.465)	(0.517)	(0.530)	(0.495)	(0.933)
Firm size (log)	4.333	4.349	4.187	5.258	5.292	4.883
	(2.637)	(2.635)	(2.655)	(2.850)	(2.857)	(2.716)
Firm age (years)	17.545	18.360	10.393	24.745	25.292	21.257
	(13.342)	(13.216)	(12.263)	(20.997)	(20.991)	(19.276)
Share firms > 50 employees	0.470	0.472	0.456	0.633	0.638	0.658
(in the sample)						
Share firms > 50 employees	0.026			0.214		
(in the population)						
Regional unempl. rate	0.075	0.075	0.070	0.088	0.088	0.086
	(0.044)	(0.044)	(0.042)	(0.016)	(0.016)	(0.016)
Observations	7718759	6929419	789340	6571307	6034561	536746

Note: Source: INPS and DADS. Standard deviations within brackets. For movers: workers' and firms' characteristics observed before moving. Unskilled workers in Italy are those classified by INPS as blue collar workers; in France are those classified as unskilled workers, drivers, employees in trade and in services to the households. Share firms > 50 employees refers to the share of workers working in firms with more than 50 employees.

Table 2 – Observed cyclicality of wage changes and of job-to-job moves. Italy

| | Dependent variable: delta log wage | | | | | | Mover(π^m) | |
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
mover	0.016***	0.013***			0.029***	0.025***		
	(0.002)	(0.002)			(0.002)	(0.002)		
unemp			-0.034	-0.072***	-0.016	-0.053**	-0.167***	-0.281***
			(0.024)	(0.026)	(0.023)	(0.026)	(0.053)	(0.069)
unemp*mover					-0.175***	-0.169***		
					(0.028)	(0.031)		
N	7710193	7573956	7710193	7573956	7710193	7573956	9083535	8703055
Ind. Fe	No	Yes	No	Yes	No	Yes	No	Yes

Note: Additional controls: gender, age, age squared, occupation, log average wage at the firm level, log average firm size, firm's age, firm's age squared, sector fixed effect, region fixed effects. Standard errors clustered at the region-year level.

Table 3 – Observed cyclicality of wage changes and of job-to-job moves. France

| | Dependent variable: delta log wage | | | | | | Mover(π^m) | |
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
mover	0.012***	0.009***			0.027***	0.025***		
	(0.002)	(0.002)			(0.008)	(0.008)		
unemp			-0.168***	-0.129	-0.151***	-0.111	-0.359***	-0.171
			(0.051)	(0.080)	(0.050)	(0.080)	(0.054)	(0.169)
unemp*mover					-0.169**	-0.195**		
					(0.086)	(0.083)		
N	6497208	5326828	6497208	5326828	6497208	5326828	8271969	6350392
Ind. Fe	No	Yes	No	Yes	No	Yes	No	Yes

Note: Additional controls: age, age squared, firm age, firm age squared, sector fixed effect, region fixed effects. Standard errors clustered at the region-year level. *** denotes significance at 1%, ** denotes significance at 5%, * denotes significance at 10%.

Table 4 – The reaction of wages to (proxies of) outside options: Italy

	Dependent variable: delta log wage				Movers	Stayers
	All					
	[1]	[2]	[3]	[4]	[5]	[6]
	no unempl control, same sample					
mover	0.012***	0.021***	0.012***	0.012***		
	(0.002)	(0.002)	(0.002)	(0.002)		
unemp	0.003	0.016	0.006	0.006	-0.021	0.009
	(0.012)	(0.012)	(0.012)	(0.012)	(0.028)	(0.012)
unemp*mover		-0.141***				
		(0.016)				
EE flows	0.097***	0.095***		0.081***	0.151**	0.046***
	(0.022)	(0.022)		(0.023)	(0.062)	(0.016)
EN flows			-0.085***	-0.070***	0.005	-0.084***
			(0.018)	(0.018)	(0.058)	(0.020)
NE flows			0.070***	0.063***	0.018	0.067***
			(0.018)	(0.017)	(0.032)	(0.018)
N	5612761	5612761	5612734	5612734	551995	5060733

Note: additional controls: whether full time worker, firm's size, mean wage at the firm level, firm's age linear and squared (all referred to the t-1 period), market, year, sector fixed effects. Market is the combination of age (3 categories), gender, whether blue collar and region. The unemployment rate is the unemployment rate at the market level computed from the Labour Force Survey (from 2004), EE EN NE flows are the composition adjusted job-to-job, employment to non employment, non employment to employment flows (see text). Standard errors clustered by type-time. *** denotes significance at 1%, ** denotes significance at 5%, * denotes significance at 10%.

Table 5 – The reaction of wages to (proxies of) outside options: France

	Dependent variable: delta log wage				Movers	Stayers
	All					
	[1]	[2]	[3]	[4]	[5]	[6]
mover	0.005***	0.009***	0.010***	0.010***		
	(0.001)	(0.002)	(0.002)	(0.002)		
unemp	-0.204***	-0.200***	-0.209***	-0.203***	-0.538***	-0.160***
	(0.004)	(0.008)	(0.008)	(0.008)	(0.026)	(0.007)
unemp*mover		-0.048**	-0.051**	-0.050**		
		(0.020)	(0.020)	(0.020)		
EE flows	0.168***	0.167***		0.193***	0.193**	0.198***
	(0.008)	(0.027)		(0.032)	(0.077)	(0.032)
EN flows			-0.081***	-0.061***	-0.162***	-0.051***
			(0.015)	(0.015)	(0.037)	(0.015)
NE flows			0.082***	0.100***	0.123***	0.097***
			(0.018)	(0.018)	(0.045)	(0.018)
N	3676844	3676844	3674413	3674413	311632	3362781

Note: additional controls: whether full time worker, firm's size, mean wage at the firm level, firm's age linear and squared (all referred to the t-1 period), market, year, sector fixed effects. Market is the combination of age (3 categories), gender, whether blue collar and region. The unemployment rate is the unemployment rate at the market level computed from the Labour Force Survey (from 2003), EE EN NE flows are the composition adjusted job-to-job, employment to non employment, non employment to employment flows (see text). Standard errors clustered by type-time. *** denotes significance at 1%, ** denotes significance at 5%, * denotes significance at 10%.

Table 6 – The reaction of wages of workers in low- and high-skill occupations: Italy

| | Dependent variable: delta log wage | |
| | Workers in low-skill occupations | Managers and professionals |
	[1]	[2]
mover	0.003**	0.025***
	(0.001)	(0.003)
unemp	-0.033**	-0.018*
	(0.015)	(0.010)
EE flows	0.020	0.101***
	(0.024)	(0.025)
EN flows	-0.090***	-0.042**
	(0.025)	(0.020)
NE flows	0.069***	0.078***
	(0.022)	(0.024)
N	3288506	2324213

Note: additional controls: whether full time worker, firm's size, mean wage at the firm level, firm's age linear and squared (all referred to the t-1 period), market, year, sector fixed effects. Market is the combination of age (3 categories), gender, whether low skilled and region. The unemployment rate is the unemployment rate at the market level computed from the Labour Force Survey (from 2003), EE, EN, NE flows are the composition adjusted job-to-job, employment to non employment, non employment to employment flows (see text). Low skilled workers in Italy are workers classified in INPS data as blue collar or apprenticeships. Standard errors clustered by type-time. *** denotes significance at 1%, ** denotes significance at 5%, * denotes significance at 10%.

Table 7 – The reaction of wages of workers in low- and high-skill occupations: France

| | Dependent variable: delta log wage | |
| | Workers in low-skill occupations | Managers and professionals |
	[1]	[2]
mover	-0.005***	0.019***
	(0.001)	(0.002)
unemp	-0.020	-0.020
	(0.024)	(0.024)
EE flows	0.275***	0.156***
	(0.043)	(0.046)
EN flows	-0.065***	-0.079***
	(0.021)	(0.022)
NE flows	0.116***	0.021
	(0.026)	(0.025)
N	2203860	1470550

Note: additional controls: whether full time worker, firm's size, mean wage at the firm level, firm's age linear and squared (all referred to the t-1 period), market, year, sector fixed effects. Market is the combination of age (3 categories), gender, whether low skilled and region. The unemployment rate is the unemployment rate at the market level computed from the Labour Force Survey (from 2003), EE, EN, NE flows are the composition adjusted job-to-job, employment to non employment, non employment to employment flows (see text). Low skilled workers in France are drivers, unskilled workers and employees in trade and in services to the households. Standard errors clustered by type-time. *** denotes significance at 1%, ** denotes significance at 5%, * denotes significance at 10%.

Table 8 – The reaction of wages of temporary and permanent workers: Italy

| | Dependent variable: delta log wage | | | |
| | Temporary | | Permanent | |
	[1]	[2]	[3]	[4]
mover	-0.027***	-0.016***	0.018***	0.020***
	(0.002)	(0.002)	(0.002)	(0.002)
unemp	0.038	-0.052**	-0.013	0.009
	(0.032)	(0.022)	(0.014)	(0.012)
EE flows	-0.003	-0.026	0.082***	0.080***
	(0.043)	(0.038)	(0.020)	(0.023)
EN flows	-0.026	-0.079**	-0.055**	-0.072***
	(0.049)	(0.035)	(0.022)	(0.019)
NE flows	-0.010	-0.084**	0.079***	0.070***
	(0.032)	(0.042)	(0.016)	(0.020)
N	257042	359077	5119312	5253645
l.firm FE	Yes	No	Yes	No

Note: additional controls: whether full time worker, firm's size, mean wage at the firm level, firm's age linear and squared (all referred to the t-1 period), market, year, sector fixed effects. Market is the combination of age (3 categories), gender, whether low skilled and region. The unemployment rate is the unemployment rate at the market level computed from the Labour Force Survey (from 2003), EE, EN, NE flows are the composition adjusted job-to-job, employment to non employment, non employment to employment flows (see text). Low skilled workers in Italy are workers classified in INPS data as blue collar or apprenticeships. Standard errors clustered by type-time. *** denotes significance at 1%, ** denotes significance at 5%, * denotes significance at 10%.

Table 9 – The reaction of wages of temporary and permanent workers: France

| | Dependent variable: delta log wage | | | |
| | Temporary | | Permanent | |
	[1]	[2]	[3]	[4]
mover	0.012***	0.015***	0.008***	0.005***
	(0.003)	(0.002)	(0.001)	(0.001)
unemp	0.062	0.049	-0.032*	-0.024
	(0.058)	(0.048)	(0.018)	(0.017)
EE flows	0.394***	0.392***	0.214***	0.230***
	(0.108)	(0.097)	(0.044)	(0.039)
EN flows	-0.183***	-0.069	-0.105**	-0.092***
	(0.058)	(0.052)	(0.016)	(0.016)
NE flows	0.424***	0.274***	0.071***	0.089***
	(0.066)	(0.057)	(0.020)	(0.019)
N	118990	133972	3355402	2964411
l.firm FE	Yes	No	Yes	No

Note: additional controls: whether full time worker, firm's size, mean wage at the firm level, firm's age linear and squared (all referred to the t-1 period), market, year, sector fixed effects. Market is the combination of age (3 categories), gender, whether low skilled and region. The unemployment rate is the unemployment rate at the market level computed from the Labour Force Survey (from 2003), EE, EN, NE flows are the composition adjusted job-to-job, employment to non employment, non employment to employment flows (see text). Standard errors clustered by type-time. *** denotes significance at 1%, ** denotes significance at 5%, * denotes significance at 10%.

Table 10 – France and Italy: Wage changes, heterogeneity by wage standard deviation. Only permanent workers.

Dependent variable: delta log wage		
	Italy	France
unemp	-0.023*	-0.017*
	(0.009)	(0.009)
low variability sectors	-0.003	-0.000
	(0.003)	(0.001)
EE flows	0.164***	0.162***
	(0.019)	(0.026)
EE *low variability	-0.136***	-0.085***
	(0.020)	(0.019)
EN flows	-0.019	0.032
	(0.017)	(0.022)
EN*low variability	-0.087***	-0.042***
	(0.020)	(0.018)
NE flows	-0.016	-0.047***
	(0.010)	(0.018)
NE * low variability	0.113***	0.056***
	(0.017)	(0.014)
N	5612734	2392846

Note: additional controls: whether full time worker, log firm size, mean wage at the firm level, firm's age linear and squared (all referred to the t-1 period), market, year, sector fixed effects. Market is the combination of age (3 categories), gender, whether low skilled and region. The unemployment rate is the unemployment rate at the market level computed from the Labour Force Survey (from 2003), EE EN NE flows are the composition adjusted job-to-job, employment to non employment, non employment to employment flows. Standard errors clustered by type-time. *** denotes significance at 1%, ** denotes significance at 5%, * denotes significance at 10%.