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Article

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Reallocation and the Role of Firm Composition Effects on Aggregate Wage Dynamics

Abstract

Aggregate wages display little cyclicality compared to what a standard model would predict. Wage rigidities are an obvious candidate, but the existing literature has emphasized the need to take into account the growing importance of worker composition effects, especially during downturns. This paper seeks to understand the role of firm heterogeneity for aggregate wage dynamics with reference to the Italian case. Using a newly available dataset based on social security records covering the universe of Italian employers between 1990 and 2015, we document that firm composition effects increasingly matter in explaining aggregate wage growth and largely reflect shifts of labor from low-paying to high-paying firms, especially in the most recent years. We find that changes in reallocation of workers across firms accounted for approximately one-fourth of aggregate wage growth during the crisis.

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1 Introduction

During downturns, aggregate wages appear to respond very little to business cycle fluctuations. This holds true even for the recent recessionary period, despite the duration and the severity of the crisis. Common explanations include wage rigidities resulting from various market frictions – see Adamopoulou et al. (2016); Verdugo (2016); Devicienti, Maida and Sestito (2007) and Dickens et al. (2007). However, the existing literature has also provided evidence that low-paid workers were more severely affected during the recent downturn and therefore composition effects might have played a particularly important role in shaping aggregate wage dynamics – see, for instance, Daly and Hobijn (2016) for the US and Verdugo (2016) for the Eurozone countries.

In this paper, we contribute to this literature by documenting the relevance of *firm* composition effects – as opposed to *worker* composition effects – for aggregate wages. We conduct our analysis on a newly available set of social security data covering the universe of employers between 1990 and 2015 in Italy and comprising a random sample of employees for the same period. We proceed by first implementing a standard Blinder–Oaxaca (BO) decomposition exercise (Blinder, 1973 and Oaxaca, 1973), augmented with employer-level characteristics. This exercise allows us to quantify separately the parts of average wage changes that are due to changes in employers' and those due to changes in workers' average characteristics in the economy. Since matched employer–employee datasets were previously not easily available, the firm side of the adjustment has often been neglected in the earlier literature. Recently, some papers have investigated and stressed the relevant role of firm heterogeneity and job characteristics for the cyclical behavior of wages of new hires and job movers (Gertler et al., 2016, Carneiro et al., 2012 and Kauhanen and Maliranta, 2017), as well as for the increasing inequality of wages (Card et al., 2013 and Song et al., 2018). Little is known about their role in explaining the evolution over time of aggregate wages.

By applying the simple BO exercise in Italy, we find that composition effects matter substantially for aggregate wage dynamics and increasingly so after the recent crisis. When we distinguish between employers' and workers' characteristics, we find that employers' characteristics, which used to matter a little, account for an increasingly large share of these effects in the recent years, and even surpassed that of workers' characteristics.

Changes in employers' characteristics may reflect changes in the characteristics of the firms populating the economy – the type of firms entering or exiting the market, the wage premia of incumbents, and other firms' characteristics,[1] or they may simply reflect changes in the identity of employers. For instance, workers may be more likely to change job and find employment in higher paying firms after recessions. If this is the case, the share of employment of higher paying firms would grow after recessions, generating aggregate wage growth even absent changes in firms' wage premia.[2] The BO decomposition cannot tell these stories apart. To distinguish between these explanations, we borrow a tool from the literature on reallocation of workers across firms – e.g., among many others, Bartelsman, Haltiwanger and Scarpetta (2013) – the Olley and Pakes decomposition (1996, from now on OP decomposition). To our

1 For instance, Litan and Hathaway (2014) show that firms are aging in the US.

2 Suppose that in the economy, there are two firms each employing 50 workers and that firm 2 pays a wage twice as high as firm 1. Employers' average wage may increase by 10% either because the wage at both firms increases by 10%, or because 15 employees move from firm 1 to firm 2.

knowledge, although there is evidence of an extensive process of workers' reallocation after the crisis (see, for instance, Foster et al., 2016, for the US and Calligaris et al., 2018, and Linarello and Petrella, 2017, for Italy), we are the first to quantify the role of this reallocation for aggregate wages.

Through the OP decomposition, we decompose aggregate wages into the simple unweighted average of the wage across firms (*within* component) and a correlation term between wage and employment across firms (the *OP* component). The first term captures changes in aggregate wages that are due to changes in firms' average wages common to all firms – due to inflation, aggregate shocks, changes in firms' average characteristics, etc.; the second term captures changes in aggregate wages that are due to workers' changing jobs and shifting between low- and high-paying firms.[3] Finally, an extension of the OP decomposition proposed by Melitz and Polanec (2015) allows to extract the contribution to the aggregate wage of entry and exit, by contrasting the average wage of these firms to that of incumbents. Our main finding is that the contribution of the OP term, and therefore changes in the allocation of workers to firms, to the aggregate wage has been steadily rising since the mid-2000s, even during the financial and sovereign debt crisis, especially in the manufacturing sector. This accounted for approximately one-fourth of aggregate wage growth, after controlling for firm-level differences in the occupational composition of their workforce.

To conclude, we suggest a possible interpretation of this employment shift from low- to high-wage firms and its contribution to aggregate wage dynamics, in terms of changes in allocative efficiency and aggregate productivity. This interpretation takes the stand from the well-documented fact that wages and labor productivity are correlated across firms. We show that this correlation holds in our data and that changes in the OP contribution to the aggregate wage are positively associated with changes in productivity at the two-digit sector level and with a measure of competition (Herfindahl index). This evidence is indirect and only suggestive, and we leave to future research a full test of our hypothesis and an exploration of its implications.

The paper proceeds as follows. After describing the data in section 2, we replicate composition studies by employing a standard tool in labor economics to assess differences among groups of workers, the BO decomposition, which we augment with employers' characteristics – section 3. We proceed by applying on wage data a standard measure of reallocation, the OP decomposition (Olley and Pakes, 1996) – section 4. Section 5 proposes an interpretation in terms of allocative efficiency of the analysis conducted on wage data. Finally, section 6 concludes and proposes avenues for future research.

2 **Data**

The source for our data consists of social security payments to the Italian National Social Security Institute (INPS) made by reporting units ("establishments") for their employees (with an open-ended or fixed-term contract) between 1990 and 2016. From this master data,

3 When workers are randomly allocated across firms, the correlation between the wage and employment is zero; when workers are reallocated to high-paying firms, the correlation between size and wages across firms becomes positive – the *OP* term increases – and the aggregate wage increases above the within term, purely as a result of a composition effect.

INPS extracts two datasets. The first dataset consists of the universe of firms with at least one employee at some point during a given calendar year – this extraction covers the years only until 2015, and it provides data at the firm level.[4] The second dataset consists of the employment histories of all workers born on the 1st or the 9th day of each month (24 dates per calendar year or 6.5% of the workforce) up to 2016. In this paper, we restrict attention to the nonagricultural business sector and use the tax filing number as the definition of firm.[5]

In the data appendix, we assess the quality of our data against the Eurostat National Accounts (ENA; ESA, 2010) and the Eurostat Structural Business Statistics (ESBS) and conclude that INPS data provide a reasonably good approximation of national aggregates from official statistics regarding employer business demographics, employment, and gross wages. INPS data do not contain balance sheet information, implying that there is no direct information on labor productivity. However, this information can be retrieved for the subset of firms that are limited companies using Cerved, the business register containing balance sheet data for the universe of firms with this legal form of incorporation. In the data appendix, we conclude that, when combined with Cerved, the INPS data also return a reasonably good picture of balance sheets, but only for firms with at least 20 employees.

Tables A1 and A2 in Appendix report a broad set of descriptive statistics on firms with at least one employee in the private nonagricultural sector and their workers, respectively. Over the 25 years considered, the share of industrial firms over the total number of firms declines from 49% to 35%, average firm size declines from 8 in 1990 to 7.4 employees in 2012 and then rises again to about 7.6 in the last 3 years, the pool of employers increases from 1.1 to about 1.4 million, and the nominal monthly gross average wage at the firm level almost doubles from 1,102 in 1990 to 2,156 euros in 2015. Regarding workers, we observe that the average age of employees in Italy increases from about 36 years in 1990 to 41 years in 2016; the share of women increases as well, from 30% to 36%, while, also due to the rising importance of the service sector, the share of blue collars declines from 64% to 59%.

3 Composition effects and the role of employers' characteristics, the BO decomposition

We use the employer–employee data from INPS to replicate and extend previous work on the rising importance of worker composition effects in explaining aggregate wage dynamics over time and particularly during and after the recent crisis (Daly and Hobijn, 2016; Verdugo, 2016). Compared to the data used in these studies, the INPS data have the advantage of covering a longer time span, thus allowing us to study the evolution of composition effects with a very long time perspective. More importantly, the availability of information on the employer side allows us to build and expand on this literature by quantifying firm composition effects, due to changing employer characteristics, along with worker composition effects, due to changes in workers' characteristics. To our knowledge, most of the existing literature has overlooked the importance of changes in employers' characteristics in explaining aggregate wage dynamics.

4 There is a provisory version of firm-level data for 2016 that we only use in the BO decomposition exercise combined with the consolidated data for workers.

5 A same tax filing number can be associated with more than one reporting unit making social security payments to INPS.

Some recent papers have stressed the increasing relevance of firm-level characteristics in explaining wage premia from job-to-job movements (Gertler et al., 2016; Carneiro et al., 2012) or wage losses from being displaced (Lachowska et al., 2018; Heining et al., 2018), as well as in determining earnings inequality in many different countries (see, for instance, Card et al., 2013; Song et al., 2018). What we seek to quantify is how much employers' characteristics matter in explaining aggregate wage growth. For this purpose, we use a standard BO decomposition (Blinder, 1973; Oaxaca, 1973) that provides us with a synthetic measure to analyze average wage changes between two consecutive years and to determine the part due to compositional effects. The BO decomposition is usually implemented to disentangle the sources of wage differences between two subgroups of the population in the same year (i.e. men and women). We use it instead to evaluate how average wages differ between pairs of consecutive years for the entire population of employees in the private sector excluding agriculture. We first run a Mincerian wage equation (Mincer, 1974) for every year, therefore allowing coefficients to change over time. Then, for every couple of consecutive years, we decompose the change in log wages in the part due to changes of the coefficients between the two years (the coefficient effect) and the part due to changes over time in average characteristics of workers of the firms they are employed at (the composition effect). More specifically, we use the micro data at the worker level,[6] matched with some employer-level characteristics to estimate the following equation for every pair of two consecutive years t:

$$\log\left(w_{ijt}\right)=\alpha_t+\beta_t^1 x_{it}+\beta_t^2 x_{jt}+\epsilon_{ijt},$$

where w_{ijt} refers to the daily wage of worker i employed in firm j in year t,[7] x_{it} are workers' characteristics (gender; age, linear and squared; a dummy for immigrants; a dummy for full-time employees; a dummy for those with a permanent contract; dummies for blue collars, white collars, or middle managers) and x_{jt} are employers' characteristics (sectors at two digit level; the logarithm of employment size, linear and squared; age, linear and squared; estimated time-invariant firm fixed effects, which capture firm-specific wage differentials).[8] Finally, ϵ_{ijt} is an error term.[9]

The mean outcome difference between years t and $t-1$ can be expressed as

$$\begin{aligned}E\left[\log\left(w_{ijt}\right)\right]-E\left[\log\left(w_{ijt-1}\right)\right]&=\left[\alpha_t+\beta_t^1E\left(x_{it}\right)+\beta_t^2E\left(x_{jt}\right)\right]-\left[\alpha_{t-1}+\beta_{t-1}^1E\left(x_{it-1}\right)+\beta_{t-1}^2E\left(x_{jt-1}\right)\right]\\&=\underbrace{\left[E\left(x_{it}\right)-E\left(x_{it-1}\right)\right]\beta_{t-1}^1}_{\text{change due to workers' composition}}+\underbrace{\left[E\left(x_{jt}\right)-E\left(x_{jt-1}\right)-E\left(x_{jt-1}\right)\right]\beta_{t-1}^2}_{\text{change due to employers' composition}}\\&+\underbrace{\left(\alpha_t-\alpha_{t-1}\right)+\left(\beta_t^1-\beta_{t-1}^1\right)E\left(x_{it}\right)+\left(\beta_t^2-\beta_{t-1}^2\right)E\left(x_{jt}\right)}_{\text{change due to differences in returns}}.\end{aligned}$$

The first and the second terms of the equation above refer to the part of variation in mean wage between years t and t-1 due to changes in workers' and employers' characteristics, respectively.

6 The data are collapsed at the worker-year level by considering the job of the longest duration, so as not to oversample workers with multiple employment spells within the same year.

7 The wages of part-time workers are in full-time equivalent units.

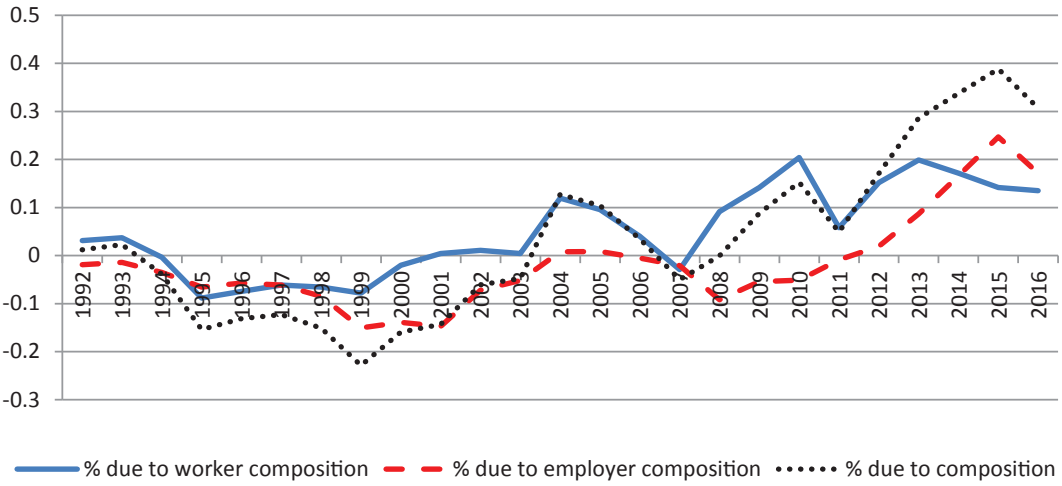
8 The estimated firm fixed effects are computed from the universe of firms dataset, controlling as much as possible for the composition of workers in the firm (type of occupation), for the different geographical location of the firms (province fixed effects), for the sector of activity (two digit sector fixed effects), for firms' age (linear and squared) and size (number of employees linear and squared) and for changes in average wages over time common to all firms (absorbed by year dummies).

9 Note that we exclude workers under work benefit schemes from this analysis, since their wages would be lower by definition and not due to changes in the characteristics of workers or firms.

Figure 1 summarizes the relative importance of composition effects and their components in explaining aggregate wage growth. The dotted line refers to the overall contribution of composition effects over time.[10] We find that composition accounts for about 40% of aggregate wage dynamics on average in the last few years. Moreover, the importance of composition effects increased significantly after the recent crisis, which is in line with Daly and Hobijn (2016). The dashed and the solid lines distinguish between the contribution of employers' and workers' characteristics. They show that employers' characteristics account for an increasing share of compositional effects in wage dynamics, so to even surpass the importance of average workers' characteristics. While our results for workers are in line with the previous literature (Hines, Hoynes and Krueger, 2001, for instance), which shows that job losses during downturns disproportionally affect workers with lower than average wages, to our knowledge, we are the first to quantify the increasing contribution of employers' characteristics in explaining aggregate wage dynamics. Given this first set of results, we believe that the firm component is worth a more thorough investigation.

Figure 2 analyzes which characteristics matter more for the compositional effect on wages.[11] It plots the average contribution of different worker- and employer-level characteristics

Figure 1 Contribution of composition effects to the wage growth, distinguishing between employers' and workers' characteristics.



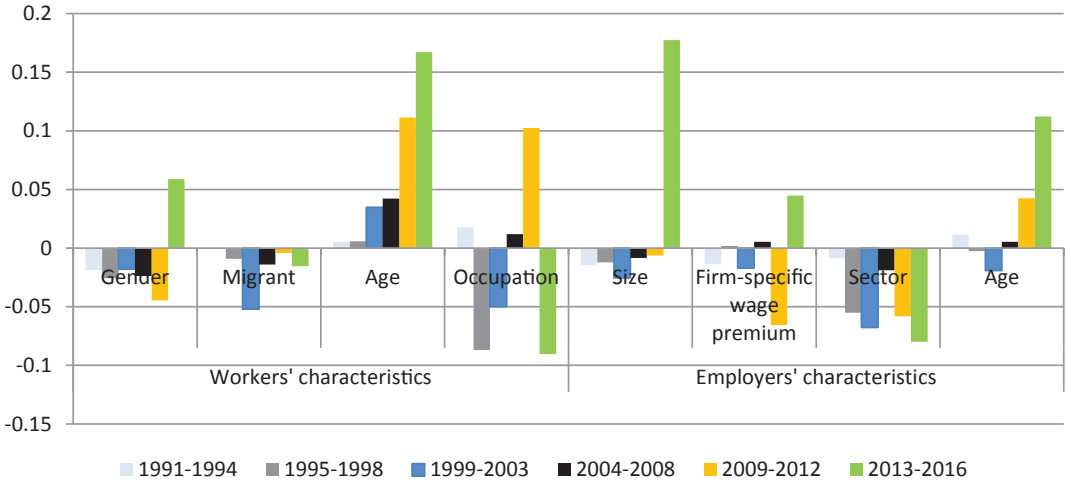
Source: own calculations on INPS data. *Note:* this figure plots the results on *composition effects* obtained from the BO decomposition (this is therefore the part of aggregate wage dynamics explained by changes in the average characteristics of employed individuals in the economy and of the firms where they are employed, keeping returns to these characteristics fixed over time). The results report the ratio between the 3-year moving average of the part of aggregate wage growth explained by changes in workers' and employers' composition and the 3-year moving average of aggregate wage growth. The blue line refers to the share of the yearly change in wage levels explained by changes in workers' characteristics, and the red line refers to the share of the yearly change in wage levels explained by changes in employers' characteristics.

10 In particular, it plots the ratio between the three-year moving average of the part of aggregate wage growth due to composition effects and the three-year moving average of aggregate wage growth. We use the moving average in order to smooth outliers. In some years, aggregate wage growth is very low. For example, for the overall private sector, it is 0.1% in 2009 and 0.3% in 2012; for private services, it is -0.2% in 1999 and -0.1% in 2002. Thus, when computing the fraction of wage variation due to changes in composition, the unsmoothed series behave erratically in certain years (due to the denominator being small and due to changing signs). These results are available from the authors upon request.

11 Composition effects refer to the type of workers who are employed in the economy (in a certain type of firms) each year.

to the aggregate wage growth in the economy over time, considering six different subperiods between 1991 and 2016.[12] Some of these characteristics are time invariant (e.g. workers' gender or firms' sector) but may still contribute to explaining the evolution of aggregate wage dynamics, since the distribution of these characteristics in the population of employed individuals may change over time. If, for instance, during recessions firms tend to fire women, who are on average paid less, the aggregate wage in the economy would increase, due to a pure composition effect on the workers' side. The figure shows that the largest contribution in terms of composition effects stems from changes in the workers' age and type of occupation and in firms' age, size, and firm-specific wage differentials. Our results confirm that the aging of the workforce significantly contributes to wage growth (Maestas et al., 2016), and this is particularly the case during recessions, possibly because younger workers tend to have less seniority and to be less costly to fire. Additionally, we find that a considerable (and increasing) portion of the aggregate wage dynamics is driven by changes in average employers' characteristics (firms' age, size, and firm fixed effects, which we define as firm-specific wage differentials). These patterns are much stronger in the industrial sector (manufacturing, in particular) rather than in the service sector (Figure 3). Moreover, we perform further robustness checks including different types of estimated fixed effects in the wage equation (time-varying employer fixed effects and time-invariant workers fixed effect).[13] By including this additional set of fixed effects, we can evaluate the relevance of employers' and workers' (observable and unobservable) characteristics in explaining aggregate wage dynamics. We still find that the role of employer characteristics was very small in the beginning of the period but has considerably increased in the most recent years, to even surpass the role of workers' characteristics (Figure A5 in Appendix).

Figure 2 The contribution of some employers' and workers' characteristics to the composition effect of aggregate nominal wages.

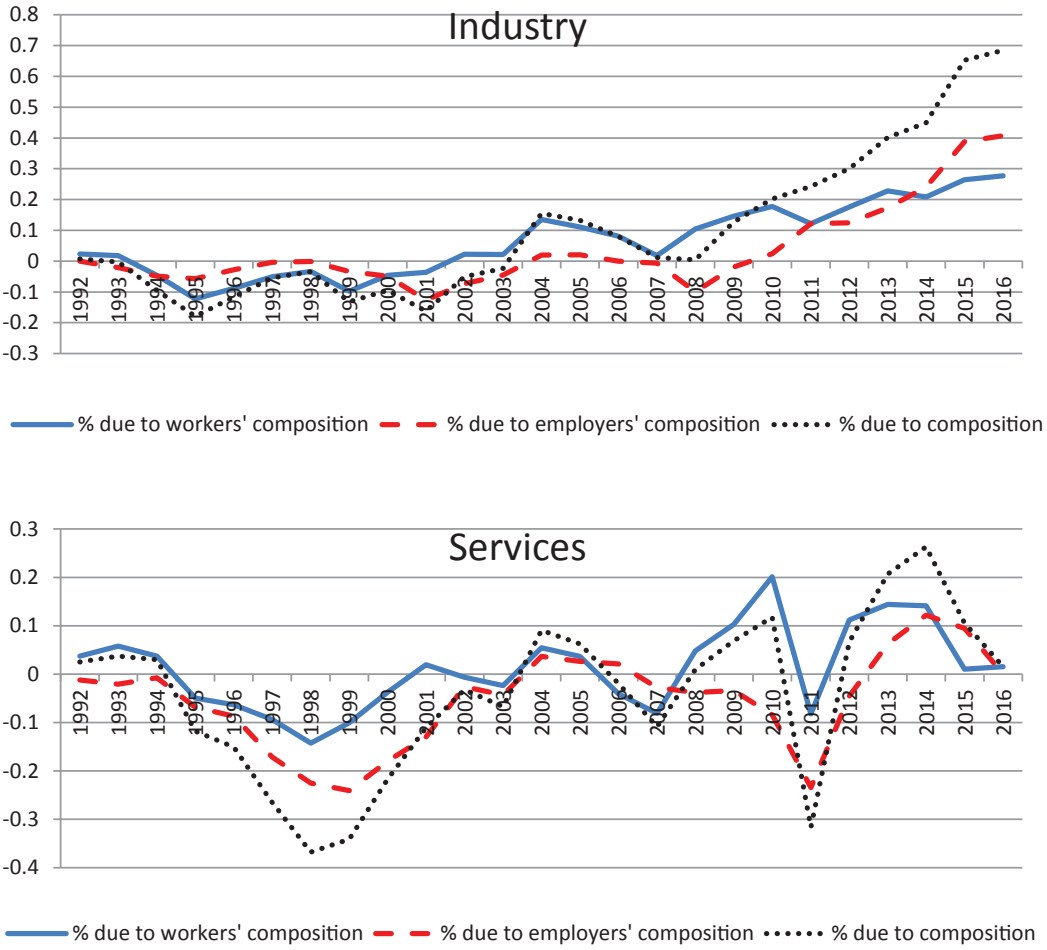


Source: own calculations on INPS data. *Note*: this figure plots the average contribution, for several subperiods, of the composition effects referred to changes in different workers' and employers' characteristics, as obtained from the BO decomposition. It therefore plots the average $(\overline{x}_{ijt} - \overline{x}_{ijt-1})\hat{\beta}_t$ in each four- or five-year period for different *x*.

12 It therefore plots the average $\left(\overline{x}_{ijt} - \overline{x}_{ijt-1}\right)\hat{\beta}_t$ in each four- or five-year period for different worker and firm-level characteristics divided by the aggregate wage change between years *t* and *t*–1.

13 Our estimated worker fixed effects are computed controlling for employers' characteristics (sector, firm age linear and squared, size linear and squared, occupational structure, and firm fixed effects). We cannot make the worker fixed effects time varying, since we are comparing a cross-section of workers over time and time-varying fixed effects at the worker level would completely absorb our variation.

Figure 3 Contribution of composition effects to the wage growth, distinguishing between employers' and workers' characteristics, by sector.



Source: own calculations on INPS data. *Note:* this figure plots the results on composition effects obtained from the BO decomposition (this is therefore the part of aggregate wage dynamics explained by changes in the average characteristics of employed individuals in the economy and of the firms where they are employed, keeping returns to these characteristics fixed over time). The results report the ratio between the 3-year moving average of the part of aggregate wage growth explained by changes in workers' and employers' composition and the 3-year moving average of aggregate wage growth. The blue line refers to the share of the yearly change in wage levels explained by changes in workers' characteristics, and the red line refers to the share of the yearly change in wage levels explained by changes in employers' characteristics.

In the rest of the paper, we dig into this firm component and we try to disentangle what drives this increasing role of employers' characteristics in aggregate wage dynamics. Several alternative explanations, which the BO decomposition cannot tell apart, could lie behind this finding. First, the type of existing firms may have changed, for instance, lower-paying firms (possibly younger or less productive) may be less likely to enter or more likely to exit the market, especially right after a deep recession. Second, all firms may have increased their wages on average. This can happen, for instance, because of a change in wage-setting policies (Gruetter and Lalive, 2008; Card et al., 2013) in response to the recent recession common to all firms, when they were forced to lower their workers' wages, by squeezing the variable component of salaries or by lowering entry wages (Adamopoulou et al., 2016). Third, it may indicate changes in the employer identity – due to workers changing jobs and moving to higher-paying firms:

workers' allocation across firms has changed substantially in the last decades (Foster et al., 2016, for the US and Calligaris et al., 2018, and Linarello and Petrella, 2017, for Italy), and this can have implications for aggregate wages. In the next section, we distinguish which mechanism lies behind the results we obtain from the BO decomposition by applying on firm-level wage data a standard tool taken from the reallocation literature, the so-called OP decomposition. This method allows us to distinguish the part of aggregate wage changes that is due to: (i) changes in the type of firms entering/exiting the market; (ii) uniform changes in the average wage of all firms; and (iii) changes in the relative size of firms, i.e. on how workers are allocated across higher/lower paying firms.

4 The OP decomposition

The OP decomposition is performed on firm-level data, and it splits the aggregate wage – i.e. the employment weighted average of the wage across firms – into two components: a within component and a between component, the so-called OP term. In the appendix, we illustrate a more general – and more involved – version of this decomposition proposed by Melitz and Polanec (2015) allowing us to disentangle also the contributions of firm exit and entry, which however turn out to be not very important for the results. The within component is the *unweighted* average of the wage across firms; the OP term is the covariance between wages and employment (relative to average firm size, i.e. standardized size) across firms:

$$\overline{w}_t \equiv \sum_{j \in J} w_{jt} s_{jt} = \tilde{w}_t + \mathrm{OP}_t$$

$$\text{within term: } \tilde{w}_t \equiv \frac{1}{|J|} \sum_{j \in J} w_{jt}$$

$$\text{OP term: } \mathrm{OP}_t \equiv \sum_{j \in J} (w_{jt} - \tilde{w}_t) \left(s_{jt} - \frac{1}{|J|} \right)$$

where J is the set of active firms in the economy, $s_{jt} \equiv \frac{e_{jt}}{E_t} = \frac{e_{jt}}{|J| e_t}$ is the employment share of firm j at time t, E_t is the aggregate employment, e_t is the average firm size, and t denotes time. Using Δ to denote first-order differences ($\Delta x_t = x_t - x_{t-1}$), we have:

$$\Delta \overline{w}_t = \Delta \tilde{w}_t + \Delta \mathrm{OP}_t$$

The OP decomposition has a structural interpretation in terms of the characteristics of the allocation: if labor is allocated randomly across firms, then the covariance between size and wages is zero and the aggregate wage is identical to the within component. In this hypothetical initial scenario, when labor is shifted from low- toward high-wage firms, then the covariance becomes positive ($\Delta \mathrm{OP}_t > 0$), while the within component remains constant at the initial level ($\Delta \tilde{w}_t = 0$). This implies that the aggregate wage increases, not because wages at the firm level increased, but purely because of a change in the way workers are allocated across firms, entirely captured by the increase in the OP term.

Similarly to the way we displayed results for the BO decomposition, Figure 4 shows the contribution of the OP term to aggregate wage changes, $\Delta \mathrm{OP}_t^m / \Delta \overline{w}_t^m$, in the nonagricultural business sector and for manufacturing and service sectors separately from 1999 to 2015 – where

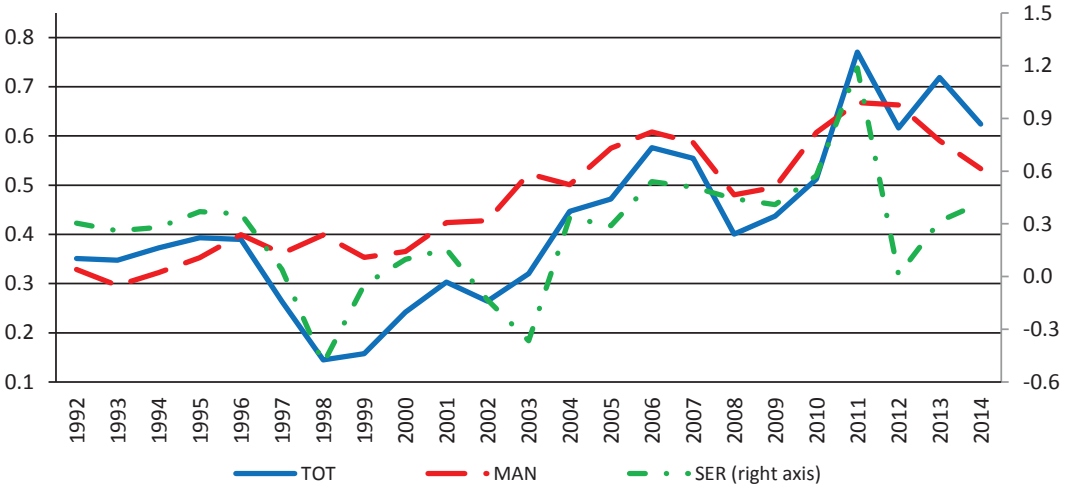
m denotes the three-year moving average centered around t, $\Delta x_t^m = \sum_{h=-1}^{1} \Delta x_{t+h}$.[14] The contribution of the OP term starts rising in the nonagricultural business sector and in the manufacturing sector after 2000 and in the service sector after 2004. It continues rising steadily through the crisis period, particularly in the manufacturing sector, except at around the trough of the financial and sovereign debt crisis, in 2008 and 2012, respectively. The sectoral difference, as well as the drops at the troughs of the crisis, is in line with the results we obtain from the BO decomposition. These results do not depend on entry and exit, whose effects tend to cancel against one another: net entry contributes negatively but slightly to the growth of aggregate wages, approximately −0.2 percentage points throughout the period of the analysis, because entering firms tend to pay lower wages than exiting firms – see Section A2 and Figure A6 in Appendix.

Next, we use the OP decomposition to construct a counterfactual exercise and quantify the contribution of the reallocation of workers – from low- to high-wage firms – to the dynamics of the aggregate wage. To construct this counterfactual, we compute the part of wage growth not related to workers reallocation by "fixing their allocation" to a base year, $\mathrm{OP}_b / \overline{w}_b$, and running the within component forward as in the data. Using the identity $1 = \tilde{w}_{b+s} / \overline{w}^c_{b+s} + \mathrm{OP}_b / \overline{w}_b$, we readily obtain the counterfactual aggregate wage level in year $b+s$ $(\overline{w}^c_{b+s})$:

$$\overline{w}^c_{b+s} = \frac{\tilde{w}_{b+s}}{1 - \mathrm{OP}_b / \overline{w}_b}$$

Using this artificial series, we construct the counterfactual growth rate for the aggregate wage and find that approximately one-third of aggregate wage growth is explained by the shift of employment composition from low- to high-wage firms in the period after 2004 (Table 1).

Figure 4 Contribution of the OP term to aggregate wage changes ($\Delta \mathrm{OP}_t^m / \Delta \overline{w}_t^m$), by sector.



Source: our calculations based on INPS data on the universe of firms. Data on 2016 are not yet available for all firms and are thus discarded. *Note*: $\Delta x_t^m = \sum_{h=-1}^{1} \Delta x_{t+h}$ with Δ denoting first differences. TOT = private nonagricultural sector (blue line), MAN = manufacturing sector (red line), and SER = private services (green line; right axis)

14 Again, we use a moving average to avoid outliers due to very small numbers in the denominator in certain years. The unsmoothed results are available from the authors upon request.

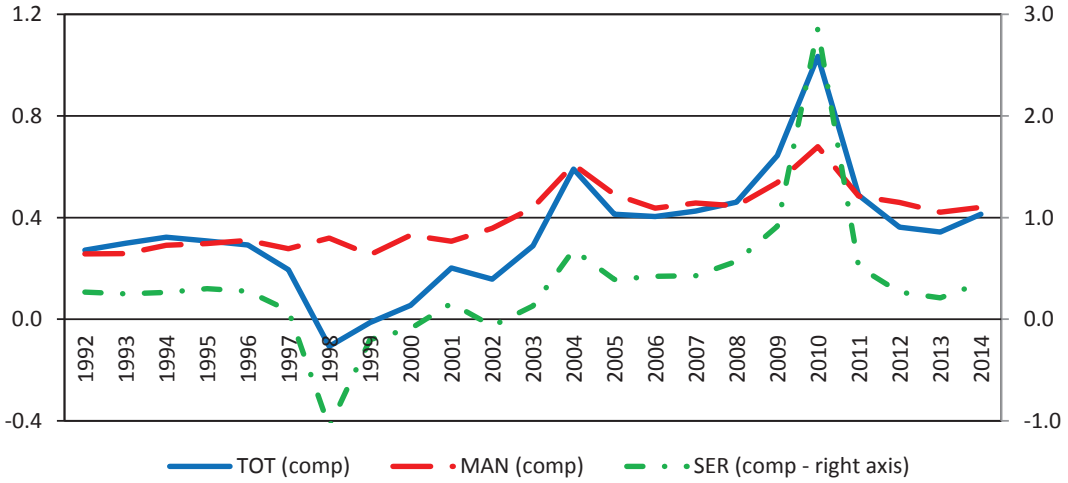
Figure 5 plots the series for the actual aggregate wage against the artificial series obtained by compounding the counterfactual growth rates using as a base the year when the OP term starts increasing – 2002 in the manufacturing sector and 2004 in the service sector and nonagricultural business sector.

Table 1 Percentage contribution of the OP term to aggregate wage growth in different periods

	Private Sector			Manufacturing			Private Services		
Years	Wage growth	Counterfactual wage growth	Fraction due to OP term	Wage growth	Counterfactual wage growth	Fraction due to OP term	Wage growth	Counterfactual wage growth	Fraction due to OP term
					Wages (%)				
2002–2015	27.3	19.2	29.7	41.6	28.8	30.8	17.6	12.7	27.7
2004–2015	22.2	15.1	31.8	33.3	22.9	31.1	14.5	9.6	33.9
2004–2008	11.8	8.9	24.7	15.1	10.8	28.3	9.9	7.2	26.6
2008–2015	9.3	5.7	38.4	15.8	10.9	31.0	4.2	2.2	48.7
					Wages net of differences in firm occupation structure across firms (%)				
2002–2015	68.0	49.2	27.6	89.1	64.1	28.1	58.8	41.5	29.4
2004–2015	70.5	53.4	24.3	88.8	67.2	24.3	62.8	46.5	26.0
2004–2008	28.5	22.7	20.3	34.3	26.7	22.2	25.5	19.5	23.7
2008–2015	32.7	25.0	23.6	40.6	32.0	21.1	29.7	22.6	23.9

Notes: The table displays, for different time intervals, actual wage growth and the counterfactual wage growth (obtained keeping the contribution of the *OP* term to the aggregate wage constant, i.e. keeping the distribution of workers between low- and high-paying firms constant). Results in the bottom half of the table are obtained by applying the OP decomposition to log-firm wages after controlling for the share of middle managers, white collars, and blue collars.

Figure 5 Contribution of the OP term to aggregate wage changes $\left(\Delta \mathrm{OP}_t^m / \Delta \bar{w}_t^m\right)$, by sector and net of changes in workers' composition.



Note: our calculations based on INPS data on the universe of firms. Data on 2016 are not yet available for all firms and are thus discarded. *Note*: $\Delta x_t^m = \sum_{h=-1}^{1} \Delta x_{t+h}$ with Δ denoting first differences. TOT= private nonagricultural sector (blue line), MAN = manufacturing sector (red line), and SER = private services (green line; right axis). We correct for workers' composition by using the residual of a regression of wages at the firm level on the occupational composition of workers in each firm, as a measure of net wages of workers' composition.

An obvious limitation of this approach is that it assumes that the distribution of worker types across firms remained invariant throughout the period of the analysis: otherwise, changes in the OP contribution could reflect changes in workers' composition as well as changes in workers' allocation. For example, if high-wage firms are indeed firms employing high-wage workers (e.g. white-collar rather than blue-collar workers), then a rising OP contribution may reflect a shift toward high-wage occupations. A way to mitigate this issue is to control workers' characteristics and apply the OP decomposition to residualized firms' average wages. Ideally, we would control for the full vector of workers' characteristics included in the BO decomposition, but this information is available only for a sample of workers. Thus, the results would be severely biased, due to the unequal treatment of small and large firms: since we would have virtually no small firm with a representative enough sample of workers to adjust that firm's wage, the remaining sample of firms would be severely skewed toward larger firms.[15] However, our firm-level data do include firm-level information about the total number of workers employed in different occupations: middle managers, white collars, and blue collars. This is one of the covariates with the highest economic significance in the BO decomposition, together with age, which, however, we are unable to control here. When making this adjustment, the contribution of the OP term to the aggregate wage growth, encouragingly, remains high and on similar dynamics, even if it slightly decreases to approximately one-quarter, see Figure 5 and Table 1.

5 Interpreting our results in terms of productivity-enhancing reallocation of workers

We conclude our analysis by suggesting a possible interpretation of our results, placing the paper in the context of the recent literature on the importance of resource reallocation for aggregate productivity.[16] As documented by numerous studies, and for different countries, wages are strongly correlated with productivity at the firm level – among others, Baily, Hulten and Campbell (1992) for the US; Bagger, Christensen and Mortensen (2014) for Denmark; and Iranzo, Schivardi and Tosetti (2008) for Italy. A standard explanation for this fact is that frictions hinder the efficient allocation of resources, and rent sharing allows workers to extract some of the rents created in production. Then, the shift in employment composition – from low- to high-wage firms – could reflect a movement of workers from low- to high-productivity firms. Consistently with the structural interpretation of the OP decomposition, we measure changes in the allocation of workers across firms using the change in the share of the average wage explained by the OP term $\Delta(\mathrm{OP}/\overline{w})$.

Here, we provide some indirect evidence indicating that there may be room for this interpretation, although we are unable to sufficiently corroborate our claim due to data limitations, and we leave a more thorough exploration to future work. The data limitation is that, as it is usually the case, productivity data are available only for limited companies, which are legally compelled to publish their balance sheets. While for large firms this legal form is common, small firms incorporating as limited companies are a strongly selected sample. Figure 6

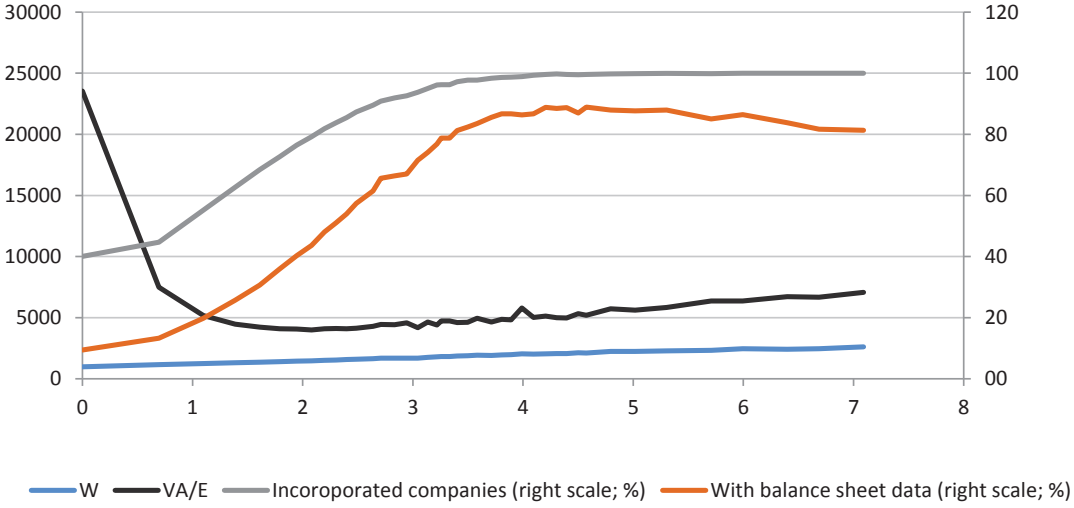
15 As we will discuss, the OP decomposition is very sensitive to the omission of small firms, which usually represent a large share of the total number of firms, even more so in Italy.

16 Restuccia and Rogerson (2008), Hsieh and Klenow (2009), Guner, Ventura and Xu (2008), and Bartelsman, Haltiwanger and Scarpetta (2013).

displays the average labour productivity (for the sample of limited companies in Cerved that can be merged to firms in INPS) and the average wage (for the firms in INPS, i.e. for the entire population of employer businesses) conditional on (log) class size. In the figure, we also report the fraction of firms in INPS that are incorporated businesses and the fraction of firms in INPS that can be merged with Cerved and, therefore, for which we have labor productivity data (right scale). The average wage rises monotonically with the firm size. Instead, firm labor productivity, for our limited sample, is U-shaped: it is extremely high for very small firms and declines with size for firms up to 10–20 employees large and increases monotonically thereafter. The fraction of firms with balance sheet data steeply increases from 10% for firms with one employee to 70% for firms with 20 employees. Table 2 displays the correlation between log size, log firm wage and log labor productivity in 2007[17]: the correlation of employment with labour productivity becomes positive and economically significant only when firms are larger than 20 employees – and it is in line with that with wages.

The OP share of the average wage is extremely sensitive to the censoring of small firms; thus, we are unable to check our interpretation by directly performing our OP analysis on wage and productivity data at the same time.[18] Therefore, we resort to indirect evidence. We compute

Figure 6 Average labor productivity and average wage by (log) class size, and fractions of incorporated businesses and of firms with balance sheet data within the universe of employer businesses.



Note: our calculations based on INPS and Cerved. The figure displays the average labor productivity for the sample of limited companies in Cerved that can be merged to firms in INPS and the average wage for the firms in INPS, i.e. for the entire population of employer businesses, conditional on (the natural logarithm of) class size (left scale). It also reports the fraction of firms in INPS that are incorporated businesses and the fraction of firms in INPS that can be merged with Cerved and, therefore, for which we have labour productivity data (right scale).

17 Results are fundamentally the same when considering different years or when averaging the correlation matrix across years. We pick 2007 as it is the year before the onset of the financial crisis.

18 This is perhaps not surprising: the OP term is the difference between the employment-weighted and the -unweighted average of the wage across firms; excluding small firms affects the second term much more strongly than the first, because the firm size distribution is highly skewed. Linarello and Petrella (2017), using representative balance sheet data for the universe of Italian firms, show that the OP contribution to aggregate labour productivity has been increasing in Italy since the mid-2000s. They also show that this contribution becomes nil when restricting the data to firms with 20 employees or more, explaining the difference with the findings in Calligaris et al. (2018).

Table 2 Correlations between log size, log firm wage and log labor productivity

	Year 2007					
	All firms			$E \geq 20$		
	ln(E)	ln(W)	ln(VA/E)	ln(E)	ln(W)	ln(VA/E)
ln(W)	29.8%			13.7%		
ln(VA/E)	-4.5%	51.2%		11.8%	79.6%	
ln(LC)	19.4%	77.4%	61.8%	12.9%	90.6%	80.8%

Source: own calculations on INPS–Cerved data. The first panel shows correlations for the entire sample of firms for which these data are available (entire population of employers with at least one employee in the nonfarm business sector for employment, E, and wages, W, and limited companies for value added per capita, VA/E). The second panel computes these same correlations only for the firms with more than 20 employees. The table shows that data on value added are more reliable, on average, for large enough firms.

Table 3 Regressions at the sectoral level

Dep var:	Delta OP share			
	(1)	(2)	(3)	(4)
%Δ (productivity)	0.047** (0.021)			0.040* (0.021)
%Δ (productivity) *post 2009	−0.017 (0.030)			−0.008 (0.029)
Herfindahl index		−0.194* (0.112)		−0.346* (0.224)
Herfindahl index *post 2009		−0.061 (0.153)		−0.204* (0.125)
%Δ (employment)			−0.005*** (0.000)	−0.038 (0.043)
%Δ (employment) *post 2009			0.068 (0.052)	0.113* (0.070)
No observations	812	1,392	1,392	812
Sector FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: "Delta OP share" is the difference between years t and t–1 of the share of the average wage explained by the OP term (from INPS data) and captures the change in the allocation of workers across firms over time, "%Δ (productivity)" is the percentage variation in the sectoral average value added per worker between years t and t–1 (from Cerved data), "Herfindahl index" is the Herfindahl index computed using firm employment data in each sector (from INPS data), and "%Δ (employment)" is the percentage variation in the sectoral employment between years t and t–1 (from INPS data). Robust standard errors are given in parenthesis. Columns 1 and 4 include only years from 2000 onward, when the value-added data are reliable from Cerved. Columns 2 and 3 include years from 1990 onward. Sectors: NACE Rev. 2, two digits, private sector excluding agriculture and mining.

the annual percentage change in labor productivity (valued added per worker) at the two-digit sector level (NACE Rev. 2) between consecutive years in the period 2000–2014 and relate it to the corresponding changes in the OP share of the average wage in each sector.[19] The resulting panel is 58 sectors for 14 years, for a total of 812 observations. We also relate the latter to annual

19 This is the period for which value-added data from Cerved are more reliable and consolidated. Balance sheet data are available since 1995 but coverage increased significantly between 1995 and 2000.

percentage changes in sectoral employment and the Herfindahl index that we construct using firm-level employment data from INPS (24 years, 1392 observations). The regressions include sector and year fixed effects and a dummy for the years after 2009 to capture any differential effect of the crisis. Table 3 reports the results for each determinant and for all of them simultaneously. We find that during the period considered, the OP share of the average wage increased more in sectors where labour productivity also increased more. In addition, the sectors where the OP share increased more tended to have a lower degree of industrial concentration (as measured by the Herfindahl index calculated on employment), i.e. are the sectors where we would expect reallocation to be stronger. Finally, the shift in the composition of employment underlying the rising OP share during the financial and sovereign debt crisis may reflect the destruction of jobs in sectors that were hit hardest, rather than a purely compositional shift from low- to high wage firms, or job creation at high-wage firms. However, we find a positive association (although barely significant), rather than a negative one, between changes in the OP share and changes in employment during the crisis.

We think that these results, though indirect and inconclusive, are worth reporting along with the interpretation of the rising importance of firm composition effects on aggregate wages in terms of reallocation from low- to high-productivity firms. This interpretation is suggestive but could be fruitfully explored in future research with more exhaustive data. If our interpretation turns out to be realistic, it would imply that researchers can use wage data, more easily available, rather than productivity data, usually difficult to obtain for non-listed companies, for the analysis of allocative efficiency.

6 Conclusions

Composition effects have played an important role in determining the dynamics of aggregate wages during the last decade. In this paper, we focus on the role of firm heterogeneity for aggregate wage dynamics, with reference to the Italian case. By performing a standard BO decomposition exercise, augmented with employer-level characteristics, we distinguish between employers' and workers' characteristics. We show that the contribution of composition effects has risen during the last years and that the role of employers' average characteristics has increased quite dramatically, to even surpass that of workers' characteristics. As opposed to worker composition effects, which have been extensively investigated by the previous literature, the firm side of the adjustment is usually overlooked.

By applying to wage data a standard measure of reallocation, we document that this increased role of employers' composition effects can be ascribed to employment shifts from low-paying to high-paying firms. According to our estimates, this reallocation of workers across firms has accounted for approximately one-fourth of aggregate wage growth during the recent recessionary period. Finally, we suggest an interpretation, i.e. this employment shifts from low- to high-wage firms may reflect workers' movements from low- to high-productivity firms. Owing to the limitations of our productivity data, we could only provide some indirect and temptative evidence of this interpretation, namely, that the contribution of these employment shifts to wage dynamics appears to be positively associated with sectoral changes in productivity and negatively associated with market concentration. We leave a more thorough analysis of this interpretation to future research.

Declarations

Availability of data and material

The data that support the findings of this study are available from the INPS, but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are however available from the authors upon reasonable request and with permission of INPS.

Competing interests

The authors declare that they have no competing interests.

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Not applicable.

Authors' contributions

All authors contributed equally to the analysis and read and approved the final manuscript.

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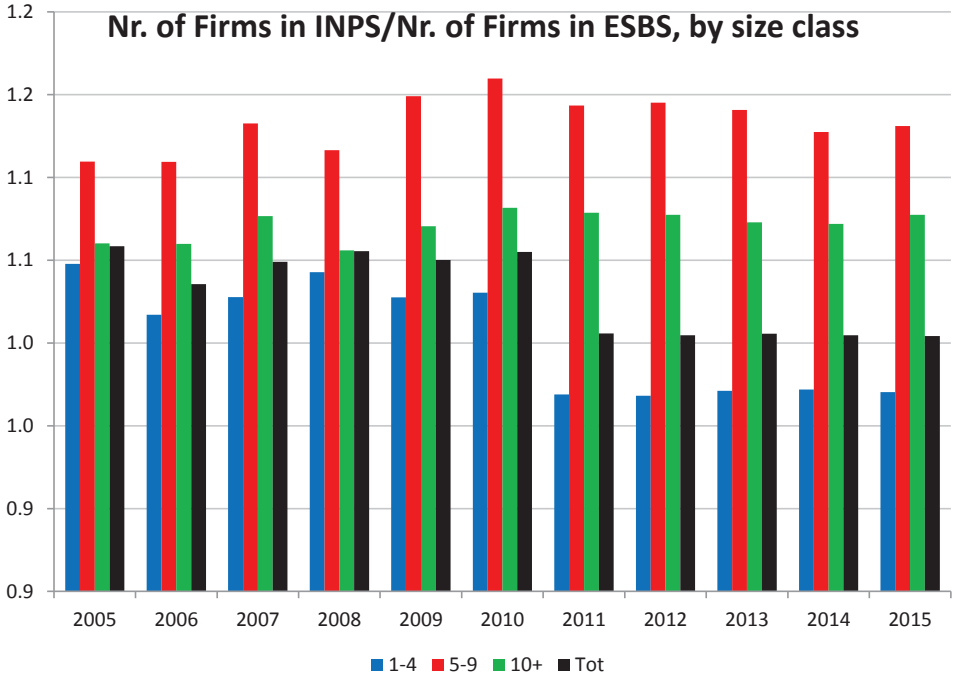
Appendix

A1 Data

This section assesses the quality of the INPS data against official statistics from Istat National Accounts (INA; ESA, 2010) and ESBS, available at the aggregate level. The top panel of Figure A1 in Appendix displays the ratio of the number of firms in the INPS database to the number of employer businesses reported in ESBS. ESBS reports data for the period 2005–2016 and breaks down employer businesses in three size categories: 1–4, 5–9, and 10 employees or more. The number of firms in INPS is larger than in ESBS, because INPS includes all firms with at least one employee at some point during the year, while ESBS includes only firms with at least one employee for at least 6 months during the year.[20] Next, Figure A2 in Appendix displays the entry and exit rates constructed from INPS data and those from ESBS. We consider a firm as entering or exiting when all reporting units with the same tax identification number enter or exit.[21] Both the entry rate and the exit rate in the INPS data are somewhat smaller and

Figure A1 Representativeness of INPS and ESBS databases, class size.

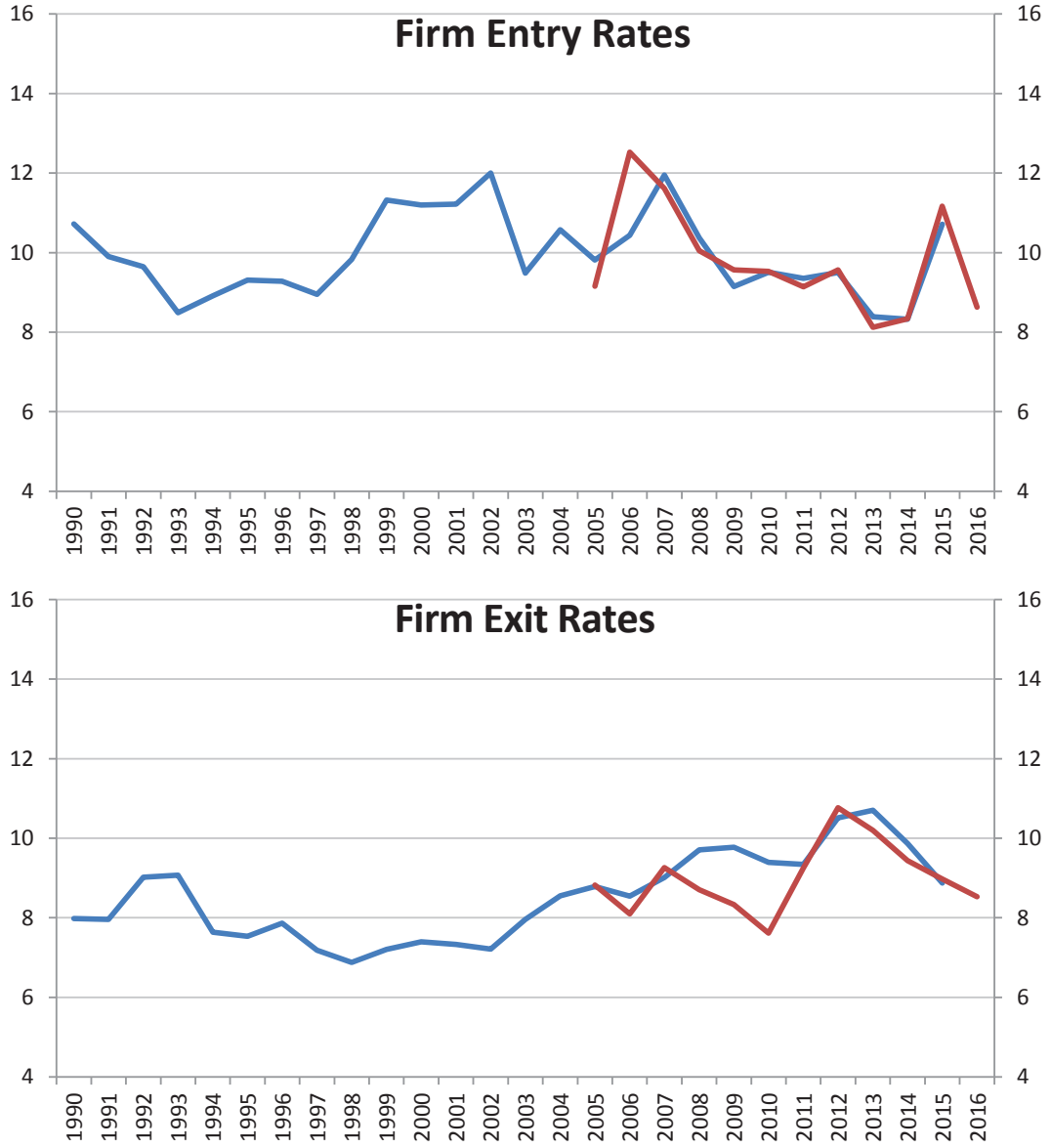


Source: our calculation based on INPS and Eurostat, *Structural Business Statistics* data.

20 INPS reports the average number of employees, which is generally not an integer. A firm that has an average size between four and five employees can be assigned either to the 1–4 class size or to the 5–9 class size. We choose to assign firms with employment ≤4 to the 1–4 class size and firms with employment >4 and ≤9 to the 5–9 class size. As a result, the number of firms in the 1-4 class size is understated, while the number of firms in the 5–9 class size is overstated relative to the ESBS methodology, explaining why the discrepancy with respect to ESBS is smaller for the former class size than for the latter (the blue and red bars in Figure A1).

21 In INPS, several entry and exit dates can be associated with a same reporting unit. We consider entry to be the earliest such date and check that there are no earlier records for that entity. As for exit, we follow a two-step procedure. First, we consider only candidate dates that are reported in the same year as the event is supposed to occur – for example, if the 2009 record reports an exit date equal to 2011, then this information is ignored. Second, we consider only the maximum among candidate exit dates. Following this procedure guards us against inconsistencies in the data (firms that exit and reenter) while limiting biases in the final years of the sample (skipping step, one would produce significant larger biases, as more spurious exits would be left undetected in the last few years of the sample).

Figure A2 Representativeness of INPS and ESBS entry and exit rates.



Source: our calculation based on INPS and Eurostat, *Structural Business Statistics* data.
Note: the blue line displays statistics from INPS and the red line from ESBS data.

smoother than in the ESBS. The entry rate across the two registers displays a similar declining pattern over the crises. Instead, the exit rate is significantly lower than the entry rate in the first years of the sample to become similar in the last years consistently with an expanding and shrinking pool of firms (Table A1 in Appendix).

In Figure A3 in Appendix, we report the year to year percentage change in total employment and the wage per employee from INPS, comparing these quantities with the corresponding statistics from INA. In principle, the labor input measure in INPS should correspond to the number of positions from INA, which however are corrected, among other things, to account for the nonobserved economy – approximately 16% of full-time equivalent employees on average between 2013 and 2016 according to the Italian National Statistical Institute (Istat, 2018). Indeed, the number of positions accounted for in INPS is somewhat smaller than that in INA (the ratio between these two quantities rises from 0.82 in 1995,

Table A1 Descriptive statistics on universe of firms paying contribution at INPS

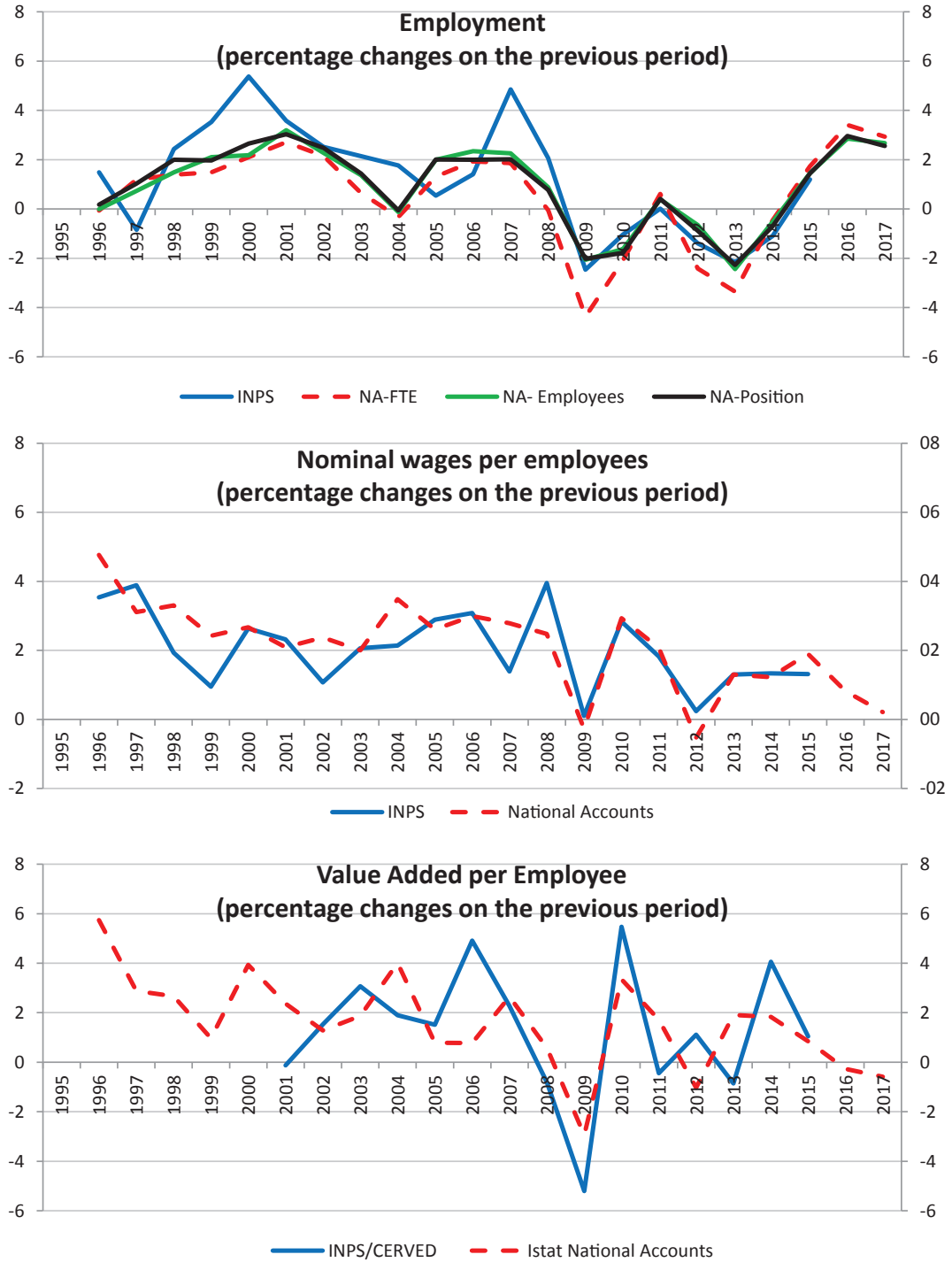
Year	% of firms in industry	% of firms in manufacturing	Monthly nominal wage per employee		Firm size		N. of firms	N. of employees
			Mean	SD	Mean	SD		
1990	0.49	0.32	1,102	457	7.96	182.28	1,116,988	8,886,276
1991	0.48	0.32	1,217	495	7.96	181.01	1,120,616	8,921,224
1992	0.48	0.31	1,288	539	7.86	188.06	1,122,465	8,823,486
1993	0.47	0.31	1,334	556	7.8	184.21	1,084,613	8,462,596
1994	0.47	0.31	1,382	579	7.83	180.24	1,059,330	8,297,098
1995	0.47	0.30	1,441	620	7.87	179.07	1,063,816	8,370,518
1996	0.47	0.30	1,492	646	7.94	172.87	1,069,946	8,494,919
1997	0.46	0.30	1,550	670	7.96	163.06	1,058,114	8,422,835
1998	0.46	0.29	1,580	697	7.97	156.18	1,082,870	8,627,422
1999	0.45	0.28	1,595	711	7.86	138.33	1,136,160	8,931,878
2000	0.44	0.27	1,637	766	7.97	139.11	1,181,331	9,411,951
2001	0.44	0.27	1,675	821	7.98	140.12	1,222,381	9,748,518
2002	0.44	0.26	1,693	788	7.73	133.23	1,293,289	9,993,794
2003	0.44	0.25	1,728	819	7.7	129.98	1,325,116	10,208,096
2004	0.43	0.24	1,765	837	7.59	127.86	1,369,570	10,388,312
2005	0.42	0.24	1,816	892	7.56	128.7	1,380,839	10,444,820
2006	0.42	0.23	1,872	938	7.55	131.95	1,403,808	10,592,187
2007	0.42	0.22	1,898	994	7.53	133.46	1,474,112	11,105,779
2008	0.41	0.22	1,973	1,030	7.57	128.97	1,496,808	11,335,465
2009	0.40	0.22	1,975	1,006	7.48	146.85	1,478,607	11,056,102
2010	0.39	0.21	2,031	1,061	7.43	169.79	1,471,727	10,941,586
2011	0.38	0.21	2,068	1,070	7.46	165.14	1,467,731	10,943,035
2012	0.37	0.21	2,073	1,086	7.35	167.58	1,468,616	10,790,006
2013	0.36	0.21	2,100	1,140	7.46	169.2	1,415,186	10,556,232
2014	0.36	0.21	2,128	1,149	7.61	174.12	1,371,093	10,440,510
2015	0.35	0.20	2,156	1,175	7.59	174.64	1,392,761	10,565,555

Source: own calculations on INPS data for the universe of firms. Statistics of wages are weighted by the number of employees in the firm.

the first year for which ESA 2010 data are available, to 0.89 in 2015), but the two series display a remarkably similar cyclical pattern, especially during the financial and sovereign debt recessions – top panel. As for the wage, we compare the average monthly wage from INPS with the annual gross wage per position from INA, rescaled by 1/12. The ratio between the two quantities oscillates between 0.92 and 0.98 over the entire 21 years of the sample. The two percentage change series display similar long-term trends and move closely together at least during the crises period.

Finally, Figure A4 in Appendix evaluates the representativeness of the INPS sample, when matched to balance sheet data for limited liability companies (using Cerved). The figure reports the fraction of firms in INPS that can be traced back to Cerved by class size. The fraction of employers who are incorporated in Cerved has grown over time to approximately 0.25 and 0.70 for class sizes 1–9 and 10–49 employees and to 0.85 for class sizes 50–249 and 250+ employees. However, even if the aggregate value added per employee from INPS–Cerved is much lower than the corresponding measure from the INA (the mean of the ratio between the two

Figure A3 Firm-level evolution of employment, average wages, and value added per employee over time.

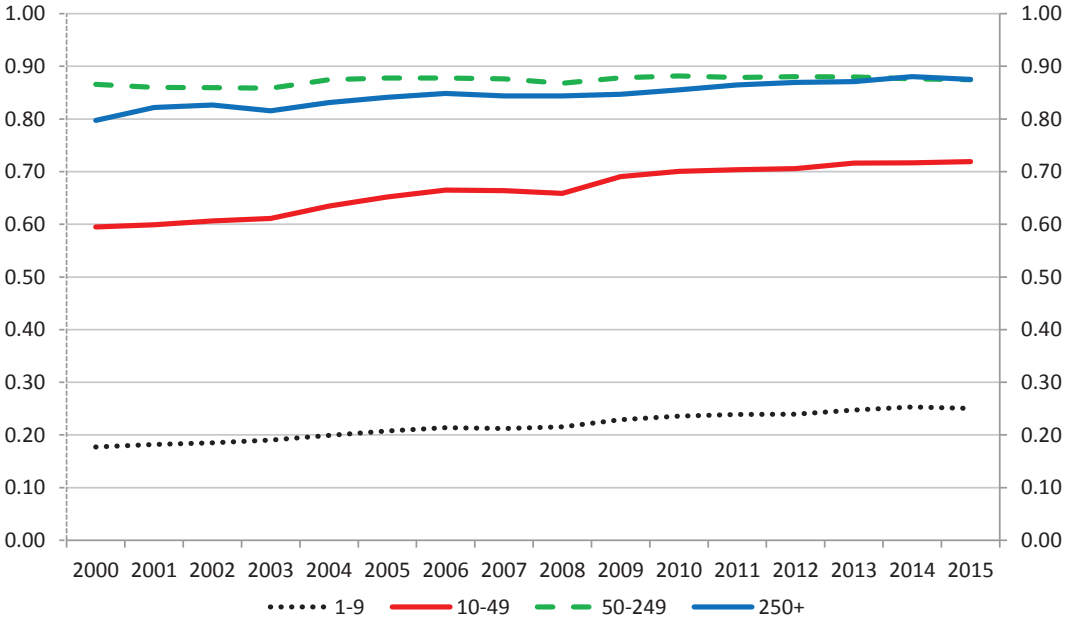


Source: our calculation based on INPS and Istat, ENA data.

quantities was at 0.68 between 2005 and 2015), the two series display a remarkably similar cyclical pattern during the recessionary period, less so prior to the recession (see Figure A3 in Appendix, lowest panel).[22]

22 We also compare wages from INPS–Cerved using the wage measure from Cerved. The wage measure from Cerved is approximately 1.5 times that from INPS and corresponds to the labour cost, defined as the gross wage plus social security contributions paid by the employer. Interestingly, the percentage change series of the aggregate wage computed from INPS and the labour cost computed from INPS–Cerved move remarkably close with one another, the correlation being 0.85.

Figure A4 Percentage of firms in INPS with balance sheet information (from CERVED), by employment size class.



Source: our calculation based on INPS and Cerved data.

A2 Dynamic OP decomposition

The *dynamic* OP decomposition proposed by Melitz and Polanec (2015) disentangles the contribution of firms' entry and exit – two potentially important sources of changes in the allocation of resources over the cycle – to the dynamics of the aggregate wage. It is defined as:

$$\Delta\overline{w}_t \equiv \Delta\tilde{w}_t^C + \Delta OP_t^C + \sigma_t^E\left(\overline{w}_t^E - \overline{w}_t^C\right) - \sigma_{t-1}^X\left(\overline{w}_{t-1}^X - \overline{w}_{t-1}^C\right)$$

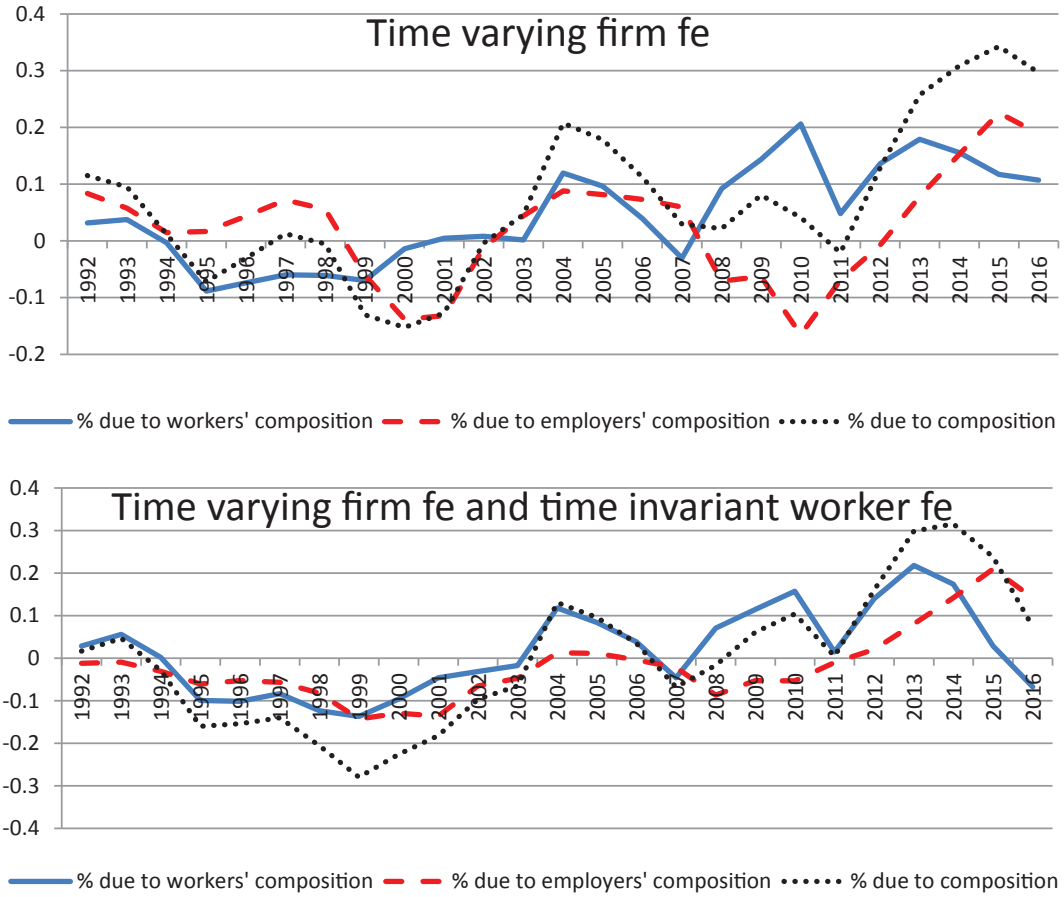
where C, E, and X denote the set of continuing firms (firms that are active both at t and t–1), entering firms (firms that enter at t), and exiting firms (firms that exit at t–1), respectively, $\sigma_{t-1}^X \equiv \sum_{i\in X_{t-1}} s_{it-1}$ is the labor share at time t–1 of exiting firms, and $\overline{w}_{t-1}^X$ is the employment-weighted average wage that firms in such group pay – similarly for σ_t^E, $\overline{w}_t^E$, and $\overline{w}_t^C$. $\Delta\tilde{w}_t^C + \Delta OP_t^C$ is simply the time difference of the static *OP* decomposition discussed earlier, computed on the subset of firms surviving between time t and time t–1.

Figure A6 in Appendix displays the actual path of aggregate wages against the counterfactuals where the OP contribution to the aggregate wage growth rate is set to zero (black dotted line, "without OP"), or the net-entry contribution to the aggregate wage growth rate is set to zero (blue solid line, "without net-entry"). The contribution of net entry is negative and stable, around −0.2 percentage points. Firms that enter or exit the market both pay lower wages than incumbents, yet new firms tend to pay wages even lower than firms that exit, so the negative contribution of entry dominates the positive contribution of exit.

Overall, the net contribution of the combined entry and exit terms turns out to be small relative to movements of the within and OP terms.[23] Thus, results for the dynamic OP can be

23 Of course, to the extent that the within and OP terms have opposite sign and partly compensate one another, the contribution of net entry to the dynamic of the aggregate wage may be sizable. Here, we only observe that changes in the static OP term and the OP term of the dynamic OP decomposition can be easily related to one another if the OP term of the dynamic OP decomposition is large relative to the net-entry term.

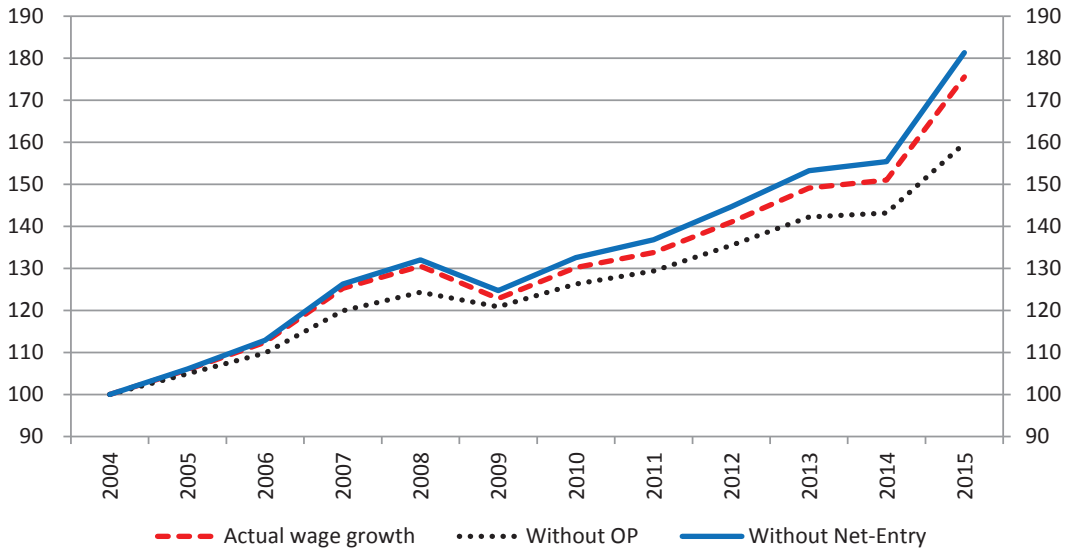
Figure A5 Contribution of composition effects to the wage growth, distinguishing between employers' and workers' characteristics and different types of fixed effects.



Source: own calculation based on INPS data. *Note:* this figure plots the results on composition effects obtained from the BO decomposition (this is therefore the part of aggregate wage dynamics explained by changes in the average characteristics of employed individuals in the economy and of the firms where they are employed, keeping returns to these characteristics fixed over time). The results report the ratio between the 3-year moving average of the part of aggregate wage growth explained by changes in workers' and employers' composition and the 3-year moving average of aggregate wage growth. The blue line refers to the share of the yearly change in wage levels explained by changes in workers' characteristics, and the red line refers to the share of the yearly change in wage levels explained by changes in employers' characteristics.

readily related to changes in the static OP decomposition; for ease and brevity of exposition, we limit ourselves to the static OP decomposition in the main text. All results for the dynamic OP decomposition remain available upon request from the authors.

Figure A6 Dynamic OP decomposition and contribution of OP and net entry to aggregate wage growth.



Source: our calculation based on INPS data.

Table A2 Descriptive statistics on workers (at the contract level)

	Daily nominal wage		Age		%	% full	% blue	% white	% middle	%	N. of	N. of
Year	Mean	SD	Mean	SD	female	time	collars	collars	managers	industry	employees	firms
1990	49.92	26.20	36.32	11.00	0.30	0.96	0.64		0.32	0.64	674,316	263,731
1991	51.53	25.64	36.38	10.97	0.30	0.95	0.64		0.33	0.63	683,562	267,286
1992	54.58	28.09	36.52	10.92	0.30	0.95	0.63		0.33	0.63	683,060	269,335
1993	56.64	28.77	36.70	10.79	0.31	0.94	0.63		0.34	0.61	656,778	261,026
1994	58.39	29.77	36.74	10.69	0.31	0.93	0.62		0.34	0.60	648,803	257,610
1995	60.17	30.64	36.60	10.57	0.32	0.92	0.63		0.34	0.60	654,221	259,404
1996	62.02	31.46	36.62	10.52	0.32	0.91	0.63	0.32	0.02	0.59	665,853	264,966
1997	64.28	32.91	36.64	10.42	0.32	0.91	0.63	0.32	0.02	0.58	665,207	262,301
1998	65.77	34.01	36.78	10.41	0.33	0.90	0.62	0.32	0.02	0.58	677,306	266,600
1999	66.64	34.31	36.75	10.37	0.33	0.89	0.62	0.31	0.02	0.56	702,670	277,117
2000	67.97	35.53	36.87	10.34	0.33	0.89	0.61	0.31	0.02	0.55	747,457	292,300
2001	69.39	36.51	37.04	10.32	0.34	0.88	0.61	0.31	0.03	0.54	774,424	303,645
2002	70.60	37.15	37.04	10.28	0.33	0.87	0.62	0.30	0.03	0.53	810,678	324,062
2003	72.30	37.94	37.30	10.26	0.34	0.86	0.62	0.30	0.03	0.52	818,378	329,247
2004	74.65	39.02	37.56	10.22	0.34	0.85	0.61	0.30	0.03	0.51	826,770	336,332
2005	76.51	39.87	37.94	10.24	0.34	0.84	0.60	0.31	0.03	0.50	821,421	336,031
2006	78.71	40.91	38.24	10.27	0.35	0.83	0.60	0.31	0.03	0.49	835,521	341,087
2007	80.38	41.51	38.34	10.35	0.35	0.82	0.60	0.30	0.03	0.49	879,014	362,206
2008	84.25	44.03	38.56	10.39	0.35	0.81	0.60	0.30	0.03	0.48	895,650	369,088
2009	85.83	44.42	39.11	10.43	0.36	0.80	0.59	0.31	0.03	0.46	882,614	365,012
2010	87.71	45.55	39.41	10.48	0.36	0.79	0.59	0.31	0.03	0.45	877,436	362,978
2011	89.07	46.39	39.69	10.52	0.36	0.79	0.60	0.31	0.03	0.44	880,748	363,405
2012	90.33	46.92	40.04	10.58	0.37	0.77	0.60	0.31	0.03	0.43	871,845	362,267
2013	92.29	47.79	40.47	10.59	0.37	0.75	0.59	0.32	0.03	0.42	844,600	346,920
2014	92.98	48.05	40.88	10.68	0.37	0.74	0.59	0.32	0.03	0.41	835,498	338,086
2015	93.94	48.03	41.12	10.80	0.37	0.73	0.59	0.32	0.03	0.40	856,844	345,811
2016	94.22	48.00	41.31	10.95	0.36	0.72	0.59	0.32	0.03	0.40	869,931	346,633

Source: own calculations on INPS data; data are summarized at the contract level and refer to all employees born on the 1st and 9th day of each month. *Note:* Data on middle managers and white collars are reported together before 1997. Number of firms where at least one worker in the sample transited in the considered year.