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ABSTRACT

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

Aggregate wages display little cyclicality compared to what a standard model would predict. Wage rigidities are an obvious candidate but a recent strand of the literature has emphasized the need to take into account the growing importance of worker composition effects during downturns. With reference to the Italian case we document that also firm composition effects increasingly matter in explaining the aggregate wage dynamics, i.e. aggregate wage growth has been lifted up by the increase in the employment weight of high wage firms. To the extent that this reallocation occurs towards more productive firms, the composition effects may also reflect an efficiency enhancing mechanism. We use a newly available dataset based on social security records covering the universe of Italian employers be-tween 1990 and 2013 and employ a standard measure of allocative efficiency on wages paid across firms. We show that this measure has improved over time since prior to the recent downturn and that it is aligned, at the sectoral level, with measures of productivity growth and market openness to competition. We then focus on the recent downturn and find that large firms were able to adjust wages more than small firms, and that small firms instead adjusted employment to a larger extent. Finally, we document that the continued improvement in the measure of allocative efficiency over this period correlates positively with measures of economic activity (evolution of employment and value added) across sectors.

JEL Classification: D61, E24

Keywords: aggregate wage dynamics, reallocation, allocative efficiency, firm composition effects

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1. Introduction[1]

During downturns aggregate wages appear almost unresponsive to business cycle fluctuations. This holds true even for the recent recessionary episode, despite the duration and the severity of the crisis. Common explanations are wage rigidities as resulting from various market frictions – see Adamopoulou et al. (2016), Verdugo (2016), Devicienti Maida Sestito (2007), Dickens et al. (2007). However, a recent strand of the literature has 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 – see Daly and Hobijn (2016) for the U.S., Verdugo (2016) for the Eurozone countries. In this paper we contribute to the literature by documenting the presence of *firm* composition effects – as opposed to *worker* composition effects – on the aggregate wage, arising from the reallocation of resources from low- to high-wage firms. In addition, we propose and corroborate a specific interpretation of this empirical finding, which is grounded in the literature on reallocation – Restuccia and Rogerson (2008), Hsieh and Klenow (2009) Bartelsman, Haltiwanger, and Scarpetta (2013). If recessions affect low-productivity firms more severely than high-productivity firms – Caballero and Hammour (1994), Foster, Grim and Haltiwanger (2016) – and more productive firms pay higher wages – Bagger, Christensen and Mortensen (2014) –, then during recessions the allocation of resources will shift from low- to high-wage firms increasing the aggregate wage, even in the absence of wage changes at the firm level. To our knowledge, we are the first to provide evidence of firm composition effects on the aggregate wage and to propose this interpretation of this empirical finding. Under this interpretation, firm composition effects on the aggregate wage are associated with a corresponding firm composition effect on aggregate productivity. Thus, in principle, the rise in the aggregate wage resulting from this mechanism may be associated with an improvement in aggregate competitiveness vis-a-vis trading partners. Finally, we note that the approach adopted in this paper (of using firm data on wages as a proxy for firm productivity) may prove useful for studies on reallocation. Measures of allocative efficiency are sensitive to the availability of data on the bottom part of the productivity distribution. While comprehensive data on value added may be difficult to come by, administrative data on wages constructed from social security records are widely available for many countries and long periods of time.

Our analysis is conducted on a newly available set of social security data covering the universe of employers between 1990 and 2013 in Italy, and comprising a sample of employees for

[1] We are grateful to Matteo Bugamelli, Andrea Linarello, Francesco Manaresi, Paolo Sestito, Luigi Federico Signorini, Roberto Torrini, Eliana Viviano, and seminar participants at the Bank of Italy lunch seminar for helpful comments. The views expressed in this paper are those of the authors and do not necessarily reflect those of the Bank of Italy.

the period between 1990 and 2014. After describing the data in section 2, we replicate composition studies by employing a standard tool in labour economics to assess differences among groups of workers, the Blinder-Oaxaca (Oaxaca, 1973) decomposition, which we augment with firm characteristics – section 3. We find that firms characteristics became positive and significant during the recent crisis and we proceed by applying on wage data a standard measure of allocative efficiency, the Olley and Pakes (1996) decomposition (OP) – section 4. Olley and Pakes note that aggregate productivity (in our case the aggregate wage) can be decomposed exactly into the simple average of productivity across firms (within component) and a correlation term, between productivity and size (the OP term). To the extent that workers are not randomly distributed across firms, and more productive firms are larger, this correlation is positive. An increase of the OP term is interpreted as an improvement in allocative efficiency. We find that the OP contribution to the aggregate wage has increased since before the crisis, starting in 2006. We also provide evidence that small firms tended to respond to adverse shocks by cutting employment, while larger firms tended to respond by curbing wages. We decompose the OP contribution to the aggregate wage into a quantity component and a price component and we show that the first component is countercyclical (consistently with small firms adjusting employment more than large firms) and the second component is procyclical (consistently with large firms curbing wages more than small firms). The second component dominates on the first one at the trough of the crisis, resulting in a temporary reduction of the OP contribution to the aggregate wage, which then resumes growing.

Furthermore, we suggest that the rise in the OP contribution to the aggregate wage is associated with the improvement in the allocative efficiency of workers across firms over the last decade, which has been documented in other recent studies – Calligaris, Del Gatto, Hassan, Ottaviano, Schivardi (2016) Gamberoni, Giordano, Paloma (2016), Linarello Petrella (2017). Since we only have value added data for the subset of firms that are limited liability companies and since the OP decomposition is sensitive to the omission of small firms, we cannot test this claim directly.[2] Instead, in section 5, we contrast the time path of the OP contribution to the aggregate wage against the same measure derived from labour productivity data from Linarello and Petrella (2017) (who

[2] The OP term is equal to difference between the employment-weighted average and the unweighted average of productivity. Small firms represent the vast majority of firms but account for a relatively small fraction of total value added and employment. Thus, omitting small firms severely distorts the unweighted average, while leaving the weighted average relatively unaffected. Indeed, Calligaris et al. (2016) and Gamberoni et al. (2016) use data for limited liability companies and find no improvement in allocative efficiency prior to the crisis, while Linarello and Petrella (2017) using data on the universe of firms find that the OP term has been increasing since 2005 – though more markedly after 2009. Linarello and Petrella show that these results can be (at least in part) reconciled with one another once accounting for sample differences. They truncate their data by class size and/or legal form and show that results are sensitive to the omission of small firms which are not limited liability companies, especially regarding the period before the crisis.

use productivity data on the universe of Italian firms rather than on limited liability companies only), and we find that the two series strongly co-move. Second, we show that changes of the OP contribution to the average wage are positively correlated with changes in labour productivity at the two digit sector level – accounting for sector and time fixed-effects – suggesting that reallocation could have been the driver of both productivity growth and firm composition effects on wages. Furthermore, we find that changes in the OP contribution to the average wage at the sectoral level are negatively correlated with market concentration – as measured by the Herfindhal index –, indicating that these composition effects were indeed stronger in sectors where competition is more intense, and which are more prone to reallocation. Finally, we show that, despite the contemporaneous increase of the unemployment rate, the rise of the OP contribution during this period is positively correlated with output and employment growth, across two digit sectors, indicating that the improvement in the allocation of resources was also associated with job creation rather than job destruction. Section 6 concludes.

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 contract, a fixed-term contract, or an apprenticeship contract) between 1990 and 2014. From this master data, 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 runs only up to 2013 and provides data at the firm level. The second 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). In this paper we restrict attention to the non-agricultural business sector and use the tax filing number as the definition of firm[3].

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 we 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 accounting information, implying that there is no direct information on labour productivity. However a subset of the employers in INPS can be merged with Cerved, the business register

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

containing balance sheet data for the universe of Italian limited liability companies. In the data appendix we conclude that, when combined with CERVED, the INPS data also returns a reasonably good picture of balance sheets, but only for firms with at least 10 employees.

Tables 1 and 2 report some descriptive statistics on firms and workers respectively. Over the 24 years of the sample the share of industrial firms over the total number of firms declines from 49 to 36%, average firm size declines approximately from 8.0 to 7.4 employees, the pool of employers increases from 1.1 to 1.4 million, and the nominal monthly gross wage almost doubles, from 1100 to 2100 euros. Table 1 also shows that the share of industrial firms in the economy has declined even more rapidly during the recent crisis, while the average firm size has declined more slowly. This suggests that firms composition, and not only workers composition, may matter for the aggregate wage dynamics.

Figure 1 digs into the reasons behind the limited response of aggregate wages to the adverse cyclical conditions by focusing on the recent crisis and analyzing wage and employment adjustments by firm size. The Figure reports the evolution of firm value added (VA), wage per employee (W, employment-weighted) and firm employment (E) computed by size cell and rescaled to a base year. Changes in value added are meant to proxy the magnitude of the shocks affecting firms in a particular size class; changes in wages and employment are meant to proxy the firms' response to these shock along the price and quantity dimensions. Firms are partitioned in four size classes: micro (1-9), small (10-49), medium (50-249) and large firms (250 employees or more). The value added plots suggest that the financial crisis hit all firms with a similar intensity, except for large firms which were affected for a more prolonged period of time. Instead, the sovereign debt crisis hit small- and medium-size firms harder and more persistently, while large firms rebounded quickly. The response along the wage and employment margins differs by class size. Large firms appear to be more responsive along the wage margin while small firms appear to be more responsive along the employment margin.[4,5] The fact that larger firms, which are on average more productive and pay higher wages, became relatively larger during the recent crisis suggests that

[4] Employment in the firm extraction of the INPS data is not adjusted for short time work benefits (STWB, or Cassa Integrazione Guadagni). A firm resorting to STWB would then appear to reduce the wage bill, while leaving employment unchanged. Therefore, the wage per employee would appear to decline. While this remains a potential issue, in a companion paper we show that medium-size firms used STWB more intensely than large firms – Adamopoulou et al. (2016).

[5] The entry and exit plots in Figure 2 show that the entry rate for the small-size class (which accounts for the vast majority of entries and exits) dropped sharply in 2009, much more than the exit rate rose. The entry and exit rates somewhat recovered in 2010 and then kept deteriorating, particularly the exit rate which displays a lagged response. Over the six years between 2008 and 2013 the net entry rate of small firms decreases by a staggering 6 percentage points, first driven by the continued decline of the entry rate and then by the rise of the exit rate.

part of the small cyclical response of aggregate wages may be due to workers' reallocation towards (and therefore to the relatively larger share of workers employed in) larger, higher paying, firms.

3 Composition effects and the role of firm characteristics, the Blinder-Oaxaca decomposition

We use the employer-employee data from INPS to replicate and extend previous work on the rising importance of composition effects over time and particularly during the crisis in explaining aggregate wage dynamics – Daly and Hobijn (2016), Verdugo (2016). Compared to the data used in these studies, the INPS data has the advantage of covering a longer time-span, thus allowing us to study the evolution of composition effects with a very long time perspective and to evaluate how they evolved prior to the recent crisis. Second, the availability of information on the employer-employee matches allows us to disentangle and separately evaluate composition effects due to workers' characteristics and composition effects due to firms' characteristics. For the decomposition of wage changes between two consecutive years we use a standard Blinder-Oaxaca decomposition (Oaxaca, 1973). For this analysis we use the micro data at the worker level and we match them to the firms' universe to get information on firms' size, sector and age. 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. The Oaxaca decomposition provides us with a synthetic measure of the changes in the composition of the workforce and it is based on a standard linear model of wage formation (Mincer, 1974):

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

where w_{ijt} refers to the daily wage of worker *i*, employed in firm *j* in year *t*;[6] x_{it} are workers' characteristics (gender; age; 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; a dummy for workers that were under short term work benefits at some point during the year), and x_{jt} are firm characteristics (sector at one digit level; size and age). Finally ϵ_{ijt} is an error term. Note that we allow coefficients to change yearly.

The mean outcome difference between year *t* and *t-1* can be expressed as:

[6] Note that for part-time workers we multiply the daily wage by two, in order not to confound the effect of daily hours with the effect of wages.

$$E[\log(w_{ijt})] - E[\log(w_{ijt-1})] = [\beta_t^1 E(x_{it}) + \beta_t^2 E(x_{jt})] - [\beta_{t-1}^1 E(x_{it-1}) + \beta_{t-1}^2 E(x_{jt-1})] =$$
$$\underbrace{[E(x_{it}) - E(x_{it-1})]\beta_{t-1}^1}_{\substack{change\ due\ to\ workers'\\ composition}} + \underbrace{[E(x_{jt}) - E(x_{jt-1})]\beta_{t-1}^2}_{\substack{change\ due\ to\ firms'\\ composition}} + \underbrace{(\beta_t^1 - \beta_{t-1}^1)E(x_{it}) + (\beta_t^2 - \beta_{t-1}^2)E(x_{jt})}_{change\ due\ to\ differences\ in\ returns}$$

The first and the second term of the equation above refer to the change in mean wage due to changes in workers' and firms' characteristics between year *t* and year *t-1*.

Figure 3 summarizes the relative importance of composition effects and their components. The dotted line refers to the overall contribution of composition effects to the wage growth over time. We find that the importance of composition effects changed widely after the recent crisis, in line with Daly and Hobijn (2016). While before 2009, the contribution of composition effects was on average negative and non-significant (none of the effects reach statistical significance at conventional level before 2009), after 2009 compositional effects start to be positive and statistically significant. The dashed and the solid lines, instead, distinguish between the contribution of firms' and workers' characteristics. They show that, at least before the crisis, most of the composition effect was driven by workers' characteristics. These results on workers are in line with the previous literature (Hines, Hoynes and Krueger, 2001 for instance), that shows that job losses during downturns disproportionally affect workers with lower than average wages. Figure 4 analyses which characteristic drove this positive composition effect and shows that a large part is due to changes in the workers' age and occupation. What we add into the standard Oaxaca decomposition analysis are firms' characteristics. We find that there is an increasing positive contribution of firm characteristics after the crisis. Figure 4 shows that an increasing part of changes in average aggregate wages over time is due to the fact that more workers are allocated to larger and older firms in the service sector, which tend to pay higher wages.

In the reminder of the paper we propose and corroborate the interpretation according to which the rising importance of firm composition effects on the aggregate wage reflects the improvement in the allocation of resources: if more productive firms pay higher wages and employment shifts from low-productivity and low-wage firms to high-productivity and high-wage firms, aggregate productivity and the aggregate wage will rise, even if the average wage paid by individual firms and their productivity do not vary.

4 Allocative efficiency and aggregate wage dynamics, the OP decomposition

An extensive literature has documented the importance of the allocation of resources in determining the aggregate productivity level when firms are heterogeneous – Olley and Pakes

(1996) and more recently Restuccia and Rogerson (2008) and Hsieh and Klenow (2009). To the extent that more productive firms also pay higher wages, for example due to labour market frictions (Bagger, Christensen, and Mortensen, 2014), an improved allocation of resources, coming in the form of an employment shift towards more productive firms over time, will result in average wage increases even in the absence of wage increases at the firm level. A similar argument applies if recessions are cleansing and more productive firms, that also pay higher wages, are more likely to withstand negative shocks and retain their employment levels. Foster, Grim and Haltiwanger (2014) argue that the recent recessionary period was characterized by cleansing in the U.S. though to a lesser extent compared to previous downturns. As such, firm composition effects on the aggregate wage may then result from an improvement in the allocation of resources across firms. As long as the shift benefits firms paying not only higher wages but also characterized by a higher productivity and a lower unit labour cost, such composition effects will improve external competitiveness. To assess whether the allocation of resources has improved in Italy and whether this may have resulted in composition effects raising the dynamics of wages, we employ a standard measure of allocative efficiency, the Olley and Pakes decomposition (1996).

Given a quantity x_i measured at the firm level (the wage, or labour productivity) and the corresponding quantity measured at the aggregate level, $\bar{x}$, defined as the employment weighted mean of x_i across firms, the Olley and Pakes decomposition is the unweighted mean of x_i, $\tilde{x}$, plus a residual component, the OP term, which turns out to be the covariance between x_i and the employment level (relative to the average) across firms:

$$\bar{x}_t \equiv \sum_{i \in I} x_{it} s_{it} = \tilde{x}_t + OP_t$$

$$within\ term: \tilde{x}_t \equiv \frac{1}{|I|} \sum_{i \in I} x_{it}$$

$$OP\ term: OP_t \equiv \sum_{i \in I} (x_{it} - \tilde{x}_t)(s_{it} - \frac{1}{|I|}),$$

where I is the set of active firms in the economy, $s_{it} \equiv \frac{e_{it}}{E_t} = \frac{e_{it}}{|I| e_t}$ is the employment share of firm i at time t, E_t is aggregate employment, e_t is average firm size and t denotes time. The OP term can be defined equivalently as the difference between the employment-weighted mean of x and the unweighted mean of x; thus, it has a natural interpretation as a measure of allocative efficiency when applied to productivity: if firms differ in terms of productivity and resources are randomly allocated, then the covariance between size and productivity is zero and aggregate productivity equals the unweighted average ($\bar{x} = \tilde{x}$). Instead, if more resources are allocated to more productive firms, the covariance between size and productivity is positive and aggregate productivity is larger than the unweighted average ($\bar{x} > \tilde{x}$). To assess the impact of reallocation to changes in the aggregate level $\bar{x}$, we focus on the relative contribution of the OP term to $\bar{x}$, $\frac{OP}{\bar{x}}$. As resources are reallocated to more productive firms, aggregate productivity rises along with the OP term, even if no change in productivity occurs at the firm level ($\tilde{x}_t$ is unchanged), and the ratio $\frac{OP}{\bar{x}}$ increases. Vice versa, if the wage increases by the same factor across all firms, then the contribution of the *OP* term to aggregate productivity, $OP/\bar{x}$, remains constant.

Similarly, when applying the decomposition to wages, a rise in the contribution of the OP term signals a rise of the aggregate wage that is due to a shift of workers from low to high wage firms, rather than to wage changes at the firm level. If firms paying a higher wages also have a higher productivity, then, changes in the contribution of the OP term will reflect changes in aggregate efficiency. Figure 5 displays the ratio $OP/\bar{x}$ over the sample period for the nonagricultural business sector and for manufacturing and the service sector separately. Starting in 2006 the percentage contribution of the OP term started increasing, temporarily dropping at the trough of the two crisis, in 2009 and 2013. As we show below, these drops are not due to a reversal in the allocation of resources, from high- to low-wage firms, but rather to the greater ability of large firms to curb wages relatively to small firms. Focusing on the manufacturing and service sectors, we find that the OP contribution to the aggregate wage level was stable until 2002 and has been rising steadily in the manufacturing sector after that (with the exception of 2009), while it has declined until 2002 and then started rising after 2004 in the service sector (dropping in 2009 and 2013).

Next we compute the *dynamic* OP decomposition proposed by Melitz and Polanec (2014). This decomposition allows us not only to disentangle the contribution of firms' entry and exit – two potentially important sources of changes in the allocation of resources over the cycle – to the dynamic of the aggregate wage, but also to determine whether movements of the OP term are due to wage or employment adjustments at the individual firm level. The *dynamic* OP decomposition is defined as:

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

where C, E and X denote the set of continuing firms (firms that are active both at *t* and *t*-1) of 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 labour 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 $\overline{w}_t^C$. $\Delta\widetilde{w}_t^C + \Delta OP_t^C$ is simply the time difference of the static OP decomposition discussed above, computed on the subset of firms surviving between time *t* and time *t*-1.

Intuitively, the dynamic OP decomposition is an identity unbundling the contribution of firms that exit or enter, therefore allowing to compute the OP decomposition on the set of continuing firms. Because the OP decomposition is computed on the same set of firms both at *t* and *t*-1, we can trace changes in the OP term back to employment and wage changes at the firm level. While entry and exit cancel each other in steady state, their net contribution may deviate markedly away from zero over the cycle, if entry and exit rates swing asymmetrically – as we have documented to be the case over the period under examination – and within quantities differ from one another – i.e. if $\overline{w}_{t-1}^{X}$ differs from $\overline{w}_{t-1}^{E}$. In practice, as we document below, the net contribution of the combined entry and exit terms turns out to be small relative to movements of the within and OP terms. Thus, results for the dynamic OP can be readily related to changes in the static OP (i.e. to the slope of the "OP line" in Figure 5) and the dynamic OP decomposition can be used to analyze whether the movements of the static OP term are driven by employment or wage adjustments at the firm level.[7]

Figure 6 displays the percentage point contribution of the within, OP and net-entry terms against the dynamics of the aggregate wage (then, for example, the "OP line" is the ratio $\Delta OP_t^C / \overline{w}_{t-1}$). The contribution of net entry is negative and stable, around -0.4 ppt. 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. This may depend on worker composition differing across firms (e.g. new firms employ younger workers) or wage rigidities (firms that exit where unable to lower wages). The sharp slowdown of the aggregate wage in 2009 is due, in similar proportions, to the slowdown of the within term – the contribution of which remains positive throughout the period – and the decline of the OP term – the contribution of which turns negative in 2009. A similar, somewhat less pronounced, pattern is observed following the onset of the sovereign debt crisis in 2012, though the OP term continues to decline in 2013 while the within term rebounds. As for the comparison over time, Figure 6 also

[7] 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. We do not claim that that entry and exit are not important for reallocation.

indicates that the OP term has become negative at the trough of each cycle (the shaded areas) and the within component has progressively slowed down between 1992 and 1994 and then again during the recent downturn, while it had recovered by 2004 following the 2002 slowdown.

The negative contribution of the OP term to aggregate wage dynamics in 2009 and 2012-2013 indicates that the cross-sectional covariance between size and wages declines during the crises period. Heuristically, this can be due to either large firms cutting wages more than small firms; or to high-wage firms cutting employment more than low-wage firms. To try and assess which of the two hypothesis is substantiated by the data we perform a shift-share decomposition of the OP:

$$\Delta OP_t^C = cov\left(\frac{e_{it}}{e_t}, w_t \middle| i \in C_t\right) - cov\left(\frac{e_{it-1}}{e_{t-1}}, w_{t-1} \middle| i \in C_t\right)$$
$$= \underbrace{cov\left(\Delta\frac{e_{it}}{e_t}, w_t \middle| i \in C_t\right)}_{quantity} + \underbrace{cov\left(\frac{e_{it}}{e_t}, \Delta w_t \middle| i \in C_t\right)}_{price} + cov\left(\Delta\frac{e_{it}}{e_t}, \Delta w_t \middle| i \in C_t\right).$$

Results are reported in Figure 7. According to the decomposition, changes in the covariance between size and wages across firms can be viewed as stemming from changes in the correlation between size and wage changes – which we refer to as the “price effect” – or between wage and size changes – which we refer to as the “quantity effect” – plus a cross term. The cross term is an interaction and does not have an obvious interpretation: it can be viewed as a relevant component of the price and/or quantity effects. However, adding the cross term to either the quantity or price terms does not change their cyclical behavior (in particular it does not flip the sign of the quantity term in 2009). We therefore disregard the cross term and proceed with a *qualitative* interpretation of the decomposition results. The quantity effect is countercyclical suggesting that low wage (small) firms cut employment more than high wage (large) firms; as a result, the OP, i.e. the covariance between wages and (relative) size, should increase. The price effect is procyclical meaning that large firms curb wages more than small firms, which should lower the OP other things equal. The second effect dominates, and the OP decreases in 2009 contributing to the slowdown of the aggregate wage dynamics. Note that these results are consistent with the qualitative patterns of employment and wages by class size over the crisis highlighted in the data section: large firms adjust wages more, while small firms adjust employment more when hit by a shock. The finding that large firms are more responsive along the wage margin is consistent with the empirical analysis of Rosolia (2015), who finds that, while contractual wages respond slowly to cyclical conditions due to the staggered nature of the Italian wage setting institutional framework, the extra-contractual components display a significant degree of responsiveness. To the extent that large firms are more productive and that more productive firms pay higher wages, and are not constrained by the minima set in national contracts, then these firms are better able to adjust wages than small firms. We further pursue this line of inquiry in a companion paper, Adamopoulou et al. (2016).

5. Reallocation and efficiency: destruction or creation?

The previous sections provide extensive evidence of a wage enhancing reallocation of labour across firms that took place in Italy during the last decades. In this section we explore whether this reallocation was also efficiency-enhancing and we provide some suggestive evidence on whether the underlying forces were solely destructive or also creative.

An increase in the OP contribution indicates that the covariance between size and wages across firms has been rising. We may interpret this as evidence that the employment composition has been shifting towards high-wage and high-productivity firms, thus that composition effects over this period may partly reflect an improvement in the allocation of resources. An alternative, less benign, interpretation is that over time employment has been shifting towards firms paying higher wages, but not towards firms with a higher productivity; or that larger firms granted higher wage increases, unrelated to productivity changes – for example because of higher unionization levels and higher firing costs at these firms.[8]

While we are unable to study in a unified framework the relationship between employment, wages and productivity at the firm level – due to the lack of comprehensive information on productivity – we provide some indirect evidence of the relationship between productivity dynamics and changes in the allocation of resources as captured by the changes in OP contribution to aggregate wages that support our interpretation. As mentioned in the data appendix, INPS-Cerved severely underrepresent small employers and the small firms in this merged dataset (small limited liability companies with at least one employee) are likely to be much more productive than the average small employer in INPS.[9] Indeed, while in INPS the smaller the size category, the lower the wage, firms with 9 employees or less in INPS-Cerved display a higher value added per worker than larger firms.[10] As shown by Linarello and Petrella (2017), the omission of small firms severely distorts the OP decomposition on productivity, thus we are not able to perform the same analysis on

[8] Prior to the Jobs Act, which was enacted in 2015, a worker could be reinstated by court order if the layoff was deemed unlawful and the firm had more than 15 employees.

[9] Also, labour services provided by the owner – which are not accounted for in our data -- amount to a larger fraction of total labour services for small firms, biasing their labour productivity upwards.

[10] This could also be due to small firms having a higher share of irregular workers or "quasi-employee" (workers who are formally self-employed though performing at the firm the same tasks as an employee), who are not accounted for in the INPS data.

productivity as on wages. This is because while small businesses account for a relatively small employment share, their number is large, therefore their omission biases severely the unweighted average of aggregate productivity while leaving the weighted average relatively unaffected.

Instead, we compare the OP contribution to aggregate wages with series for the OP contribution to aggregate labour productivity computed from ASIA, the administrative register covering the universe of Italian employer businesses for 2005, 2008 and 2011 through 2013 that contains data on value added and employment.[11] Results are reported in Figure 5 which shows that the two series generally move in line with one another.[12] The OP contribution to the aggregate productivity is higher in 2008 than in 2005, suggesting it might have started to increase prior to the onset of the recessionary period, as we find to be the case for the OP contribution to the aggregate wage. While the official start of the financial crisis in the U.S. is the fourth quarter of 2007, the crisis reached Italy with some delay and 2008 is still a year of positive (although slowing) employment and output growth as it can be seen in Figure 1. Focusing on the manufacturing and the service sectors, we find that the OP contribution on aggregate productivity and on the aggregate wage move together in the manufacturing sector; instead, the OP contribution to aggregate productivity declines slightly in the service sector between 2005 and 2008 before starting to rise in line with the OP contribution to the aggregate wage.

We then proceed by contrasting the evolution of the OP contribution to the aggregate wage with the evolution of labour productivity across sectors. Even though INPS-Cerved is not comprehensive enough to compute a reliable OP decomposition on value added per worker across employers, we can use it to compute average labour productivity at the sector level since small firms have a relatively small employment weight. We measure labour productivity as value-added per worker and we correlate its year-to-year changes to the year-to-year changes in OP contribution to the average wage across sectors.[13] Columns 1 and 2 of Table 3 display regressions for the entire period, 1994-2013, as well as for the period during which the OP contribution to the aggregate

[11] We thank Linarello and Petrella who kindly provided us with the numbers displayed in Figure 5 and refer the interested reader to their work – Linarello and Petrella (2017) – for a more thorough examination of changes in allocative efficiency and productivity in Italy over this period. When computing the OP decomposition on value added per worker using INPS-Cerved we obtain a contribution which is much smaller though displaying a similar pattern. The contribution is negative for private services and it is around 11% for manufacturing.

[12] We showed that the results of the OP decomposition computed with wages and with value added per worker are similar. Since administrative data on wages constructed from social security records are more easily available than data on value added, using firm data on wages as a proxy for firm productivity may prove useful for future studies on reallocation.

[13] We follow previous literature and we exclude from the analysis the Financial sector-NACE 2002 (J) which was at the center of the Great Recession, as well as Mining (CA-CB), Refining (DF), and Energy (E) since the developments in these sectors are often susceptible to external factors (e.g. price volatility).

wage has started to increase, i.e. 2006-2013. The regressions include sector and time fixed effects. The results suggest that the OP contribution to aggregate wages increased in those sectors where productivity increased more, especially after 2006. We interpret this positive relation as evidence corroborating the conjecture that composition effects on the average wage at the sectoral level reflect changes in allocative efficiency leading also to increases in the average sectoral productivity.

Next, if resources are shifted towards more productive firms as a result of market forces, then such shift should be more likely to occur in sectors where competition is stronger. Table 3, columns 3 and 4 correlate the level of the Herfindahl index (computed using employment), i.e. a standard measure of market concentration, with the changes of the OP contribution to the aggregate wage across sectors.[14] The results suggest that the OP contribution increased more in sectors characterized by stronger competition, i.e. sectors more prone to reallocation. All in all we take our results as suggestive of functioning market forces. More productive firms paying higher wages were able to withstand the crises and preserve their employment levels better than less productive firms, resulting in an improved allocation of resources.

However, we showed that this improvement was accompanied, during the recessionary years, by increasing firm mortality rates and declining entry rates and by the emergence of widespread unemployment. We do not claim in this section that this process was optimal; rather, that conditional on the occurrence of a large negative shock and provided that the shock was unavoidable: 1) the shock impacted prevalently less productive firms; 2) that the process might have contributed to enhance the aggregate wage dynamics due to the shift in the relative composition of employment towards more productive, high-wage firms; 3) that such composition effect on wages might have been accompanied by a corresponding composition effect on aggregate productivity.

We cannot conclude whether the growth in allocative efficiency recorded during the recessionary years was permanent or transitory, i.e. whether with the start of the recovery in 2015 the employment composition shifted back towards less productive firms, because our data covers the period up to 2013 only. However, the regressions in Table 3, columns 5 to 8 show that, over time and across sectors, positive changes in the OP contribution to the aggregate wage level are associated to less severe changes in demand shocks but also to less severe changes in employment conditions. The relationship remains positive even during the recessionary years although it is not statistically significant.[15] This suggests that the rise in the OP contribution to the aggregate wage

[14] An increase in the value of the Herfindahl index indicates an increase in concentration, and therefore a decrease in the degree of competition.
[15] These regressions control for unobserved heterogeneity across sectors as well as for year-specific shocks.

level was not necessarily the result of layoffs by less productive firms in more affected sectors but also of productivity-enhancing reallocation in less affected sectors. Therefore, the recovery may be accompanied by a further improvement in the allocative efficiency measures.

6. Conclusions

Composition effects played an important role in determining the dynamics of aggregate wages during the last decade. We argue that part of such composition effects in Italy was the result of a shift in the allocation of resources towards more productive firms paying also higher wages. Assuming that wages and productivity are positively correlated across firms, we applied a standard measure of allocative efficiency, the Olley and Pakes decomposition (1996), to wages and showed that such a measure started to increase prior to the recent downturn, at least in manufacturing, and kept increasing throughout the crisis – except at the trough of the crisis, due to the ability of larger firms to cut wages. We show that such trends are positively correlated with productivity growth across sectors and negatively correlated with sectoral concentration, which hinders market forces leading to reallocation. We interpret these findings as suggestive evidence that a common factor, namely improvements in allocative efficiency, may have been at the root of these patterns and we conclude that at least part of aggregate wage increases over the last decade could have resulted from positive developments in the underlying economic structure.

While the downturn produced massive unemployment and led to severe resource underutilization, we find that larger, more productive, high-wage firms withstand to the crisis better and retained their employment levels, further increasing the OP contribution to the aggregate wage level. We also argue that these firms were able to adjust wages to a larger extent than smaller firms. Finally, we show that during the crises changes in the OP contribution to the average wage level across sectors were positively correlated with employment and value added growth, suggesting that they might have not been necessarily the result of increasing layoffs by smaller, less productive firms.

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Tables and figures

Table 1: Descriptive statistics, universe of firms paying contribution at INPS

Year	% of firms in Industry	% of firms in Manufacturing	Monthly wage per employee		Firm size		N Firms	N Employees (1000)
			mean	sd	mean	sd		
1990	0.49	0.32	1102	457	7.96	182.3	1,116,992	8891
1991	0.48	0.32	1217	495	7.96	181.0	1,120,621	8920
1992	0.48	0.31	1288	539	7.86	188.1	1,122,468	8823
1993	0.47	0.31	1334	556	7.80	184.2	1,084,614	8460
1994	0.47	0.31	1382	579	7.83	180.2	1,059,329	8295
1995	0.47	0.30	1441	620	7.87	179.1	1,063,816	8372
1996	0.47	0.30	1492	646	7.94	172.9	1,069,946	8495
1997	0.46	0.30	1550	670	7.96	163.1	1,058,116	8423
1998	0.46	0.29	1580	697	7.97	156.2	1,082,872	8630
1999	0.45	0.28	1595	711	7.86	138.3	1,136,162	8930
2000	0.44	0.27	1637	766	7.97	139.1	1,181,332	9415
2001	0.44	0.27	1675	821	7.98	140.1	1,222,383	9755
2002	0.44	0.26	1693	788	7.73	133.2	1,293,290	9997
2003	0.44	0.25	1728	819	7.70	130.0	1,325,115	10203
2004	0.43	0.24	1765	837	7.59	127.9	1,369,569	10395
2005	0.42	0.24	1816	892	7.56	128.7	1,380,837	10439
2006	0.42	0.23	1872	938	7.55	132.0	1,403,806	10599
2007	0.42	0.22	1898	994	7.53	133.5	1,474,110	11100
2008	0.41	0.22	1973	1030	7.57	129.0	1,496,808	11331
2009	0.40	0.22	1975	1006	7.48	146.9	1,478,586	11060
2010	0.39	0.21	2031	1055	7.43	169.6	1,471,068	10930
2011	0.38	0.21	2068	1070	7.46	165.1	1,467,732	10949
2012	0.37	0.21	2073	1086	7.35	167.6	1,468,611	10794
2013	0.36	0.21	2100	1139	7.44	169.1	1,414,664	10525

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

Table 2: Descriptive statistics on workers (at the contract level)

Year	Daily wage mean	Daily wage sd	Age mean	Age sd	% Female	% Full time	% Blue collars	% White collars	% Middle managers	% Industry	N Employees	N Firms
1990	47.98	41.56	36.32	11.00	0.30	0.96	0.64	0.32		0.64	674,323	275,097
1991	52.72	46.07	36.38	10.97	0.30	0.95	0.64	0.33		0.63	683,562	279,240
1992	57.04	101.73	36.52	10.92	0.30	0.95	0.63	0.33		0.63	683,054	281,303
1993	58.82	82.45	36.70	10.79	0.31	0.94	0.63	0.34		0.61	656,780	273,051
1994	62.52	155.91	36.74	10.69	0.31	0.93	0.62	0.34		0.60	648,790	269,532
1995	62.32	501.87	36.60	10.57	0.32	0.92	0.63	0.34		0.60	654,213	271,591
1996	63.44	50.98	36.62	10.52	0.32	0.91	0.63	0.32	0.02	0.59	665,874	277,402
1997	65.83	57.88	36.64	10.42	0.32	0.91	0.63	0.32	0.02	0.58	665,189	275,443
1998	68.43	267.70	36.78	10.41	0.33	0.90	0.62	0.32	0.02	0.58	677,313	278,839
1999	69.44	209.62	36.75	10.37	0.33	0.89	0.62	0.31	0.02	0.56	702,667	289,796
2000	69.93	127.29	36.87	10.34	0.33	0.89	0.61	0.31	0.02	0.55	747,452	305,346
2001	71.46	114.35	37.04	10.32	0.34	0.88	0.61	0.31	0.03	0.54	774,441	317,081
2002	72.92	84.91	37.04	10.28	0.33	0.87	0.62	0.30	0.03	0.53	810,656	338,477
2003	74.20	76.96	37.30	10.26	0.34	0.86	0.62	0.30	0.03	0.52	818,386	343,671
2004	77.19	145.20	37.56	10.22	0.34	0.85	0.61	0.30	0.03	0.51	826,728	349,247
2005	78.72	110.82	37.93	10.24	0.34	0.84	0.60	0.31	0.03	0.50	822,301	349,395
2006	81.03	88.65	38.24	10.27	0.35	0.83	0.60	0.31	0.03	0.49	836,545	354,814
2007	82.50	75.67	38.34	10.35	0.35	0.82	0.60	0.30	0.03	0.49	880,269	376,583
2008	86.52	92.70	38.56	10.39	0.35	0.81	0.60	0.30	0.03	0.48	897,100	383,582
2009	88.04	105.54	39.11	10.43	0.36	0.80	0.59	0.31	0.03	0.46	884,268	379,699
2010	90.12	223.53	39.40	10.47	0.36	0.79	0.59	0.31	0.03	0.45	879,297	377,338
2011	91.55	93.72	39.69	10.52	0.36	0.79	0.60	0.31	0.03	0.44	882,700	377,665
2012	92.99	91.31	40.04	10.57	0.37	0.77	0.60	0.31	0.03	0.43	873,231	375,006
2013	95.12	101.79	40.48	10.58	0.37	0.75	0.59	0.32	0.03	0.42	845,808	358,291
2014	95.36	92.66	40.86	10.67	0.37	0.74	0.59	0.32	0.03	0.42	840,787	351,484

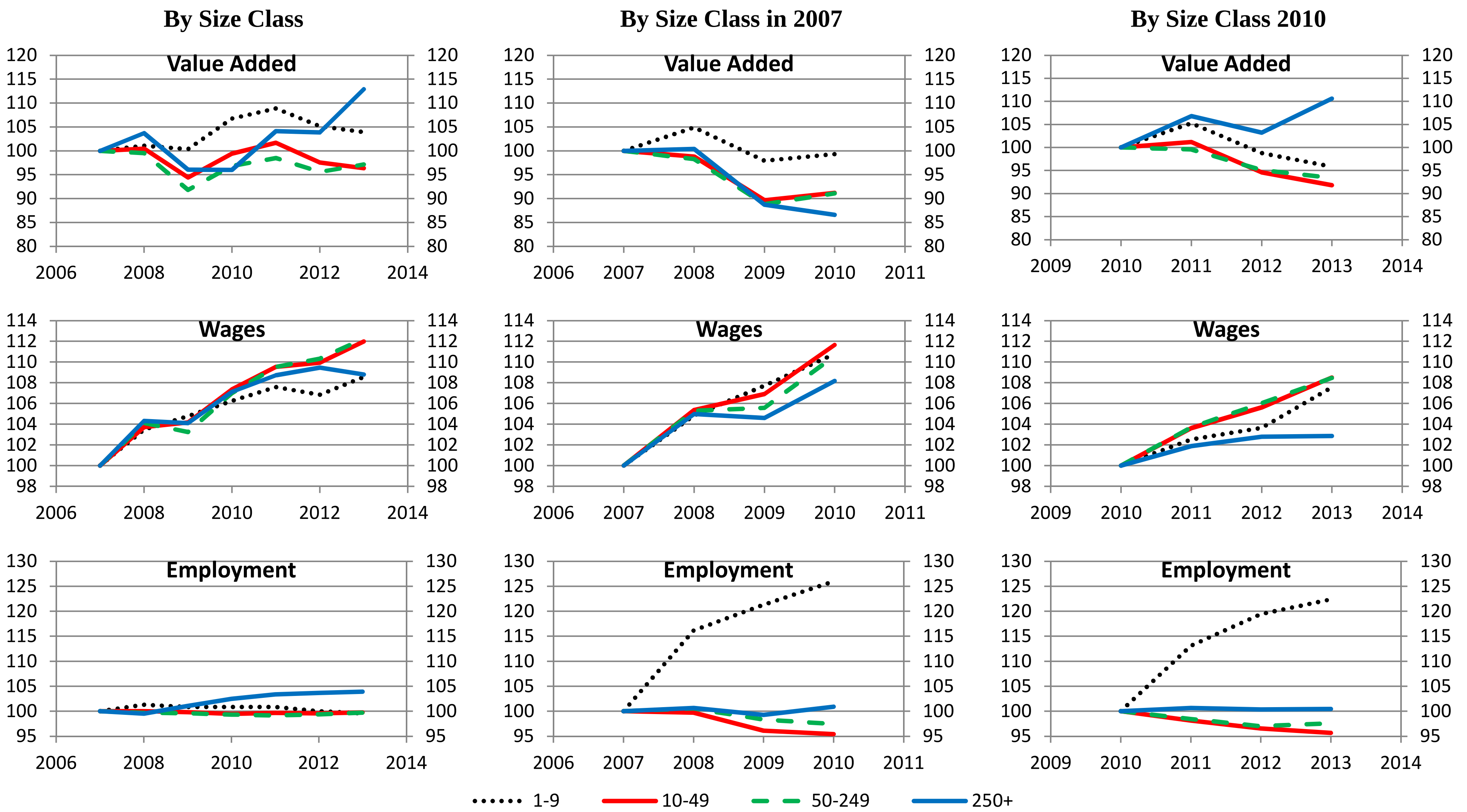
Source: own calculations on INPS data, data are summarized at the contract level and refer to all employees born on the 1st and 9th day of each month. Note: Data on middle managers and white collars are reported together before 1997. Number of firms where at least one worker in the sample transited in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

Table 3: Regressions at the sectoral level

Dep var:	Delta *OP* contribution							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
%Δ(productivity)	0.014	0.007						
	(0.010)	(0.006)						
%Δ(productivity) *post2006		0.049**						
		(0.024)						
Herfindahl index			-0.022***	-0.039*				
			(0.008)	(0.023)				
Herfindahl index *post2006				-0.137				
				(0.124)				
%Δ(demand)					0.014*	0.011*		
					(0.007)	(0.006)		
%Δ(demand) *post2006						0.017		
						(0.022)		
%Δ(employment)							0.034	0.031
							(0.031)	(0.039)
%Δ(employment) *post2006								0.008
								(0.041)
No obs.	360	360	414	414	360	360	414	414
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

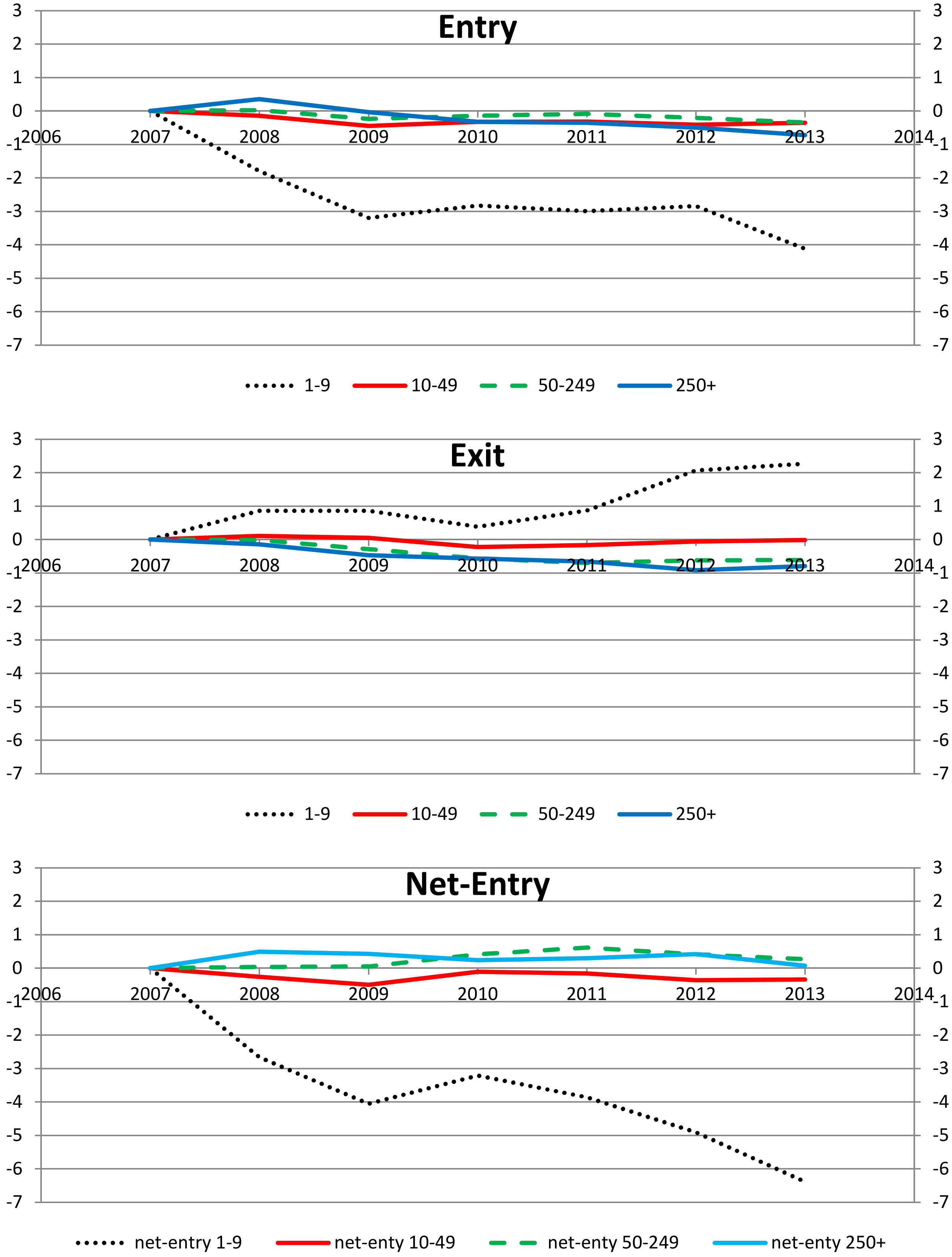
Notes: "Delta *OP* contribution" is the difference between the static *OP* contribution to the aggregate wage between year *t* and *t-1* (from INPS data); "%Δ(productivity)" is the percentage variation in the sectoral average value added per worker between year *t* and *t-1* (from CERVED data); "Herfindahl index" is the Herfindahl index computed using firm employment data in each sector (from INPS data); "%Δ(demand)" is the percentage variation in the sectoral average value added between year *t* and *t-1* (from CERVED data); "%Δ(employment)" is the percentage variation in the sectoral employment between year *t* and *t-1* (from INPS data). Robust standard errors clustered by sector in parenthesis. Columns 1, 2, 5 and 6 include only years from 1994 onward, when the value added data are available from CERVED. Columns 3, 4, 7 and 8 include years from 1990 onwards. Sectors: food(DA), textile(DB), leather(DC), wood(DD), paper(DE), chemical (DG), rubber & plastic (DH), other non-metallic mineral products (DI), metal products (DJ), M&E (DK), electric and optical equip. (DL), transport equip. (DM), manufacturing (DN), construction (F), trade (G), hotels & restaurants (H), transport storage (I), real estate and business activities (K).

Figure 1: Descriptives by class size, focusing on the great recession



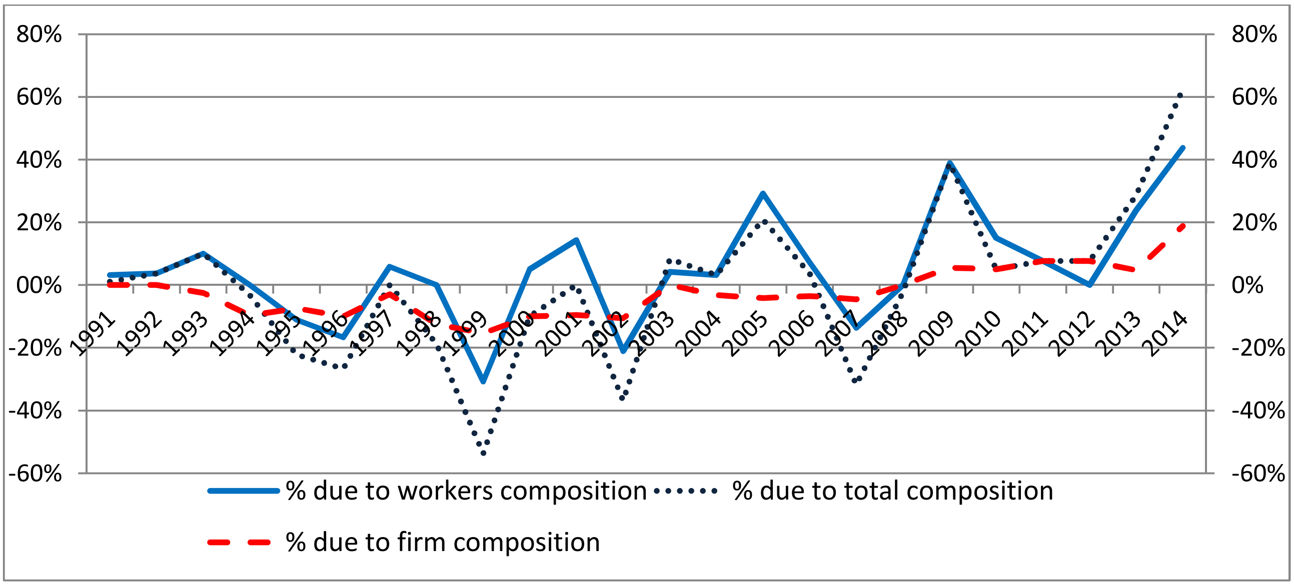
Source: Our calculation based on INPS-Cerved data. Note: A firm is assigned to a particular size class according to one of three procedures, each corresponding to one of three columns. To construct the sets of plots in the last two columns, we classify firms by their size in the year preceding each recessionary episode – i.e. 2007 and 2010 – and follow them over time. This introduces a severe survivor bias, particularly for micro firms, which account for 97% of exits on average and face a mortality rate five times larger than small firms and ten times than medium-size and large firms. Thus, with regard to small firms (and only for small firms) we comment results also for entry and exit.

Figure 2: Entry and exit rates (ppt deviation from pre-crises levels, 2007)



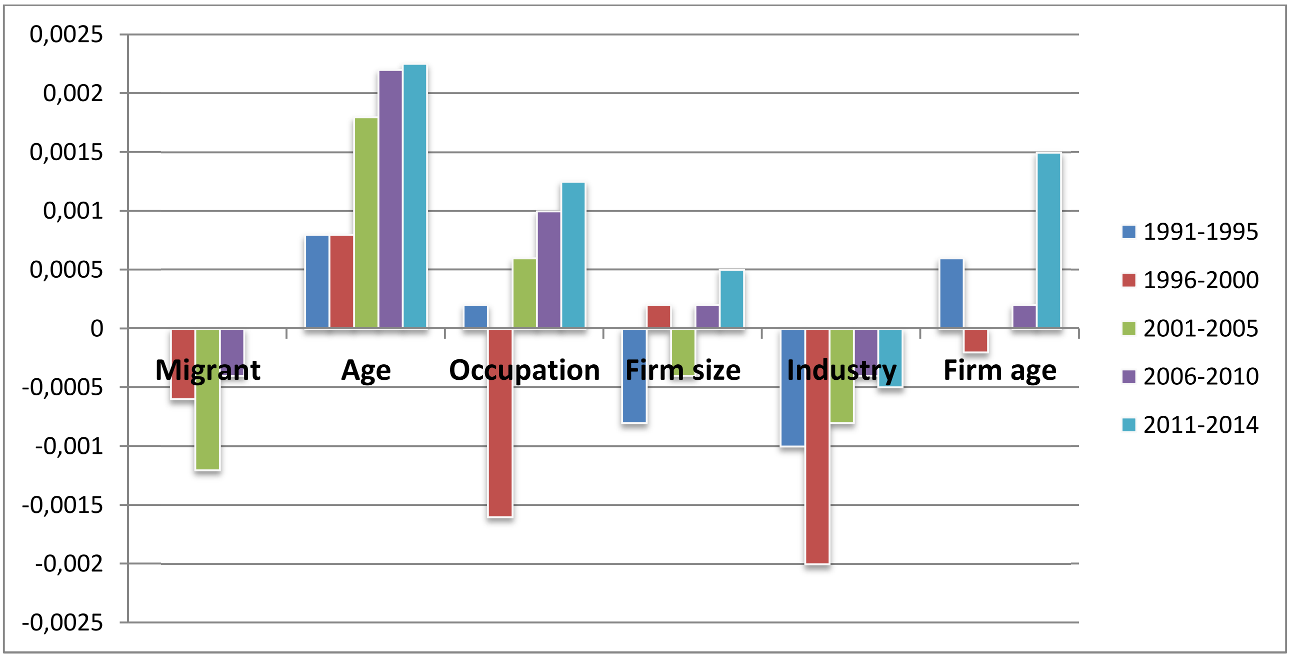
Source: Our calculation based on INPS data.

Figure 3: Contribution of composition effects to the wage growth, distinguishing between firms' and workers' characteristics.



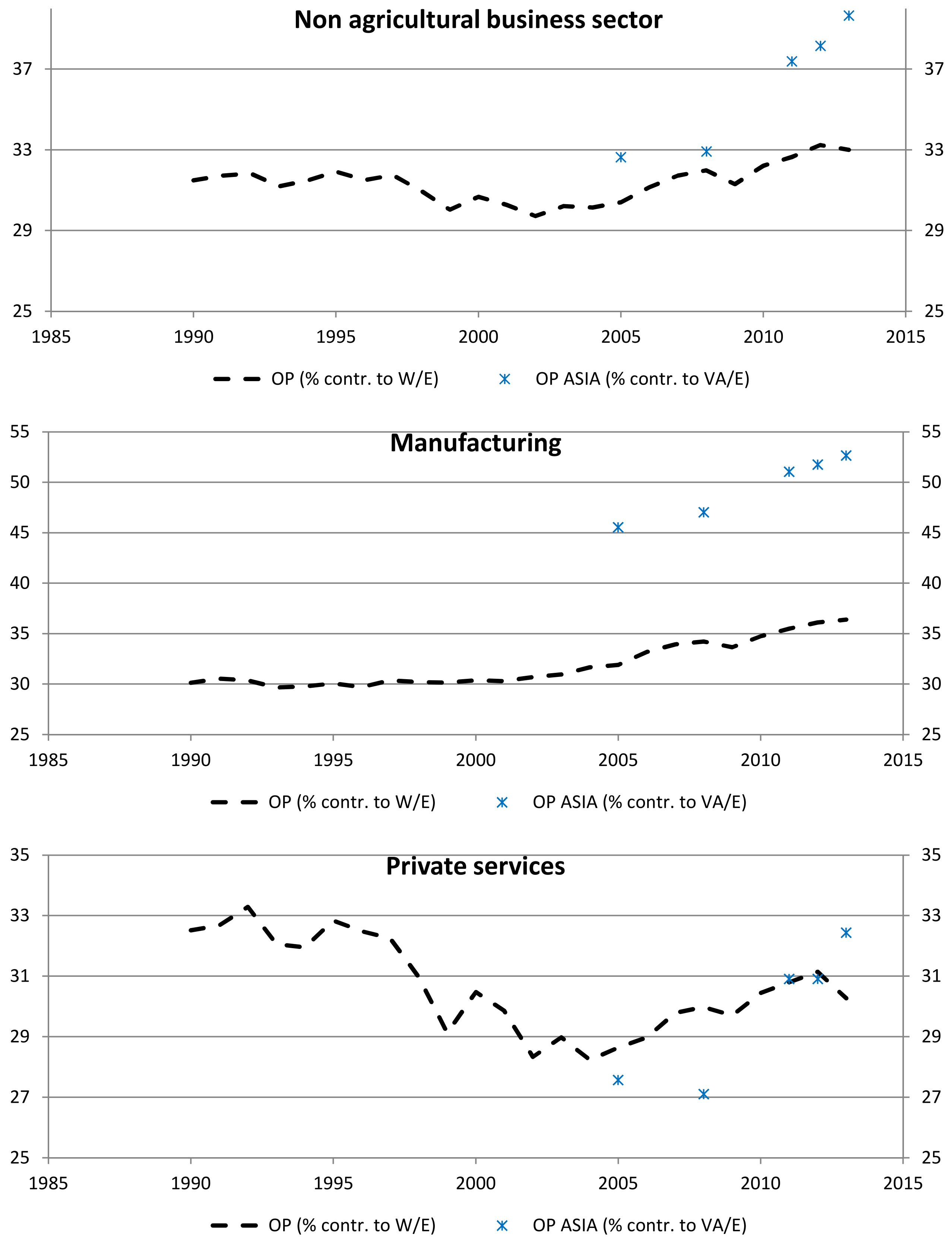
Source: own calculations on INPS data. Note: this figure plots the results on composition effects obtained from the Oaxaca decomposition. The blue line refers to the share of the yearly change in wage levels explained by changes in workers' characteristics, the red line refers to the share of the yearly change in wage levels explained by changes in firms' characteristics.

Figure 4: The contribution of some firms' and workers' characteristics to the composition effect of aggregate wages



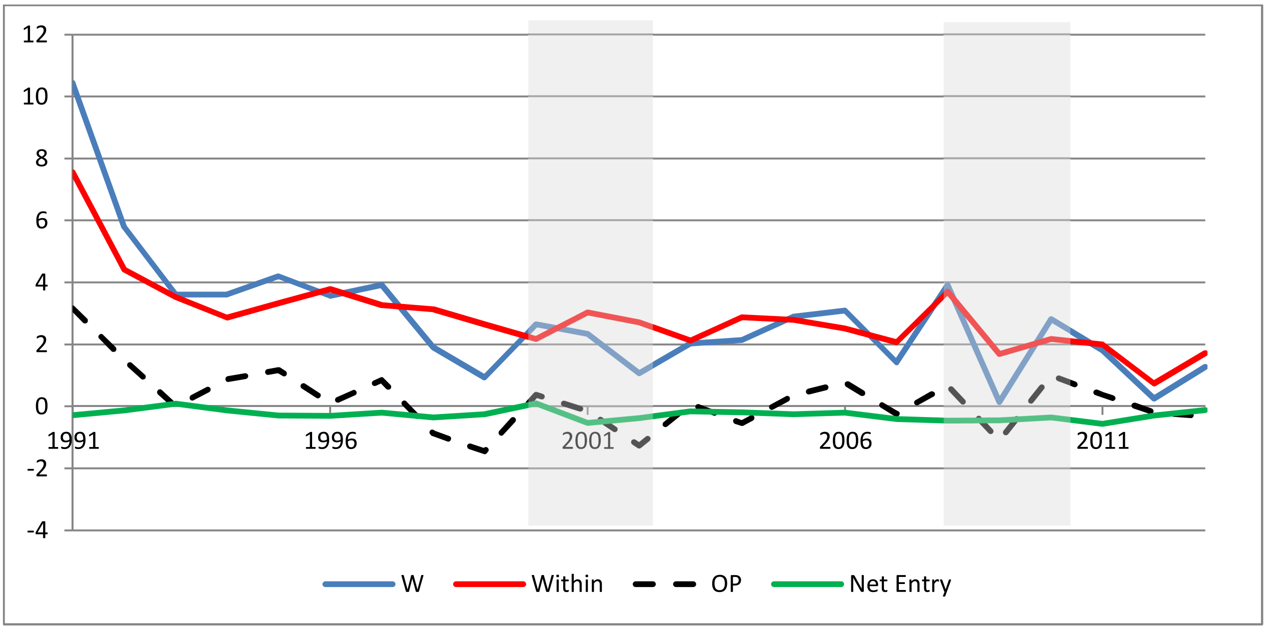
Source: own calculations on INPS data. Note: this figure plots the results on the contribution over time of the composition effects by workers' and firms' characteristics as obtained from the Oaxaca decomposition.

Figure 5: Static OP Contributions



Source: our calculations based on INPS data (black dashed line). Note: The figure shows the ratio of the static *OP* term over the average wage. The points in blue report the static *OP* term over the average productivity taken from Linarello and Petrella (2017). The static OP is based on levels.

Figure 6: dynamic OP decomposition (percentage points)



Source: own calculation on INPS data. Note: The figure reports the evolution over time of each term of the dynamic *OP*. The dynamic *OP* is based on wage growth.

Figure 7: Components of OP term (percentage points)

Source: our calculation based on INPS. Note: The figure decomposes the evolution of the *OP* growth into a *quantity* (adjustment in size) and a *price* component (adjustment in wages).

DATA APPENDIX

This section assesses the quality of the INPS data against official statistics from Eurostat National Accounts (ENA; ESA 2010) and Eurostat Structural Business Statistics (ESBS), available at the aggregate level. The top panel of Figure A1 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 2005-2014 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.[16] Next, Figure A2 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.[17] Both the entry rate and the exit rate in the INPS data are somewhat smaller and 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, consistently with an expanding pool of firms (Table 1).

In Figure A3 we report the year to year percentage change of total employment and the wage per employee from INPS, comparing these quantities with the corresponding statistics from ENA (Eurostat National Accounts). In principle, the labour input measure in INPS should correspond to the number of positions from ENA, which however are corrected, among other things, to account for the non-observed economy – approximately 15% of full time equivalent employees on average between 2011 and 2013 according to the Italian National Statistical Institute, ISTAT (2015). Indeed, the number of positions accounted for in INPS is somewhat smaller than in ENA (the ratio between these two quantities rises from 0.82 in 1995, the first year for which ESA 2010 data is available, to 0.90 in 2013), 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 ENA, rescaled by 1/12. The

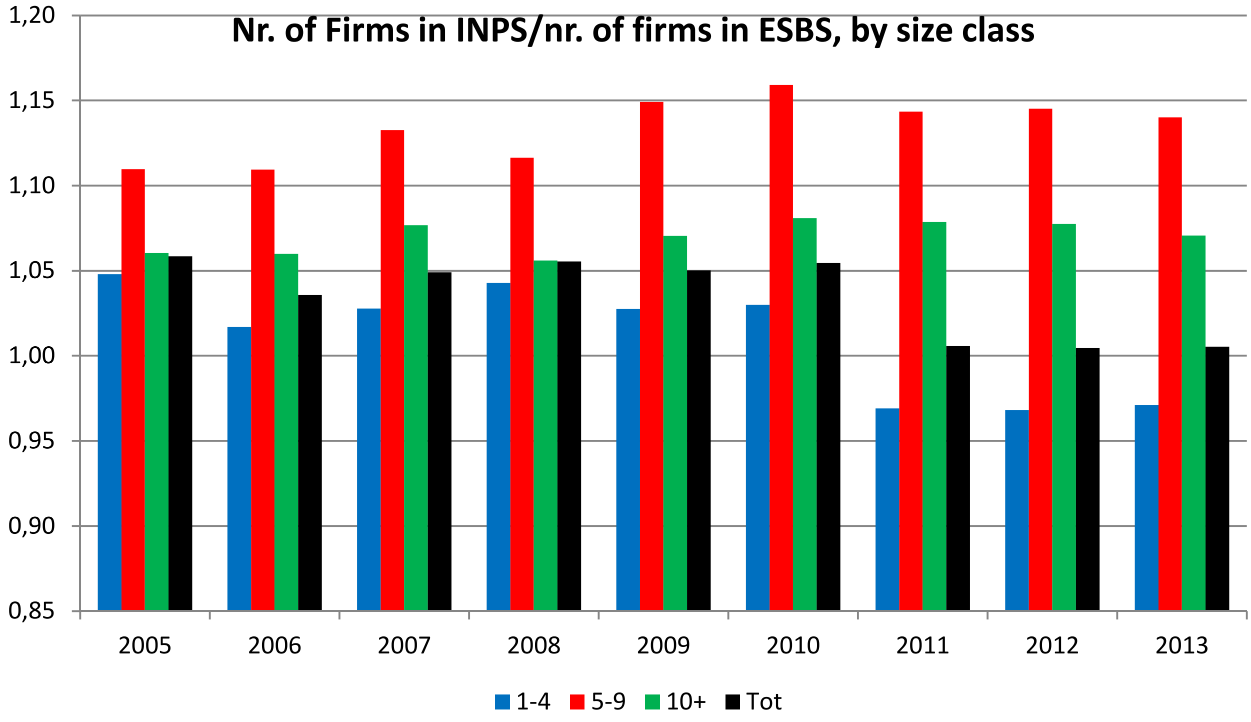
[16] INPS reports the average number of employees which is generally not an integer. A firm that has average size between 4 and 5 employees can be assigned either to the 1-4 size class or to the 5-9 size class. We choose to assign firms with employment ≤ 4 to the 1-4 size class and firms with employment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

[17] 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 which 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).

ratio between the two quantities oscillates between 0.92 and 0.97 over the entire 24 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 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 which can be traced back to Cerved, by class size. The fraction of employers which are incorporated in Cerved has grown over time to approximately 0.25 and 0.70 for size classes 1-9 and 10-49 employees and to 0.85 for size classes 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 ENA (the ratio between the two quantities being approximately constant at 0.62 between 2005 and 2013), the two series display a remarkably similar cyclical pattern during the recessionary period, less so prior to the recession (See Figure A3, lowest panel).[18]

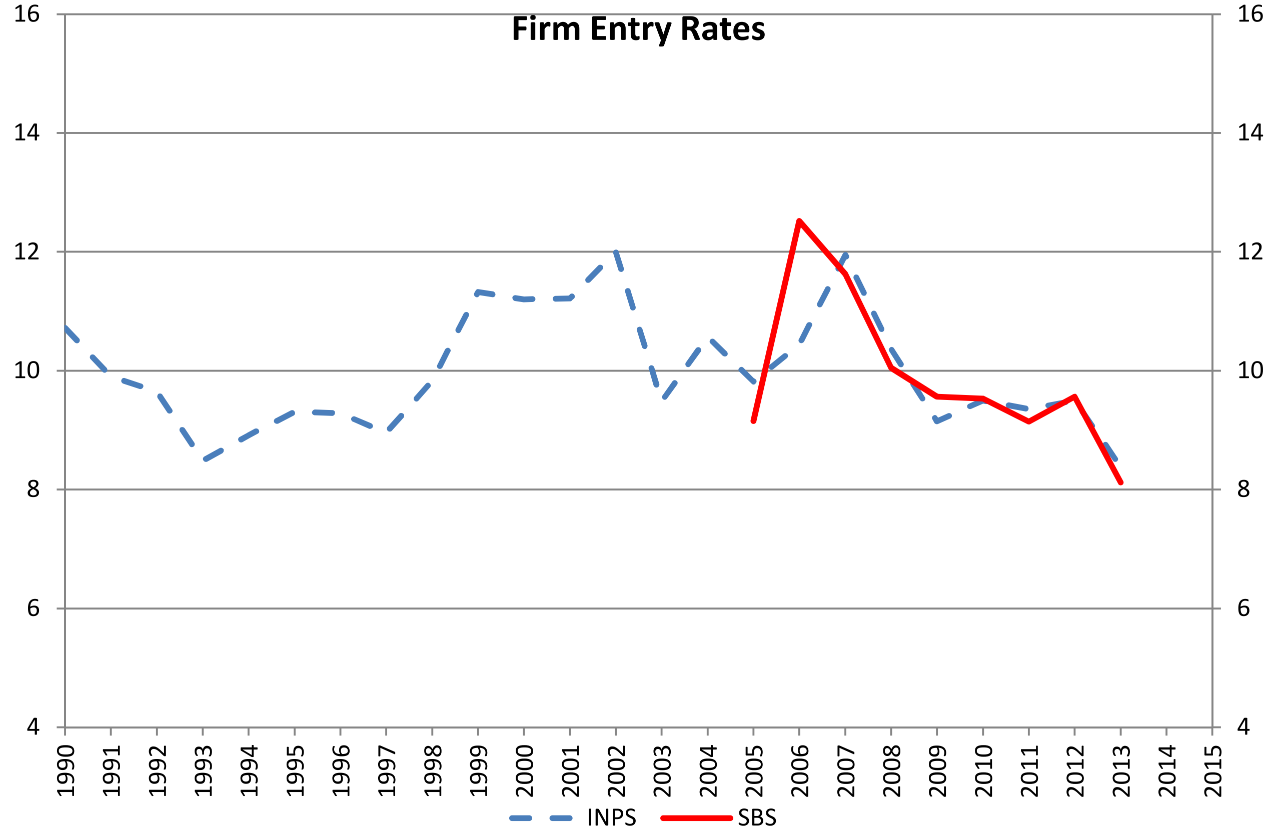
Figure A1: representativeness of INPS and ESBS databases, class size

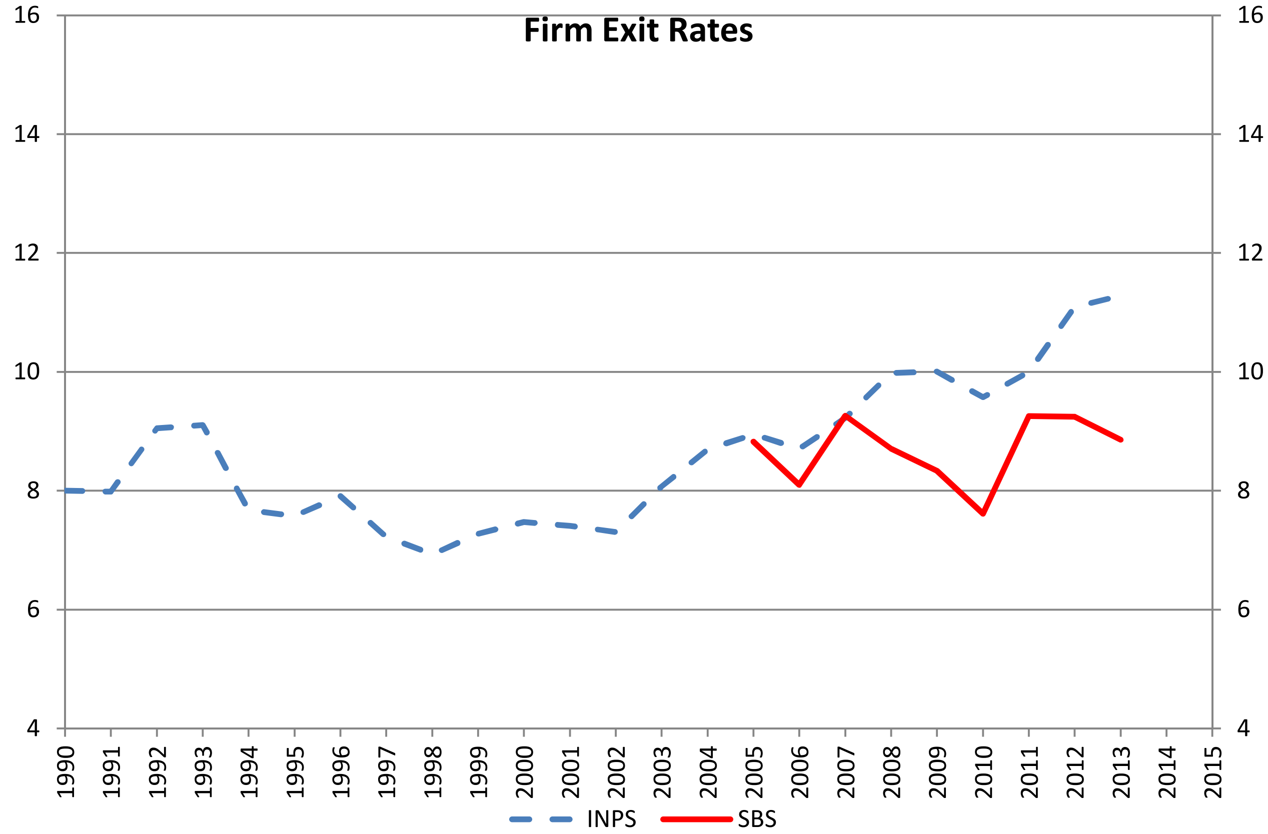


Source: our calculation based on INPS and Eurostat, *Structural Business Statistics* data

[18] 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.

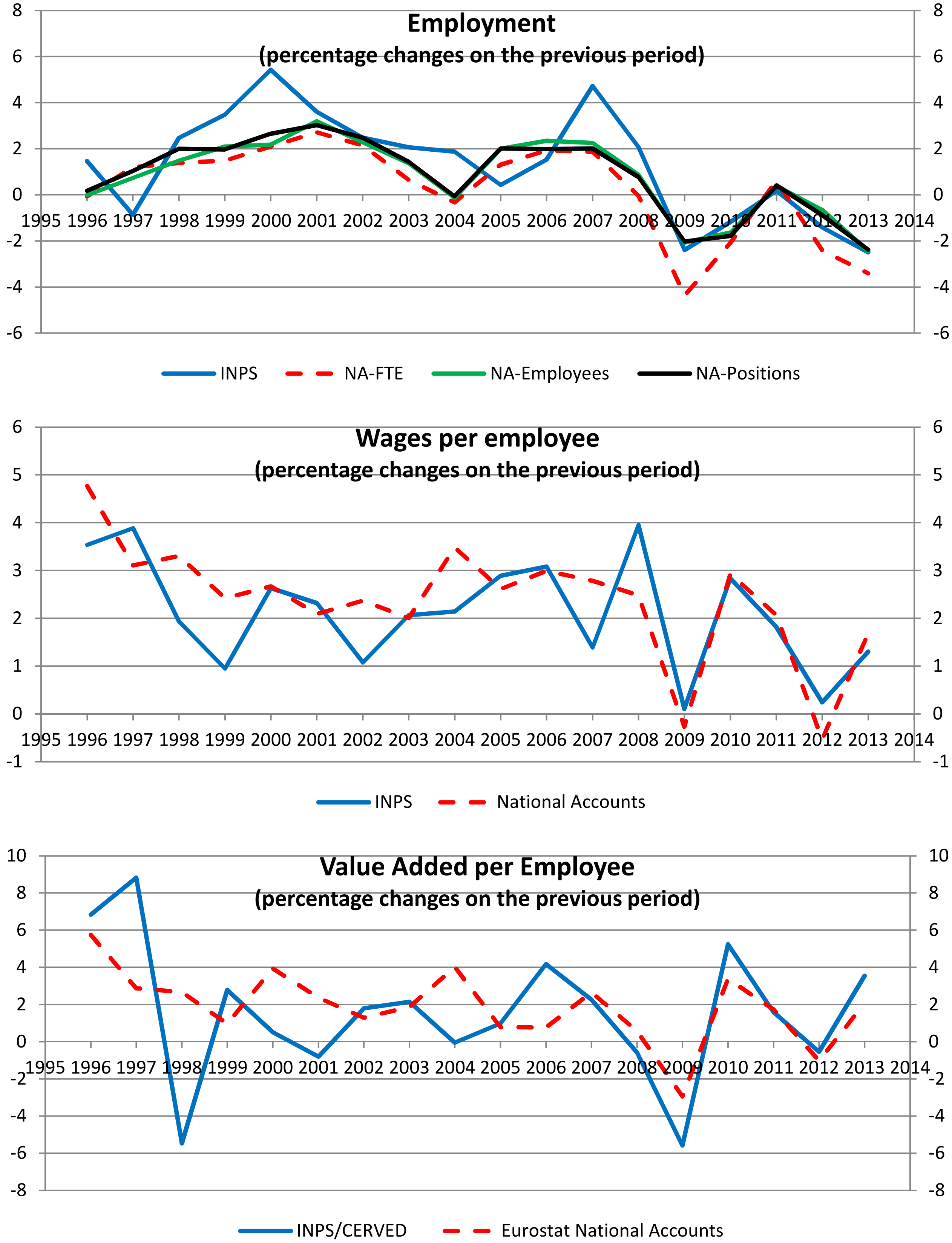
Figure A2: representativeness of various INPS and ESBS, entry and exit rates





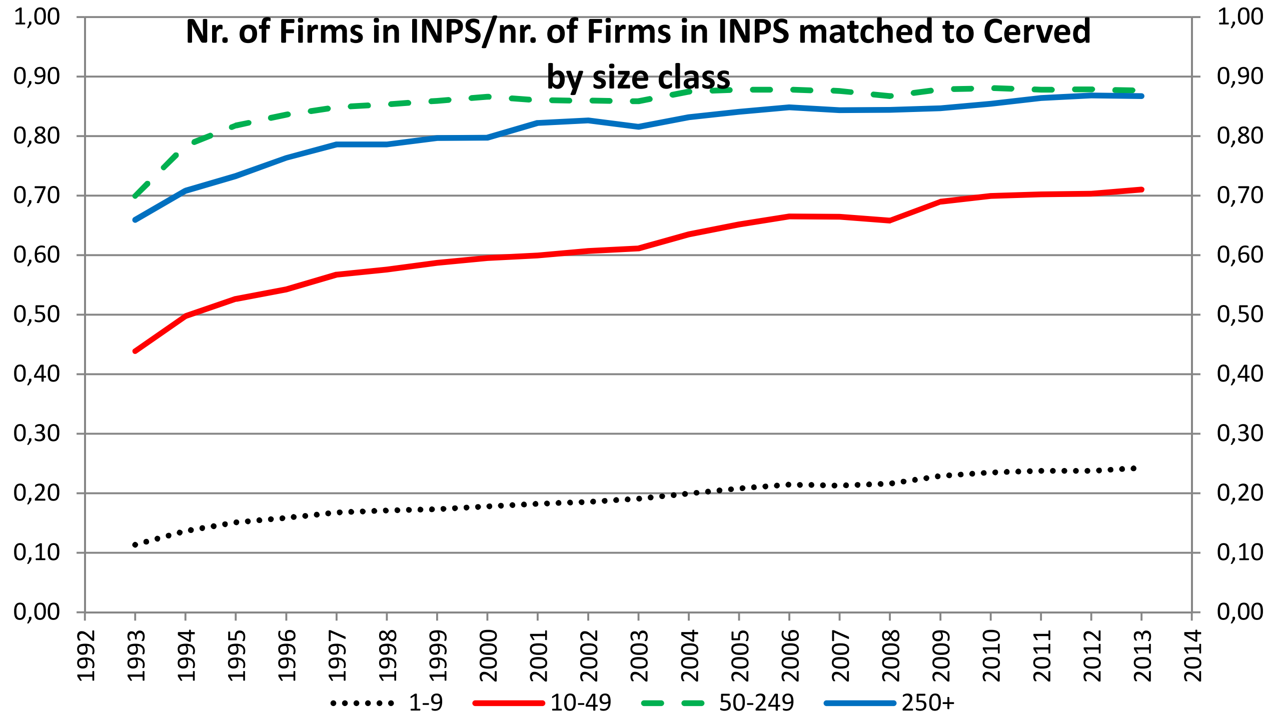
Source: our calculation based on INPS and Eurostat, *Structural Business Statistics* data

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



Source: Our calculation based on INPS and Istat, *Eurostat National Accounts* data.

Figure A4: Firm level evolution of employment, average wages and value added per employee over time



Source: our calculation based on INPS and Cerved data.