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ALLOCATIVE EFFICIENCY AND AGGREGATE WAGE DYNAMICS IN ITALY

by Effrosyni Adamopoulou*, Emmanuele Bobbio*, Marta De Philippis* and Federico Giorgi*

Abstract

Aggregate wages display little cyclicality compared with 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 firm composition effects also matter increasingly in explaining aggregate wage dynamics, i.e. aggregate wage growth has been raised 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 from 1990 to 2013 and employ a standard measure of allocative efficiency on wages paid across firms. We show that this measure has improved progressively since before the recent downturn, being 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: D22, J31
Keywords: Wage dynamics, allocative efficiency

Contents

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1. Introduction[1]

During downturns aggregate wages appear unresponsive to business cycle fluctuations. This holds true even for the recent recessionary episode, despite the duration and severity of the crisis. Common explanations are wage rigidities as resulting from various market frictions – see Adamopoulou et al. (2016), Verdugo (2016), Devicienti et al., 2007; Dickens et al., 2007. However, a recent strand of literature has provided evidence that lower-paid workers are usually more severely affected during recessions and therefore composition effects might have played an important role, especially during the recent downturn – see Daly and Hobijn (2016) for the U.S., Verdugo (2016) for Eurozone countries and D'Amuri (2014) with specific regard to Italy. We study the presence of firm-related composition effects, driven by the relocation of workers in different firms: to the extent that more productive firms also tend to pay higher wages – Bagger Christensen Mortensen, 2014 – a shift of resources towards more productive firms induced by the crisis might have resulted in composition affects supporting the dynamics of the aggregate wages. At least part of the "excessive" aggregate wage growth taking place during a downturn might therefore have a more benign interpretation, being related to such efficiency enhancing reallocation.

We document the relevance and the evolution over time of these firms compositional shifts in explaining aggregate wage growth. To corroborate our partially benign interpretation of their role – which to our knowledge we are the first to suggest – we analyze them both after and before the recent crisis and we compare them to the corresponding composition effect contributing to aggregate productivity – Restuccia and Rogerson (2008) and Hsieh and Klenow (2009) and Linarello and Petrella (20156) for Italy. We also correlate them to relevant sectorial level characteristics – within the non-agricultural business sector – , like business cycle conditions, average productivity growth and indexes of market concentration.

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 the period between 1990 and 2014. 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 Blinder-Oaxaca (1973) decomposition, which we augment with firm characteristics – section 3. We find that firms characteristics became positive and significant during the crisis and we proceed by applying on the data a standard measure of allocative efficiency, the Olley and Pakes (1996) decomposition (OP) – section 4. Olley and Pakes find that the aggregate productivity, or in our case the aggregate wage, can be

[1] We are grateful to Matteo Bugamelli, Andrea Linarello, Francesco Manaresi, Paolo Sestito, Roberto Torrini, Eliana Viviano, Luigi Federico Signorini and seminar participants to 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.

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, but actually more productive firms are larger, this correlation will be positive and aggregate productivity larger than the within component. An increase of the OP term is therefore interpreted as an improvement in allocative efficiency. We confirm that the OP term contribution to the aggregate wage increased over time starting approximately in 2002, along with the OP contribution to aggregate productivity, as measured by value added per worker – as documented by Linarello and Petrella (2016). Over this period aggregate wages have increased more than aggregate productivity in Italy and contrary to most other advanced countries, the labor share has been increasing – Torrini (2015). We do not claim that aggregate wage changes corresponded to equivalent aggregate productivity changes, rather than a part of the increase in aggregate wages resulted from improvements in allocative efficiency which also contributed to aggregate productivity. We then proceed to correlate changes in the OP contribution to the average wage level with changes in productivity across sectors and indexes of market concentration finding a positive relationship in the first case and a negative relationship in the second case. We interpret these patterns as signs that the relocation of workers may have induced efficiency enhancing mechanisms. Next, in section 5 we focus on the recent recessionary period and we find that small firms (possibly less productive firms) tended to adjust employment more, while larger (possibly more productive firms) tended to curb wages more, and we show how this differentiated pattern of firms' reaction to the crisis explain the dynamics of the OP contribution to the aggregate wage level. Finally, we conclude by showing that, while the increase in the OP contribution to the aggregate wage level over this period was accompanied by rising unemployment, it actually increased more in sectors where value added and employment increased more (or decreased less).

2. Data

The source for the data consists of social security payments made by legal entities to the Italian National Social Security Institute (INPS) for all employees with open-ended, fixed-term, and apprenticeship contracts between 1990 and 2014. From this master data, INPS extracts two datasets. The first 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, 6.5% of the workforce). In this paper we use the firms' extraction, which contains the following information: a firm unique identifier; information on the average number of employees over the year and the gross wage bill by occupational category – blue collar, white collar, middle and top manager; the two digit sector code

(NACE 2002) and the province code; the date of entry and exit (if any). We mainly restrict attention to the non-agricultural business sector and use the unique identifier as the definition of firm. Tables

Table 1 report descriptive statistics. Over the 24 years of the sample the fraction of firms in industry declines from 49 to 36%, average size declines from 8 to 7.4 employees, the pool of employers increases from 1.1 to 1.4 million, and the nominal monthly gross wage doubles from around 1000 to around 2000 euros.

We now compare our data with official statistics on firm demographics and from the National Accounts to assess the representativeness of the data and their quality. The top panel of Figure A1 in the Appendix displays the ratio of the number of firms in INPS to the number of firms reported in Eurostat Structural Business Statistics (SBS). SBS reports the breakdown by class size for firms with 1 to 4, 5 to 9 and 10 or more employees for the period 2005-2014. INPS tends to include more firms than SBS, which adopts a more stringent definition of active employer business, as one employing a worker for at least 6 months during the year.[2] Next, Figure A2 in the Appendix displays the entry and exit rates constructed from INPS data and those derived from SBS statistics. For each legal entity paying social security contributions the firm extraction of the INPS dataset reports an entry and exit date.[3] We consider a firm as entering or exiting when all legal entities with the same fiscal code enter or exit. Both the entry rate and the exit rate in the INPS data are somewhat smaller and smoother than in the SBS. 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 1 we report the year to year percentage change of total employment and the wage per employee from INPS. We compare these quantities from our dataset with the official National Account statistics (NA). In principle, the labor input measure in INPS should correspond to the number of positions from NA. The ratio between these two quantities rises from 0.82 to 0.90 between 1995 and 2013 and the two series display a similar cyclical pattern – the series from INPS being a bit more volatile, left panel. As for the wage, we compare the average monthly wage from INPS with the gross wage per position from NA, rescaled by 1/12. The ratio between the two quantities oscillates between 0.92 and 0.97

[2] Firm's employment can be non-integer in INPS. Then , for example, a firm that has 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. Our definition of an active firm only implies that our dataset contains more firms than the SBS overall.

[3] Several entry and exit dates can be associated with the same legal entity. We consider entry to be the earliest such date and check that there are no prior records for that entity. As for exit, we follow a two-step procedure. First, we consider only candidate dates which are recorded in the same year to which the event refers to. For example, it may occur that the 2006 record associated with a legal entity reports an exit date equal to 2009 but that the 2009 record does not. In this case, we would consider the report to be a valid candidate only if it were recorded in 2009. 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 (note that skipping step one would instead generate significant biases, as more spurious exits would be left undetected in the latter years of the sample).

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.

INPS data does not contain accounting information. However a sub set of the employers in INPS, those who are limited liability companies, can be merged with Cerved, the business register containing balance sheet data for the universe of Italian limited liability companies. In the lower panel of the same figure we report the fraction of firms in INPS which can be traced back to Cerved, by class size. The fraction of employers which are incorporated 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+ respectively. The aggregate value added per employee from INPS-Cerved is much lower than the corresponding measure from the NA (value added at base prices per position) the ratio between the two quantities being approximately constant at 0.62 between 2005 and 2013. However the two series display a remarkably similar cyclical pattern during the recessionary period, less so prior to the recession.[4]

We conclude that INPS data provides a reasonably good approximation of national aggregates from official statistics regarding employer business demographics, employment and gross wages. When combined with CERVED, it also returns a reasonably good picture of balance sheets regarding firms with at least 10 employees.

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

We use the INPS data to replicate and extend previous work on the rising importance of composition effects over time and particularly during the crises in explaining aggregate wage dynamics – Daly et al. 2011, D’Amuri 2014, Verdugo 2016. Table 2 reports the descriptive statistics. Compared to the data used in these studies, the INPS data has the advantage of covering a long time-span, 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 is collapsed at the worker-year level by considering the contract of the longest duration, so as not to oversample workers with multiple

[4] 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 labor cost, gross wages plus social security contributions paid by employers. Interestingly, the percentage change series of the aggregate wage computed from INPS and the labor cost computed from INPS-Cerved move remarkably close with one another, the correlation being 0.85.

employment spells. 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*;[5] x_{it} are workers' characteristics (gender; age; 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; 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:

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

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 2 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 changes widely after the recent crisis, in line with Daly et al. (2012). 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 displaying a positive and statistical significant sign. 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 is driven by workers' characteristics, in particular by changes in the workers' age and occupation. These results on workers are in line with the previous literature (D'Amuri 2014, Hines, Hoynes and Krueger, 2001 for instance), that show that job losses during downturns disproportionally affect workers with lower than average wages. What we add into the standard Oaxaca decomposition analysis are firms' characteristics. We find that there is an increasing

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

positive contribution of firm characteristics after the crisis: our Oaxaca decomposition shows that an increasing part of changes in average aggregate wages over time is due to the fact that more workers are allocated i) to larger firms and ii) to the service sector, that usually pay higher wages.

The rising importance of composition effects lends itself to different interpretations. On the one hand, policy interventions may affect the way firms adjust along the employment margin. For example, if employment protection varies across workers, firms may decide to layoff less protected workers first. If less protected workers are paid less, e.g. because workers with temporary contracts tend to be younger and have less seniority, such a decision will increase the average wage purely via a positive composition effect – Cappellari et al. (2012). In addition, if these workers are also more productive it will also decrease average productivity – see van Ours and Stoeldraijer (2011) for a discussion of the empirical evidence on the relationship between age and worker productivity. Similarly, an unexpected pension reform, such as the one enacted in Italy at the end of 2011, may force firms to retain older workers and slow down the hiring rate (or increase the firing rate) of other, younger, workers – Boeri and Garibaldi (2016), Carta and D'Amuri (2016). On the other hand, composition effects may be the result of an efficient market response. If firms layoff least productive workers first, and to the extent that wages and productivity are correlated to each other at the individual level, this would result in a positive composition effect on both average wage and productivity. The same applies on the firm side: if more productive firms pay higher wages and employment shifts towards them, this would boost both aggregate wage and aggregate productivity. The latter is the channel that we study in the next section.

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, Haltiwanger and Grim (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, wage composition effects may then be the result of an improved allocation or resources. As long as the shift benefits firms paying not only higher wages but also characterized by a lower labour share, such composition effects will also be accompanied by an improved external position. To assess whether the allocation of resources has improved in Italy and whether this may have resulted in composition effects rising the dynamics of wages we employ a standard measure of allocative efficiency, the Olley and Pakes decomposition (1996).

In our context the Olley and Pakes decomposition (OP) is defined as the difference between the employment-weighted and the unweighted mean wage (or productivity, e.g. value added per worker) across firms and it is identically equal to the covariance between wage and size computed across firms:

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

$$within\ term: \tilde{w}_t \equiv \sum_{i\in I} w_{it}$$

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

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 w_{it} is the wage (or productivity) in firm i at time t; $\bar{w}_t$ and $\tilde{w}_t$ are the weighted and the unweighted average wage across firms respectively, and $\bar{w}_t$ is also the aggregate wage. The contribution of the OP term to the aggregate wage level, $OP_t/\bar{w}_t$, has a natural interpretation as a measure of allocative efficiency when applied to productivity: if firms differ in terms of productivity and resources are allocated randomly, then the covariance between size and productivity is zero and aggregate productivity is equal to average (unweighted) firm productivity, $\bar{w}_t = \tilde{w}_t$. However, if more resources are allocated to more productive firms, then the covariance between size and productivity is positive and aggregate productivity is larger than the (unweighted) average firm productivity, $\bar{w}_t > \tilde{w}_t$, even if $\tilde{w}_t$ did not change. We apply the OP decomposition to wages; al long as more productive firms also pay higher wages, changes in the contribution of the OP term to the aggregate wage level will reflect changes in aggregate efficiency.

Figure 3 displays such ratio ($OP_t/\bar{w}_t$) over the sample period for the nonagricultural business sector and for manufacturing and private services separately. Starting in 2002 the percentage contribution of the OP term starts increasing, it then temporarily drops in 2009 and keeps rising until 2012. Looking at the heterogeneity across 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 since then, while it has declined until 2002 and then started rising after 2004 in the service sector. An increase in the OP contribution means that the covariance between size and wages across firms has been rising faster than the within term. We interpret this as evidence that the employment composition has been shifting towards high wage and possibly 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 having a higher productivity; or that larger firms granted higher wage increases and that such wage increases were unrelated to productivity changes, for example because of higher unionization levels and higher firing costs at large firms increasing workers' bargaining power.[6] 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 the latter dimension, here we provide some indirect evidence of the relationship between wage and productivity dynamics and changes in the allocation of resources. This does not amount to evidence that wage increases were largely in line with productivity, and in fact Torrini (2015) shows that differently than in other countries the labor share has been increasing in Italy since 2001 and explores the reasons behind this pattern. Here we simply claim that part of the composition effects that enhanced the aggregate wage dynamics might have been accompanied by a corresponding productivity-enhancing shift in the allocation of resources.

As mentioned in the data description section, INPS-Cerved severely underrepresent small employers and the firms in this dataset, i.e. small limited liability companies with at least one employee, are likely to be much more productive than the average employer.[7] Indeed, while in our data the smaller the size category, the lower the wage, firms with 9 employees or less display a higher value added per worker than larger firms.[8] The omission of small firms severely distorts the OP decomposition results, thus we are not able to perform the same analysis on productivity as on wages using the same dataset. Instead, we recurred to ASIA, the administrative register covering the universe of Italian employer businesses for 2005, 2008 and 2011 to 2013 and containing data on value added and employment.[9] Results are reported in Figure 3 which shows a higher OP contribution to the aggregate productivity level in 2008 than in 2005, suggesting that the OP contribution might have started to increase prior to the onset of the recessionary period, as we find to be the case for aggregate wages. Comparing the manufacturing and the service sector we also find that while the OP contribution appears to be rising in manufacturing

[6] 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.

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

[8] This could also be due to small firms having a higher share of self-employed workers, who are not accounted for in the INPS data.

[9] We thank Linarello and Petrella who kindly provided us with these numbers and refer the interested reader to their work – Linarello and Petrella (2016) – 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.

throughout the period covered by ASIA, it declines slightly in the service sector between 2005 and 2008 and then steadily increases between 2008 and 2013. It should be noted that 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.

While INPS-Cerved is not comprehensive enough to compute a reliable OP decomposition on value added per worker for employers we can use it to compute average productivity at the sector level, as small firms have a relatively small employment weight. We then proceed to contrast the evolution of the OP contribution to aggregate wages to the evolution of average productivity (as measured by value added per worker) across sectors. We drop from the analysis mining, refining, energy and finance.[10] Figure 4 displays scatter plots for the pre-crisis period, 2003-2008, and for the crisis period, 2008-2013. It suggests that the OP contribution to aggregate wages increased in those sectors where productivity increased more. We interpret this positive relation as suggestive of the hypothesis that composition effects at the sectoral level may reflect changes in allocative efficiency leading at the same time to increases in sectoral productivity.

Next, if resources are shifted to more productive firms as a result of market forces, then such shift should be more likely to take place in sectors which are more competitive. Figure 5 displays the Herfindahl index, a standard measure of market concentration, at time *t* against the change in the OP contribution to the average level between *t* and *t*+5 across sectors.[11] After removing the outliers (red line), the figure suggests that the OP contribution increased more in sectors characterized by higher competition (green line), thus possibly more prone to reallocation.

We complement this graphical evidence by running over the entire sample period and across sectors a regression of year to year changes in the OP contribution to the aggregate wage level against year to year productivity changes[12] and the Herfindahl's index (the index is computed using employment, not value added, because there are less missing values), allowing for sector and time fixed effects. The result are reported in table 3 and provide a statistical confirmation of the graphical impressions derived from the scattered plots discussed above: over time and across sectors increases in the OP percentage contribution are positively associated to changes in productivity and are more likely to occur in less concentrated sectors.

[10] NACE 2002, Mining (CA) and (CB), Refining (DF), Energy (E) and Finance (J).

[11] An increase in the values of the Herfindahl index indicates an increase in concentration, and therefore a decrease in the degree of competition.

[12] This regression starts from the year 2002, when the matching rate between INPS and Cerved improves.

5. A closer look at the recent downturn, 2008-2013

Next we take a closer look to the crisis years. We start by providing some descriptive evidence on the evolution of wages, employment and value added across firms belonging to different size classes; we then compute the *dynamic OP decomposition* proposed by Melitz and Polanec (2014), which allows us to disentangle firms' entry and exit – two potential important sources of changes in the allocation during the recessionary years – and we dissect the dynamic OP term by performing a shift-share analysis of its components. Finally, we extend the cross sectoral analysis of the previous section by correlating changes in the OP contribution with changes in economic activity (output and employment levels) to verify whether shifts in the allocation of resources were mainly driven by destructive forces and to try and provide some hints about possible future developments.

In Figure 6 we report the evolution of firm value added (VA), the wage per employee (W, employment – weighted) and firm employment (E) computed by size cell and rescaled to a base year. Changes in average firm value added are meant to proxy for the magnitude of the shock affecting firms in a particular size class; and W and E the response of firms to the shock along the price and quantity margins. Firms are partitioned in four size classes: micro (1-9), small (10-49), medium (50-249) and large firms (250 employees or more). A firm is assigned to a particular size class according to one of three procedures, each corresponding to one of three columns in Figure 6. To construct the left column we reclassify firms in each year. The center and right columns each focus on a distinct phase of the crises: the financial crisis, from 2008 to 2010, and the sovereign debt crisis, from 2011 to 2013, the last year covered by our sample. As noted above the financial crisis reached Italy with some delay with respect to the US and it is common to consider 2008 as the starting year of the recessionary period for Italy. To construct these two sets of plots we then classify firms by their size in the year preceding each phase of the crises – 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 higher than small firms (ten times higher than medium and large firms). Thus, we only comment results for this size class when it comes to entry and exit.

The value added plots suggest that the financial crisis hit all firms with a similar intensity, except than for large firms which were affected for a more prolonged period of time. Instead, the sovereign debt crises hit small- and medium-size firms harder and more persistently, while large firms rebounded quickly. Such differentiated patterns over the two phases of the crisis may reflect the different nature of underlying shocks: the external nature of the demand shock characterizing the financial crisis – with larger, export-oriented firms being affected more severely – and the credit supply shock during the sovereign debt crisis – possibly impacting disproportionately small- and medium-size firms with links to local banks – see Bugamelli et al. (2010) and Banca d'Italia (2012, 2014).

During the 2009 downturn average wages paid by firms slowed down sharply and employment declined. The response along two such margins of adjustment differs by class size. Large firms cut wages, while wages remained constant in medium firms and continued to grow in small firms which cut employment more, instead. 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. The wage per employee would therefore appear to decline. While this remains a potential issue, in a companion paper we show that medium firms used STWB more intensely than large firms – Adamopoulou et al. (2016). In 2012 wages slowed down more sharply in micro and in large firms, possibly reflecting the combination of a more severe shock hitting smaller firms and a higher sensitivity of wages in large firms – applying our reading of the response to the 2009 shock to 2012 as well. Wages at large firms continued to slow down and dropped in 2013. Employment dropped more and more persistently in small and medium firms.

Figure 7 shows that firms have been shrinking during the most severe years of the recessionary period: the probability of moving to a lower size class is strongly countercyclical and the probability of moving to a higher size class is strongly procyclical, and this is particularly so for small firms. As mentioned above, small firms account for approximately 97% of exits, a similar figure holding for entries. The entry and exit plots in Figure 8 show that the entry rate in this size class 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.

Summing up, Figures 6 to 8 suggest that the first phase of the crisis hit large firms more severely while the second phase affected smaller firms disproportionately more. Also, large firms appear to be more responsive along the wage margin while small firms appear to be more responsive along the employment margin. We argue that these broad patterns are consistent with the evolution of the OP contribution to aggregate wages outlined in the previous section. The finding that large firms are more responsive along the wage margin is consistent with the empirical analysis in Rosolia (2015), who finds that, while the contractual wage respond slowly to cyclical conditions due to the staggered nature of the Italian wage setting institutional framework, the extra-contractual component 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 binding 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). To establish a link between the evolution of this statistic and changes in employment and wages across firms we turn to the *dynamic OP decomposition* introduced by Melitz and Polanec (2014):

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

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 labor share at time t-1 of exiting firms and $\bar{w}_{t-1}^X$is the employment-weighted average wage that firms in such group pay – similarly for σ_t^E, $\bar{w}_t^E$ and $\bar{w}_t^C$. $\Delta\tilde{w}_t^C + \Delta OP_t^C$ is simply the time difference of the static OP outlined above computed on the subset of continuing firms at time t and t-1. Intuitively, the dynamic OP decomposition is an identity unbundling the contribution of firms that exit or entry, therefore allowing to compute the OP decomposition on the set of continuing firms. As we shall see below, because the OP decomposition is computed on the same set of firms both at t and t-1, we can then trace changes in the OP term back to employment and wage changes at the firm level. In addition, 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 – $\bar{w}_{t-1}^X$ and $\bar{w}_{t-1}^E$. In practice the net contribution of the combined entry and exit terms turns out to be small relative to 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 3.[13]

Figure 9 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 $\Delta OP_t^C/\bar{w}_{t-1}$). 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,

[13] 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 and the OP term of the dynamic OPdecomposition can be easily related to one another if the OP term of dynamic OP decomposition is large relative to the net entry term.

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. Figures A3 and A4 in the Appendix display results for the OP decomposition performed on manufacturing and services separately and for the 1992 recessionary period and the 2002 slowdown. These figures reveal that in manufacturing both the within and OP term have moved together along the cycle contributing in similar proportions to the dynamics of the aggregate wage, and that the adjustment in manufacturing has been more pronounced. As for the comparison over time, the figures indicate that the OP term has become negative at the trough of each cycle 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 term exploiting the linearity of the covariance operator:

$$\begin{aligned}\Delta OP_t^C &= cov\left(\frac{e_{it}}{e_t}, w_t \middle| i \in C_t\right) - cov\left(\frac{e_{it-1}}{e_{t-1}}, w_{t-1} \middle| i \in C_t\right) \\ &= cov\left(\Delta\frac{e_{it}}{e_t}, w_t \middle| i \in C_t\right) + cov\left(\frac{e_{it}}{e_t}, \Delta w_t \middle| i \in C_t\right) + cov\left(\Delta\frac{e_{it}}{e_t}, \Delta w_t \middle| i \in C_t\right).\end{aligned}$$

Results are reported in Figure 10. 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 – 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 respective cyclical patterns (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 (possibly small) firms cut employment more than high wage (possibly 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 cut 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 crises highlighted in the previous section: large firms adjust wages more, while small firms adjust employment more. As for the comparison across sectors and over time, Figures A3 and A4 in the Appendix indicate that the negative correction of the dynamic OP term at the trough of the cycle is primarely driven by the price affect. Also, compared with manufacturing the cross term is markedly procyclical in services during the recent downturn suggesting a more stringent tradeoff between wage and employment adjustments at the through of the crisis in this sector.

All in all we take these results as suggestive of functioning market forces. Larger, possibly more productive firms paying higher wages were able to withstand the crises and preserve their employment levels better than smaller, less productive firms, resulting in an improved allocation of resources. Large, more productive firms were also able to adjust wages, suggesting that wage rigidities may not be such an important constraint at least for such firms. While this second phenomena may have contributed negatively to the dynamics of the OP term, we take it at as an indication of the ability of the system to adjust to negative shocks.

The rise in the OP term during the recessionary years was accompanied by rising firm mortality rates and declining firm creation rates and by the emergence of mass unemployment. We do not claim this process was efficient; rather, that conditional on the occurrence of a large negative shock and provided that the shock was unavoidable: 1) it was better for the shock to impact prevalently on 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 only to 2013. However, the scatter plots in Figure 11 show that, during the recessionary years and across sectors, changes in the OP contribution to the aggregate wage level were associated to less severe demand (as measured by sectoral value added) and employment conditions. This suggests that the rise in the OP contribution to the aggregate wage level was not simply the result of layoffs by less productive firms and that 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 may have been 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. We showed that such trends are positively correlated with productivity growth across sectors and negatively correlated with sectoral concentration, which should hinder 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 found 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 argued that these firms were able to adjust wages to a larger extent than smaller firms. Finally we showed 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 simply the result of increasing layoffs by smaller, less productive firms.

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Tables

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

Year	% of firms in Industry	% of firms in Manufacturing	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)

	Daily wage		Age		% Females	% Full time workers	% Blue collars	% White collars	% Middle managers[14]	% Industry	N Employees	N Firms[15]
Year	mean	sd	mean	sd								
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

14 Data on middle managers and white collars are reported together before 1997.
15 Number of firms where at least one worker in the sample transited in the considered year.

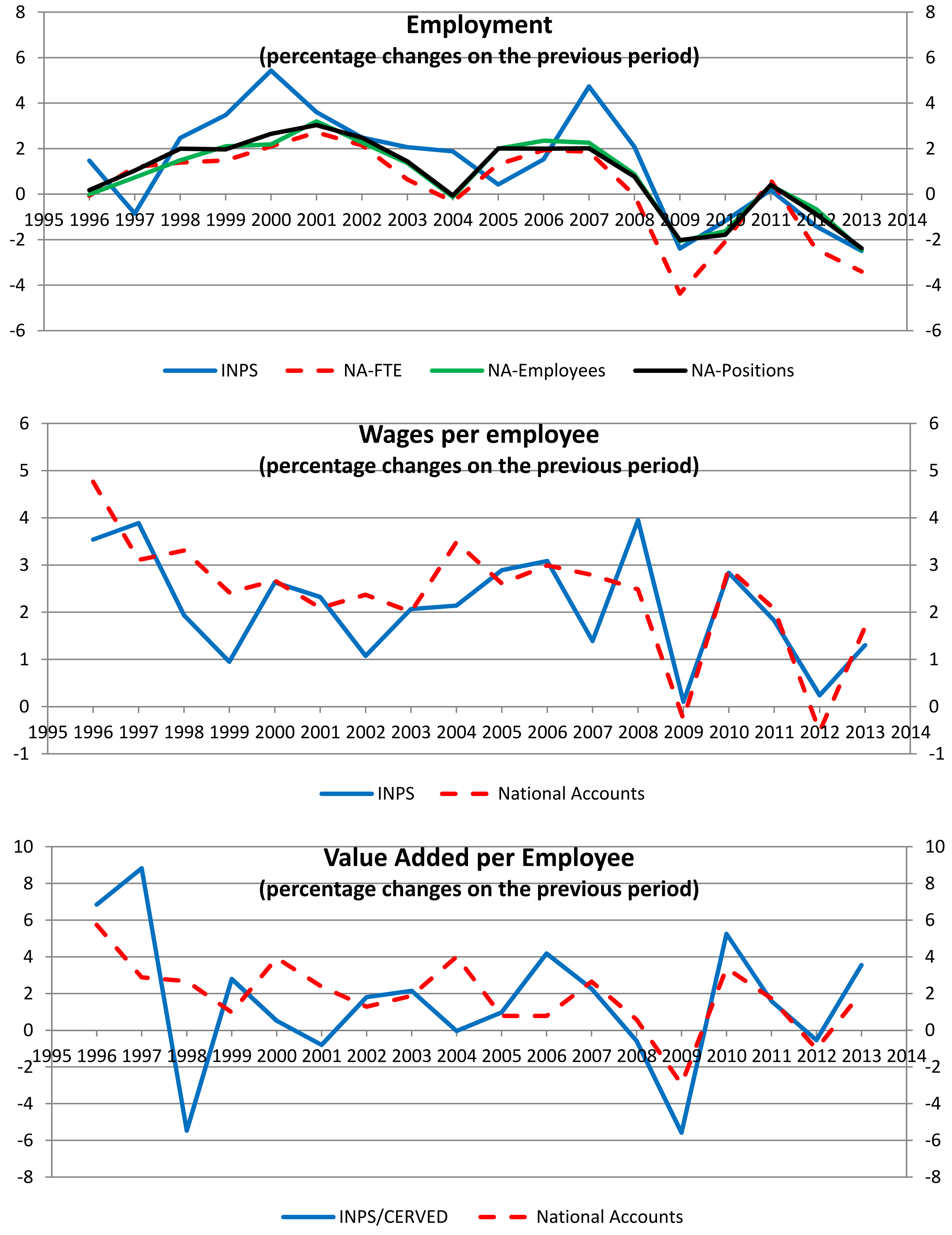
Table 3: Regressions at the sectorial level

dep var:	Delta OP contribution			
	(1)	(2)	(3)	(4)
	from 2002		from 1990	
% change VA pw	0.051**	0.049**		
	(0.021)	(0.024)		
Herfindahl's index$_{t-1}$			-0.014	-0.022***
			(0.015)	(0.008)
N obs	216	216	414	414
Sector FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes

Note: Delta OP contribution is the difference between the OP contribution to aggregate wage in yeat t and in year t-1 (from the INPS universe of firms data); % change VA pw is the percentage variation in the sectorial average value added per worker between year t and t-1 (from CERVED data); Herfindahl's index$_{t-1}$ is the Herfindahl's index computed on the firms' size in each sector. Robust standard errors clustered by sector in parenthesis. Columns 1 and 2 include only years from 2002 onward because the coverage of the CERVED data is better.

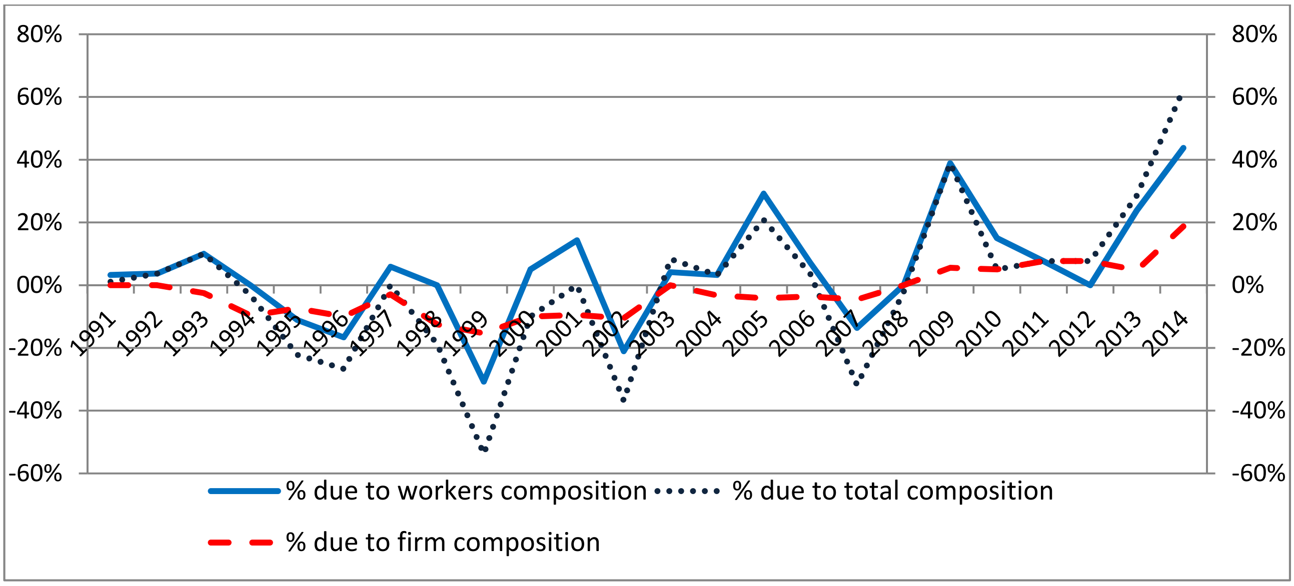
Figures

Figure 1: Firm level evolution of employment, average wages and value added per employee over time



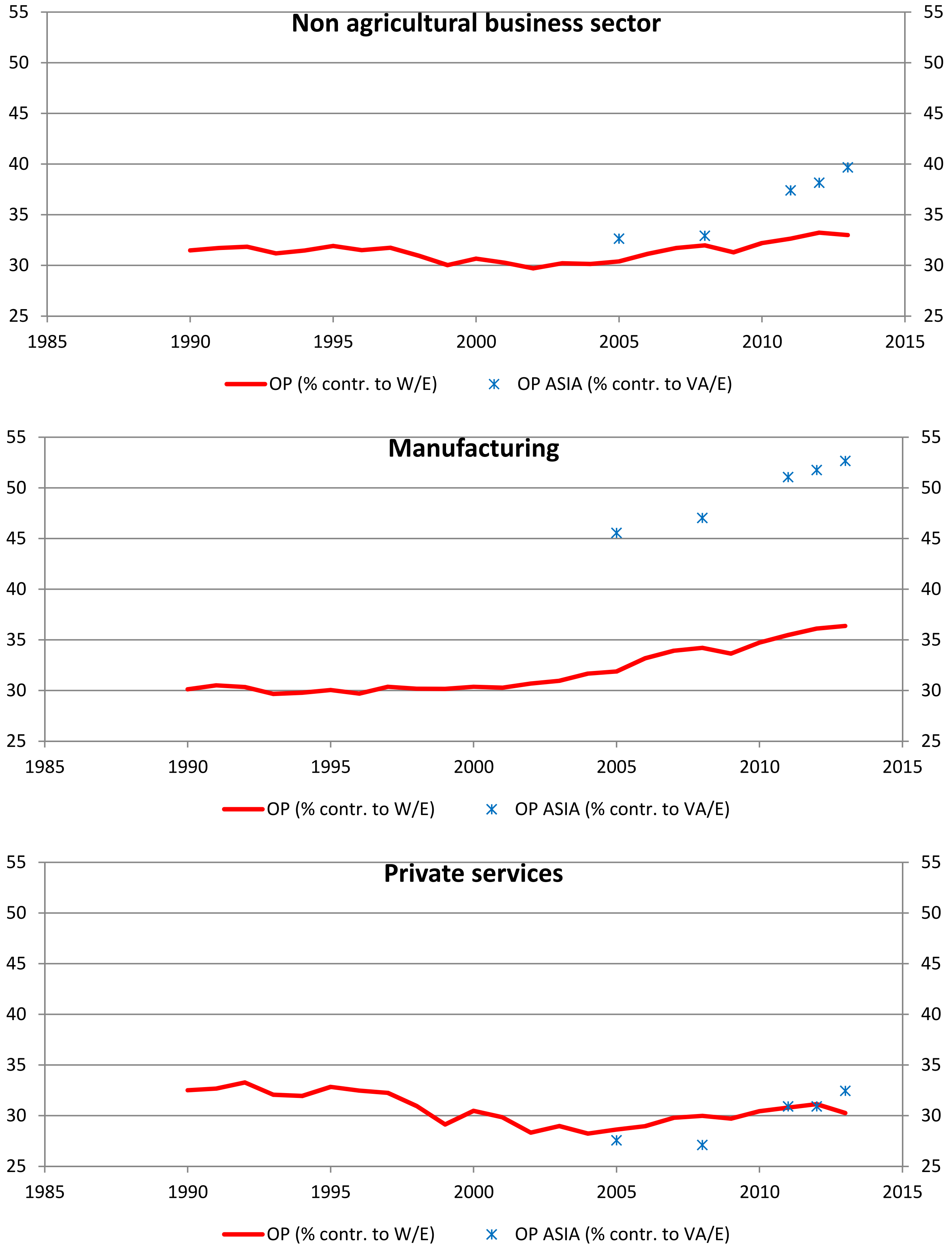
Source: Our calculation based on INPS and Istat, *National Accounts* data

Figure 2: Contribution of composition effects to the wage growth, distinguishing between firms' and workers' characteristics.



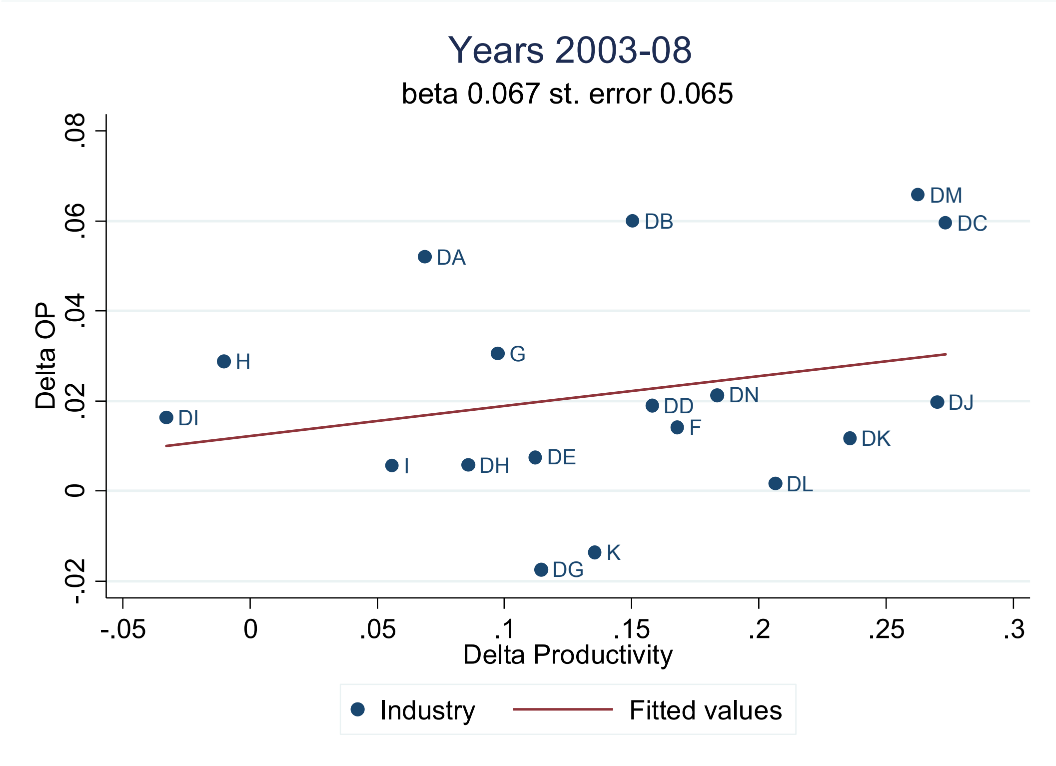
Source: own calculations on INPS data. Note: this figure plots the results on composition effects obtained from the Oaxaca decomposition. The blue line refers to the share of the yearly change in wage levels explained by changes in workers' characteristics, the red line refers to the share of the yearly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

Figure 3: Static OP Contributions



Source: our calculation based on INPS data

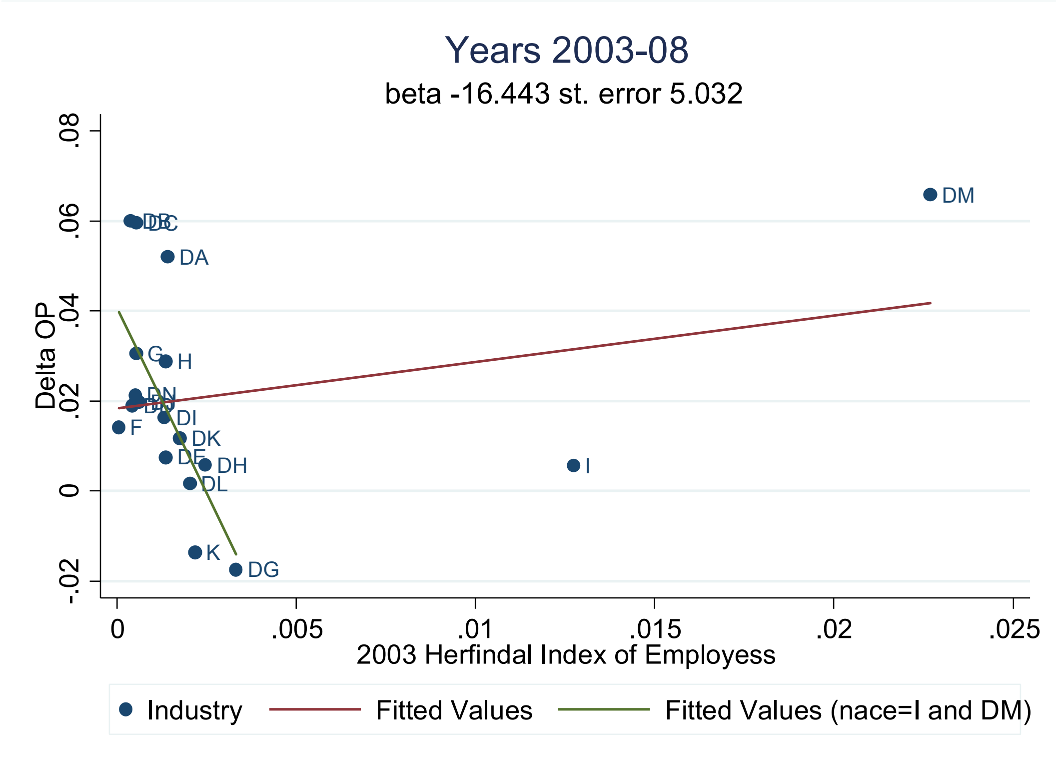
Figure 4: The evolution of the OP contribution to the average wage and sectoral productivity

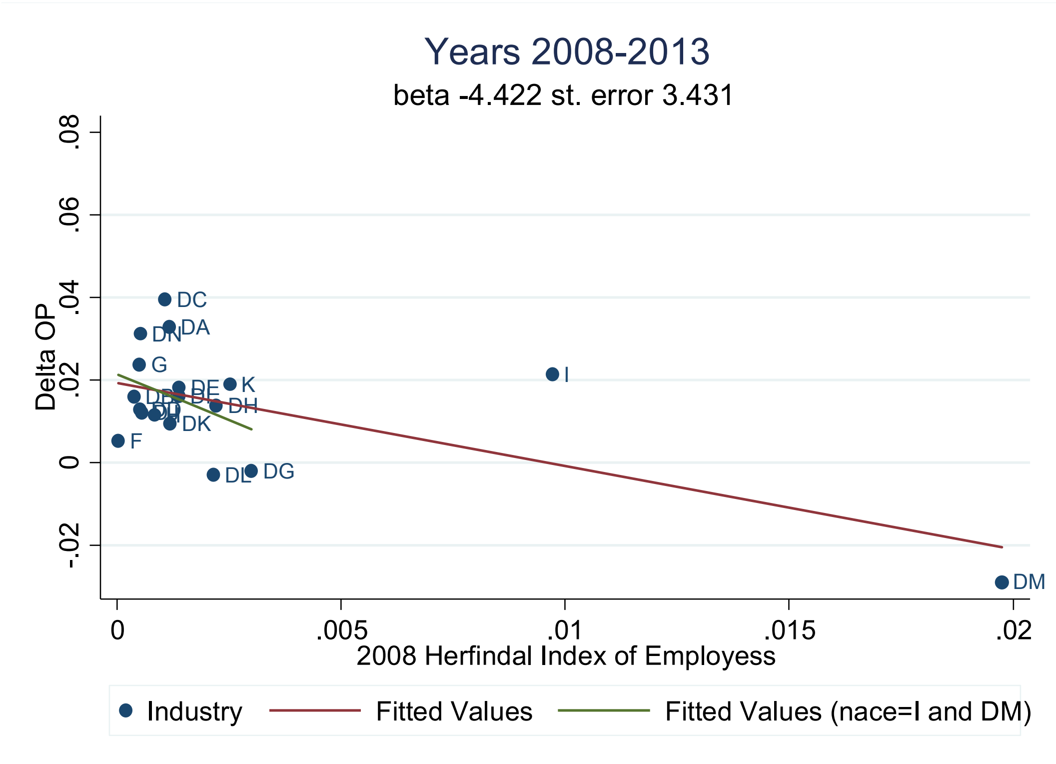


Industry: mining(CA,CB), food(DA), textile(DB), leather(DC), wood(DD), paper(DE), refining(DF), chemical (DG), rubber plastic (DH), other non metallic mineral products (DI), metal products (DJ),
M&E (DK), electric and optical equip. (DL), transport equip. (DM), manufacturing (DN), energy (E), construction (F), trade (G), hotels restaurants (H), transport storage (I), finance (J), real estate and business activities (K)

Source: Our calculation based on INPS-Cerved

Figure 5: The evolution of the OP contribution to the average wage and sectoral concentration

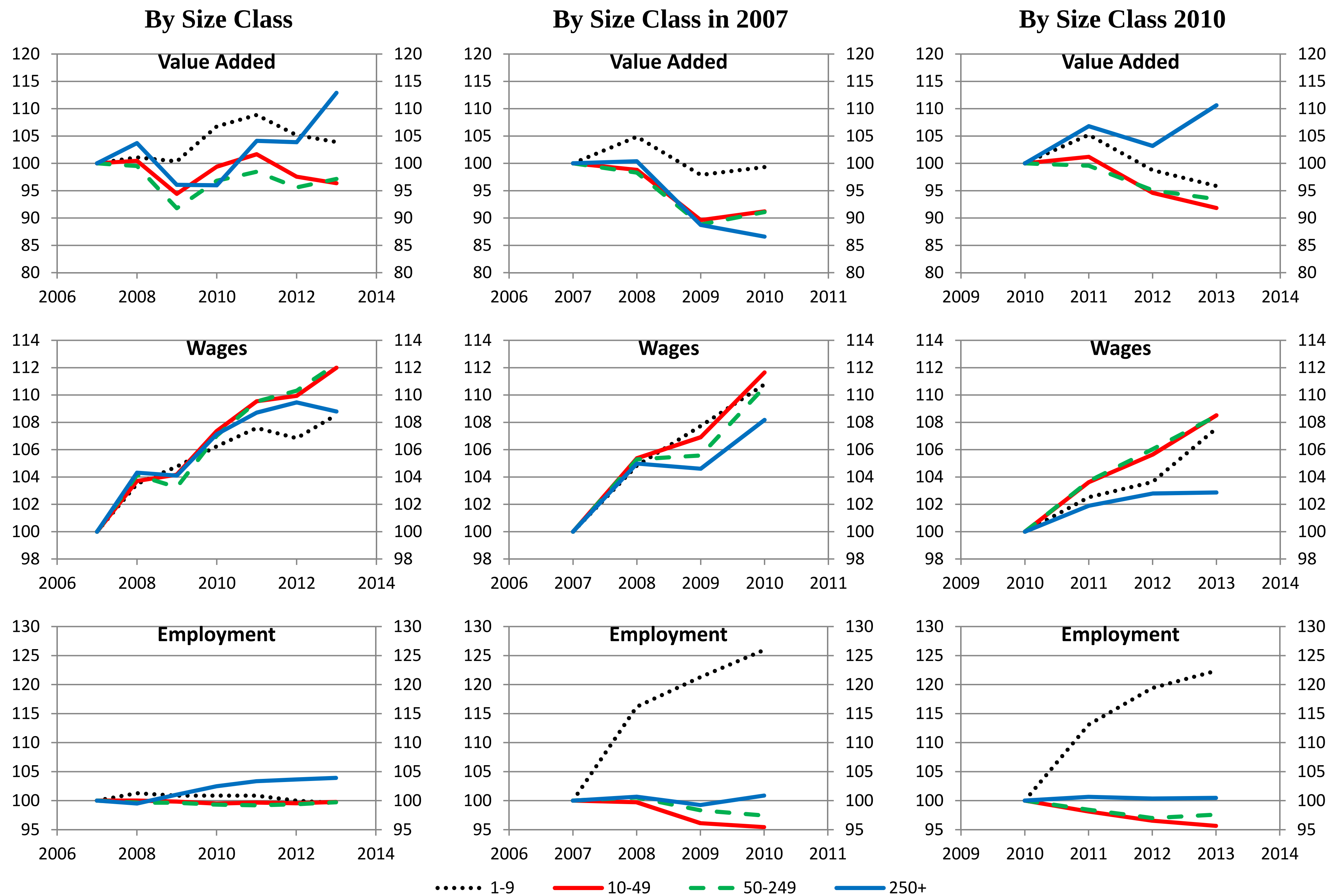




Industry: mining(CA,CB), food(DA), textile(DB), leather(DC), wood(DD), paper(DE), refining(DF), chemical (DG), rubber plastic (DH), other non metallic mineral products (DI), metal products (DJ),
M&E (DK), electric and optical equip. (DL), transport equip. (DM), manufacturing (DN), energy (E), construction (F), trade (G), hotels restaurants (H), transport storage (I), finance (J), real estate and business activities (K)

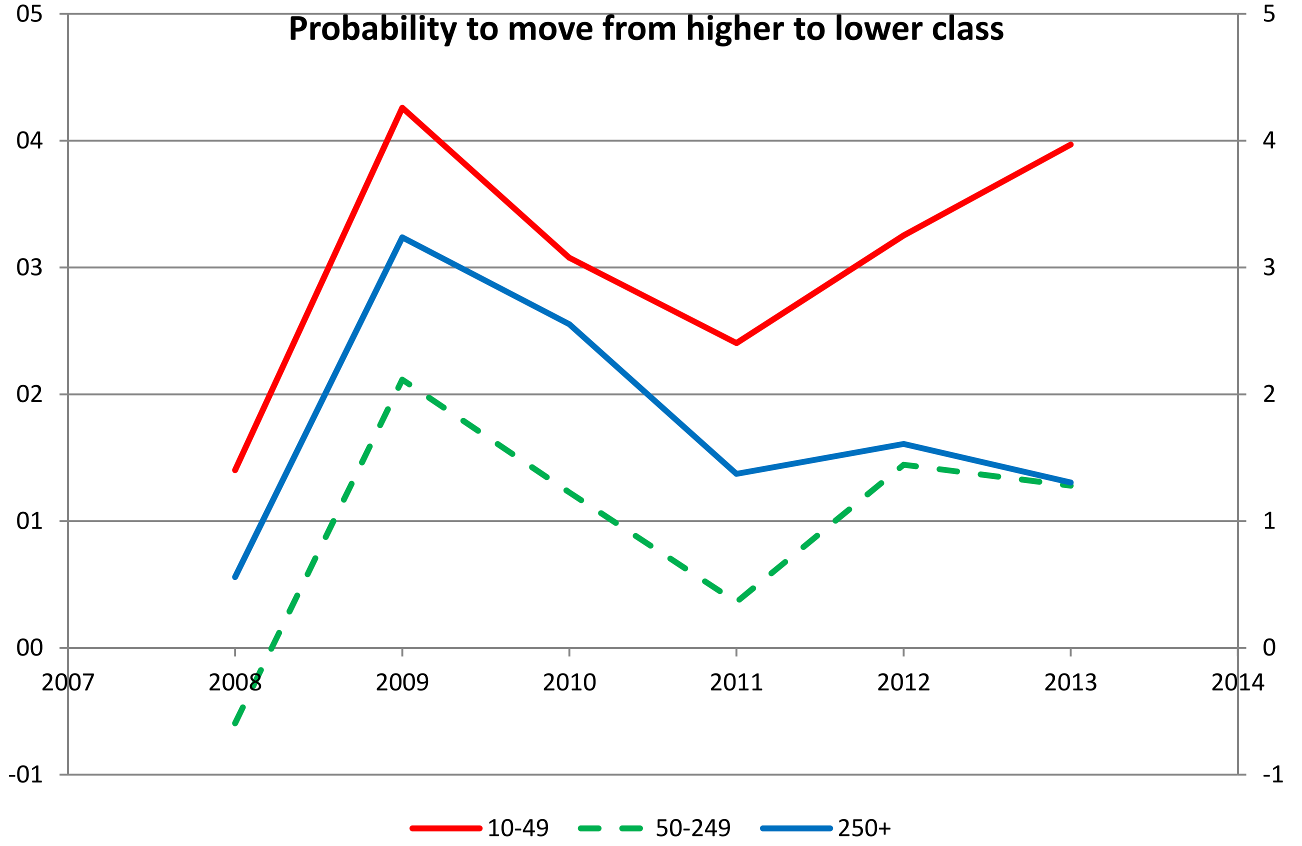
Source: our calculation base on INPS

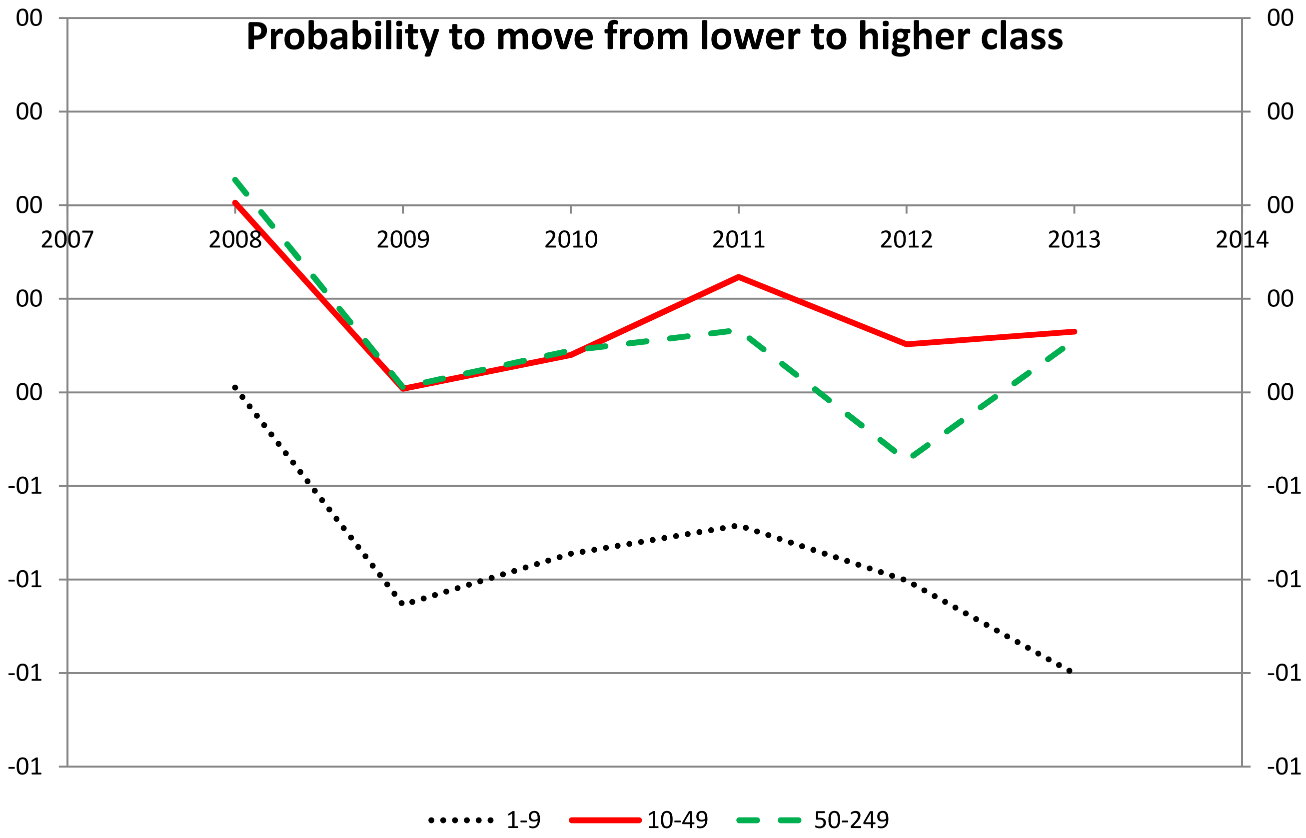
Figure 6: descriptives by class size, focusing on the great recession



Source: Our calculation based on Istat data, *National Accounts*

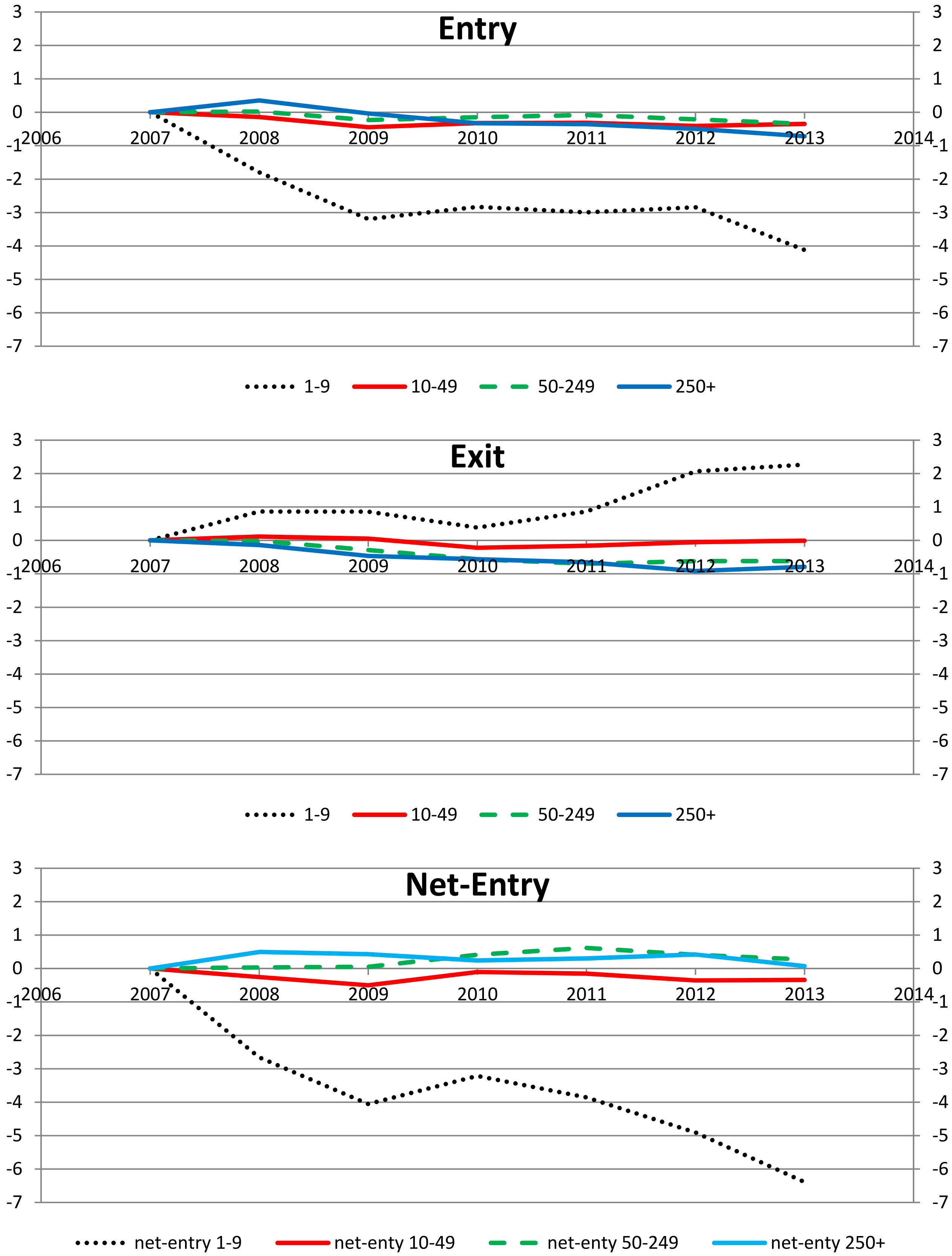
Figure 7: changes in class size over time (ppt deviation from pre-crises levels, 2007)





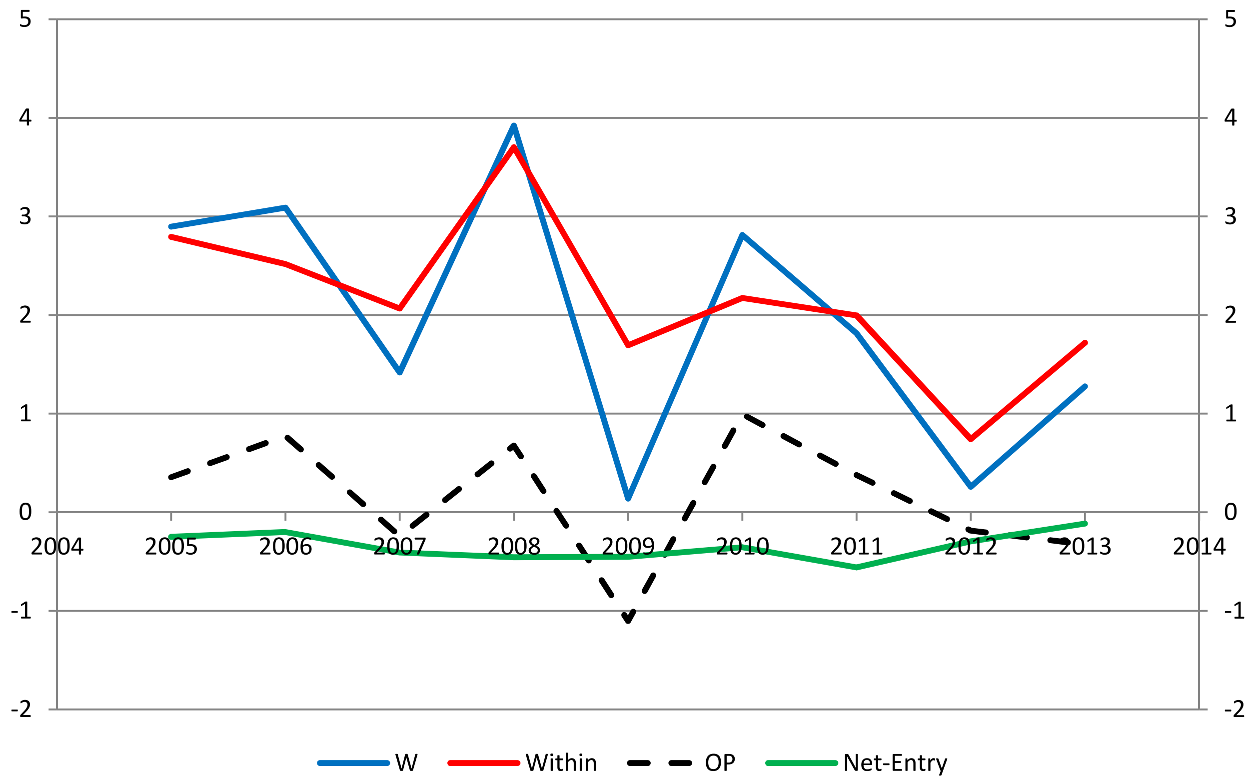
Source: Our calculation based on INPS

Figure 8: entry and exit rates (ppt deviation from pre-crises levels, 2007)



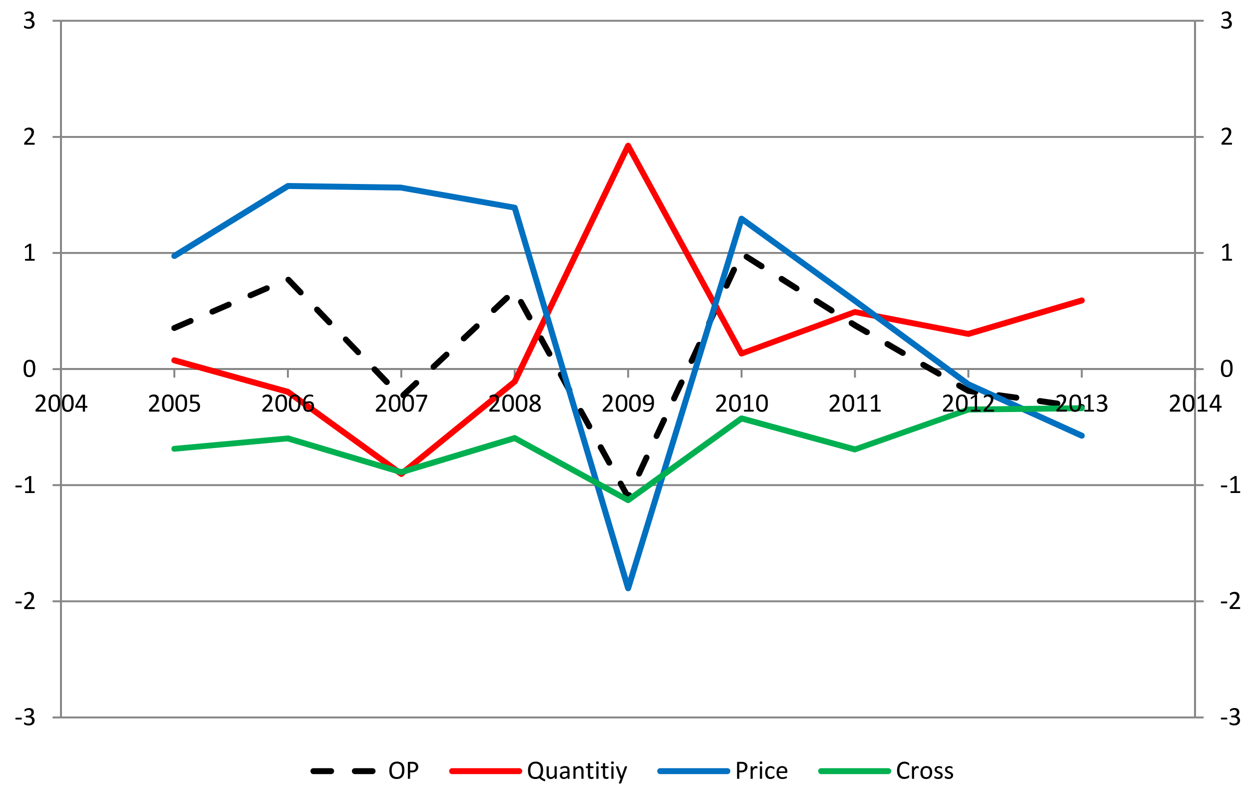
Source: Our calculation based on INPS data

Figure 9: dynamic OP decomposition (percentage points)



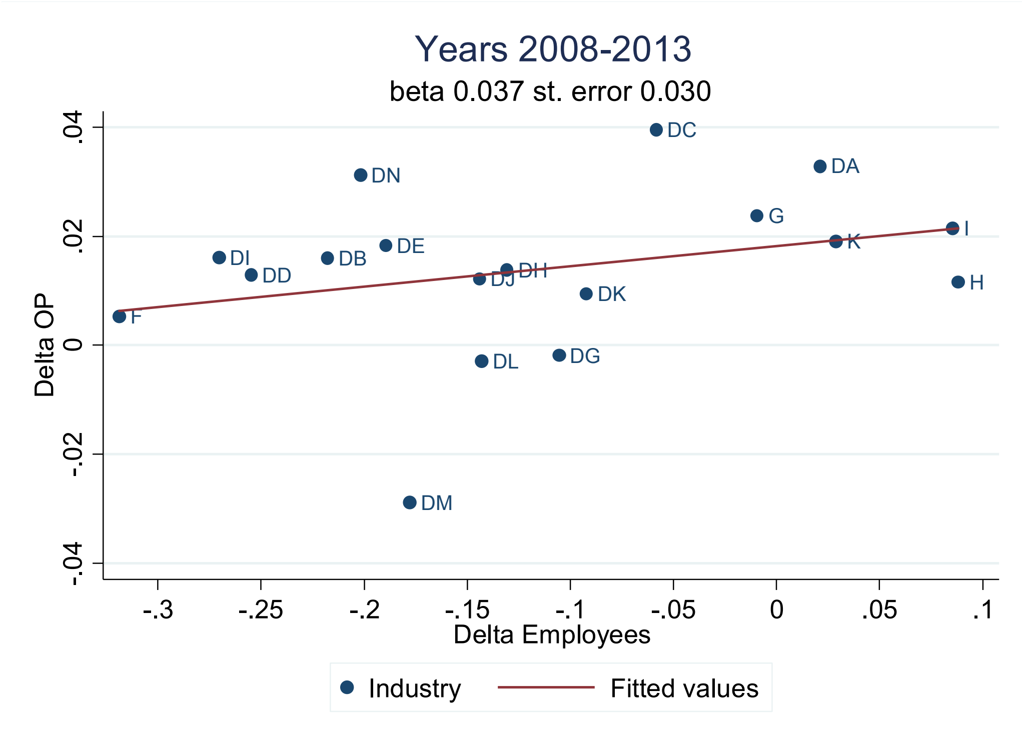
Source: own calculation on INPS data. Non Agricultural Business Sector.

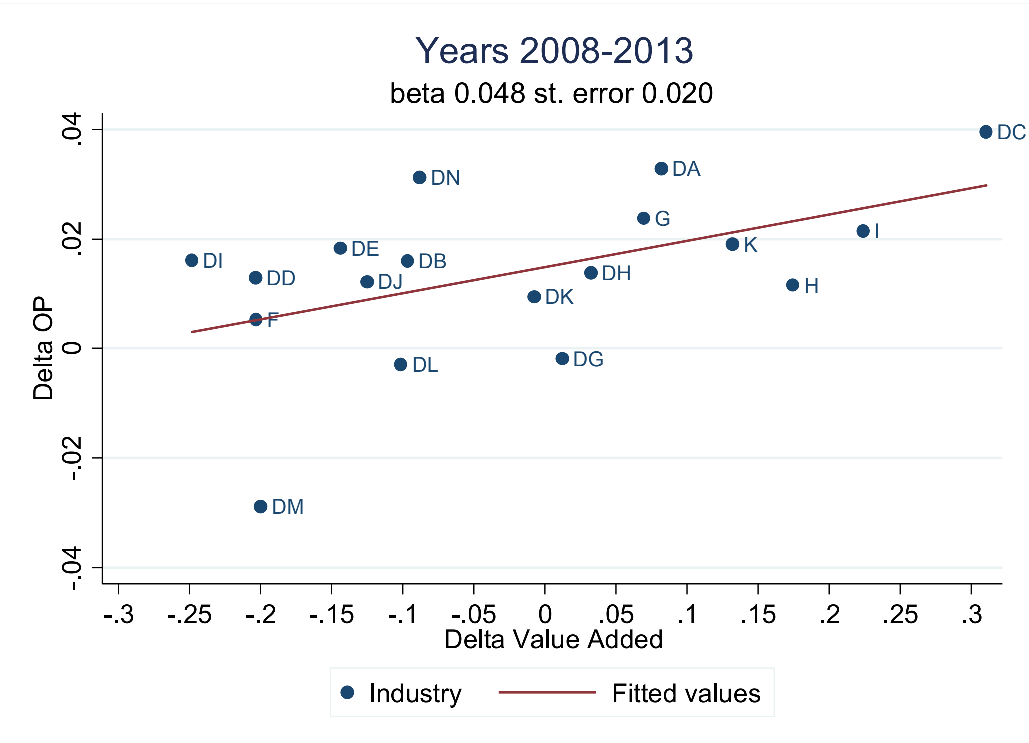
Figure 10: Components of OP term (percentage points)



Source: our calculation based on INPS. Non Agricultural Business Sector.

Figure 11: The evolution of the OP contribution to the average wages during the recessionary period, employment and value added growth across sectors



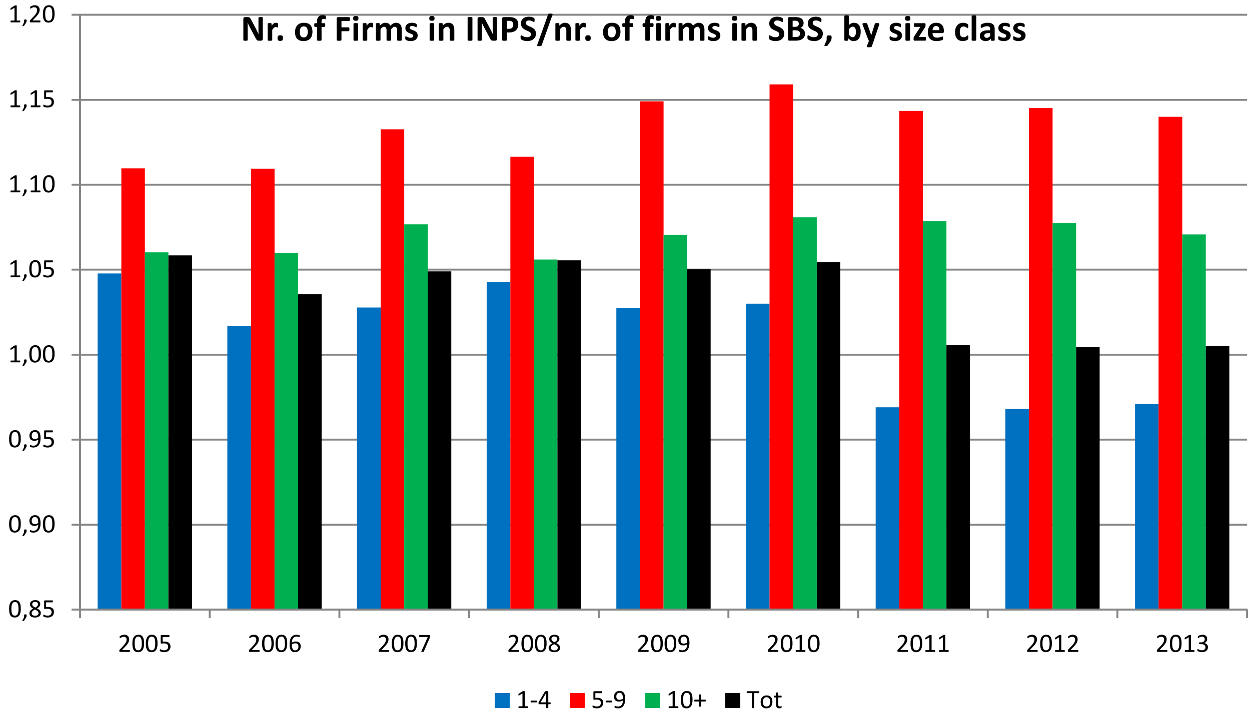


Industry: mining(CA,CB), food(DA), textile(DB), leather(DC), wood(DD), paper(DE), refining(DF), chemical (DG), rubber plastic (DH), other nonmetallic mineral products (DI), metal products (DJ),
M&E (DK), electric and optical equip. (DL), transport equip. (DM), manufacturing (DN), energy (E), construction (F), trade (G), hotels restaurants (H), transport storage (I), finance (J), real estate and business activities (K)

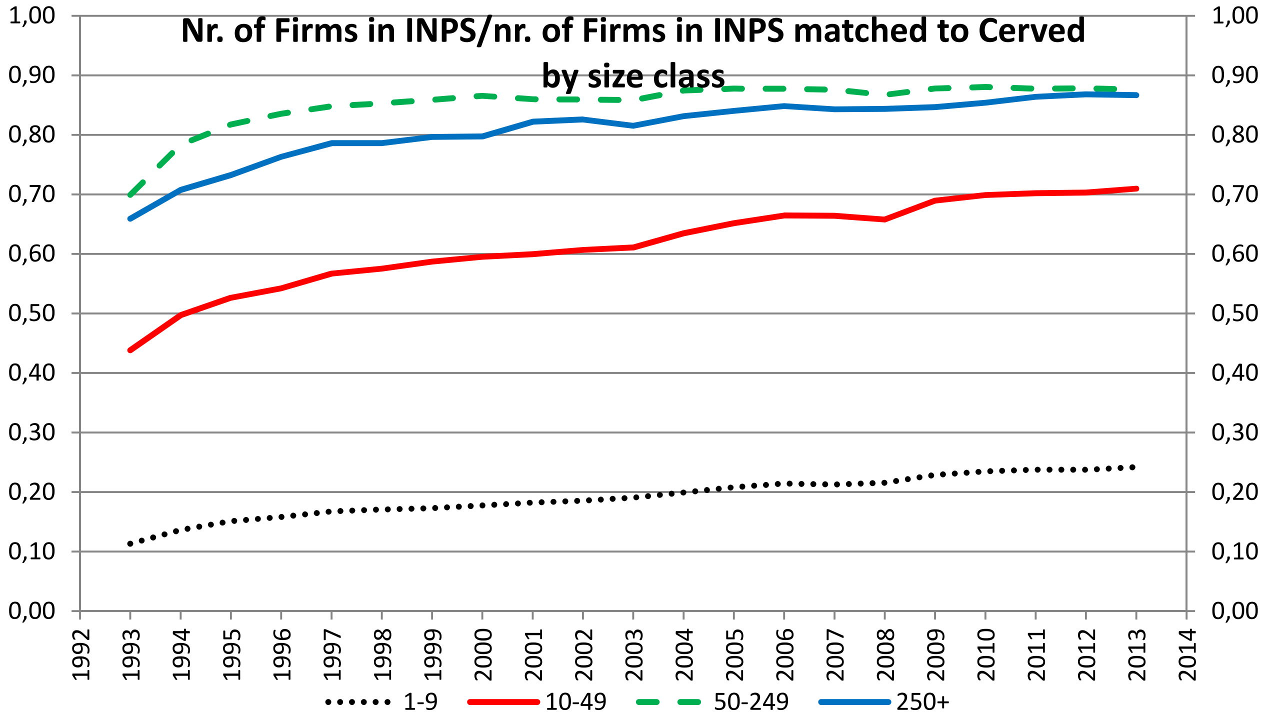
Source: our calculation based on INPS-Cerved

APPENDIX

Figure A1: representativeness of various databases, class size

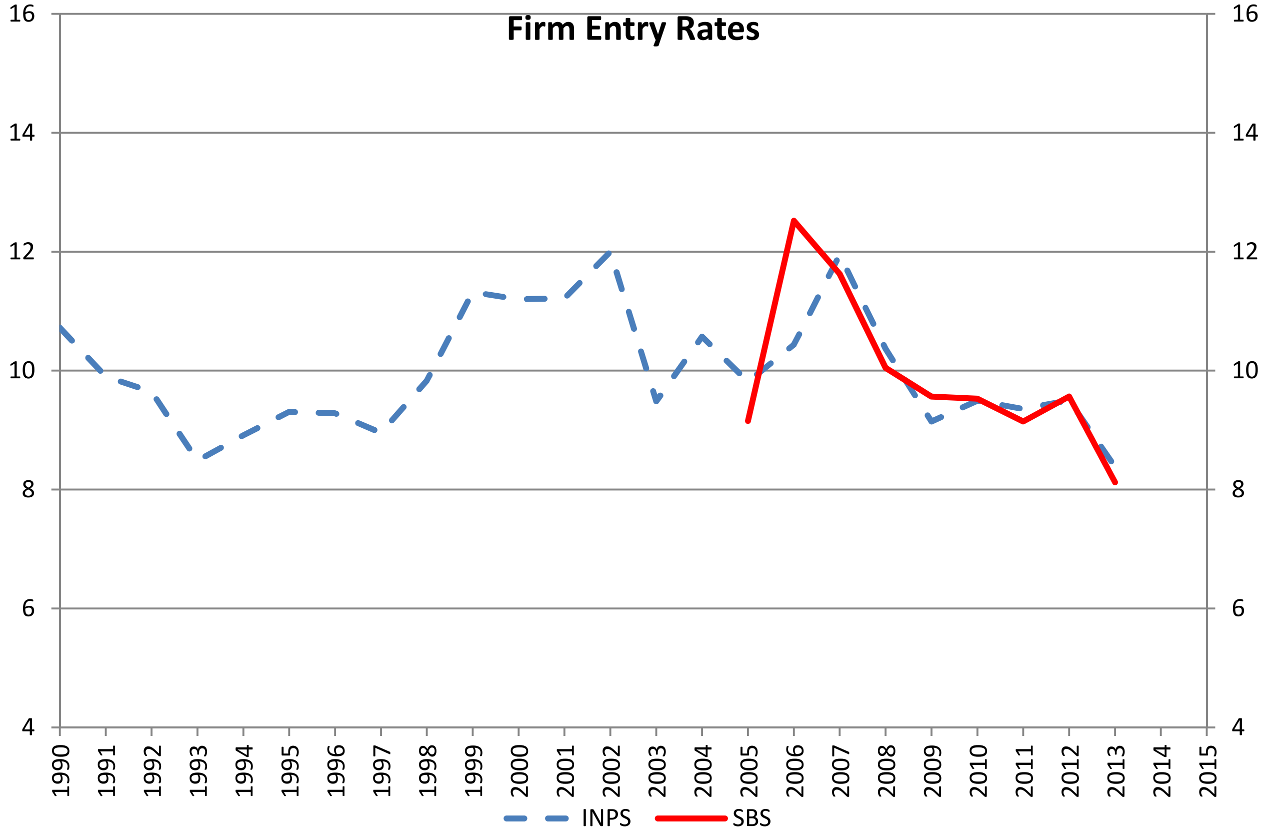


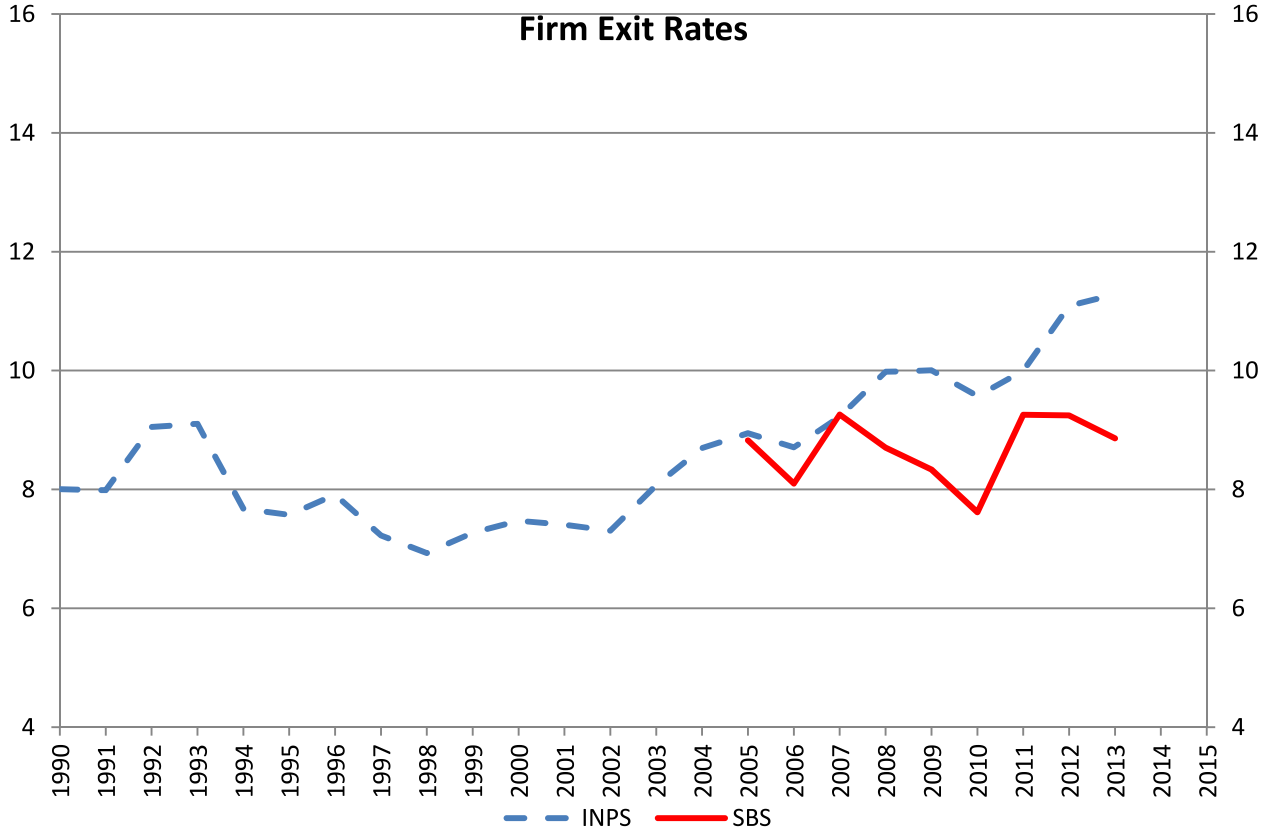
Source: our calculation based on INPS and Eurostat, *Structural Business Statistics* data



Source: our calculation based on INPS and Cerved data

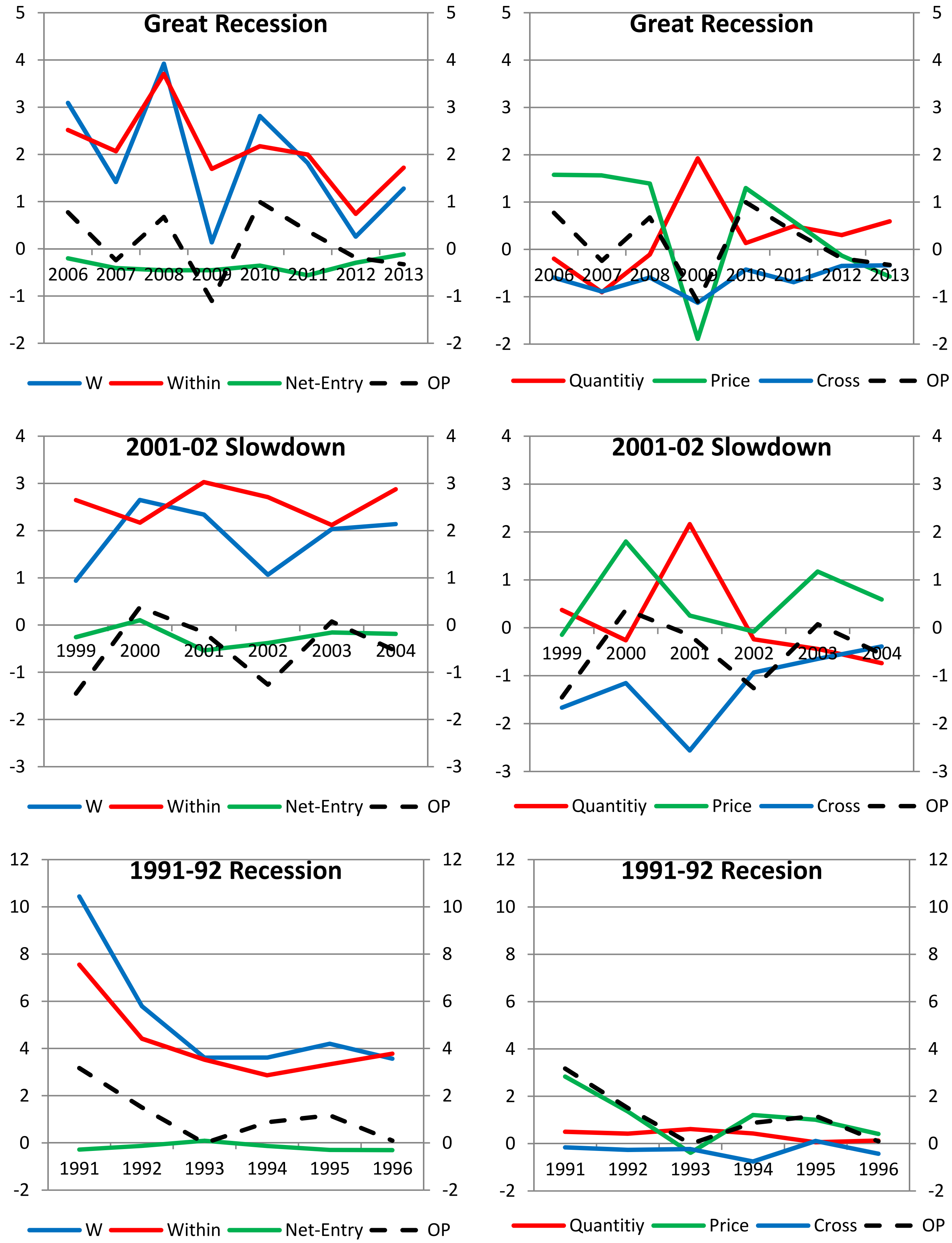
Figure A2: representativeness of various databases, entry and exit rates





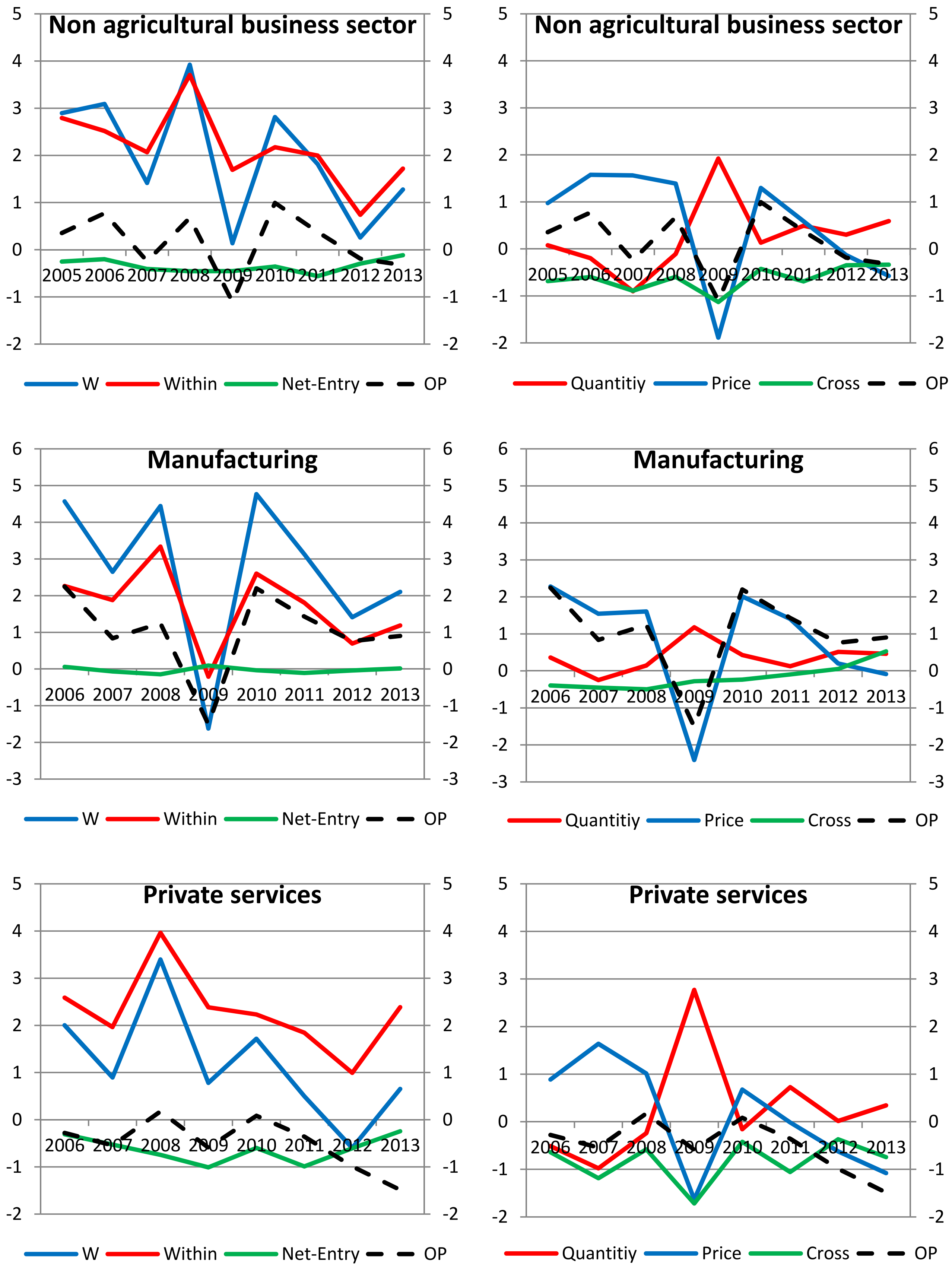
Source: our calculation based on INPS and Eurostat, *Structural Business Statistics* data

Figure A3: dynamic OP decomposition (left) and components of OP term (right), by time period



Source: own calculation on INPS data. Non Agricultural Business Sector.

Figure A4: dynamic OP decomposition (left) and components of OP term (right), by sector



Source: our calculation based on INPS.