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## What Do Cooperative Firms Maximize, if at All?
Evidence from Emilia-Romagna in the pre-Covid Decade

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# What Do Cooperative Firms Maximize, if at All?
# Evidence from Emilia-Romagna in the pre-Covid Decade°

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**Abstract**

The Italian region Emilia-Romagna ranks first among the world's most important cooperative districts. Using a unique dataset covering all firms registered in the region, we investigate the performance of active firms in the period 2010-18. By focusing on employment, revenue and profits of cooperative firms as compared to conventional firms, we disentangle the differences between the average performance of the two types of companies and detect the presence of a "size effect" driving much of the difference between them. Moreover, our results strengthen previous empirical evidence about the countercyclical role of cooperative firms: they seem to optimize a mixture of employment and profits, assigning a greater weight to the former during downturns and stagnation. Finally, we examine the regional logistics industry and compare also the profitability of employees in the two segments of the sector.

**JEL Codes**: L21, L25

**Keywords**: cooperative firms, employment, Gini decomposition

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## 1. Introduction

An apparent lasting issue in comparative economics deals with the differences between cooperative firms (sometimes labelled labour-managed firms, LMF)[1] and conventional, i.e, non-cooperative firms (NCFs, hereafter). To tackle this issue, theory is of little help. The overcited approach pioneered by Ward (1958) and retained by his epigones, is patently inadequate. His formulation, according to which a *workers' firm*[2] would maximize added value, net of non-labour costs per member, raises two severe objections. On the theoretical grounds, in a competitive economy - as well as under monopoly, as shown in Gal-or *et al.* (1980) - such formulation entails the annoying negative relationship between output price shock and output response[3]. Moreover, such approach finds no empirical support.

However, one may arguably disregard such extreme and unlikely market structures. In reality, CFs operate in oligopolistic markets[4]; more precisely, in *mixed oligopolies*, i.e., concentrated industries hosting companies pursuing different goals (see De Fraja and Delbono, 1990). Unfortunately, again, theoretical models do not provide significant insights about the "correct" maximand of cooperative firms, nor for the properties of the equilibria resulting from market interaction with profit-maximizing companies (see, for instance, Craig and Pencavel 1993, Perotin 2006 and the literature cited in Delbono and Reggiani 2013).

As for the objective function, an interesting route is explored by Kahana and Nitzan (1989).[5] Under price-taking behaviour, a workers' firm (in which labour force coincides with membership), selects inputs and output to maximize (i) income per worker/member subject to an employment constraint or, alternatively, (ii) employment subject to a profit per worker/member constraint (bounded below

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[1] We do prefer "cooperative firms" because such a category encompasses various types of companies, including cooperatives that are not owned and/or run by workers.

[2] A *worker's firm* is one in which all workers are members and all members are workers: Sertel (1982).

[3] This is the well-known perverse effect, and it is not the only one. As shown in Delbono and Lambertini (2014), in an oligopolistic supergame among Ward-like firms, in equilibrium tacit collusion is *increasing* in the number of participants, as opposed to the standard conclusion with profit-maximizing players.

[4] A notable exception is provided by some markets for childcare services, disadvantaged people, elderly: here buyers are often local public institutions auctioning the provision of such services to groups of *social cooperatives* (much active in Italy since the early '90s of the last century). Such markets often fit the form of oligopsony.

[5] For clarity, the route explored by Kahana and Nitzan (1989) goes back to Law (1977) who considers an augmented utility function of LMFs' members to include the membership size in addition to income. Law's paper, in turn, was inspired by Fellner (1947).

by the union wage). Standard duality arguments show the equivalence between (i) and (ii), both formulations trying to capture the concern for employment that should shape the behaviour of firms owned and controlled by workers-members. Of course, for a given number of workers, an LMF becomes indistinguishable from a profit-maximizer. We shall come back to the relevance of this approach in the conclusions. Here it suffices to note that the comparative statics by Kahana and Nitzan (1989) may avoid perverse effects, depending on whether labour is a normal input.[6]

Hence, being the theory inconclusive and/or unfit to stylize actual markets, one is forced to resort to empirical investigation. This paper provides a simple descriptive statistical analysis to contribute to such still tiny stream of research and to have an insight about the underlying behavioural premises driving the choices of cooperative firms. We try to infer their implicit objective function from observed behaviour as measured by their performance.

Our benchmark is provided by the Italian region Emilia-Romagna (ER, hereafter) in the period between the great recession of 2009 and the dramatic downturn fuelled by the pandemics in 2020. Moreover, the regional setting allows one to detect the aggregate effect of the overall cooperative *magnitude*. With this, we mean the set of: (i) cooperative firms; (ii) NCFs controlled by cooperative firms; (iii) consortia of cooperative companies; (iv) cooperative associations. While the weights of (iii) and (iv) are negligible in terms of number of employees - our rough estimate amounts to about 500 white collars altogether - and revenues, the size of (ii) is highly significant, especially in the insurance, banking and facility management industries and cannot be ignored. Hence, by now, CFs will mnemonics for both (i) and (ii), provided that we will specify if we refer to (i) or (ii) when needed.

Our main findings can be summarized as follows:

- CFs and NCFs are very different in average size, particularly when looking at the subset of firms above the median revenue[7], in terms of employment, revenue and profits.
- Employment and revenues are much more countercyclical in CFs than in NCFs.
- CFs "profits"[8], especially in recessions and stagnating periods, are pressed and employment levels are stabilized or increased.

[6] If this is the case, the supply function of an LMF is positively sloped; Kahana and Nitzan (1980), p. 537.

[7] We choose operating revenue (or revenue from sales) as a comparable variable between both types of firms instead of the so-called "value of production" recorded in production CFs's balance sheets because it has no clear counterpart in NCFs.

[8] We postpone to Section 3 a discussion on the interpretation of "profits" in CFs.

- CFs seem to *optimize*[9] their employment levels under a non-negative profit constraint (or profits under an employment constraint).
- The industry case study of logistics strengthens the above conclusions hinting at a remarkable difference in labour productivity between CFs and NCFs.

The empirical literature mostly related to our contribution includes a group of papers testing and confirming that cooperative firms tend to act countercyclically as for their employment decisions and that no perverse effect seems to emerge as a reaction to output demand shocks. These conclusions have been validated, for instance, by: Burdin and Dean (2009, 2012) for some Uruguay's industries; Craig and Pencavel (1992, 1995) for the plywood industry of the US Pacific Northwest; Delbono and Reggiani (2013) for production cooperatives in the Italian economy immediately after the 2008 financial crisis; Navarra (2016) for a sample of Italian cooperatives between 2000 and 2005. All these papers detect an employment stabilizing effect of cooperatives' behaviour. While NCFs tend to adjust employment relatively to fluctuations in demand, production cooperatives adjust pay to protect workplaces, at least towards their members (see Perotin 2012 for a disquisition on the subject).

This paper is organized as follows. In Section 2 we sketch the Emilia-Romagna economy in the period 2010-18, describe the dataset and illustrate our sample. Section 3 focuses on a comparative analysis of cooperative firms wrt to conventional firms in terms of employment, revenue and profits. In Section 4 we divide our sample in two groups depending on the revenue being above or below the median and proceed to compare the relative performance of CFs vs NCFs. Section 5 examines an industry case study by briefly replicating the aforementioned analysis for the regional logistics sector. Here we also deal with the apparently huge handicap of CFs wrt NCFs in terms of labour productivity. Section 6 concludes.

## 2. The dataset and sample

As measured by the impact of CFs on employment and GDP, Italy ranks top in Western countries and ER comes first among the Italian regions.[10] Hence, ER represents a fairly sound environment to examine the relative performance of CFs versus NCFs, as well as the differences within CFs.

[9] We do prefer this word to *maximize*, as the latter refers to a standard conceptual frame which unfits the variety of organizations belonging to our set of CFs.

It is worth emphasizing that modern cooperatives differ significantly from Sertel's ideal type of workers' cooperative often assumed in the theoretical literature. Indeed, the so-called *membership ratio* (number of members over the number of employees) is lower than one, especially in the biggest CFs. Unfortunately, the value of such ratio is absent in the balance sheets and it is only occasionally made public through reports of CFs associations at the aggregate (industrial and/or territorial) level. However, to envisage an order of magnitude, in a large sample of Italian production CFs part of Legacoop, the membership ratio was roughly 0.7 around approximately ten years ago (Delbono and Reggiani, 2013).

The source of our dataset is the ER Chamber of Commerce which collects the balance sheets of all companies registered in its regional database. Specifically, we focus on the 2010-2018 time set because this period has the most accurate dataset and comes after the deep downturn following the 2008 financial crisis. The following table summarizes the regional GDP and the employee trends compared to the national ones.

Table 1. GDP (at market prices, million euros, linked values, basis 2015) and employees, ER and Italy (source, Istat)

| | GDP | | Employment | |
|---|---|---|---|---|
| Year | ER | Italy | ER | Italy |
| 2010 | 148.361 | 1.711.622 | 1.906.496 | 22.526.851 |
| 2011 | 152.278 | 1.723.612 | 1.934.279 | 22.598.244 |
| 2012 | 147.925 | 1.672.284 | 1.927.925 | 22.565.972 |
| 2013 | 146.834 | 1.641.333 | 1.904.093 | 22.190.535 |
| 2014 | 148.316 | 1.641.346 | 1.911.463 | 22.278.918 |
| 2015 | 149.111 | 1.654.204 | 1.918.318 | 22.464.753 |
| 2016 | 151.636 | 1.675.210 | 1.967.141 | 22.757.840 |
| 2017 | 155.147 | 1.703.002 | 1.973.043 | 23.022.958 |
| 2018 | 157.870 | 1.716.622 | 2.004.879 | 23.214.951 |

When inspecting this database, one must give attention to the geographical interpretation of figures about employment. Both CFs and NCFs registered in ER – especially the largest ones – employ

[10] See, for instance, Navarra (2016), International Co-operative Alliance (2017), Zamagni (2019) and Euricse (2020). The cooperative movement in Italy evolved around three main associations (Legacoop, Confcooperative and Agci, now coordinating their actions under the label ACI) including the vast majority of sizeable cooperative organizations in terms of revenue and employment. In 2017, 60% of cooperative firms registered in ER adhere to an association, accounting for almost 90% of overall cooperative employment (Regione Emilia-Romagna, 2019).

labour force also outside the regional boundaries (from here on, *employees*); on the other hand, in the regional area we observe employees of CFs and NCFs registered in other regions (*local production unit employees*). In this paper we will focus on the *employees*. This means that we shall emphasize the economic consequences of decisions taken in the corporate headquarters located in ER, being obviously aware that they happen also elsewhere. First of all, we partition the total number of firms registered in ER into the two groups.

Table 2. Number of CFs and NCFs *registered* in ER

| | NCF | CF | TOTAL |
|---|---|---|---|
| 2010 | 68.127 | 4.475 | 72.602 |
| 2011 | 68.979 | 4.411 | 73.390 |
| 2012 | 68.193 | 4.351 | 72.544 |
| 2013 | 67.889 | 4.290 | 72.179 |
| 2014 | 68.141 | 4.252 | 72.393 |
| 2015 | 68.762 | 4.176 | 72.938 |
| 2016 | 69.960 | 4.093 | 74.053 |
| 2017 | 70.656 | 3.983 | 74.639 |
| 2018 | 70.750 | 3.798 | 74.548 |

While we start considering the entire set of firms registered in the Chambers of Commerce of ER, our intention is to focus on a sample composed only by those actually *active* firms. Therefore, we exclude all companies – both CF and NCF – that did not submit their balance sheets and/or that do not have employees at all.

Table 3. Number of CFs and NCFs *active* in ER

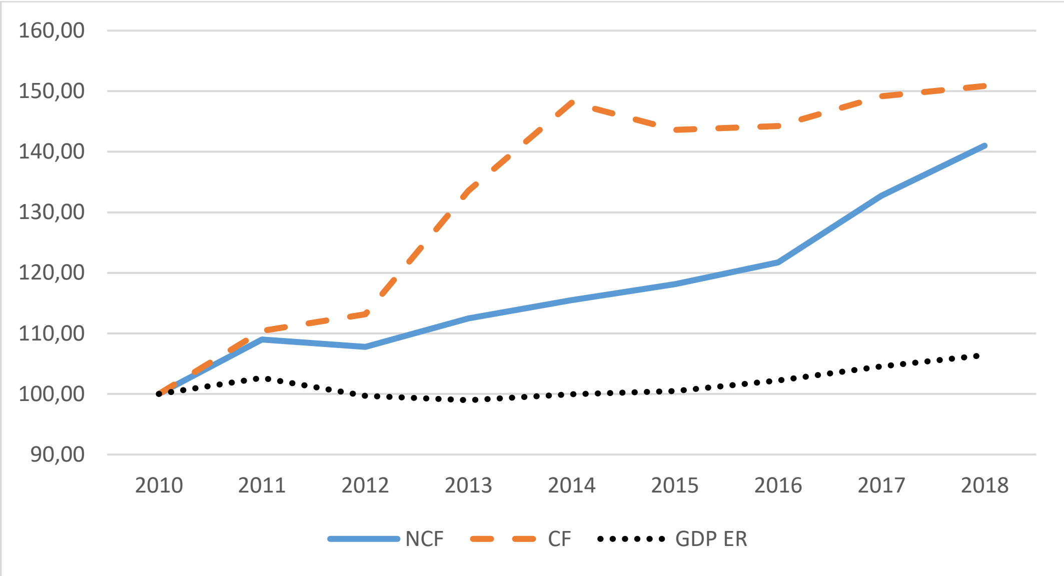
| | NCF | % NCF | CF | % CF |
|---|---|---|---|---|
| 2010 | 36.778 | 91,57 | 3.386 | 8,43 |
| 2011 | 37.280 | 91,64 | 3.403 | 8,36 |
| 2012 | 37.212 | 91,55 | 3.433 | 8,45 |
| 2013 | 36.439 | 91,39 | 3.433 | 8,61 |
| 2014 | 36.255 | 91,50 | 3.369 | 8,50 |
| 2015 | 37.582 | 91,75 | 3.378 | 8,25 |
| 2016 | 38.556 | 91,98 | 3.363 | 8,02 |
| 2017 | 39.425 | 92,28 | 3.296 | 7,72 |
| 2018 | 39.639 | 92,56 | 3.186 | 7,44 |

Table 3 summarizes the composition of the resulting sample: having our dataset been cleared from inactive firms, its size considerably shrinks.

Moreover, due to entries and exits, the list of active firms varies over time: restricting the attention solely to persistently active firms over the entire time span would reduce the sample even more.

To provide an insight on the economic relevance of both types of firms in the regional system, we summarize their revenues in Table 4A[11] and plot them in Figure 1.

Figure 1. Revenues and GDP (2010 = 100)



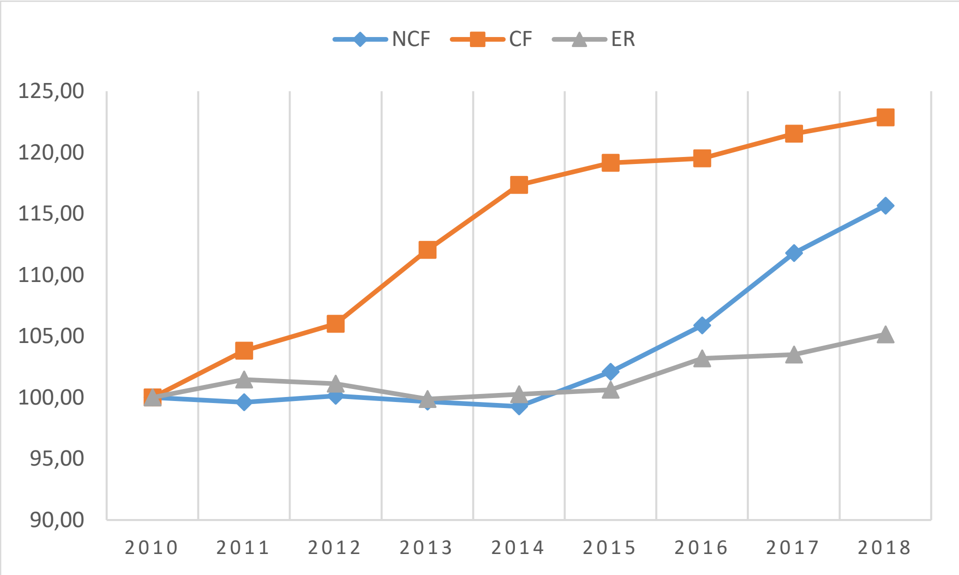

In order to assess the effects of the cooperative magnitude on the regional employment levels and trends, we now examine the distribution of the labor force occupied in the two subsets of total employment (Table 5A and Figure 2). While in the considered period the number of employees increases by about 50,000 and 96,000 units in the CFs and NCFs, respectively, the relative weight of CFs vrt NCFs *raises* within the regional occupied labor force.

If we divide the time frame into two sub-periods (2010-14, 2015-18), the different patterns of CFs and NCFs reactions to "macroeconomic" trends at the regional level is even clearer. It is noteworthy to observe a neat countercyclical behavior in both revenue (Fig. 1) and employment (Fig. 2) of the cooperative segment in the period 2010-14. When both the regional and national GDP are

[11] When citing a Table, a number followed by A (e.g., Table 4A) indicates that such a Table can be found in the Appendix.

stagnating (Table 1), revenue and employees uplift at quite a fast pace in CFs, while this is not the case in NCFs, especially regarding the employment level

Figure 2. Employees (2010 = 100)




In the period 2015-18, instead, when the GDP grows by almost 6% and employment by 4.5% in ER, the CFs' revenue and employment increase less (5%, 3%, respectively), whereas in the NCFs revenue increases by 19% and employment by 13%.

Table 6. Employees per type of firms, descriptive statistics[12]

| | 2010 | | | 2018 | | |
|---|---|---|---|---|---|---|
| | CF | NCF | Total | CF | NCF | Total |
| Obs | 3386 | 36778 | 40164 | 3186 | 39639 | 42825 |
| Average | 64.64 | 16.25 | 20.33 | 84.40 | 17.44 | 2.42 |
| Median | 9.00 | 5.00 | 6.00 | 9.00 | 6.00 | 6.00 |
| CV | 1.21 | 25.38 | 6.97 | 1.06 | 36.96 | 8.76 |
| G | 0.852 | 0.723 | 0.765 | 0.877 | 0.731 | 0.779 |

[12] The entire time series of this statistics and the next ones are available upon request. *Obs* indicates the number of observations.

Other substantial differences emerge among CF and NCF (Tables 5A and 6). Considering, for instance, the last year of our interval, while representing less that 8% of the sample, CFs account for over 28% of total employment. Incidentally, this confirms that the presence of CFs is biased towards labor-intensive industries.

Besides being greater than NCFs in terms of average number of employees, CFs also differ regarding the overall distribution of labor force around their average size (Table 6). This is self-evident from the values of the Coefficient of Variation (CV), the difference between average and median and the value of the Gini index (G). These features underline the presence of a heavy right tail and a strong positive skewness in the distribution of employment across CFs. This is another reason why it is not advisable to use the average as a proxy of the distribution, or any other econometric tool based on it, as, for instance, the OLS.

## 3. CFs vs NCFs: employment, revenues and profits

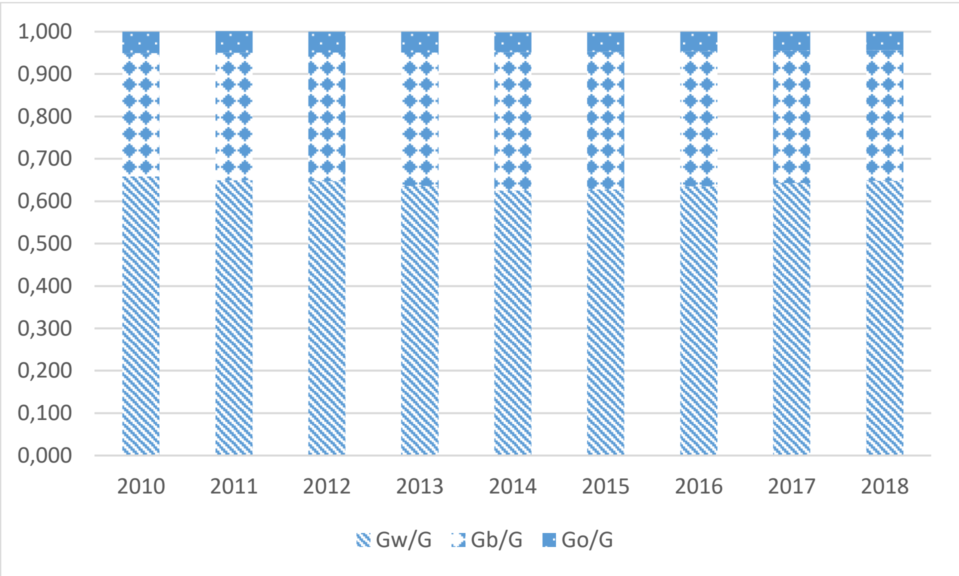
To elaborate on the differences between the two distributions of employees in both types of firms, we decompose the Gini index by following the approach pioneered by Dagum (1997). Accordingly, the differences among all pairs of values embedded in the Gini formula are subdivided into three components: inequality *within* the group ($G_w$); inequality *between* the groups ($G_b$) and the *overlapping* factor ($G_o$).

The overlapping factor represents an important, and often neglected aspect in the analyses of the key factors driving inequalities in statistical distributions. To clarify its relevance - if not too pedagogically - suppose that all CFs are "large" (wrt to some dimension), whereas all NCFs are "small". Here their size is fully explained by the nature of the company. In the opposite scenario, suppose the distributions of the two groups of firms fully coincide; in this case, the size is not explained at all by the company being CF or NCF. In reality, however, the distributions of two groups - CFs and NCFs in our setting - usually overlap; hence, to continue our illustration, we will observe also small CFs and large NCFs. Here is where $G_o$ kicks off, by measuring a portion of total variability which is not captured by $G_w$ nor by $G_b$. To add a potential policy implication of Dagum's approach, consider a setting in which all rich people are college graduate, and all poor people are not. To reduce poverty, one may then tax the graduate ones. In presence of an overlap between the two distributions, however, such a policy would result in making poor graduates even poorer and the population of rich nongraduated people even richer; the ultimate goal of reducing poverty would be weakened as the size of the overlap grows.

The overall number of firms[13] is then divided in the two groups - CFs and NCFs – and all differences are analyzed according to the above decomposition of the Gini index. $G_w$ measures the variability observed in each group and it is by far the most relevant component, since it accounts for almost two thirds of the total variability ($G_w/G$ = 65.9% in 2010 and 64.8% in 2018). The differences between employees in CFs and NCFs are captured by $G_b$, which accounts for roughly 30% of the value of G. The last component $G_o$ is responsible for approximately 5% of total variability. Table 7A quantifies and Figure 3 visualizes the factorization of G.

To summarize, concerning the distributions of employees around their average, the differences inside each group count more that double the external ones (i.e., wrt the other group).

Figure 3. Employment, Gini decomposition, relative weights




We now focus on profits (Table 8). This is instrumental to the attempt of inferring the implicit objective function motivating CFs' behavior. However, before proceeding, it is worth stressing that the very meaning of profits may be misleading when referred to CFs. It would be preferable to use another term to capture the counterpart of NCFs' profits, as, for instance, *social dividend*, i.e., a

[13] To the best of our knowledge, this is the first application of Dagum's (1997) method with reference to distributions of *firms*' characteristics and performances. Indeed, usually it has been applied to individuals or households; e.g., Giorgi (2011) and Costa (2016). The component we measure with $G_o$ is the one that Dagum (1997) labels as the "intensity of transvariation between subpopulations".

residual to be computed differently from the procedure delivering profits in NCFs.[14] Moreover, our overall sample includes a large variety of CFs: workers', producers', users', social, credit's and so on (see Zamagni and Zamagni 2011). Hence these different roles of members within their CFs may entail differences in CFs' ultimate goals. Furthermore, by CFs in this paper we mean also the joint stock companies controlled by cooperative holdings which may maximize profits to be distributed as dividends to the controlling cooperative firms. This withstanding, we conform to the prevailing terminology, while recommending caution when comparing "profits" between CFs and NCFs as well as within heterogeneous CFs.

Table 8. Profits (million euros, prices 2015)[15]

| | NCF | CF |
|---|---|---|
| 2010 | 617 | 302 |
| 2011 | 734 | - 223 |
| 2012 | 475 | 10 |
| 2013 | 2.177 | - 650 |
| 2014 | 3.810 | - 339 |
| 2015 | 5.257 | 449 |
| 2016 | 6.001 | 415 |
| 2017 | 7.620 | 292 |
| 2018 | 9.165 | 506 |

Let us first concentrate on the CFs performance. It is worth observing that the dramatic shock in aggregate demand hitting the constructions industry, between the first and the second decade of this century, explains mostly of the negative sign (and the remarkable size) of CFs' aggregate profits in three years. Among the top companies operating in the construction industry at the *national level*, some of them were indeed CFs all registered in ER. Hence, their eventual bankruptcy being preceded by substantial losses, these drive down the overall figure at the regional level.

It is useful to analyze jointly the trends of employment (from Table 5) and profits (from Table 8) in the two categories of firms, as compared to the regional GDP (from Table 1).

[14] At least in *production* CFs, the so-called profits are calculated net of rebates distributed to members and are mostly plough-back into equity (= capital + indivisible reserves + operating profits). See Delbono and Reggiani (2013) and Navarra (2016) on the production CFs' policy about profits in some Italian groups of CFs. See also Zamagni (2019) on the strategic role of indivisible reserves as a buffer to be used during slums to the end of safeguarding employment.

[15] Because of the coverage of the available data, we do not consider part of the insurance and the banking industries from both groups. This happens only for profits.

Table 9. Profits, GDP and Employees (2010 = 100)

| | Profits | | GDP | Employees | | |
|---|---|---|---|---|---|---|
| | NCF | CF | ER | NCF | CF | ER |
| 2010 | 100,00 | 100,00 | 100,00 | 100,00 | 100,00 | 100 |
| 2011 | 119,05 | -73,88 | 102,64 | 99,60 | 103,82 | 101,46 |
| 2012 | 76,98 | 3,36 | 99,71 | 100,14 | 106,01 | 101,12 |
| 2013 | 353,06 | -215,25 | 98,97 | 99,67 | 112,04 | 99,87 |
| 2014 | 618,01 | -112,23 | 99,97 | 99,27 | 117,35 | 100,26 |
| 2015 | 852,64 | 148,49 | 100,51 | 102,09 | 119,16 | 100,62 |
| 2016 | 973,38 | 137,45 | 102,21 | 105,89 | 119,51 | 103,18 |
| 2017 | 1236,06 | 96,72 | 104,57 | 111,79 | 121,53 | 103,49 |
| 2018 | 1486,56 | 167,29 | 106,41 | 115,66 | 122,87 | 105,16 |

Table 9 shows other striking differences between CFs and NCFs. For instance, let us consider the interval 2010-14, a period of stagnation in which the Italian GDP falls by over 4% (Table 1) and the regional one is experiencing a zero growth. As for the NCF, while their revenue increases by about 15% and their profits *grows* six-fold, their employment level slightly *decreases*. In contrast, the CFs' revenue goes up by 48%, profits *decrease* by 21.2% and, above all, employment *raises* by more than 17%. In the 2015-18 timeframe, when the regional GDP is growing at an average rate of 1.5% per year, the revenue and employment levels of CFs grow slower (5% and 3%, respectively, in 4 years) and their profits increase by 13%. The NCFs, instead, uplift their revenue by 19%, profits by 74% and employment by 13%.

In the entire time span, while the regional GDP is at a standstill averaging a rate of about 0.65% per year, the performances of CFs and NCFs are very different, especially as for the way in which employment and profits accompany the course of their revenues. The latter increases by 41% for the NCFs and by slightly more (48%) for the CFs. However, such a similar expansion in revenue yields drastically diverging consequences: profits grow fourteenfold in CNF and only 67% in CFs, whereas the number of employees increase by less than 16% in NCF and almost by 23% in CFs. Here is one of the major findings of our statistical investigation. We have indeed registered a remarkable difference in the reaction to demand shocks hitting both the local and national economy. While (basically profit-maximizing) NCFs tend to be procyclical, CFs tend to stabilize their employment and, given their critical mass, they contribute to flatter also the overall regional employment level, at the cost of profits.

To obtain a quantitative summary of the relationships among revenues (RV), profits (PR) and employment (EM) within the two group of firms, we calculate the correlation for all relevant pairs. The next three tables collect the value of the correlation coefficient for the entire sample (Table 10), the CFs (Table 11) and the NCFs (Table 12). The first column considers the companies whose revenue and employment level we know from Tables 3 and 4; the other columns of all three Tables refer to companies whose profit we know too (from Table 8). Considering the averages reported in the bottom line of Table 10, we notice a fairly low correlation between profits and employees as well as between profits and revenues. We see in Table 11 that this occurs because of the extremely tiny correlation featuring the same pairs of variables in the CFs. For these firms, these correlations are quite impressively low, and even negative in some years. This confirms the trade-off faced by CFs when trying to enhance both profits and employment levels, with a bias in favor of the latter, especially during downturns. This is not the case with NCFs. The bottom line of Table 12, indeed, seems to confirm that profits (PR), revenue (RV) and employment (EM) are significantly (and always positively) correlated.

Table 10. Correlation between EM, RV and PR: all firms

| | EM-RV | EM-RV | EM-PR | RV-PR |
|---|---|---|---|---|
| 2010 | 0,55 | 0,55 | 0,08 | 0,29 |
| 2011 | 0,53 | 0,53 | 0,16 | 0,19 |
| 2012 | 0,51 | 0,51 | 0,16 | 0,33 |
| 2013 | 0,51 | 0,55 | 0,25 | 0,30 |
| 2014 | 0,48 | 0,55 | 0,24 | 0,47 |
| 2015 | 0,52 | 0,60 | 0,23 | 0,41 |
| 2016 | 0,53 | 0,59 | 0,16 | 0,45 |
| 2017 | 0,53 | 0,56 | 0,16 | 0,38 |
| 2018 | 0,53 | 0,58 | 0,14 | 0,40 |
| Average | 0,52 | 0,56 | 0,18 | 0,36 |

Table 11. Correlation between EM, RV and PR: CFs

| | EM-RV | EM-RV | EM-PR | RV-PR |
|---|---|---|---|---|
| 2010 | 0,51 | 0,50 | 0,22 | 0,36 |
| 2011 | 0,47 | 0,47 | 0,05 | 0,08 |
| 2012 | 0,47 | 0,47 | 0,12 | 0,12 |
| 2013 | 0,46 | 0,50 | -0,01 | -0,02 |
| 2014 | 0,44 | 0,52 | 0,08 | 0,09 |
| 2015 | 0,50 | 0,62 | 0,16 | 0,24 |
| 2016 | 0,50 | 0,60 | 0,14 | 0,19 |
| 2017 | 0,50 | 0,58 | 0,00 | 0,03 |
| 2018 | 0,50 | 0,59 | -0,14 | -0,17 |
| Average | 0,48 | 0,54 | 0,07 | 0,10 |

Table 12. Correlation between EM, RV and PR: NCFs

| | EM-RV | EM-RV | EM-PR | RV-PR |
|---|---|---|---|---|
| 2010 | 0,67 | 0,67 | 0,19 | 0,33 |
| 2011 | 0,73 | 0,73 | 0,15 | 0,25 |
| 2012 | 0,64 | 0,64 | 0,27 | 0,45 |
| 2013 | 0,67 | 0,71 | 0,42 | 0,48 |
| 2014 | 0,61 | 0,71 | 0,52 | 0,64 |
| 2015 | 0,63 | 0,72 | 0,49 | 0,51 |
| 2016 | 0,65 | 0,71 | 0,49 | 0,58 |
| 2017 | 0,65 | 0,69 | 0,48 | 0,62 |
| 2018 | 0,65 | 0,71 | 0,53 | 0,62 |
| Average | 0,66 | 0,70 | 0,39 | 0,50 |

## 4. Small vs large firms

Comprehending the substantial differences between the distribution of employees in the CF population vis-à-vis the NCF one, we now try to detect the presence of a *size effect* capable of affecting the distribution of employees in the two subpopulations. To this end, we rank firms wrt their revenue level and divide each subpopulation in two groups depending on their position being above (large firms) or below (small firms) the median revenue.

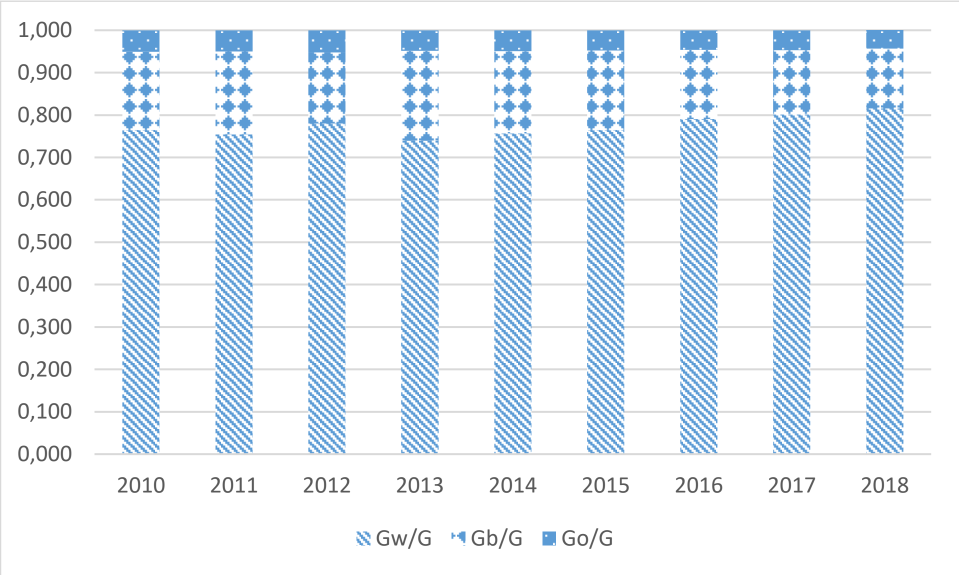
From Table 13A, we see that CFs account in 2018 for over 11% of employees, although representing less than 7% of the subsample of small firms. In the overall period, the number of CFs employees is reduced by over one fourth while we observe a mild increase in NCFs ones. Descriptive statistics confirm what emerges in the general sample (Table 4), even if the differences between types of firms are not so sharp (Table 14).

Table 14. Employees, small firms, descriptive statistics

| | 2010 | | | 2018 | | |
|---|---|---|---|---|---|---|
| | CF | NCF | Total | CF | NCF | Total |
| Obs | 1623 | 18459 | 20082 | 1452 | 19961 | 21413 |
| Average | 8.32 | 4.18 | 4.52 | 6.79 | 3.92 | 4.12 |
| Median | 4.00 | 3.00 | 3.00 | 4.00 | 3.00 | 3.00 |
| CV | 5.28 | 3.45 | 9.38 | 0.59 | 1.98 | 1.08 |
| G | 0.57 | 0.493 | 0.514 | 0.508 | 0.450 | 0.461 |

We now decompose the value of the Gini index: the results can be found in Table 15A and visualized in Figure 4. It is apparent that the variability within groups is by far the most important component explaining the total variability ($G_w/G$ = 76.4% in 2010) and it is increasingly relevant over time, while the weight of $G_b$ decreases and the overlap is stable at less than 5% of overall variability.

Figure 4. Employment, small firms, Gini decomposition, relative weights




Replicating the same analysis for large firms, we notice (Table 16A) that while representing only a stable 8% of the sample, CFs account for almost 30% of employment in 2018 and their number of employees grows in the period by more than 26%, against an increase of about 18% in NCFs's employees. In the region, the trend of large firms differs markedly from the one of small firms, suggesting that the main differences between the two type of firms concentrate mostly in the subset of the large ones.

Table 17 shows that the average number of employees per large firm is much higher in CFs than in NCFs (and increasing over time) and the gap too is much higher than for small firms. Overall, the two distributions exhibit more differences than their respective distributions among small companies.

Table 17. Employees, large firms, descriptive statistics

| | 2010 | | | 2018 | | |
|---|---|---|---|---|---|---|
| | CF | NCF | Total | CF | NCF | Total |
| Obs | 1763 | 18319 | 20082 | 1734 | 19678 | 21412 |
| Average | 116.48 | 28.41 | 36.14 | 149.39 | 31.15 | 40.73 |
| Median | 22.00 | 12.00 | 12.00 | 25.00 | 12.00 | 12.00 |
| CV | 0.86 | 19.94 | 5.39 | 0.84 | 27.88 | 6.79 |
| G | 0.819 | 0.671 | 0.725 | 0.843 | 0.681 | 0.741 |

Proceeding with the analysis of total variability, we observe that $G_w$ is still the main driving component, although not as much as for small firms, and $G_b$ accounts for over one third of the total value of G (Table 18A and Figure 5).

Figure 5. Employment large firms, Gini decomposition, relative weights

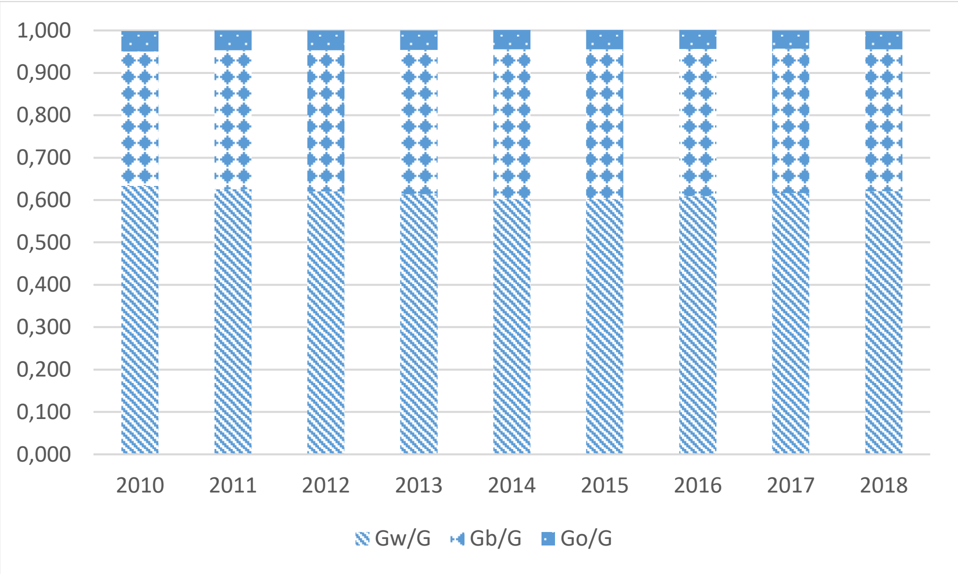
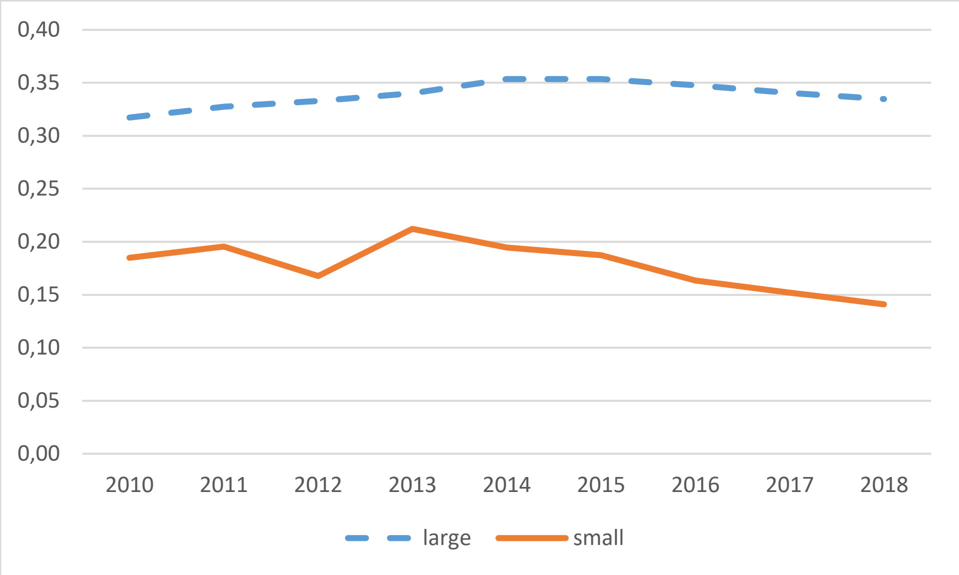



Figure 6 provides an additional insight about $G_b$ which is used to compare the distributions of employees summarized in Figures 4 and 5. As we know, the greater is the value of the ratio $G_b/G$, the broader is the difference between CFs and NCFs, and numbers confirm that the "size effect" matters in disentangling the different performances of either firm. Indeed, during the entire period under scrutiny, the main differences between the two types of firms concentrate especially on the subset of large companies, as the value of $G_b/G$ oscillates steadily around 35% for large firms, while for small firms the value of such ratio is significantly lower and decreasing over time.

Figure 6. Employment, Gb/G, large versus small firms




We may conclude this portion of our analysis by underlying the presence of a relevant “size effect”. Indeed, most of the differences between the two groups of firms concentrate on differences between the subsets of their *larger* firms.

## 4. The logistics industry

The regional logistics industry may provide a useful benchmark to develop the previous analysis. In fact, our sample is very heterogeneous as for the variety of industries considered, preventing one from extracting easy-to-interpret figures about performance. Moreover, among the companies that we label CFs, the sample includes various types of cooperative firms; here, instead, we concentrate on a sector hosting only *production* (or labor) cooperative firms. Hence it should be easier to reappraise some of our previous findings.

However, before dwelling with figures, it is worth noting some peculiarities of this regional industry. In 2017 only about one third of CFs belong to a cooperative association (Regione Emilia-Romagna, 2019; see also footnote 10 above) and many of such CFs are qualified as *spurious*, i.e., fake. Indeed, the cooperative associations claim that the logistics sector is the one that mostly attracts CFs created to underpay workers, circumvent rules and prone to frequent bankruptcies in order to avoid periodical controls by authorities.

To begin with, let us notice that CFs operating in this industry represent in 2018 slightly more than 21,5% of our overall sample investigated in previous sections of this paper. Such a proportion has been declining over time (27.8% in 2010), whereas the number of NCFs has been growing by over 17% in the same period.

Of course, the sample we are going to employ has been cleared as we did with the entire regional sample. Tables 19A, 20A and 21A summarize, respectively, the number of firms, revenues and employees, for both CFs and NCFs in the regional logistics industry. It emerges that employees are almost split evenly between CFs and NCFs, although the former group is much less numerous than the latter. This confirms that also in this highly labor-intensive sector, that CFs are larger than NCFs, as summarized in Table 22.

Table 22. Employees, logistics, descriptive statistics

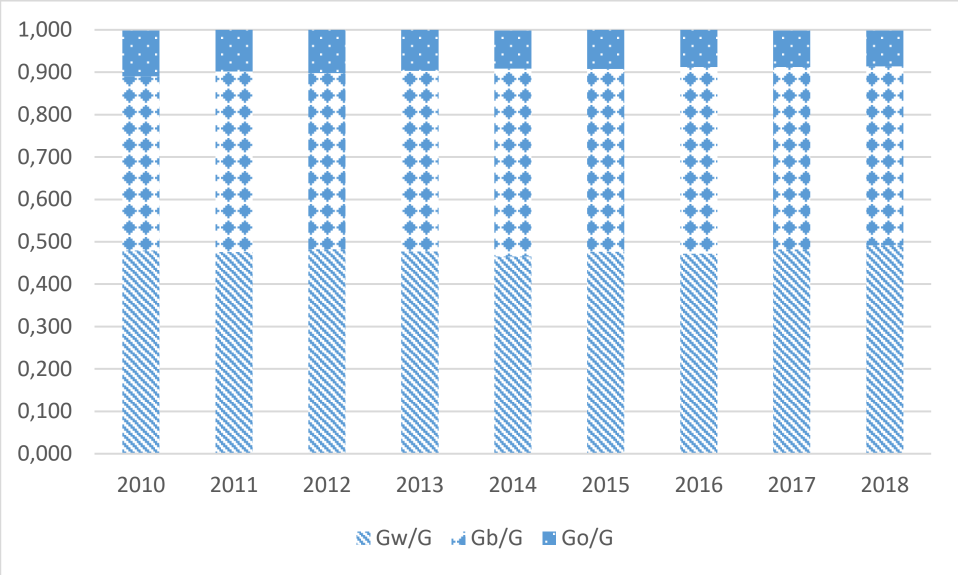
| | 2010 | | | 2018 | | |
|---|---|---|---|---|---|---|
| | CF | NCF | Total | CF | NCF | Total |
| Obs | 452 | 1173 | 1625 | 377 | 1376 | 1753 |
| Average | 49.73 | 18.97 | 27.52 | 65.09 | 20.13 | 29.80 |
| Median | 17.00 | 6.00 | 8.00 | 18.00 | 7.00 | 8.00 |
| CV | 1.61 | 5.29 | 3.17 | 1.36 | 7.21 | 3.52 |
| G | 0.694 | 0.720 | 0.740 | 0.731 | 0.75 | 0.755 |

As for the contribution of the three components concurring to the overall variability, Table 23 collects data for the extreme years of our time interval and Figure 7 illustrates the relative weights.

Table 23. Employment, logistics industry, Gini decomposition

| | $G_w$ | $G_b$ | $G_o$ | $G$ | $G_w/G$ | $G_b/G$ | $G_o/G$ |
|---|---|---|---|---|---|---|---|
| 2010 | 0.355 | 0.304 | 0.080 | 0.740 | 0.480 | 0.411 | 0.108 |
| 2018 | 0.371 | 0.319 | 0.064 | 0.755 | 0.491 | 0.423 | 0.085 |

Figure 7. Employment, logistics, Gini decomposition, relative weights




It is interesting to remark that, as compared to the overall sample, in this case the variability within (between) groups is much lower (higher); consequently, the type of company, more than the differences within each type of distribution, matters greatly in explaining how employment differs across companies. Moreover, the overlap factor is more significant than in the overall economy.

Given the fairly homogeneous nature of the services offered in this industry, we compare now the revenue per employee in the two groups. The obtained values may be interpreted as proxies of the average labour productivity in the two segments.

Table 24. Revenue per employee (thousand euros, prices 2015), logistics

| | NCF | CF |
|---|---|---|
| 2010 | 222 | 101 |
| 2011 | 252 | 109 |
| 2012 | 249 | 111 |
| 2013 | 258 | 108 |
| 2014 | 258 | 99 |
| 2015 | 257 | 108 |
| 2016 | 250 | 103 |
| 2017 | 248 | 111 |
| 2018 | 249 | 115 |
| 2019 | 252 | 127 |

The difference between types of firms is stably large: it takes about *two* employees in CFs to obtain the same revenue generated by *one* employee in NCFs. This handicap should raise serious concerns about the efficiency of CFs that may be worth exploring further in the future.[16] Table 25 shows that this enormous gap is reflected also in profits, which are always greater in NCFs since 2013. Instead, in the early years of our time span, firms operating in the regional logistics industry have been severely hit by the stagnation and incur substantial losses, whatever type they belong. To move towards the same analysis as we did before through the computation of correlation coefficients, we need to record the profits.

Table 25. Profits (million euros, prices 2015), logistics

| | NCF | CF |
|---|---|---|
| 2010 | -19 | -26 |
| 2011 | -37 | -2 |
| 2012 | -62 | -23 |
| 2013 | 8 | -23 |
| 2014 | 43 | -16 |
| 2015 | 1 | 8 |
| 2016 | 101 | 2 |
| 2017 | 114 | 0 |
| 2018 | 97 | 11 |

In general, the relationships among our main variables are hugely different for CFs vs NCFs, as we can verify in Tables 26 and 27, which collect the correlation coefficients. Notice that we report two bottom lines, depending on whether we compute the simple arithmetic mean, which may be misleading when measuring also negative yearly correlations, or when averaging (*) the absolute values of the coefficients.

[16] For such an exploration it would also be necessary to examine wages in the two segments; see Clemente *et al*. (2012) for the case of Spain and the rich bibliography.

Table 26. Correlation between EM, RV and PR, logistics, CFs

| | EM-RV | EM-RV | EM-PR | RV-PR |
|---|---|---|---|---|
| 2010 | 0,29 | 0,29 | -0,37 | 0,08 |
| 2011 | 0,29 | 0,29 | -0,10 | 0,23 |
| 2012 | 0,28 | 0,28 | -0,01 | 0,18 |
| 2013 | 0,30 | 0,30 | -0,05 | 0,02 |
| 2014 | 0,31 | 0,31 | 0,04 | 0,10 |
| 2015 | 0,33 | 0,33 | 0,05 | 0,14 |
| 2016 | 0,34 | 0,34 | 0,04 | 0,18 |
| 2017 | 0,35 | 0,35 | 0,03 | 0,17 |
| 2018 | 0,36 | 0,36 | -0,01 | 0,12 |
| Average | 0,32 | 0,32 | -0,04 | 0,14 |
| Average* | 0,32 | 0,32 | 0,08 | 0,14 |

Table 27. Correlation between EM, RV and PR, logistics, NCFs

| | EM-RV | EM-RV | EM-PR | RV-PR |
|---|---|---|---|---|
| 2010 | 0,67 | 0,67 | 0,02 | -0,05 |
| 2011 | 0,63 | 0,63 | -0,24 | -0,47 |
| 2012 | 0,65 | 0,65 | -0,40 | -0,40 |
| 2013 | 0,63 | 0,63 | -0,13 | -0,23 |
| 2014 | 0,66 | 0,66 | 0,08 | -0,03 |
| 2015 | 0,62 | 0,62 | -0,05 | -0,20 |
| 2016 | 0,61 | 0,61 | 0,36 | 0,35 |
| 2017 | 0,58 | 0,58 | 0,43 | 0,42 |
| 2018 | 0,58 | 0,58 | 0,36 | 0,34 |
| Average | 0,62 | 0,62 | 0,05 | -0,03 |
| Average* | 0,62 | 0,62 | 0,23 | 0,28 |

Some remarks are in order. First, as compared to the overall sample (Tables 11 and 12), CFs exhibit an even lower correlation between employment and revenue, which is in turn much lower than the one observed for NCFs. Second, when distancing from zero (as in 2010 and 2011, the worst years of our interval), the correlation between employment and profits levels for CFs is negative. Third, looking at the bottom line of Tables 26 and 11, the behavior of CFs reveals an almost negligible correlation between profits and employment as well as revenues. On the contrary, for the NCFs, Table 27 reveals that such correlations are not negligible, although much lower than in the overall economy (Table 12).

Notwithstanding the aforementioned peculiarities, we can summarize our analysis of the regional logistics industry as follows. Here, more than in the entire economy, CFs seem to care more about employment than about profits. As compared to NCFs, the CFs attitude of protecting employees[17] is associated with a poorer performance in terms of labor productivity, as it is evident from the lower level of both revenue per worker and aggregate profits.

## 5. Conclusions

In this paper we investigate the ER economy in order to shed light on the differences between the performance of cooperative firms and the conventional ones. A related key question we aimed at tackling deals with the objective function of cooperative firms as apparently revealed by their decisions. We employ a unique data set covering the entire universe of firms registered in ER from which we select appropriately the sample. Our statistically descriptive analysis, although simple, allows us to underline that: CFs are larger, in terms of employees, than NCFs; a "size effect" seems at work in driving differences between CFs and NCFs; CFs tend to act countercyclically, or at least more resiliently than NCFs during downturns; CFs tend to stabilize employment by sacrificing profits.

As for the last evidence, we argue that our analysis seems to support the model by Kahana and Nitzan (1989) and the predecessors of their approach: their formulation of the objective function of CFs finds in our paper an empirical validation. Hence, the assumption of maximizing employment under a profit constraint (or, equivalently, maximizing profits under an employment constraint) not only normally avoids perverse effects, but it fits quite squarely the empirical evidence offered in this paper as well as in previous empirical research. In other words, Kahana and Nitzan (1989)'s approach appears capable of overcoming both objections that we can address (as we did in Section 1) to the original Ward (1958)'s formulation of cooperatives' goal (labor-managed firms', in his own world).

A subtle issue may arise when observing countercyclical behavior by CFs because this may seemingly echo Ward's perverse effect. However, it is easy to relate our empirical findings, on the one hand, and some testable predictions stemming from the approach modeled by Kahana and Nitzan (1989) as well as the setting considered by Ward (1958), on the other. Indeed, both Ward (1958) and Kahana and Nitzan (1989) assume price-taking behaviour and ideal (in the sense of

[17] All workers or mainly the member ones; this is an aspect that would require knowing at least the average membership ratio which is unfortunately unavailable, also because, as we know, most CFs of the logistics do not adhere to any cooperative association.

Sertel's workers' firms) LMFs, while our sample is extracted from *real oligopolistic markets* where profit-maximizing firms cohabit with *heterogeneous* (as for the operating sector, the nature of their membership and being cooperative firms or joint stock companies controlled by cooperative firms) CFs in which the *membership ratio is sizably lower than one*. The basic difference between Ward's and Kahana and Nitzan's models deals with the specification of the objective function. Hence, notwithstanding they share some assumptions, the different formulation about what cooperatives are supposed to maximize is crucial enough to yield very different properties of the resulting comparative statics. Our empirical findings seem to support the view, captured by Kahana and Nitzan (1989)'s behavioral assumption, that CFs do care about their own employment levels even if it entails sacrificing profitability.

There is another implication of our results. It is by now well known that the main source of income inequality is *labour* income inequality[18]. Hence, to shrink the former, actions to reduce the latter are in order. By preserving employment, especially during slums, CFs participate in the process of containing labour income inequality because unemployment, by zeroing market revenues of a fraction of labor force, cannot but uplift income inequality. We may claim that CFs strategies operate as an *ex-ante* redistributive mechanism, as opposed to ex-post public policies designed to mitigate the consequences of falls in labour incomes[19]. Moreover, we know that the pay-ratio within CFs employees (at least in cooperative firms, not necessarily in companies controlled by cooperatives) is usually lower than in NCFs[20]. By limiting wage dispersion between white collars and blue collars, CFs provides another contribution to limit, once again *ex-ante*, an exceedingly high-income inequality among their employees and then, given their critical mass, also within the employed in ER as a whole.

Last but not least, we believe that, while showing how different regional producers reacted to the financial crisis and the subsequent recession, our empirical analysis may also establish a fairly

[18] See, for instance, the interesting contribution by Milanovic (2019) and the large bibliography cited there.

[19] This is particularly true in social CFs which function combining workers and users of a vast range of social services and hire people with profiles in high risk of employment exclusion. Incidentally, excluding the constructions sector, anecdotical evidence indicates that during recessions CFs have resorted to social welfare nets in lower proportions than their NCFs counterparts. According to Kruse (2016, p. 1), a large empirical evidence suggests that: "Employee ownership companies have more stability, higher survival rates, and fewer layoffs in recessions, potentially leading to lower unemployment in the overall economy. … The broader sharing of economic rewards may help reduce economic inequality." Production cooperatives belong to such a category of companies.

[20] For instance, in its ethical code, Legacoop sets an upper bound of 8 between the values of the highest and the lowest salary within the various layers of their organization.

useful benchmark to assess in due time the economic effects of the pandemic severely hitting also the ER economy.

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# Appendix

Table 4A. Revenue (million euros, 2015 prices)

| | NCF | % NCF | CF | % CF |
|---|---|---|---|---|
| 2010 | 161.421 | 79,24 | 42.291 | 20,76 |
| 2011 | 175.933 | 79,03 | 46.694 | 20,97 |
| 2012 | 173.980 | 78,42 | 47.866 | 21,58 |
| 2013 | 181.584 | 76,27 | 56.481 | 23,73 |
| 2014 | 186.410 | 74,85 | 62.633 | 25,15 |
| 2015 | 190.693 | 75,85 | 60.731 | 24,15 |
| 2016 | 196.533 | 76,31 | 60.999 | 23,69 |
| 2017 | 214.238 | 77,25 | 63.080 | 22,75 |
| 2018 | 227.608 | 78,11 | 63.799 | 21,89 |

Table 5A. Number of employees

| | NCF | % NCF | CF | % CF |
|---|---|---|---|---|
| 2010 | 597.671 | 73,20 | 218.853 | 26,80 |
| 2011 | 595.291 | 72,37 | 227.222 | 27,63 |
| 2012 | 598.517 | 72,07 | 231.998 | 27,93 |
| 2013 | 595.706 | 70,84 | 245.200 | 29,16 |
| 2014 | 593.293 | 69,79 | 256.832 | 30,21 |
| 2015 | 610.156 | 70,06 | 260.778 | 29,94 |
| 2016 | 632.859 | 70,76 | 261.545 | 29,24 |
| 2017 | 668.166 | 71,53 | 265.973 | 28,47 |
| 2018 | 691.254 | 71,99 | 268.899 | 28,01 |

Table 7A. Employment, Gini decomposition

| | $G_w$ | $G_b$ | $G_o$ | G |
|---|---|---|---|---|
| 2010 | 0.504 | 0.222 | 0.039 | 0.765 |
| 2011 | 0.497 | 0.230 | 0.039 | 0.765 |
| 2012 | 0.498 | 0.233 | 0.038 | 0.769 |
| 2013 | 0.492 | 0.244 | 0.038 | 0.774 |
| 2014 | 0.488 | 0.254 | 0.037 | 0.780 |
| 2015 | 0.498 | 0.238 | 0.037 | 0.774 |
| 2016 | 0.494 | 0.248 | 0.036 | 0.778 |
| 2017 | 0.500 | 0.243 | 0.035 | 0.778 |
| 2018 | 0.505 | 0.240 | 0.034 | 0.779 |

Table 13A. Employees, small firms

| NCF | % NCF | CF | %CF |
|---|---|---|---|
| 77.198 | 85,11 | 13.503 | 14,89 |
| 72.370 | 84,88 | 12.892 | 15,12 |
| 77.239 | 86,04 | 12.534 | 13,96 |
| 68.752 | 83,91 | 13.185 | 16,09 |
| 67.279 | 85,12 | 11.762 | 14,88 |
| 68.676 | 85,75 | 11.417 | 14,25 |
| 71.201 | 87,24 | 10.417 | 12,76 |
| 76.979 | 87,89 | 10.608 | 12,11 |
| 78.257 | 88,82 | 9.855 | 11,18 |

Table 15A. Employees, small firms, Gini decomposition

| | $G_w$ | $G_b$ | $G_o$ | G |
|---|---|---|---|---|
| 2010 | 0.393 | 0.095 | 0.026 | 0.514 |
| 2011 | 0.363 | 0.094 | 0.024 | 0.481 |
| 2012 | 0.400 | 0.086 | 0.027 | 0.513 |
| 2013 | 0.352 | 0.101 | 0.023 | 0.476 |
| 2014 | 0.354 | 0.091 | 0.023 | 0.468 |
| 2015 | 0.351 | 0.086 | 0.022 | 0.459 |
| 2016 | 0.358 | 0.074 | 0.021 | 0.453 |
| 2017 | 0.374 | 0.071 | 0.022 | 0.467 |
| 2018 | 0.376 | 0.065 | 0.021 | 0.461 |

Table 16A. Employees, large firms

| | NCF | % NCF | CF | % CF |
|---|---|---|---|---|
| 2010 | 520.473 | 71,71 | 205.350 | 28,29 |
| 2011 | 522.921 | 70,93 | 214.330 | 29,07 |
| 2012 | 521.278 | 70,37 | 219.464 | 29,63 |
| 2013 | 526.954 | 69,43 | 232.015 | 30,57 |
| 2014 | 526.014 | 68,22 | 245.070 | 31,78 |
| 2015 | 541.477 | 68,47 | 249.361 | 31,53 |
| 2016 | 561.658 | 69,10 | 251.128 | 30,90 |
| 2017 | 591.187 | 69,83 | 255.365 | 30,17 |
| 2018 | 612.997 | 70,29 | 259.044 | 29,71 |

Table 18A. Employees, large firms, Gini decomposition

| | $G_w$ | $G_b$ | $G_o$ | G |
|---|---|---|---|---|
| 2010 | 0.459 | 0.230 | 0.035 | 0.725 |
| 2011 | 0.455 | 0.238 | 0.034 | 0.727 |
| 2012 | 0.451 | 0.242 | 0.034 | 0.727 |
| 2013 | 0.451 | 0.250 | 0.034 | 0.735 |
| 2014 | 0.446 | 0.262 | 0.034 | 0.741 |
| 2015 | 0.446 | 0.262 | 0.034 | 0.741 |
| 2016 | 0.450 | 0.257 | 0.033 | 0.739 |
| 2017 | 0.456 | 0.252 | 0.032 | 0.740 |
| 2018 | 0.460 | 0.248 | 0.032 | 0.741 |

Table 19A. Number of CFs and NCFs, logistics

| | NCF | % NCF | CF | % CF |
|---|---|---|---|---|
| 2010 | 1.173 | 72,18 | 452 | 27,82 |
| 2011 | 1.199 | 73,56 | 431 | 26,44 |
| 2012 | 1.194 | 73,75 | 425 | 26,25 |
| 2013 | 1.192 | 73,95 | 420 | 26,05 |
| 2014 | 1.209 | 74,45 | 415 | 25,55 |
| 2015 | 1.266 | 75,58 | 409 | 24,42 |
| 2016 | 1.289 | 75,96 | 408 | 24,04 |
| 2017 | 1.345 | 77,34 | 394 | 22,66 |
| 2018 | 1.376 | 78,49 | 377 | 21,51 |

Table 20A. Revenue (million euros, 2015 prices), logistics

| | NCF | % NCF | CF | % CF |
|---|---|---|---|---|
| 2010 | 4.946 | 68,49 | 2.275 | 31,51 |
| 2011 | 5.403 | 69,40 | 2.382 | 30,60 |
| 2012 | 5.593 | 69,79 | 2.420 | 30,21 |
| 2013 | 5.684 | 70,47 | 2.381 | 29,53 |
| 2014 | 5.838 | 70,70 | 2.420 | 29,30 |
| 2015 | 6.147 | 70,51 | 2.571 | 29,49 |
| 2016 | 6.101 | 70,34 | 2.572 | 29,66 |
| 2017 | 6.509 | 70,32 | 2.747 | 29,68 |
| 2018 | 6.887 | 70,93 | 2.823 | 29,07 |

Table 21A. Number of employees, logistics

| | NCF | % NCF | CF | % CF |
|---|---|---|---|---|
| 2010 | 22.247 | 49,74 | 22.479 | 50,26 |
| 2011 | 21.407 | 49,57 | 21.780 | 50,43 |
| 2012 | 22.464 | 50,67 | 21.866 | 49,33 |
| 2013 | 22.029 | 49,92 | 22.102 | 50,08 |
| 2014 | 22.620 | 48,17 | 24.337 | 51,83 |
| 2015 | 23.903 | 50,06 | 23.841 | 49,94 |
| 2016 | 24.437 | 49,42 | 25.009 | 50,58 |
| 2017 | 26.279 | 51,44 | 24.807 | 48,56 |
| 2018 | 27.700 | 53,03 | 24.537 | 46,97 |