Are cooperatives more productive than investor-owned firms? Cross-industry evidence from Portugal*

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Abstract

We analyse empirically whether cooperatives and investor-owned firms differ in terms of productive efficiency. Using rich Portuguese panel data covering a wide range of industries, we apply two different empirical approaches to estimate potential differences in productive efficiency. The results from our benchmark random-effects model show that cooperatives are significantly less productive, on average, than investor-owned firms, both at the aggregate level and for most of the industries considered. However, the results derived from a System-GMM approach, which is our preferred empirical strategy, are much less conclusive, and we cannot conclude that cooperatives are generally less efficient that investor-owned firms. With either approach, though, we find no evidence that cooperatives are *more* productive than investor-owned firms in any industry.

Keywords: Cooperatives; investor-owned firms; productive efficiency

JEL Classification: D24; J54; P12; P13

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1 Introduction

In this paper we document how two different forms of organizing production affect the productivity of the firm. More specifically, we examine whether and how productive efficiency differs between cooperatives and investor-owned firms (henceforth IOFs). The dominant type of firm in modern economies is the IOF, where the right to residual control is assigned to the suppliers of capital in proportion to the capital supplied. Nevertheless, since the start of the modern cooperative movement in the mid-19th century, cooperatives have continued to grow and prosper as an alternative way of organizing production, and they have today a widespread presence is several industries and countries.[1] In many countries, the cooperative is a significant, and sometimes dominant, organizational form in several industries.[2]

Despite the worldwide (and in some sectors significant) presence of cooperatives, evidence on the merits of this organizational form with respect to productive efficiency is relatively scarce and far from consensual. Whereas the theoretical literature on cooperatives versus IOFs is quite rich (though also quite divergent), the empirical evidence is for the most part confined to case studies or, at best, industry-specific analyses. Furthermore, the available evidence is found in two completely separate and seldom cross-referenced strands of the literature; one on worker cooperatives (labour managed firms) and another on agricultural producer cooperatives.[3]

In the present paper we contribute to the literature by performing a cross-industry empirical analysis of the productivity of cooperatives relative to IOFs, using rich panel data from Portugal. Applying two different empirical strategies, random-effect (GLS) estimation and System-GMM estimation, we estimate different variants of an augmented Cobb-Douglas production function and test for differences in productive efficiency between cooperatives and IOFs, based on data from 2010-2012. We perform this analysis both at aggregate level and at industry-level, across 13 different industries. We also perform a series of robustness checks and extensions to the main analysis. This

[1] According to the latest (2015) figures from Cooperatives Europe (Cocolina, 2016), there are almost 180,000 cooperatives just in Europe, an increase of 9% from 2009. These cooperatives employ more than 4.5 million people and are present in a wide range of sectors. The largest sectors are industry and services (36%), agriculture (30%) and housing (22%) if measured by number of firms, and agriculture (39%), retail (30%) and consumer (12%) if measured by annual turnover.

[2] In terms of market shares, figures from the European Commission (http://ec.europa.eu/growth/sectors/social-economy/cooperatives/index_en.htm) show that, in several countries, cooperatives are dominant in the agricultural industry (83% in the Netherlands, 79% in Finland, 55% in Italy and 50% in France). In addition, cooperatives are strongly present in industries such as forestry, banking, retail, pharmaceutical and health care, with cooperative market shares in the range of 20-60% in several countries.

[3] See Section 2 for a theoretical discussion of cooperatives versus IOFs, and Section 3 for a review of the empirical literature.

includes estimating a translog production function instead of a Cobb-Douglas function.

Our results based on GLS estimations show a very clear picture, namely that cooperatives are significantly less productive than IOFs, both at the aggregate level and for a majority of the 13 different industries considered. In 8 of these industries, we find that cooperatives would significantly increase their output if they used the same amount of inputs but adopted the (estimated) technology of IOFs, whereas the IOFs would produce significantly less with the same amount of inputs if they adopted the 'cooperative technology'. In 2 of the remaining 5 industries we find significant partial evidence of the same, and we find no significant indications of cooperatives being more productive than IOFs in any industry. These results are remarkably insensitive to a number of different robustness checks, and a similar picture also emerges when we perform the same analysis on a subsample of firms where the cooperative category is restricted to labour-managed firms.

However, the results based on System-GMM estimations, which is our preferred empirical strategy, are much less conclusive. At the aggregate level, the System-GMM-results also indicate that cooperatives are less productive than IOFs, although the productivity differentials are less precisely estimated. Only for a particular subset of firms, namely those with less than ten workers (which we dub 'micro firms'), do the aggregate-level System-GMM estimates clearly suggest that cooperatives are less productive. At industry level, the System-GMM approach yields an even less clear-cut picture. In the benchmark estimations based on Cobb-Douglas technology, we only find statistically significant underperformance of cooperatives in two industries. In the remaining industries, we find no statistically significant difference in productive efficiency between the two organizational types. At industry level, the System-GMM-results are actually considerably more in line with the GLS results when we estimate a translog production function. In this case, we find statistically significant (though partial) evidence of cooperatives being less productive in 6 of the 13 industries. And again, we find no evidence of the opposite in any industry.

We also estimate productivity differentials for a sub-sample of firms in which the type of cooperative is restricted to labour-managed firms (LMFs). The analysis in this part of the paper is restricted to 6 industries in which the number of LMFs is sufficiently large to perform the estimations. Whereas our GLS-estimates suggest that LMFs are less productive than IOFs, the estimates based on System-GMM show no indications of LMFs being significantly different than IOFs with respect to productive efficiency.

The rest of the paper is organized as follows. In the next section we place our analysis in a proper theoretical context by offering a precise definition of the difference between an IOF and a cooperative and discussing the available theoretical arguments for why IOFs might be more or less productive than cooperatives. In Section 3 we give a relatively brief review of the empirical literature on productivity differences between the two organizational forms. The data we use are described in Section 4, whereas in Section 5 we present our empirical strategies. Our results are presented in Section 6. The paper is concluded by Section 7, where we summarise and discuss our main results.

2 Theoretical context

A firm is usually owned by someone who transacts with the firm; a 'patron' of the firm. As noted by Hansmann (1999), this is true for both cooperatives and for IOFs. In light of this basic insight, a cooperative can be generally defined as a firm owned by patrons other than those who supply capital to the firm. A consumer cooperative is owned by its consumers (or a subset of them), whereas a producer cooperative is owned by the suppliers (or a subset of the suppliers) of a particular input to production.[4] In addition, cooperatives are usually characterised by a governance structure where both earnings and votes are distributed to members/owners in proportion to the amount of transactions each member has with the firm.

Whereas the neoclassical theory of the profit-maximising firm is a standard model used to describe the behaviour of IOFs, there is no such universally accepted 'workhorse model' of the cooperative firm. In particular, how to define the objective of a cooperative firm is a long-standing issue in the literature. Perhaps the most ambitious attempt to develop a unified theory of cooperatives was made by Carson (1977), who sets up a general theory of a firm (a so-called 'G-firm') that maximises a function that is monotonically increasing in the utilities of its members/owners, and where each member may supply some of the firm's inputs and/or consume some of its outputs. This implies firm behaviour that generally lies somewhere between profit-maximisation and welfare-maximisation. The former case appears only under perfect competition in all input and output markets. Otherwise, a consumer cooperative would charge lower output prices of its members, and a producer cooperative would pay higher input prices to its members, compared with an IOF (which also appears as a special case of the G-firm).

[4]Hansmann (1999) argues that even an IOF could be seen as a particular type of producer cooperative; a capital (or lenders') cooperative.

How are the efficiency properties of cooperatives likely to differ from those of an IOF? We can conceptually distinguish between three types of efficiency: (i) productive efficiency, (ii) allocative efficiency, and (iii) scale efficiency. For a given production function, models of cooperatives based on a neoclassical framework, such at the above-described theory of the G-firm, are in principle able to explain if and how cooperatives and IOFs differ in terms of allocative and scale efficiency. For example, the Carson-model predicts that, all else equal, cooperatives will operate at a (weakly) large scale than IOFs. However, such models cannot explain if and how cooperatives differ from IOFs with respect to productive efficiency, which is the main question we ask in our empirical analysis. Possible explanations for such differences are mainly based on agency and transaction cost theories.

There are two main agency problems, with potential implications for productive efficiency, related to the running of a firm: (i) an agency problem between the owner(s) (principal(s)) and the manager (agent), and (ii) an agency problem between the manager (principal) and the suppliers of inputs, including workers (agents). An overview of the agency-based arguments in the literature suggests that the former (latter) agency problem is larger (smaller) in cooperatives than in IOFs.

It is a well-known argument in the literature on labour-managed firms, which is a particular type of producer cooperative, that the cooperative form of firm organisation yields a gain in productive efficiency because of reduced agency and monitoring costs in the relationship between managers and workers (which, in the case of labour-managed firms, are also owners). Employee participation is thought to stimulate incentives for workers to exert more effort, to invest more in firm-specific human capital, and to monitor each other (see, e.g., Estrin and Jones, 1992, and Fakhfakh et al., 2012). Similar arguments have also been put forward for other types of producer cooperatives, where the firm is owned by the suppliers of other inputs than labour. Because of a better alignment of interest between the firm and its suppliers, information rents – and thus procurement costs – are lower for a cooperative than for an IOF.[5] Gains in productive efficiency due to informational advantages have also been claimed for consumer cooperatives. The argument is that consumer-members would be more willing to truthfully reveal information to their cooperative – for example about the types of products and services needed – than to an IOF (see, e.g., Staatz, 1984, and Sexton and Iskow, 1993). All of the above arguments can also be thought of as different variants of the same general argument, namely that a cooperative ownership structure can be seen as a

[5] See Bontems and Fulton (2009) for a formal treatment of this argument.

form of vertical integration (either backwards or forwards), which implies lower transaction costs compared to an IOF.[6]

On the other hand, a cooperative ownership structure might aggravate the agency problem in the relationship between owners and managers, and thereby lead to lower productive efficiency. At least three different (but still related) arguments have been put forward in the literature. First, the absence of a cooperative stock market value implies a lack of external information available to measure managerial performance, which in turn implies a larger need for internal monitoring (Porter and Scully, 1987). Furthermore, incentives for internal monitoring might also be lower in cooperatives because ownership tends to be highly diffused (Sexton and Iskow, 1993). Finally, compared with an IOF, it might be more difficult to design managerial incentive schemes in cooperative firms which align the manager's and the owners' objectives; partly because of the more unclear and diffuse nature of the cooperative's objectives, and partly because of the lack of equity-based management incentives mechanisms (i.e., a stock market value) that are available to IOFs (Ortmann and King, 2007).

There are also some other arguments derived from a non-neoclassical framework indicating that productive efficiency might be lower in cooperatives than in IOFs. Cook (1995) and Banerjee et al. (2001), among others, claim that cooperatives are less efficient because of internal rent-seeking, where members engage in (costly) activities in order to increase their share of the generated surplus. Furthermore, the typically higher diffusion of ownership in cooperatives might lead to lower efficiency due to larger costs of collective decision making (Hansmann, 1999).

Finally, there is a set of arguments which relate more specifically to allocative and scale inefficiencies of cooperatives. Porter and Scully (1987) invoke an agency cost argument in claiming that cooperatives are likely to suffer from scale inefficiencies. Achieving the cost-minimising scale of operation requires sufficient patronage. However, since the cost of control increases as the number of principals (patrons) increases, cooperatives tend to operate at an inefficiently low scale. Regarding potential allocative inefficiencies of cooperatives, a much-discussed argument is derived from the so-called 'horizon problem'. Because members of a cooperative benefit from investments only during the period in which they are members, this might erode incentives to invest in long-lived assets whose productive life is longer than the expected period of cooperative membership. A similar problem does not exist for IOFs, since existing shareholders can always sell their shares

[6] See, e.g., Nilsson (2001) for a further discussion.

at a market value that will reflect the expected present value of future investment returns. This potential horizon problem for cooperative investments has given rise to the 'underinvestment hypothesis', namely that cooperatives will suffer from allocative inefficiencies due to underinvestment in capital (see, e.g., Sexton and Iskow, 1993, or Ortmann and King, 2007). This is also related to the concern that cooperatives will suffer from capital starvation because of difficulties in accessing external finance and because of members' limited wealth (see Fakfakh et al., 2012, for a further discussion). Contrary to this, though, some authors (e.g., Estrin and Jones, 1992) argue that a cooperative ownership structure could stimulate, through positive externalities among members, the process of collective capital accumulation, leading to the hypothesis that cooperatives will be characterised by relative capital scarcity at the early stages of their life spans, but relative capital abundance in later stages.

3 A brief literature review

As the discussion in the previous section shows, most of the arguments for why there might be productivity differences between cooperatives and IOFs are general in nature and therefore apply, at least to some extent, to all types of cooperative ownership forms. Despite this, the empirical literature on this topic, besides being relatively scant, is divided in two distinctly separate strands. There is a literature focussing exclusively on labour-managed firms and how this particular type of producer cooperative compare with IOFs in terms of productivity and efficiency. Then there is a parallel literature addressing the same set of questions regarding cooperatives versus IOFs, but focussing exclusively on the agricultural sector.

In the latter strand of the literature, the scope of analysis is not only restricted to the agricultural sector, but many of the studies in this literature are also restricted to one particular industry, namely dairy processing. The results from these studies are somewhat mixed. Porter and Scully (1987) and Ferrier and Porter (1991) find that cooperatives are less efficient then their investor-owned counterparts, whereas Singh et al. (2001), Doucouliagos and Hone (2000) and Boyle (2004) conclude that cooperatives are either equally or more efficient than IOFs. In studies from other agricultural industries, Akridge and Hertel (1992) find a negative efficiency effect of a cooperative ownership structure in the US grain and supply industry, whereas Sexton et al. (1989) find no evidence of allocative inefficiency of cooperatives in the US cotton industry. On the other hand, in a series of studies using data from the Italian wine industry, Maietta and Sena (2004, 2008, 2010) find that cooperatives tend to be more efficient than conventional firms, and that cooperative organization is conducive to improvement in productive efficiency in response to adversities such as tightening financial constraints or increased competitive pressure.

In a review and discussion of the early literature on agricultural cooperatives, Sexton and Iskow (1993) attribute the mixed results partly to a lack of relevant or reliable data in many studies, arguing that this makes it hard to draw strong conclusions.[7] In a more recent study, again based on data from the dairy industry, Soboh et al. (2012) find that cooperatives are less efficient when using a traditional measure of input oriented technical efficiency, but show that these differences are reduced (or eliminated) when using an alternative approach that account for differences in firm objectives emanating from the two types of ownership structure.

The (early) literature on productivity differences between labour-managed firms and IOFs is nicely summarised by Doucouliagos (1997), who also performs a meta-analysis based on 23 statistically independent studies. A striking feature of this literature, taken as a whole, is the lack of solid evidence for systematic differences in productivity or efficiency between the two organizational forms. In the studies reviewed by Doucouliagos (1997), no such differences are found in the five studies using production frontier estimates[8], and in four of the five studies using regression techniques to estimate production functions.[9] The only exception is Berman and Berman (1989), who find that labour-managed firms are less productive than IOFs in the US plywood industry.[10] Furthermore, although many individual studies suggest that labour-managed firms are less capital-intensive than IOFs, which might imply differences in total factor productivity, these differences disappear in the meta-regressions. A different conclusion is reached in a more recent paper by Arando et al. (2015), who perform an econometric case study of the retail chain Eroski, which is part of the Mondragon group of worker cooperatives in the Basque Country of Spain. They find that stores with cooperate ownership tend to be more productive than conventional stores with no employee ownership within the same chain.

Besides drawbacks related to lack of data, and besides an absence of a clear pattern of results, a common feature of the studies in both of the above-mentioned strands of the literature is a narrowness of scope. In most studies, the analysis is restricted to a single industry and/or a small

[7] See also Soboh et al. (2009) for a more comprehensive and updated literature review.

[8] Porter and Scully (1987), Cote (1989), Sterner (1990), Defourny (1992) and Pollitt (1995).

[9] Sterner (1990), Estrin (1991), Ferrantino et al. (1995), Pollitt (1995).

[10] However, in a subsequent study based on more recent data from the same industry, Craig and Pencavel (1995) find a small advantage for worker cooperatives with respect to productive efficiency.

sample of firms.[11] A recent and notable exception is Fakhfakh et al. (2012) who study productivity differences between labour-managed firms and IOFs using a large and representative sample of French firms covering several industries.[12] Interestingly, the authors find that labour-managed firms are at least as efficient as IOFs in all industries and that, on average, firms would produce more if they all adopted the labour-managed firms' industry-specific technologies.

In the present paper, our empirical approach is much the same as in Fakfakh et al. (2012). The main difference lies in an even wider scope of study, where we include all types of cooperatives and make comparisons across a substantially larger number of industries. Detailed descriptions of our data and empirical approach are given in the subsequent sections.

4 Data

We use data from the survey *Sistema de Contas Integradas das Empresas* (SCIE), conducted by the Portuguese National Institute of Statistics (INE) for the period 2004-2012. This annual survey includes firm-level data collected for any entity which produces goods or services in that year, in any economic sector, regardless of its size and legal form.[13] The survey also includes unique firm identifiers which allow us to trace firms over time and conduct panel data analysis. Until 2009, the organizational form of the firm was given by two broad categories: *Sole Proprietorship* ('Empresa em Nome Individual') and *Societies* ('Sociedades'). However, in 2010 and 2011 this classification was further broken down and includes *Cooperatives* among thirty different legal forms of the firm.[14]

SCIE covers around one million firms every year, with the majority (65-70%) falling in the *Sole Proprietorship* category. This type of firm is excluded from our analysis on the grounds that, in practice, many such enterprises operate only on a part-time basis. In our analysis, we want to distinguish between cooperatives and investor-owned firms. We identify cooperatives directly by the legal form given in the data in 2010 and 2011. The residual group of firms in the *Societies* category are then classified as IOFs.[15]

[11] A literature review summarising the relative performance of cooperatives versus IOFs and integrating both strands of the literature – worker cooperatives and agricultural cooperatives – is provided by Logue and Yates (2006). However, they apply a somewhat broader concept of performance, beyond 'productivity' in the strict economic meaning of the concept, which allows them to conclude that cooperatives in general perform well relative to IOFs.

[12] Two separate data sets are used, covering seven and four industries, respectively.

[13] The only exceptions are public administration and financial services (banking and insurance), which are excluded from the survey.

[14] The legal rules for cooperatives in Portugal are specified in Article 3 of 'Código Cooperativo', which draws on the principles set down by the International Co-operative Alliance, including principles such as 'democratic management' and 'autonomy and independence'. See Fernandes (2006) for some historical background on cooperatives in Portugal.

[15] We will also use a narrower definition of IOFs as a robustness check.

Although we are able to accurately determine whether or not a firm is organized as a cooperative, the data does not contain more detailed information about type of cooperative. However, in an extension to our main analysis, we apply an imputation procedure developed by Monteiro and Stewart (2015) to identify labour-managed firms and subsequently perform our analysis on a subset of firms where the type of cooperative is restricted to worker cooperatives. In addition, when interpreting our results, we also rely on information from other sources regarding the prevalence of different types of cooperatives in different industries in Portugal in order to see whether cross-industry differences in our results are systematically related to the cross-industry distribution of different cooperative types. As we show in Section 6, there does not appear to be any clear relation of this form.

The information in SCIE is gathered from two detailed financial statements (balance sheet and income statement), which implies that we have a rich set of information about each firm. Key variables, apart from type of organization, include gross output, value added, capital stock, employment, industry affiliation, regional location and a firm birth indicator. In addition, the data set includes workforce characteristics such as gender distribution, share of full-time workers and share of paid workers, and information on whether the firm provides formal training to the workforce or is involved in research activities. We also know if the firm is engaged in international trade through import or export activities.

Unfortunately, due to a change in the accounting rules at the start of 2010, the availability and continuity of some relevant variables were not assured. We therefore limit our main analysis to the period from 2010 to 2012, during which all relevant variables are available. The only exception is the detailed classification of organizational form, which, as mentioned, is only available for 2010 and 2011. We therefore extrapolate, for each firm, the organizational form of 2010-2011 to 2012 and also make the assumption that firms born in 2012 are investor-owned.[16,17] In order to facilitate a cross-industry analysis, we also follow the approach of Fakhfakh et al. (2012) and drop industries (defined at the 5-digit level) where cooperatives are absent or represent less than 2% of the firms in that industry.[18] With these restrictions, and after some standard cleaning of the data, our final sample consists of 685 cooperatives and 10,164 IOFs.

[16] No firm changed the organisational form between 2010 and 2011, which suggests that extrapolation to 2012 might be innocuous, although we have no information on entry of cooperatives in 2012.

[17] We check the robustness of our approach in two different (and opposite) ways: (i) using only with data from 2010 and 2011, and (ii) extending the extrapolation of firm types to 2015.

[18] As a robustness check, we also perform the aggregate-level analysis without this restriction.

Each firm in our sample is classified as belonging to one of thirteen different industries, where this classification of industries is based on a mildly aggregated version of the official 2-digit classification. In Figure 1 we display how cooperatives are distributed across these 13 industries.[19] We see that cooperatives are reasonably well represented across a wide spectrum of economic activity. In most industries, the share of cooperatives lies somewhere in the interval of 5-15%. Exceptions are *Textile, clothing and other*, *Other manufacturing*, *Retail trade* and *Artistic and cultural associations*, where the share of cooperatives is less than 5%.[20] At the other end, cooperatives are relatively strongly present in industries such as *Food*, *Beverages* and *Social work*, where they constitute around 15% of the total number of firms.

[Figure 1 here]

Mean values of the main variables in our sample are reported in Table 1, where the statistical significance (given by a t-test) of the difference between the means of these variables for the two groups of firms (cooperatives and IOFs) is presented in the last column. It is evident that cooperatives produce, on average, more than IOFs. The output differential is large (35%) and statistically significant. It is even larger (50%) if output is alternatively measured by value added (not shown in the table). More generally, whether measured by input use or output, cooperatives are (on average) considerably larger than IOFs. This feature is consistent with a recent study on cooperatives versus IOFs in Portugal using a different data set (Monteiro and Stewart, 2015), and it is also consistent with the characteristics of the European dairy sector, where cooperatives are prevalent (Soboh et al., 2012). However, it contrasts with much of the existing literature, which does not show a consistently clear pattern in terms of the relative size of cooperatives, although prior evidence is mainly sectorial and/or restricted to labour managed firms.[21]

[19] When making our industry classification, we have tried to maximise the level of disaggregation while still ensuring a sufficiently large sample size in each category. Notice also that *Agriculture and other* includes forestry and fishing, and that *Food* and *Beverages* belong to the manufacturing sector.

[20] Although we have imposed a minimum threshold of 2% cooperatives in each industry (at the 5-digit level), data cleaning has brought the cooperative share below this threshold in the *Other manufacturing* category.

[21] See, e.g., Fakhfakh et al. (2012) on France, Pencavel et al. (2006) or Jones (2007) on Italy, and George (1982) on Denmark.

[Table 1 here]

Cooperatives in Portugal also appear to be more capital intensive than IOFs. This is also confirmed by more disaggregated figures, which shows that the capital-labour ratio of cooperatives is at least as high as for IOFs in 10 out of the 13 industries considered in our study. This also runs counter to prior evidence showing that cooperatives tend to be less capital intensive than IOFs (see, e.g., Doucouliagos, 1997, and Jones, 2007), although, once more, this evidence is mainly restricted to worker cooperatives.[22]

The composition of the workforce also differs between the two groups, with cooperatives employing a significantly lower share of full-time and male workers, on average. This confirms previous work on Portuguese cooperatives (Monteiro and Stewart, 2015) but contrasts with other evidence showing that the share of male workers in cooperatives is either similar or higher than in IOFs (e.g., Fakhfakh et al., 2012, or Bartlett et al., 1992).

Regarding the other variables, the considerably lower birth rate of cooperatives relative to IOFs is a well-established and documented fact. Another noticeable difference is that, while cooperatives do not differ from IOFs in terms of export activities, the share of firms that import goods is significantly lower for cooperatives than for IOFs. This might reflect the importance of local linkages often associated with cooperatives (Bartlett et al., 1992).[23]

5 Empirical strategy

We test for productivity differences between cooperatives and IOFs by estimating different variants of an augmented Cobb-Douglas production function with three inputs (similar to, e.g., Harris et

[22] On the other hand, Fakhfakh et al. (2012) find no significant difference in capital intensity between cooperatives and labour-managed firms.

[23] In some cases local linkages might be compulsory, for example in the case of agricultural cooperatives that are obliged to buy inputs (raw materials) from their members.

al., 2005). Our most general specification is given by[24]

$$\begin{aligned}\ln Y_{it} \quad = \quad & \beta_0 + (\beta_1 \ln L_{it} + \beta_2 \ln K_{it} + \beta_3 \ln M_{it})\, IOF \\ & + (\beta_4 + \beta_5 \ln L_{it} + \beta_6 \ln K_{it} + \beta_7 \ln M_{it})\, COOP \\ & + \beta_8 WF_{it} + \beta_9 OFA_{it} + \beta_{10} HHI + \sum_{j=1}^{12} \theta_{ij} EA + \sum_{k=1}^{6} \phi_{ik} REG_{ik} + a_i + \nu_t + \epsilon_{it},\end{aligned} \tag{1}$$

where Y is real gross output, L is total employment, K is tangible fixed assets, M is real intermediate inputs, and IOF and $COOP$ are two binary variables that equal, respectively, 1 and 0 (0 and 1) if the firm is an IOF (a cooperative). This specification implies that we allow the production function of cooperatives and IOFs to differ with respect to the intercept (measured by β_4), the marginal product of labour (measured by $\beta_5 - \beta_1$), the marginal product of capital (measured by $\beta_6 - \beta_2$) and the marginal product of materials (measured by $\beta_7 - \beta_3$). Allowing for such a flexibility is in line with most of the agency-based arguments for why cooperatives and IOFs might differ in terms of productive efficiency, which are related to incentive effects that might be embodied in the production factors of the two organizational forms.

Among the other control variables, WF is a vector of three variables that control for the workforce composition of each firm. It includes the share of full-time workers, the share of unpaid workers and the gender composition of the workforce. Furthermore, OFA is a vector of five indicator variables used to control whether the firm provides training, performs R&D activities, is a start-up, or is engaged in international trade through imports or exports. We control for market power by including the variable HHI, which is the Herfindahl-Hirschman index of market concentration defined at the five-digit level of economic activity classification in each year. We also add a dummy variable (EA) indicating the economic activity (based on the 13 industries defined in the previous section), and another indicator variable, REG, that is equal to one if the firm is located in a specific region defined at NUTS 2 of Portugal. Finally, we include a firm-fixed effect (a_i) and a year-fixed effect (v_t). Given the wide scope of our analysis, using data from all economic sectors, we convert all financial variables to real terms (Prices = 2012) using deflators defined according to three broadly homogeneous economic sectors: agriculture, manufacturing and services (source: AMECO).

We estimate our production function using two different estimation strategies. As a benchmark, we use a random-effects model (GLS) applied to our three-year unbalanced panel sample. The

[24] As a robustness check, we also estimate a translog production function (see Section 6.1.1).

Breusch and Pagan Lagrangian multiplier test for random effects clearly rejects OLS estimation, and the presence of the time invariant $COOP$ variable does not allow us to perform a fixed-effects estimation of Eq. (1).[25] Thus, we present results from GLS estimations.

However, there are two sources of potential bias in the results derived from the random-effects model. First, there is an endogeneity issue related to a potential simultaneity of input and output level decisions. Second, there might be some unobserved firm characteristics that are correlated with the choice of being organised as a cooperative or as an IOF. In order to deal with these potential problems, and similarly to Fakhfakh et al. (2012), we also present results using a System-GMM estimator, which is our most preferred empirical strategy. Although our productivity estimates are based on the 2010-2012 period, most of the variables in our data are available for the period 2004-2012, which allows us to use lagged variables as instruments and therefore perform System-GMM estimations.[26]

The System-GMM estimator is an extended version of the Generalized Method of Moments (GMM) of Arellano and Bond (1991) that combines lagged values of variables as instruments for the first-differenced equations with equations in levels with lagged variables in differences as instruments (Arellano and Bover, 1995). Like the GMM estimator, the System-GMM estimator is sufficiently flexible to account for the endogeneity of inputs and for a possible correlation between unobserved firm characteristics and organizational form that affects output.[27] However, because the System-GMM estimator exploits additional moment conditions inherent in adopting a system of equations in differences *and* in levels, it also allows us to recover the effect of the time-invariant $COOP$ variable, which is crucial to our analysis.

Our System-GMM estimations are derived using the following procedure. We eliminate the firm-fixed effect in the equations in differences using orthogonal deviations instead of a first-difference transformation. We choose orthogonal deviations in order to minimise the gap effect in our short and unbalanced panel.[28] The interactions with the three inputs for cooperatives and IOFs, and variables regarding workforce composition (shares of full-time workers, upaid workers and males) and firm attributes (training, R&D, exports, imports) are all treated as endogenous variables. We use two and longer lags of their levels as instruments for the orthogonal deviation equation and

[25] In our data, there are no firms that change their ownership structure from cooperative to IOF or vice versa.

[26] One important exception is K, which is only available from 2010, implying that only the 2012 observations of this variable is instrumented in the System-GMM estimations.

[27] See Syverson (2011) for a further discussion of the endogeneity problem associated with the estimation of production functions.

[28] Roodman (2009) gives several advises on how to optimally implement the difference and system-GMM estimators.

lagged first differences as instruments for the level equation.[29] Following Jones (2007), we treat $COOP$ as a pre-determined variable.[30] We use first and longer lags for the transformed equation and lag 0 of the instrumenting variable in differences for the levels equation.[31] The remaining variables (firm birth, market concentration and year) are considered to be exogenous. In order to test the validity of the instruments used and to support the approach used, we report the Hansen statistic. Finally, we report statistics that are robust to heteroskedasticity and serial correlation, using a two-step GMM estimation procedure, following the correction proposed by Windmeijer (2005).

6 Results

Our results are presented in two stages. First, we show the results from estimation of Eq. (1) using all firms in our sample. This gives us an estimate of the aggregate productivity differences between cooperative and IOF. We then proceed by estimating Eq. (1) at industry level, using the industry classification detailed in Section 4, in order to explore how productivity differences between cooperatives and IOFs are distributed across different industries. At both stages of the analysis, we will present several extensions and robustness checks regarding sample selection, specification of the production function, time frame of the analysis, and variable definitions. In each case considered, we present results from both GLS and System-GMM estimations.

6.1 Aggregate productivity differences

Estimation results for different variants of Eq. (1), using the whole sample of firms, are presented in Table 2. The GLS estimates are reported in Columns 1-4. The estimates in Column 1 are based on a version of Eq. (1) that includes only the three inputs in addition to industry-, region- and time-fixed effects. In subsequent columns, we show similar estimates when more controls are cumulatively added to the model, such as workforce composition (Column 2), firm attributes on training, R&D, start-up, and imports/exports (Column 3), and information on market concentration (Column 4). Finally, the estimates based on System-GMM (with all controls included) are presented in Column

[29] Usually we use lags 2 to 4, but in some instances we adjust the initial and longest lags in order to pass the Hansen test .

[30] The Difference-in-Hansen test validates the instruments used for this variable.

[31] Usually we use lags 1 to 3, but in some instances we adjust the longest lag in order to pass the Hansen test .

5.[32] Table 2 also reports p-values indicating whether each of the coefficients associated with the three inputs are significantly different for the two types of firms, and whether these three coefficients and the intercept of the production function are jointly different.

[Table 2 here]

There are significant differences between the results based on the two different empirical approaches. The GLS estimations indicate that cooperatives and IOFs use significantly different production technologies, and that these differences are related to differences in the intercept (which is lower for cooperatives) and in the marginal products of both labour (which is lower for cooperatives) and capital (which is higher for cooperatives). The size and significance of the estimated coefficients, and their differences across the two groups of firms, are fairly consistent across the four different specifications of the model (Columns 1-4). The estimated input parameters are also stable across different specifications.

For the GLS estimations, the remaining coefficients appear with the expected sign and are all statistically significant. Output increases (decreases) with the share of full-time (unpaid) workers, and is also higher in firms that provide training and engage in R&D. Involvement in international trade, in particular exports, is also associated with higher output. This accords with the well-known empirical findings that exporters tend to be among the most productive firms.[33] Firms are also less productive in their first year of activity and tend to be more productive when operating in more concentrated industries. Finally, there also appears to be a small productivity advantage associated with a higher share of male workers, but the statistical significance of this relationship is relatively weak.

When we use the System-GMM approach, the estimated coefficients are different in magnitude (compared to the GLS estimates) but still economically meaningful. However, the estimated technological differences between cooperatives and IOFs vanish to a large extent when using the System-GMM approach. Although the p-value of 0.14 is not very high, we cannot, based on the

[32] In the System-GMM estimations, the Hansen test (p-value = 0.146) does not reject the validity of the overall instruments used (84), and the Difference-in-Hansen test (p-value = 0.919) validates the instruments used for $COOP$ as a pre-determined variable.

[33] See, e.g., Wagner (2007) for a survey of the empirical literature on the relationship between exports and productivity.

System-GMM estimations, statistically reject the hypothesis that cooperatives and IOFs use similar technologies.

6.1.1 Are cooperatives more productive than IOFs?

When we estimate a production function where we allow the technology to differ between cooperatives and IOFs along several different dimensions, we cannot conclude directly from the estimated coefficients in Table 2 whether cooperatives are more or less efficient than their investor-owned counterparts. Put differently, our flexible formulation of the production function given by Eq. (1) implies that we cannot measure differences in total factor productivity by a single coefficient. We therefore follow the approach of Fakhfakh et al. (2012) and compare the predicted output of cooperatives and IOFs using, in turn, each of the two sets of estimated parameters. In other words, we keep the estimated technology constant and calculate whether cooperatives (IOFs), with their respective input use, will produce more or less with their own technology compared with the technology of IOFs (cooperatives). This approach gives us two sets of estimates of potential differences in productive efficiency between the two categories of firms.

Based on the full sample of firms, the predicted outputs of each type of firm, when using each of the two estimated technologies, are given in the first row (based on GLS estimates) and second row (based on System-GMM estimates) in Table 3 below. For cooperatives, each value reported in the column labelled "Coop technology" is the predicted output, given the actual input use of cooperatives, based on the estimated production function for cooperatives. On the other hand, each value reported in the column labelled "IOF technology" is the predicted output, again given the actual input use of cooperatives, based on the estimated production function of IOFs. The difference between these predicted outputs (reported in the column labelled "Diff") can then be interpreted as the *predicted output gain* for the 'average' cooperative firm of using its own technology instead of the technology of the 'average' investor-owned firm, when the input use is kept constant (at the actual level). The interpretation of the reported values in the columns referring to IOFs is obviously equivalent.

For estimates based on GLS, the reported figures based on the overall sample show a very clear and consistent picture. For a given input use, cooperatives would increase output by adopting the technology of IOFs, and, vice versa, IOFs would reduce output by adopting the technology of cooperatives. These differences are highly statistically significant and also of quite similar magnitude. In other words, cooperatives use, on average, a less efficient technology than investor-owned firms. Notice also that the estimated productivity differentials are of considerable magnitude. For example, our GLS estimates indicate that, on average, a cooperative firm could increase its output by almost 60% (without using more inputs) by replacing its technology with an 'IOF technology'.[34]

The estimates based on System-GMM paint a roughly similar picture, although they do not allow us draw conclusions with the same degree of confidence. The sign of the productivity differentials, which go in the same direction as the differentials based on GLS estimates, are actually of a larger magnitude, but with a lower degree of statistical significance. The predicted output loss of IOFs if they adopt the technology of cooperatives is (weakly) statistically significant, whereas the predicted output gain of cooperatives if they adopt the technology of IOFs is not statistically significant, though the p-value of 0.15 is not that high.

[Table 3 here]

Overall, our estimates of aggregate productivity differences between cooperatives and IOFs suggest that cooperatives are (on average) less productive, but the confidence with which we can draw this conclusion depends somewhat on the chosen empirical approach.

6.1.2 Robustness and extensions

In Table 3 we also show the results of a series of robustness checks and extensions, in each case reporting estimates from both empirical strategies (GLS and System-GMM).[35] These alternative estimations are based on the following criteria:

(i) Value added. As an alternative to estimating real gross output, we estimate real value added, which implies that $Materials$ is excluded as an independent variable in Eq. (1).[36] The resulting productivity estimates are reported in the 3rd and 4th rows of Table 3.

[34] The estimated productivity differential of 0.465 is, in percentage terms, equivalent to

$$e^{0.465} - 1 = 0.59201.$$

[35] In Table 3 we only report results from the counterfactual exercise of substituting the technology used by each category of firms, based on the estimated production functions for each firm type. The underlying estimated production function coefficients, for each of the robustness checks and extensions, are reported in Tables A1 and A2 in the Appendix.

[36] Notice that this variable is not constructed but given directly by the data set and available for a somewhat larger number of firms.

(ii) Narrower definition of IOFs. In the main analysis we have defined IOFs as a residual category consisting of all firms that are not classified as cooperatives in the data. As an alternative, we also adopt a narrower definition, where a firm is classified as an IOF if, in the data, it is listed as a private or public liability company.[37] This implies a reduction in the number of firms by around 9%. Results based on this alternative definition of IOFs are presented in the 5th and 6th rows of Table 3.

(iii) Using only data from 2010 and 2011. Our main results are based on a sample in which the data on organizational form – cooperative or IOF – is imputed for the year 2012, where we assume that the organizational form remains unchanged from 2011 to 2012 and where firms created in 2012 are classified as IOFs. Under these assumptions, if cooperatives created in 2012 are less productive than IOFs, our productivity differential estimates reported in the first and second rows of Table 3 are likely to be downward biased. The 7th and 8th rows of Table 3 report estimates based on data only from 2010 and 2011.

(iv) Data cleaning. The main sample is constructed by removing industries in which the incidence of cooperatives is less than 2%. To check whether our results are sensitive to this data cleaning decision, we report, in the 9th and 10th rows of Table 3, the productivity estimates based on a sample where firms in all industries that include at least one cooperative firm are included.

(v) Firm size. We also explore if and how productivity differences between cooperatives and IOFs depend on firm size. We do this by splitting the sample into two categories: micro firms (defined as firms with less than ten workers) and larger firms (with a workforce of at least ten workers). Estimates based on these two subsamples are given in Rows 11-12 and 13-14, respectively, in Table 3.

(vi) Translog production function. Our benchmark results are based on estimations of Cobb-Douglas production functions. As a robustness check, we also estimate the following Transcendental

[37] These categories correspond to "sociedade por quotas", "sociedade anónima", "sociedade em comandita" and "sociedade em nome colectivo".

Logarithmic ('translog') production function:

$$
\begin{aligned}
\ln Y_{it} &= \beta_0 + \left[\begin{array}{c} \beta_1 \ln L_{it} + \beta_2 \ln K_{it} + \beta_3 \ln M_{it} \\ +\gamma_1 (\ln L_{it})^2 + \gamma_2 (\ln K_{it})^2 + \gamma_3 (\ln M_{it})^2 \\ +\gamma_4 (\ln L_{it}) (\ln K_{it}) + \gamma_5 (\ln L_{it}) (\ln M_{it}) + \gamma_6 (\ln K_{it}) (\ln M_{it}) \end{array}\right] IOF \\
&+ \left[\begin{array}{c} \beta_4 + \beta_5 \ln L_{it} + \beta_6 \ln K_{it} + \beta_7 \ln M_{it} \\ +\gamma_7 (\ln L_{it})^2 + \gamma_8 (\ln K_{it})^2 + \gamma_9 (\ln M_{it})^2 \\ +\gamma_{10} (\ln L_{it}) (\ln K_{it}) + \gamma_{11} (\ln L_{it}) (\ln M_{it}) + \gamma_{12} (\ln K_{it}) (\ln M_{it}) \end{array}\right] COOP \qquad (2) \\
&+\beta_8 WF_{it} + \beta_9 OFA_{it} + \beta_{10} HHI + \sum_{j=1}^{12} \theta_{ij} EA + \sum_{k=1}^{6} \phi_{ik} REG_{ik} + a_i + \nu_t + \epsilon_{it}.
\end{aligned}
$$

The results based on this alternative technology specification are reported in Rows 15-16 of Table 3.

(vii) Labour-managed firms. A weakness of our data is that we are not able to identify the exact type of cooperative with certainty. However, by applying an imputation procedure used by Monteiro and Stewart (2015), we are able to identify one particular type of cooperatives, namely labour-managed firms (LMFs), with a reasonable degree of approximation.[38] This allows us to investigate whether this particular type of cooperative is different from the overall population of cooperatives in terms of productive efficiency. Rows 17-18 in Table 3 report productivity estimates based on a sample where we restrict the type of cooperatives to LMFs.

(viii) Sample size. Because of the relatively low incidence of cooperatives in most industries, the samples of cooperatives and IOFs used in the main analysis are of very different size. In order to check if this has any impact on our results, we redo the analysis using a smaller sample of IOFs that are more comparable to the sample of cooperatives. We perform two different versions of this robustness check, using two different sample selection criteria. In the first version, we draw a representative sample of 8% of the IOFs in each year based on firm size and industrial activity. In the second version, we select a number of IOFs that is identical to the number of cooperatives, for each year, using a matching procedure based on firm size, industry and region. The results are shown in Rows 19-22 in Table 3.

(iv) Longer panel. Another weakness of our analysis is that we have a short panel, due to

[38] The imputation procedure itself is identical to the one used by Stewart and Monteiro (2015), and we refer to that paper for a detailed description the procedure. The additional step performed in the present study is that we also convert the previous classification of economic activities (CAE REV 2.1) to the one used in the present data set (CAE REV 3).

the fact that firm type (cooperative or IOF) is only identified in the years 2010 and 2011. Our main analysis is based on a panel where we extrapolate firm classification one year forward, to 2012. However, we have also redone the analysis by using a longer panel where we extend the extrapolation to (and including) the year 2015. Unfortunately, the Hansen test did not validate the instruments used in the System-GMM estimation and we therefore report only the results based on GLS (in the last row of Table 3).[39]

The overall picture emanating from Table 3 is that the System-GMM results tend to be more sensitive to different specifications and sample selection criteria than the results based on GLS estimations. The GLS results are remarkably stable across all the different alternatives considered in Table 3. Not only are all the estimated productivity differentials in the same direction, and all estimated with a very high degree of precision, but the magnitudes of these productivity differentials are also highly robust to all robustness checks and extensions. Interestingly, the largest difference from the benchmark results occurs when the sample of cooperatives is restricted to LMFs, where it appears that the disadvantage in productive efficiency is even higher for LMFs than for the average cooperative firm.

Although the results based on System-GMM are less robust to different specifications and sample selection criteria, there is still some consistency across the different alternatives. In almost all cases, the estimated productivity differentials have the same sign and are consistent with the GLS results. The only exceptions are when we estimate value added and when we consider only larger firms, but the estimated differences in productivity are very far from being statistically significant in these cases.

However, although the System-GMM approach yields productivity differentials of mostly the same sign as the GLS estimates, these differentials are estimated with a considerably lower degree of precision in System-GMM. There are two notable exceptions though. First, the estimated productivity differentials turn highly statistically significant when restricting the sample to the years 2010 and 2011, even if this makes the panel even shorter. This might indicate that our extrapolation strategy is not innocuous. If cooperatives are really less productive than IOFs, and since cooperatives that enter the market after 2011 will be (wrongly) classified as IOFs, extrapolation of firm type for years beyond 2011 will lead to an underestimation of the true productivity differential between cooperatives and IOFs. The fact that the magnitude of the productivity differentials

[39] With the longer panel, the System-GMM approach produced valid instruments at industry level. These results are presented in Section 6.2.

based on GLS estimates decreases monotonically with the length of the extrapolation period, might suggest that such a bias exists.[40]

Second, the results from the System-GMM approach seem to depend crucially on firm size. More specifically, there are statistically significant productivity differences between cooperatives and IOFs, with the former being less productive than the latter, if we only consider firms with less than 10 employees ('micro firms'). For larger firms, the estimated productivity differences (using System-GMM) are much smaller in magnitude and far from being statistically significant.

6.2 Industry-specific productivity differences

In order to investigate if and how productivity differences between cooperatives and IOFs differ across industries, we make separate estimations for each of the 13 industries specified in Section 4. We initially make this industry decomposition by estimating Eq. (1) using the our main sample. Subsequently, we show equivalent results for three of the robustness checks detailed in the previous sub-sample, (i) estimating the translog function specified in Eq. (2) instead of the Cobb-Douglas function specified in Eq. (1), (ii) estimating Eq. (1) on a sub-sample of LMFs, and (iii) estimating Eq. (1) on a longer panel where we extrapolate the classification of firm type until the year 2015. As before, we report both GLS and System-GMM estimates.[41]

6.2.1 Benchmark estimations

Industry-specific productivity differentials based on estimations of Eq. (1) using our main sample are reported in Table 4. For the GLS estimates, we find that the results from the aggregate analysis are partly or fully confirmed also at industry level. In 8 out of the 13 industries, cooperatives are found to be significantly and consistently less productive then IOFs, in the sense that cooperatives would significantly increase their output if they adopted the IOF technology, whereas IOFs would significantly reduce their outputs if adopting the cooperative technology.[42] These productivity differentials are particularly large in industries such as *Agriculture and other*, *Electricity, water and construction*, and *Social work*. In the remaining industries the estimated productivity differentials

[40] The estimates reported in Table 3 show that, with the GLS approach, the estimated productivity differentials are largest for the case of no extrapolation and smallest for the case of extrapolation until 2015 (long panel).

[41] For each industry we only show the estimated productivity differentials for the two counterfactual scenarios, as in Table 3. The underlying regression outputs of the estimated production functions are too space consuming to display in the paper and are therefore are available upon request.

[42] These industries are *Agriculture and other; Food; Electricity, water and construction; Wholesale trade; Retail trade; Education; Social work; Artistic and cultural associations.*

go in the same direction (implying that cooperatives are less productive), but where these estimates are either not significant or not consistently significant.[43]

[Table 4 here]

It is also interesting to note that, based on the GLS estimates, the underperformance of cooperatives is consistent across very different sectors, with a very different representation of cooperatives in terms of *type*. For example, supplier-owned cooperatives is the dominant type of cooperative in industries such as *Agriculture and other*, and *Artistic and cultural associations*, whereas, in *Electricity, water and construction*, consumer cooperatives, worker cooperatives and supplier-owned cooperatives coexist.[44] The fact that the estimated relative inefficiency of cooperatives is negative and large in all these industries suggest that the productive inefficiency of cooperatives does not seem to depend particularly on the type of cooperative. This is consistent with our theoretical discussion in Section 2 where we show that many of the agency-based arguments regarding the productive (in)efficiency of cooperatives are general in nature, and do not exclusively apply to a particular type of cooperative.

When using the System-GMM approach, the results are considerably less clear-cut. In two industries – *Retail trade* and *Social work* – cooperatives are found to be significantly less productive than IOFs in a consistent way. However, for the other industries, the estimated productivity differentials tend not to be statistically significant. In 5 of these remaining industries, the sign of the estimates suggest that cooperatives are less productive, whereas, in another 5 industries, the opposite appears to be the case.

Summing up, the results in Table 4 reveal that, in all cases where the estimated differences in productivity are statistically significant in both of the counterfactual scenarios, cooperatives are found to be less productive than IOFs. However, these cases are much more prevalent for the GLS-estimates than for estimates based on System-GMM.

[43] The phrase 'not consistently significant' refers to cases where cooperatives would significantly increase their output by adopting the IOF technology but IOFs would not significantly reduce their output by adopting the cooperative technology, or *vice versa*.

[44] See Monteiro and Stewart (2015) for an overview of how different types of cooperatives are distributed across industries in Portugal.

6.2.2 Translog production function

Table 5 reports estimated productivity differentials based on estimations of Eq. (2). For the GLS-estimates, the results are very similar to the results in Table 4 based on estimations of Eq. (1). Again, in 8 out of 13 industries cooperatives are found to be significantly (and consistently) less productive than IOFs. Furthermore, comparing these eight industries with the eight industries for which a similar result was found in Table 4, seven of them are common. Thus, the productivity estimates based on GLS appear to be highly robust to the specification of a translog (instead of a Cobb-Douglas) production function.

[Table 5 here]

As before, the estimation results based on System-GMM are less clear-cut. However, it appears that the translog specification makes these results less ambiguous and qualitatively more in line with the GLS-results. In 6 out of 13 industries, the estimated productivity differentials are statistically significant in one of the two counterfactual scenarios, and in each case with a sign indicating that cooperatives are less productive.[45] Furthermore, in 5 of these 6 industries, the non-significant productivity differential (in the other counterfactual scenario) has a sign that is consistent with the statistically significant differential. Four of these industries overlap with the set of industries in which the GLS-estimates yield significant (and consistent) productivity differences. There are also a further three industries in which the System-GMM approach yields productivity differentials whose sign suggest, in a consistent way, that cooperatives are less productive, although these estimates are not statistically significant.

6.2.3 Labour-managed firms

We have also estimated industry-specific productivity differentials, based on Eq. (1), on a sub-sample of firms in which the cooperatives are restricted to LMFs (following the previously described identification procedure). In Table 6 we report the results for the 6 industries in which there are enough LMFs to perform the estimations. The results based on the GLS estimations show much the same pattern as the results based on equivalent estimations using the main sample. In three industries – *Agriculture and other*, *Textile, clothing and other,* and *Education* – LMFs are significantly and consistently less productive than IOFs. In two further industries – *Electricity,*

[45] These industries are *Agriculture and other; Electricity, water and construction; Storage, hotels, media and other; Social work; Artistic and cultural associations; Other associations.*

water and construction, and *Wholesale trade* – LMFs are significantly less productive according to one of the two counterfactual scenarios. Only in *Other manufacturing* do we find no significant evidence of any productivity differences between LMFs and IOFs.

In 5 of the 6 industries where we find significant evidence of underperformance by LMFs, we find similar evidence of underperformance by cooperatives more generally (cf. Table 4). One interesting exception is *Textile, clothing and other*, where we find strong evidence that LMFs are less productive when restricting the sample to only include this type of cooperative, but where we do not find significant productivity differences in the larger sample including all cooperatives.

[Table 6 here]

However, our results based on System-GMM are much less conclusive, as we find no significant evidence that LMFs are underperforming in terms of productive efficiency in any of the six industries. The closest we get to any indication of underperformance is in *Agriculture and other*, where the sign of the productivity differentials in the two counterfactual scenarios suggest that LMFs are less productive, and where the p-values of these estimates are relatively low (0.12 and 0.15). In the other five industries, all estimated productivity differentials based on System-GMM are far from being statistically significant.

6.2.4 Longer panel

Finally, we also estimate Eq. (1) at industry level using a longer panel where we, based on information in the years 2010-2011, extrapolate firm classifications for the years 2012-2015. The resulting estimated productivity differentials are shown in Table 7.

[Table 7 here]

The results based on GLS-estimates are very robust to this extrapolation in order to obtain a longer panel. We find statistically significant and consistent underperformance of cooperatives in the same 8 industries as we do when using the shorter panel (cf. Table 4).

Once more, however, the results based on System-GMM-estimates are very inconclusive. In fact, we find significant (though not consistent) evidence of cooperatives being more productive in two industries and less productive in a third industry. But mostly, the estimated productivity differentials are not statistically significant. As previously mentioned, this might be partly explained by the (biased) noise introduced by the extrapolation strategy.

7 Summary and discussion

In this paper we have empirically analysed if cooperatives are superior to investor-owned firms (IOFs) in terms of productive efficiency. We have done so by using panel data methods to estimate productivity differentials between the two categories of firms, based on three years (2010-2012) of firm-level data covering a wide range of Portuguese industries. Estimations from our benchmark random-effects model suggest that cooperatives are, on average, considerably less productive than their investor-owned counterparts, and this result applies to a majority of the thirteen industries considered. Our results based on GLS-estimations are also remarkably stable and consistent across a wide set of robustness checks and extensions.

However, our estimates based on the preferred System-GMM-approach are both less conclusive and considerably more sensitive to different specifications and sample selection criteria. At aggregate level, the System-GMM-results are more consistent with the GLS-results for micro firms and when using a sample consisting only of observations from 2010 and 2011, in which we have information about firm type. At industry level, the highest degree of correspondence between the two sets of results occurs when we use a translog production function. The less conclusive nature of the System-GMM results indicates that we should interpret the GLS-results with some caution, and we cannot conclusively state that cooperatives are generally less productive than IOFs. Regardless of which empirical approach we use, though, we find no consistent and statistically significant evidence that cooperatives are *more* productive than IOFs in any industry.

For the cases where we find indications of underperformance of cooperatives, what are the potential explanations? In general, productivity differences might be related to unobserved (and therefore unmeasured) input characteristics that differ systematically between cooperatives and IOFs. One possibility is that there are differences in the quality of labour used by the two types of firms. The lack of information in our data on worker characteristics such as schooling implies that the estimated productivity differences might partially be explained by differences in labour quality. However, this hypothesis is not supported by available information from other sources, which suggest that cooperatives tend to employ, on average, more educated workers than IOFs (Monteiro and Stewart, 2015).

Productivity differences might also be partly explained by differences in the degree of competition, which affects output prices as well as the competitive pressure to be productive. Indeed, the descriptive statistics show that cooperatives tend to operative, on average, in less competitive industries. However, since we control for the degree of industry concentration (by the HHI) in the regressions, we should in principle be able to neutralise such effects, at least the effects that are directly related to competitive pressure. Nevertheless, we cannot rule out the possibility that cooperatives in some cases face below-average output prices in less competitive markets, and that some of our productivity results can partly be explained by this.

Another potential source of productivity differences is differences in the characteristics of the manager, such as managerial talent and effort, which is arguably the most important unmeasured input to production, and which is generally recognised as a potentially important explanation for productivity differences across otherwise similar firms (Syverson, 2011). To the extent that we find indications of cooperatives being relatively inefficient, potential explanations related to managerial practices are in line with the theoretical discussion presented in Section 2, which points to agency problems between owners and managers as a main source of productive inefficiency in cooperatives. There is also some empirical evidence that exit rates of high-ability individuals tend to be higher in cooperatives, which might contribute to a relative lack of managerial talent (Abramitzky, 2008; Burdin, 2016). However, without the data needed for further investigation, it is not possible to elevate this explanation beyond the status of qualified speculation.

Finally, we would also like to relate our results to those of Monteiro and Stewart (2015), who find that cooperatives in Portugal tend to have a higher probability of survival than their investor-owned counterparts. This finding is seemingly at odds with any indications of cooperatives being less efficient than IOFs. However, once we account for heterogeneity across industries and firm characteristics, the results in the present study are not particularly inconsistent with the survival results in Monteiro and Stewart (2015).

For example, Monteiro and Stewart find that the significantly higher survival rate of cooperatives only applies for manufacturing firms, whereas, in a sector like agriculture, the survival rate of cooperatives is significantly *lower* than for IOFs. It is interesting to note that, in our industry-level analysis, it is precisely in the manufacturing industries that the evidence for cooperatives being less productive is weakest. In the four industries that comprise the manufacturing sector (*Food*; *Beverages*; *Textile, clothing and other*; and *Other manufacturing*), a significant and consistent finding of relative inefficiency of cooperatives is found only in the *Food* industry, and only for the GLS estimates. With the System-GMM approach, we do not find significant productivity differences in any of these industries.

Furthermore, when splitting the data according to firm size, Monteiro and Stewart find that the higher survival rate of cooperatives only applies to large firms (with more than 50 employees). Again, it is interesting to note that, in our aggregate analysis, the strongest evidence of inefficient cooperatives appears for small firms (less than 10 employees), where the estimated productivity differentials are significant and consistent under both estimation methods (GLS and System-GMM).

On a more general note, though, it is also worth emphasizing that, since cooperatives and IOFs have different objectives, the decision of whether or not to exit the industry might be based on quite different considerations for these two types of firms, which in turn makes it harder to relate differences in survival probability directly to differences in productive efficiency.

Appendix

The results from the estimations of Eq. (1), based on the main sample and for each of the robustness checks and extensions listed in Section 6.1.2, are shown in Table A1 (GLS estimations) and Table A2 (System-GMM estimations). Regression results from the estimation of Eq. (2) are shown in Table A3.

[Tables A1-A3 here]

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Figure 1: Distribution of cooperatives across industries

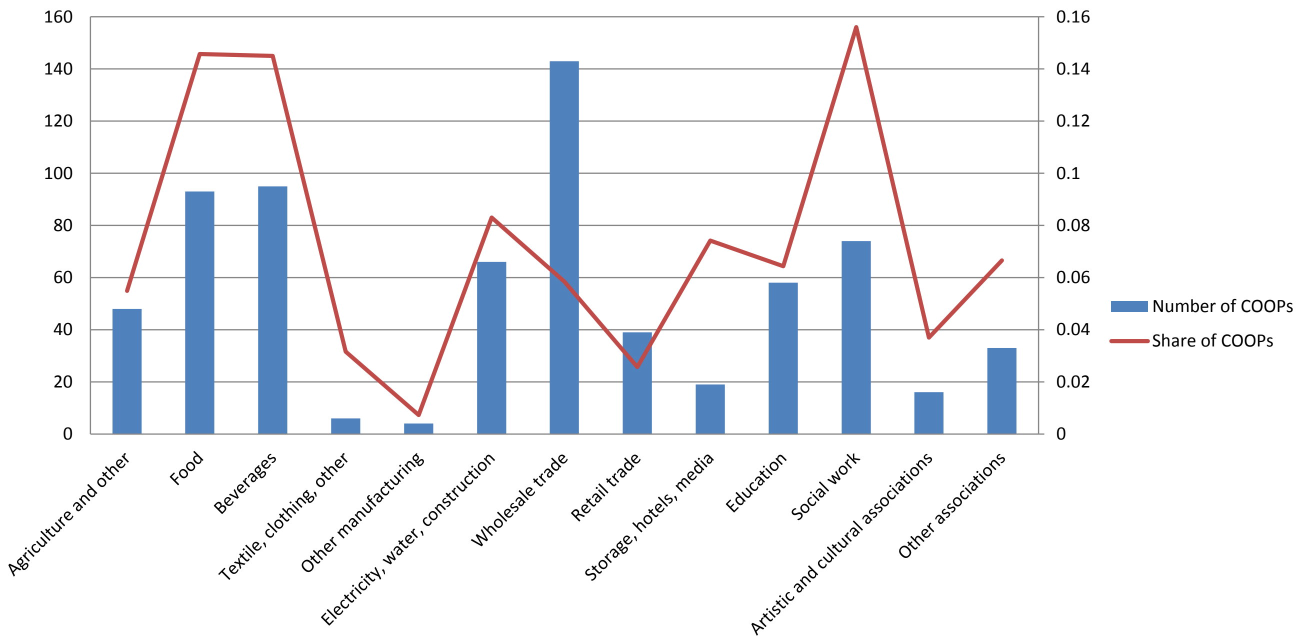

Table 1 - Variable means by type of firm, 2010-12

	Cooperatives	IOFs	Difference[a)]
ln real gross output	12.227	11.878	0.349 ***
Inputs			
ln L	2.168	1.540	0.628 ***
ln K	12.284	10.886	1.398 ***
ln M	11.920	11.403	0.517 ***
ln(K/L)	10.115	9.346	0.769 ***
Workforce composition			
Full-time workers (%)	0.924	0.955	-0.031 ***
Unpaid workers (%)	0.088	0.087	0.001
Males (%)	0.518	0.568	-0.050 ***
Other firm attributes			
Training indicator	0.128	0.122	0.006
R&D indicator	0.011	0.008	0.003
Firm birth indicator	0.004	0.042	-0.038 ***
Export indicator	0.191	0.209	-0.018
Import indicator	0.256	0.323	-0.067 ***
Market concentration			
HHI	0.110	0.082	0.028 ***
Location			
North	0.324	0.321	0.003
Algarve	0.037	0.040	-0.003
Center	0.252	0.258	-0.006
Lisbon	0.122	0.211	-0.089 ***
Alentejo	0.182	0.132	0.050 ***
Azores	0.072	0.018	0.054 ***
Madeira	0.011	0.019	-0.008 *
# observations	1,697	22,879	
# firms	685	10,164	

Notes: *** and * indicate that the mean difference between cooperatives and non-cooperatives is statistically significant at the 1% and 10% levels, respectively. a) Standard errors are clustered at firm level.

Table 2 - Cobb-Douglas regression results, log(output) as dependent variable

	GLS				System-GMM
	(1)	(2)	(3)	(4)	(5)
COOP	-1.486***	-1.417***	-1.504***	-1.499***	0.414
	(0.327)	(0.328)	(0.326)	(0.326)	(2.344)
Inputs - IOFs					
ln L	0.584***	0.572***	0.553***	0.553***	0.284***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.091)
ln K	0.145***	0.144***	0.138***	0.138***	0.111** *
	(0.006)	(0.006)	(0.006)	(0.006)	(0.059)
ln M	0.335***	0.331***	0.317***	0.317***	0.582***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.066)
Inputs - COOPs					
ln L	0.448***	0.441***	0.428***	0.428***	0.419**
	(0.039)	(0.039)	(0.038)	(0.038)	(0.204)
ln K	0.229***	0.225***	0.221***	0.221***	0.201
	(0.033)	(0.033)	(0.032)	(0.032)	(0.127)
ln M	0.356***	0.350***	0.342***	0.342***	0.329*
	(0.010)	(0.010)	(0.010)	(0.010)	(0.169)
Workforce composition					
Full-time workers (%)		0.178***	0.182***	0.183***	-0.233
		(0.048)	(0.048)	(0.048)	(0.581)
Unpaid workers (%)		-0.282***	-0.267***	-0.267***	0.088
		(0.046)	(0.045)	(0.045)	(0.336)
Males (%)		0.051*	0.053*	0.052*	-1.611**
		(0.029)	(0.029)	(0.029)	(0.640)
Other firm attributes					
Training indicator			0.083***	0.084***	0.262
			(0.015)	(0.015)	(0.194)
R&D indicator			0.114**	0.113**	0.167
			(0.045)	(0.045)	(0.171)
Firm birth indicator			-0.442***	-0.442***	-0.338***
			(0.032)	(0.032)	(0.073)
Export indicator			0.176***	0.175***	0.178**
			(0.016)	(0.016)	(0.087)
Import indicator			0.075***	0.075***	-0.001
			(0.013)	(0.013)	(0.092)
Market concentration (HHI)				0.168**	0.530***
				(0.086)	(0.192)
Industry + region + year FE	Y	Y	Y	Y	Y
P-value for differences in technology:					
L	0.001	0.001	0.002	0.002	0.528
K	0.011	0.015	0.012	0.013	0.505
M	0.436	0.483	0.347	0.349	0.172
Total	0.000	0.000	0.000	0.000	0.141
# observations	24,576	24,576	24,576	24,576	24,576
# firms	10,849	10,849	10,849	10,849	10,849
Chi^2	25,699	26,845	30,426	30,479	11,850

Notes: Significance level at which the null hypothesis is rejected: ***, 1%; **, 5%, and *, 10%. The standard errors are clustered at firm level.

Table 3 - Aggregate productivity differentials: Main sample and robustness checks

		Cooperatives					IOFs					Overall		
Sample	Methodology	Coop technology	IOF technology	Diff.		p-value	Coop technology	IOF technology	Diff.		p-value	# obser.	# firms	p-value[a)]
Main sample	GLS	12.230	12.695	-0.466	***	0.000	11.344	11.859	0.515	***	0.000	24,576	10,849	0.000
	System-GMM	11.681	12.878	-1.197	NS	0.150	10.645	11.922	1.277	*	0.063			0.141
Value added	GLS	10.971	11.375	-0.405	***	0.000	10.489	10.925	0.435	***	0.000	32,024	14,507	0.000
	System-GMM	13.585	11.181	2.404	NS	0.692	13.794	10.749	-3.046	NS	0.610			0.424
Narrower definition of IOF	GLS	12.230	12.704	-0.474	***	0.000	11.358	11.891	0.532	***	0.000	22,790	9,858	0.000
	System-GMM	11.136	13.263	-2.127	NS	0.107	10.499	12.000	1.501	NS	0.174			0.053
Only 2010 and 2011	GLS	12.175	12.684	-0.510	***	0.000	11.307	11.862	0.555	***	0.000	17,073	10,119	0.000
	System-GMM	11.367	13.094	-1.727	***	0.009	10.432	11.932	1.501	***	0.007			0.053
Data cleaning	GLS	11.988	12.393	-0.405	***	0.000	11.040	11.536	0.497	***	0.000	214,826	93,182	0.000
	System-GMM	11.681	12.948	-1.267	NS	0.139	9.852	11.551	1.699	*	0.051			0.032
Micro firms	GLS	11.042	11.465	-0.423	***	0.000	10.674	11.115	0.441	***	0.000	17,888	8,435	0.000
	System-GMM	10.750	11.658	-0.908	**	0.025	10.178	11.153	0.975	**	0.044			0.112
Other firms	GLS	13.595	14.121	-0.526	***	0.000	13.394	14.005	0.610	***	0.000	6,688	2,848	0.000
	System-GMM	14.169	14.103	0.066	NS	0.918	14.118	13.948	-0.170	NS	0.802			0.084
Translog specification	GLS	12.229	12.760	-0.531	***	0.000	11.320	11.857	0.537	***	0.000	24,576	10,849	0.000
	System-GMM	11.779	12.822	-1.043	NS	0.463	10.181	11.911	1.730	NS	0.257			0.486
LMFs	GLS	11.609	12.346	-0.736	***	0.000	11.052	11.788	0.735	***	0.000	5,918	2,768	0.000
	System-GMM	12.099	12.988	-0.890	NS	0.612	11.558	11.782	0.224	NS	0.900			0.133
Sample size	GLS	12.235	12.709	-0.474	***	0.000	11.283	11.807	0.523	***	0.000	3,522	2,389	0.000
Representative	System-GMM	12.457	12.704	-0.247	NS	0.601	11.618	11.600	-0.018	NS	0.971			0.934
Matching	GLS	12.237	12.629	-0.392	***	0.000	12.018	12.439	0.420	***	0.000	3,394	2,022	0.000
	System-GMM	12.226	12.731	-0.505	NS	0.321	11.975	12.468	0.493	NS	0.320			0.674
Extrapolation 2010-2015	GLS	12.330	12.727	-0.397	***	0.000	11.408	11.842	0.434	***	0.000	43,155	13,088	0.000

Notes: Significance level at which the null hypothesis is rejected: ***, 1%; **, 5%, and *, 10%. [a)] P-value related to overall difference in technology between cooperatives and IOFs.

Table 4 - Productivity differentials by industry

Industry	Methodology	Cooperatives: Coop technology	Cooperatives: IOF technology	Cooperatives: Diff.		Cooperatives: p-value	IOFs: Coop technology	IOFs: IOF technology	IOFs: Diff.		IOFs: p-value	Overall: # obser.	Overall: # firms	Overall: p-value[a)]
Agriculture and other	GLS	10.484	11.303	-0.819	***	0.000	10.291	11.161	0.870	***	0.000	2,111	923	0.000
	System-GMM	11.114	11.369	-0.255	NS	0.827	10.942	11.164	0.222	NS	0.833			0.984
Food	GLS	12.186	12.447	-0.261	***	0.005	12.562	12.924	0.363	***	0.000	1,692	731	0.001
	System-GMM	12.978	12.357	0.621	NS	0.529	13.042	12.860	-0.183	NS	0.860			0.153
Beverages	GLS	13.766	13.852	-0.086	NS	0.292	12.260	12.471	0.211	*	0.067	1,960	750	0.000
	System-GMM	14.554	13.843	0.711	NS	0.392	12.849	12.428	-0.420	NS	0.586			0.875
Textile, clothing and other	GLS	8.900	9.783	-0.883	NS	0.173	12.135	12.254	0.119	NS	0.845	474	196	0.002
	System-GMM	5.588	10.262	-4.675	NS	0.111	21.034	12.327	-8.707	NS	0.408			0.007
Other manufacturing	GLS	10.526	10.840	-0.314	NS	0.458	12.196	12.607	0.411	NS	0.417	1,306	523	0.443
	System-GMM	11.517	9.759	1.758	NS	0.226	12.662	12.630	-0.032	NS	0.985			0.439
Electricity, water and construction	GLS	11.829	12.761	-0.932	***	0.000	11.509	12.361	0.852	***	0.003	1,571	858	0.000
	System-GMM	12.071	12.968	-0.897	NS	0.437	12.111	12.429	0.318	NS	0.794			0.106
Wholesale trade	GLS	12.717	13.111	-0.395	***	0.000	11.382	11.660	0.278	***	0.005	6,398	2,585	0.000
	System-GMM	12.552	13.224	-0.671	NS	0.337	10.987	11.683	0.696	NS	0.247			0.013
Retail trade	GLS	11.522	11.898	-0.376	***	0.000	11.512	11.848	0.336	***	0.000	3,865	1,557	0.000
	System-GMM	11.459	11.868	-0.409	***	0.006	11.385	11.858	0.473	**	0.016			0.011
Storage, hotels, media and other	GLS	11.583	11.798	-0.214	NS	0.153	11.776	12.251	0.476	**	0.011	573	275	0.004
	System-GMM	11.593	11.775	-0.182	NS	0.800	12.056	12.259	0.203	NS	0.795			0.297
Education	GLS	12.743	13.216	-0.473	**	0.019	10.873	11.524	0.651	***	0.010	1,978	959	0.001
	System-GMM	15.625	12.849	2.776	NS	0.192	13.968	11.347	-2.621	NS	0.239			0.004
Social work	GLS	11.823	12.992	-1.169	***	0.000	10.710	11.474	0.764	***	0.000	850	547	0.000
	System-GMM	11.416	12.868	-1.452	***	0.005	10.312	11.554	1.243	**	0.039			0.009
Artistic and cultural associations	GLS	10.498	11.214	-0.716	***	0.001	10.664	11.151	0.487	*	0.062	860	447	0.000
	System-GMM	10.295	11.210	-0.915	NS	0.264	10.679	11.211	0.533	NS	0.584			0.304
Other associations	GLS	11.214	11.096	0.118	NS	0.573	10.769	11.177	0.408	*	0.073	1,118	528	0.008
	System-GMM	12.356	11.029	1.327	*	0.099	11.315	11.189	-0.126	NS	0.900			0.027

Notes: Significance level at which the null hypothesis is rejected: ***, 1%; **, 5%, and *, 10%. [a)] P-value related to overall difference in technology between cooperatives and IOFs.

Table 5 - Productivity differentials by industry, based on estimates of a translog production function

		Cooperatives					IOFs					Overall		
Industry	Methodology	Coop technology	IOF technology	Diff.		p-value	Coop technology	IOF technology	Diff.		p-value	# obser.	# firms	p-value[a)]
Agriculture and other	GLS	10.501	11.440	-0.940	***	0.000	10.455	11.162	0.707	***	0.000	2,111	923	0.000
	System-GMM	10.629	11.508	-0.879	NS	0.105	10.596	11.177	0.581	*	0.053			0.457
Food	GLS	12.181	12.512	-0.331	***	0.000	12.565	12.927	0.362	***	0.001	1,692	731	0.000
	System-GMM	12.730	12.563	0.167	NS	0.826	12.974	12.915	-0.058	NS	0.933			0.339
Beverages	GLS	13.758	13.920	-0.162	**	0.016	12.280	12.471	0.191	*	0.083	1,960	750	0.000
	System-GMM	13.986	13.853	0.133	NS	0.764	12.422	12.549	0.126	NS	0.722	1,960	750	0.182
Textile, clothing and other	GLS	8.923	10.050	-1.127	***	0.000	18.887	12.124	-6.763	*	0.080	474	196	0.000
	System-GMM	7.612	10.204	-2.592	NS	0.679	29.565	12.372	-17.193	NS	0.738			0.000
Other manufacturing	GLS	10.438	11.430	-0.992	n.d.		44.471	12.609	-31.863	n.d		1,306	523	0.000
	System-GMM	10.526	10.840	-0.314	NS	0.458	12.196	12.607	0.411	NS	0.417			0.443
Electricity, water and construction	GLS	11.845	12.755	-0.910	***	0.000	11.708	12.358	0.651	*	0.067	1,571	858	0.000
	System-GMM	11.585	13.188	-1.603	**	0.019	12.062	12.456	0.394	NS	0.652			0.093
Wholesale trade	GLS	12.712	13.179	-0.467	***	0.000	11.304	11.660	0.356	***	0.001	6,398	2,585	0.000
	System-GMM	12.723	13.105	-0.382	NS	0.285	11.117	11.672	0.554	NS	0.295			0.289
Retail trade	GLS	11.525	11.888	-0.363	***	0.000	11.404	11.847	0.444	***	0.000	3,865	1,557	0.000
	System-GMM	11.551	11.840	-0.289	NS	0.167	11.928	11.858	-0.070	NS	0.897			0.040
Storage, hotels, media and other	GLS	11.550	11.763	-0.212	NS	0.133	11.959	12.248	0.289	NS	0.352	573	275	0.000
	System-GMM	10.670	11.842	-1.173	NS	0.215	8.848	12.322	3.475	*	0.081			0.286
Education	GLS	12.703	13.288	-0.585	***	0.004	11.165	11.526	0.361	NS	0.160	1,978	959	0.000
	System-GMM	12.907	13.198	-0.291	NS	0.701	10.496	11.551	1.055	NS	0.175			0.126
Social work	GLS	11.822	13.144	-1.322	***	0.000	10.781	11.479	0.699	***	0.000	850	547	0.000
	System-GMM	11.516	12.540	-1.024	**	0.014	10.252	11.585	1.333	NS	0.168			0.021
Artistic and cultural associations	GLS	10.573	11.132	-0.559	***	0.001	10.628	11.161	0.533	***	0.000	860	447	0.000
	System-GMM	9.928	11.480	-1.552	NS	0.574	8.717	11.231	2.514	*	0.062			0.000
Other associations	GLS	11.163	11.170	-0.007	NS	0.971	11.490	11.193	-0.297	NS	0.215	1,118	528	0.008
	System-GMM	11.214	11.096	0.118	NS	0.573	10.769	11.177	0.408	*	0.073			0.008

Notes: Significance level at which the null hypothesis is rejected: ***, 1%; **, 5%, and *, 10%. [a)] P-value related to overall difference in technology between cooperatives and IOFs. "n.d." indicates that the variance matrix of the estimated coefficients is highly singular, thus not allowing to compute the p-value of the restriction imposed.

Table 6 - Productivity differentials by industry: LMFs

Industry	Methodology	LMFs: LMF technology	LMFs: IOF technology	LMFs: Diff.		LMFs: p-value	IOFs: LMF technology	IOFs: IOF technology	IOFs: Diff.		IOFs: p-value	Overall: # obser.	Overall: # firms	Overall: p-value[a)]
Agriculture and other	GLS	10.496	11.367	-0.871	***	0.000	10.202	11.174	0.971	***	0.000	1,031	469	0.000
	System-GMM	8.292	11.531	-3.239	NS	0.124	8.412	11.346	2.935	NS	0.152			0.369
Textile, clothing and other	GLS	9.629	10.427	-0.798	***	0.000	10.253	12.291	2.038	***	0.000	450	187	0.000
	System-GMM	7.421	10.940	-3.519	NS	0.621	11.159	12.364	1.205	NS	0.950			0.052
Other manufacturing	GLS	10.526	10.841	-0.315	NS	0.456	12.193	12.607	0.414	NS	0.413	1,306	523	0.442
	System-GMM	10.296	10.784	-0.488	NS	0.883	11.424	12.637	1.213	NS	0.750			0.339
Electricity, water and construction	GLS	10.421	11.043	-0.622	NS	0.664	11.209	11.831	0.622	*	0.091	1,323	768	0.000
	System-GMM	9.503	14.989	-5.486	NS	0.280	11.064	11.972	0.908	NS	0.646			0.129
Wholesale trade	GLS	13.072	13.492	-0.419	**	0.016	11.648	11.454	-0.194	NS	0.270	6,398	2,585	0.000
	System-GMM	13.127	14.452	-1.325	NS	0.623	11.825	11.614	-0.210	NS	0.944			0.683
Education	GLS	11.465	12.355	-0.890	***	0.000	10.717	11.113	0.396	*	0.071	1,167	544	0.000
	System-GMM	15.300	12.502	2.798	NS	0.703	13.409	10.945	-2.464	NS	0.773			0.546

Notes: Significance level at which the null hypothesis is rejected: ***, 1%; **, 5%, and *, 10%. [a)] P-value related to overall difference in technology between LMFs and IOFs.

Table 7 - Productivity differential by industry: Long panel

Industry	Methodology	Cooperatives					IOFs					Overall		
		Coop technology	IOF technology	Diff.		p-value	Coop technology	IOF technology	Diff.		p-value	# obser.	# firms	p-value[a)]
Agriculture and other	GLS	10.615	11.349	-0.735	***	0.000	10.194	11.093	0.899	***	0.000	3,648	1,223	0.000
	System-GMM	10.887	11.370	-0.483	NS	0.670	10.433	11.134	0.701	NS	0.474			0.314
Food	GLS	12.250	12.475	-0.225	**	0.015	12.567	12.921	0.354	***	0.001	3,236	872	0.013
	System-GMM	13.490	12.265	1.226	NS	0.239	13.585	12.831	-0.754	NS	0.475			0.098
Beverages	GLS	13.868	13.854	0.014	NS	0.859	12.357	12.345	-0.013	NS	0.930	4,243	969	0.067
	System-GMM	15.156	13.735	1.421	*	0.066	13.230	12.249	-0.981	NS	0.143			0.436
Textile, clothing and other	GLS	9.188	10.038	-0.850	NS	0.142	10.705	12.303	1.598	NS	0.346	785	222	0.335
	System-GMM	10.124	9.411	0.712	NS	0.544	15.063	12.285	-2.778	NS	0.613			0.983
Other manufacturing	GLS	10.424	10.673	-0.249	NS	0.567	12.356	12.735	0.379	NS	0.398	2,640	677	0.006
	System-GMM	13.148	7.712	5.436	***	0.002	16.622	12.763	-3.858	NS	0.154			0.000
Electricity, water and construction	GLS	11.725	12.512	-0.787	***	0.000	11.533	12.369	0.836	***	0.001	2,461	985	0.000
	System-GMM	11.063	12.561	-1.498	NS	0.246	10.888	12.504	1.616	NS	0.231			0.001
Wholesale trade	GLS	12.758	13.095	-0.337	***	0.000	11.343	11.641	0.298	***	0.001	12,732	3,242	0.000
	System-GMM	12.972	13.667	-0.695	NS	0.264	11.255	11.654	0.399	NS	0.564			0.262
Retail trade	GLS	11.594	11.993	-0.399	***	0.000	11.303	11.692	0.389	***	0.000	4,599	1,647	0.000
	System-GMM	11.593	12.087	-0.494	NS	0.124	11.084	11.712	0.628	NS	0.277			0.069
Storage, hotels, media and other	GLS	13.526	16.724	-3.198	**	0.018	11.933	12.198	0.265	NS	0.248	919	339	0.015
	System-GMM	17.838	16.919	0.919	NS	0.836	11.381	12.253	0.872	**	0.039			0.013
Education	GLS	12.977	13.396	-0.419	**	0.039	11.136	11.772	0.635	***	0.004	2,470	1,021	0.000
	System-GMM	12.230	13.216	-0.985	NS	0.177	11.382	11.704	0.322	NS	0.708			0.000
Social work	GLS	11.879	12.896	-1.017	***	0.000	10.911	11.504	0.593	***	0.001	1,671	653	0.000
	System-GMM	11.553	12.751	-1.198	NS	0.113	11.133	11.562	0.428	NS	0.680			0.000
Artistic and cultural associations	GLS	10.266	11.062	-0.796	***	0.001	10.267	11.107	0.840	*	0.002	1,529	597	0.011
	System-GMM	10.607	11.137	-0.530	NS	0.382	10.622	11.153	0.531	NS	0.564			0.139
Other associations	GLS	11.265	10.997	0.268	NS	0.169	11.000	10.988	-0.012	NS	0.950	2,222	723	0.066
	System-GMM	11.673	10.827	0.846	NS	0.395	11.398	11.032	-0.366	NS	0.667			0.318

Notes: Significance level at which the null hypothesis is rejected: ***, 1%; **, 5%, and *, 10%. [a)] P-value related to overall difference in technology between cooperatives and IOFs.

Table A1 - Cobb-Douglas regression results (GLS): Robustness and extensions

	Value added	Narrower definition of IOFs	Using 2010 and 2011	Data cleaning	Micro firms
	(1)	(2)	(3)	(4)	(5)
COOP	-0.544**	-1.585***	1.757***	-1.580***	-0.867**
	(0.271)	(0.329)	(0.331)	(0.262)	(0.425)
Inputs - IOFs					
ln L	0.829***	0.562***	0.564***	0.581***	0.491***
	(0.011)	(0.016)	(0.015)	(0.004)	(0.018)
ln K	0.180***	0.124***	0.137***	0.104***	0.138***
	(0.006)	(0.006)	(0.007)	(0.002)	(0.007)
ln M	-	0.327***	0.318***	0.321***	0.324***
		(0.011)	(0.010)	(0.003)	(0.011)
Inputs - COOPs					
ln L	0.908***	0.426***	0.413***	0.359***	-0.080
	(0.043)	(0.038)	(0.038)	(0.034)	(0.079)
ln K	0.180***	0.222***	0.221***	0.221***	0.019
	(0.027)	(0.033)	(0.032)	(0.024)	(0.035)
ln M	-	0.344***	0.362***	0.339***	0.029
		(0.026)	(0.010)	(0.023)	(0.032)
Workforce composition					
Full-time workers (%)	0.324***	0.173***	0.150***	0.162***	0.152***
	(0.045)	(0.049)	(0.056)	(0.017)	(0.051)
Unpaid workers (%)	-0.525***	-0.313***	-0.257***	-0.358***	-0.281***
	(0.036)	(0.046)	(0.051)	(0.015)	(0.043)
Males (%)	0.065**	0.070**	0.054*	0.065***	0.039
	(0.028)	(0.029)	(0.033)	(0.009)	(0.030)
Other firm attributes					
Training indicator	0.151***	0.081***	0.120***	0.082***	0.061**
	(0.016)	(0.015)	(0.018)	(0.005)	(0.026)
R&D indicator	0.108**	0.101**	0.144**	0.099***	0.077
	(0.053)	(0.046)	(0.057)	(0.020)	(0.161)
Firm birth indicator	-0.491***	-0.438***	-0.488***	-0.417***	-0.435***
	(0.035)	(0.037)	(0.041)	(0.010)	(0.035)
Export indicator	0.165***	0.172***	0.181***	0.172***	0.204***
	(0.018)	(0.016)	(0.018)	(0.006)	(0.020)
Import indicator	0.140***	0.071***	0.087***	0.090***	0.071***
	(0.015)	(0.013)	(0.016)	(0.005)	(0.017)
Market concentration (HHI)	0.091	0.156*	0.201**	-0.098**	0.180*
	(0.077)	(0.085)	(0.090)	(0.045)	(0.099)
Industry + region + year FE	Y	Y	Y	Y	Y
P-value for differences in technology:					
L	0.069	0.001	0.000	0.000	0.312
K	0.995	0.003	0.014	0.000	0.592
M	-	0.524	0.098	0.420	0.372
Total	0.000	0.000	0.000	0.000	0.000
# observations	32,024	22,790	17073	214,826	17,888
# firms	14,507	9,858	10,119	93,182	8,435
Chi^2	34,507	28,553	32,833	227,160	8,350

Notes: Significance level at which the null hypothesis is rejected: ***, 1%; **, 5%, and *, 10%. The standard errors are clustered at firm level.

Table A1 (cont.) - Cobb-Douglas regression results (GLS): Robustness and extensions

	Other firms	LMFs	Sample size		Extrapolation 2010-2015
	(6)	(7)	(8)	(9)	(10)
COOP	-3.281***	-1.158*	-1.375***	-1.512***	-1.660***
	(0.618)	(0.618)	(0.361)	(0.379)	(0.407)
Inputs - IOFs					
ln L	0.669***	0.618***	0.562***	0.665***	0.537***
	(0.028)	(0.028)	(0.035)	(0.036)	(0.012)
ln K	0.114***	0.116***	0.119***	0.110***	0.137***
	(0.012)	(0.012)	(0.015)	(0.017)	(0.0045
ln M	0.247***	0.278***	0.347***	0.285***	0.314***
	(0.022)	(0.018)	(0.021)	(0.026)	(0.008)
Inputs - COOPs					
ln L	-0.164**	0.484***	0.414***	0.471***	0.354***
	(0.084)	(0.081)	(0.039)	(0.041)	(0.044)
ln K	0.247***	0.141**	0.213***	0.203***	0.232***
	(0.070)	(0.057)	(0.031)	(0.033)	(0.030)
ln M	-0.002	0.311***	0.352***	0.318***	0.354***
	(0.052)	(0.049)	(0.027)	(0.029)	(0.036)
Labour composition					
Full-time workers (%)	0.328***	0.185**	0.078	0.133	0.146***
	(0.107)	(0.090)	(0.105)	(0.108)	(0.037)
Unpaid workers (%)	-0.815*	-0.322***	-0.381***	-0.250**	-0.341***
	(0.450)	(0.081)	(0.102)	(0.116)	(0.036)
Males (%)	0.168***	0.002	0.074	0.110	0.055**
	(0.054)	-0.058	(0.069)	(0.081)	(0.025)
Other firm attributes					
Training indicator	0.067***	0.06	0.170***	0.152***	0.075***
	(0.015)	-0.038	(0.041)	(0.036)	(0.011)
R&D indicator	0.057*	0.041	0.4581**	0.402**	0.073**
	(0.030)	-0.061	(0.214)	(0.198)	-0.031
Firm birth indicator	-0.781***	-0.425***	-0.276**	-0.271*	-0.407***
	(0.102)	(0.074)	(0.109)	(0.142)	(0.023)
Export indicator	0.060**	0.229***	0.215***	0.146***	0.138***
	(0.023)	-0.041	(0.045)	(0.045)	-0.012
Import indicator	0.051***	0.075**	0.067*	0.018	0.083***
	(0.018)	-0.035	(0.035)	(0.037)	-0.01
Market concentration (HHI)	0.165	-0.167	0.129	-0.154	-0.43
	(0.164)	(0.639)	(0.137)	(0.143)	-0.057
Industry + region + year FE	Y	Y	Y	Y	Y
P-value for differences in technology:					
L	0.050	0.110	0.000	0.000	0.000
K	0.000	0.673	0.006	0.010	0.002
M	0.962	0.507	0.827	0.278	0.247
Total	0.000	0.000	0.000	0.000	0.000
# observations	6,688	5,918	3,522	3,394	43,155
# firms	2,848	2,768	2,401	2,022	13,088
Chi^2	10,886	6,421	10,400	8,919	32,192

Notes: Significance level at which the null hypothesis is rejected: ***, 1%; **, 5%, and *, 10%. The standard errors are clustered at firm level.

Table A2 - Cobb-Douglas regression results (System-GMM): Robustness and extensions

	Value added	Narrower definition of IOFs	Using 2010 and 2011	Data cleaning	Micro firms
	(1)	(2)	(3)	(4)	(5)
COOP	11.389	5.816	1.381	-3.402	0.717
	(7.596)	(4.857)	(2.211)	(4.364)	(2.718)
Inputs - IOFs					
ln L	0.487	-0.232	0.463***	0.052	0.415***
	(0.304)	(0.335)	(0.124)	(0.079)	(0.126)
ln K	0.664**	0.946***	0.412***	0.774***	0.104**
	(0.276)	(0.301)	(0.082)	(0.124)	(0.045)
ln M	-	0.315**	0.391***	0.391***	0.576***
		(0.146)	(0.070)	(0.043)	(0.069)
Inputs - COOPs					
ln L	0.397	0.259	0.457**	0.607**	0.346
	(0.324)	(0.0396)	(0.186)	(0.290)	(0.289)
ln K	-0.104	0.308	0.301**	0.799**	0.228
	(0.537)	(0.287)	(0.150)	(0.332)	(0.217)
ln M	-	0.217	0.245	0.454***	0.306**
		(0.284)	(0.172)	(0.168)	(0.148)
Workforce composition					
Full-time workers (%)	1.036	1.327	-0.289	0.365	-0.540
	(1.051)	(0.944)	(0.590)	(0.277)	(0.515)
Unpaid workers (%)	-0.404	0.820	0.361	0.037	0.008
	(0.640)	(0.941)	(0.386)	(0.230)	(0.328)
Males (%)	-0.501	1.113	-0.096	0.610	-0.944*
	(3.822)	-1.632	(0.771)	(0.827)	(0.569)
Other firm attributes					
Training indicator	-0.241	0.209	-0.360	-0.439***	0.175
	-0.541	(0.578)	(0.238)	(0.153)	(0.201)
R&D indicator	0.973	-1.119	0.368	-0.771	-0.506
	-1.126	(1.231)	(0.274)	(0.960)	(0.474)
Firm birth indicator	-0.136	-0.260*	-0.284***	-0.193***	-0.318***
	(0.197)	(0.148)	(0.064)	(0.036)	(0.070)
Export indicator	0.040	0.174	0.046	-0.036	0.256**
	(0.150)	(0.216)	(0.082)	(0.096)	(0.103)
Import indicator	0.107	-0.256	-0.170**	-0.494***	-0.038
	(0.390)	(0.240)	(0.085)	(0.087)	(0.108)
Market concentration (HHI)	0.262	0.509*	0.443***	-0.543***	0.483***
	(0.440)	-0.303	(0.167)	(0.170)	(0.179)
Industry + region + year FE	Y	Y	Y	Y	Y
P-value for differences in technology:					
L	0.784	0.281	0.978	0.060	0.825
K	0.231	0.069	0.516	0.941	0.583
M	-	0.774	0.431	0.720	0.095
Total	0.424	0.053	0.053	0.032	0.112
# observations	32,024	22,790	17,073	214,826	17,888
# firms	14,507	9,858	10,119	93,182	8,435
# instruments	47	48	80	59	84
Hansen test	0.330	0.860	0.094	0.283	0.450
Chi^2	4,830	3,283	10,181	33,481	2,454

Notes: Significance level at which the null hypothesis is rejected: ***, 1%; **, 5%, and *, 10%. The standard errors are clustered at firm level.

Table A2 (cont.) - Cobb-Douglas regression results (System-GMM): Robustness and extensions

	Other firms	LMFs	Sample size	
	(6)	(7)	(8)	(9)
COOP	-2.674	7.953**	1.311	0.429
	(2.995)	(3.836)	(2.888)	(2.446)
Inputs - IOFs				
ln L	0.701***	0.284	0.586*	0.184
	(0.159)	(0.314)	(0.278)	(0.334)
ln K	0.127*	0.715**	0.282*	0.281*
	(0.077)	(0.283)	(0.149)	(0.159)
ln M	0.414***	0.367**	0.335**	0.452*
	(0.097)	(0.164)	(0.135)	(0.244)
Inputs - COOPs				
ln L	0.167	0.892*	0.464**	0.552***
	(0.312)	(0.526)	(0.203)	(0.184)
ln K	0.241	-0.005	0.150	0.233**
	(0.161)	(0.235)	(0.129)	(0.106)
ln M	0.648***	0.222	0.362***	0.357***
	(0.144)	(0.341)	(0.119)	(0.107)
Workforce composition				
Full-time workers (%)	-0.431	1.324	-0.442	0.703
	(1.163)	(1.098)	(0.576)	(0.766)
Unpaid workers (%)	0.360	0.583	-1.103*	0.266
	(1.841)	(1.459)	(0.580)	(0.622)
Males (%)	0.911	-0.385	0.149	-0.551
	(0.811)	(1.459)	(0.872)	(0.881)
Other firm attributes				
Training indicator	0.178	-0.996	0.346	0.298
	(0.111)	(0.987)	(0.448)	(0.279)
R&D indicator	-0.202*	0.291	0.992	0.710
	(0.113)	(0.577)	(0.911)	(0.652)
Firm birth indicator	-0.419***	-0.050	0.069	-0.149
	(0.121)	(0.210)	(0.307)	(0.273)
Export indicator	0.054	0.102	0.336	0.172
	(0.099)	(0.414)	(0.315)	(0.187)
Import indicator	-0.105	-0.888*	-0.200	0.077
	(0.077)	(0.494)	(0.250)	(0.170)
Market concentration (HHI)	-0.253	-1.556	-0.035	-0.003
	(0.297)	(1.378)	(0.217)	(0.257)
Industry + region + year FE	Y	Y	Y	Y
P-value for differences in technology:				
L	0.146	0.278	0.695	0.271
K	0.513	0.063	0.484	0.795
M	0.186	0.696	0.882	0.707
Total	0.084	0.133	0.934	0.674
# observations	6,688	5,918	3,522	3,394
# firms	2,848	2,768	2,410	2,022
# instruments	84	49	56	84
Hansen test	0.441	0.393	0.865	0.468
Chi^2	5,951	1,658	2,732	3,489

Notes: Significance level at which the null hypothesis is rejected: ***, 1%; **, 5%, and *, 10%. The standard errors are clustered at firm level.

Table A3 - Translog regression results

	GLS		System-GMM	
COOP	-1.639		20.300	
	(1.340)		(19.511)	
Inputs	**IOFs**	**COOPs**	**IOFs**	**COOPs**
ln L	0.994***	0.195	0.643	3.865
	(0.086)	(0.201)	(2.986)	(3.130)
ln K	0.087**	0.002	3.333***	-0.867
	(0.040)	(0.191)	(1.046)	(2.207)
ln M	-0.045	0.295***	-0.412	-1.024
	(0.041)	(0.123)	(0.772)	(1.809)
ln L2	0.048***	-0.028	0.206	0.05
	(0.009)	(0.026)	(0.301)	(0.307)
ln K2	0.011***	0.014*	-0.144**	0.065
	(0.002)	(0.008)	(0.063)	(0.118)
ln M2	0.030***	0.015***	0.047*	0.029
	(0.002)	(0.005)	(0.025)	(0.056)
ln L* ln K	-0.018**	0.054**	-0.001	-0.357
	(0.008)	(0.022)	(0.308)	(0.394)
ln M*ln K	-0.014***	-0.015	-0.014	0.038
	(0.003)	(0.010)	(0.088)	(0.153)
ln M*ln L	-0.043***	-0.034**	-0.062	0.086
	(0.006)	(0.017)	(0.094)	(0.217)
Workforce composition				
Full-time workers (%)	0.164***		0.952	
	(0.047)		(0.715)	
Unpaid workers (%)	-0.301***		1.006	
	(0.043)		(0.765)	
Males (%)	0.030		-2.182	
	(0.028)		(2.575)	
Other firm attributes				
Trainning indicator	0.060***		0.272	
	(0.014)		(0.496)	
R&D indicator	0.067*		-0.606	
	(0.041)		(0.508)	
Firm birth indicator	-0.387***		-0.457**	
	(0.031)		(0.222)	
Export indicator	0.147***		0.455**	
	(0.016)		(0.206)	
Import indicator	0.056***		0.149	
	(0.013)		(0.228)	
Market concentration (HHI)	0.181**		0.251	
	(0.082)		(0.442)	
Industry + region + year FE	Y		Y	
Differences in technology:				
L, L^2	0.000		0.266	
K, K^2	0.905		0.196	
M, M^2	0.013		0.865	
LK, MK, ML	0.005		0.664	
Total	0.000		0.486	

Notes: Significance level at which the null hypothesis is rejected: ***, 1%; **, 5%, and *, 10%. The standard errors are clustered at firm level.