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

Natália P. Monteiro† Odd Rune Straume‡

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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 total factor productivity between the two groups of firms. The results from our benchmark random-effects model show that cooperatives are significantly less productive, on average, than investor-owned firms. This conclusion is to a large extent confirmed by the results from System-GMM estimations. The lower productivity of cooperatives applies to a wide spectrum of industries. In six out of thirteen industries, cooperatives are outperformed by investor-owned firms in all empirical specifications considered, while there is no industry in which cooperatives are consistently found to be the more productive type of firm.

Keywords: Cooperatives; investor-owned firms; productive efficiency

JEL Classification: D24; J54; P12; P13

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†Department of Economics/NIPE, University of Minho. Email: n.monteiro@eeg.uminho.pt

‡Corresponding author. Department of Economics/NIPE, University of Minho, Campus de Gualtar, 4710-057 Braga, Portugal; and Department of Economics, University of Bergen, Norway. Email: o.r.straume@eeg.uminho.pt

1 Introduction

In this paper we document how two different forms of organizing production affects 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 estimation and System-GMM estimation, we estimate different variants of an augmented Cobb-Douglas production function and test for differences in total factor productivity between cooperatives and IOFs across 13 different industries, based on data from 2010-2012.

Our results are as striking as they are consistent. Under both estimation strategies, and in all the different empirical specifications considered, cooperatives are found to be signifi-

[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.

cantly less productive than IOFs, on average. The difference in productivity is also large in magnitude, with an average productivity differential across all industries of 50 to 60 percent, depending on the exact empirical specification. The underperformance of cooperatives applies to most industries and we are not able to identify any industry in which cooperatives are consistently more productive than their investor-owned counterparts. On the contrary, in seven out of thirteen 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'. Interestingly, this result applies to industries across which the share of different *types* of cooperatives (worker cooperatives, supplier cooperatives, consumer cooperatives) is known to be very different. This suggests that the productive efficiency of cooperatives versus IOFs is not particularly related to cooperative type, which is consistent with the fact that many of the theoretical arguments for the efficiency merits of cooperatives are relatively general in nature and do not apply exclusively to a particular type of cooperative.

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 and corresponding results. The paper is closed with a few concluding remarks in Section 6.

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

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

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).

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 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

[5] See Bontems and Fulton (2009) for a formal treatment of this argument.
[6] See, e.g., Nilsson (2001) for a further discussion.

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 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. 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. 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 sample of firms.[10] A recent and notable exception is Fakhfakh et al.

[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] 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

(2012) who study productivity differences between labour-managed firms and IOFs using a large and representative sample of French firms covering several industries.[11] Interestingly, and somewhat in contrast to the received literature, 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.[12] 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.

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.[13] 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, when interpreting our results, we 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

well relative to IOFs.

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

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

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

types. As we show in Section 5, there does not appear to be any such relation.

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.[14] 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. With these restrictions, and after some standard cleaning of the data, our final sample consists of 685 cooperatives and 10,164 IOFs.

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. 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', 'other manufacturing', 'retail trade' and 'artistic and cultural', where the share of cooperatives is less than 5%.[15] 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

[14] No firm changed the organisational form between 2010 and 2011, which suggests that extrapolation to 2012 is innocuous. As a robustness check, we also perform the analysis only with data from 2010 and 2011.

[15] 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.

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.[16]

[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.[17]

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 Barlett et al., 1992).

Regarding the other variables, the considerably lower birth rate of cooperatives relative to IOFs 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 (Barlett et al., 1992).

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

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

5 Empirical strategy and results

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

$$\begin{aligned} \ln(Output_{it}) &= \beta_0 + \beta_1 \ln(Labour_{it}) + \beta_2 \ln(Capital_{it}) + \beta_3 \ln(Materials_{it}) \\ &\quad + \beta_4 COOP + \beta_5 WF_{it} + \beta_6 OFA_{it} + \beta_7 HHI + \sum_{j=1}^{12} \theta_{ij} EA \\ &\quad + \sum_{k=1}^{6} \phi_{ik} REG_{ik} + a_i + \nu_t + \epsilon_{it}, \end{aligned} \tag{1}$$

where *Output* is real gross output, *Labour* is total employment, *Capital* is tangible fixed assets, $Materials$ is real intermediate inputs, and $COOP$ is a binary variable that equals one if the firm is a cooperative. 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).

5.1 Estimation strategies

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 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 (1).[18] 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 from System-GMM estimations. 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.

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.[19] 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.[20] The three inputs, the variables regarding workforce composition and the remaining attributes of the firm (LC and OFA, but excluding the indicator regarding firm start-up) are all treated as endogenous variables. Variables characterising the industry (such as HHI) and variables with little or no variability over time (such as $COOP$) are considered exogenous. We use two to four lags of their levels as instruments for the orthogonal deviation equation and lagged first differences as instruments for the level equation. The remaining explanatory variables of (1) are treated as being exogenous. In order to test the validity of the instruments used and to support the prefer-

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

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

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

ence for the System-GMM approach over the original difference-GMM, we report the Hansen and the difference-in-Hansen statistics. 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).

5.2 Results

We estimate total factor productivity of cooperatives versus IOFs under three different – and increasingly flexible – assumptions. First, we make the rather strong assumption that any productivity differential between the two organizational forms is common across all industries. This assumption will subsequently be relaxed when we estimate differences in total factor productivity for each industry separately. In both cases, it is assumed that the production function of cooperatives and IOFs potentially differ only with respect to the intercept. Under our final and most flexible assumption, we also allow for the possibility that cooperatives and IOFs have different production functions (i.e., that the input parameters (β_1, β_2 and β_3) of (1) are specific to the type of organizational form). In all three cases, we present results from both GLS and System-GMM estimations.

5.2.1 Common productivity differential across industries

Suppose that the productivity differential between cooperatives and IOFs is common for all economic sectors and can be captured by the single binary variable $COOP$. This implies that we constrain the parameters of (1) to be the same for both types of firms – cooperatives and IOFs – and across all industries. Under these assumptions, estimation results for different variants of (1) are presented in Table 2.

[Table 2 here]

In Column 1 we report GLS estimates when the model, apart from the dummy variable $COOP$, includes only the three inputs and the variables that capture the unobservable effect of industry, region and time. 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 and start-up (Column 3), information on imports/exports (Column 4), and information on market concentration (Column 5).

The main message that emerges from Table 2 is that, in contrast to the summary statistics of Table 1, cooperatives seem to be considerably less productive than their investor-owned counterparts, with a productivity differential of close to 50%. This result is fairly robust across all specifications. The estimated input parameters (β_1, β_2 and β_3) are also stable across different specifications. The remaining coefficients appear with the expected sign and are all statistically significant at the one percent level. 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.[21] 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.

[Table 3 here]

In Table 3 we report some robustness results using the same empirical strategy (GLS) and maintaining the assumption of a common aggregate productivity differential between cooperatives and IOFs that applies to all industries. In Column 1 we reports coefficient estimates of (1) when total productivity is alternatively measured by real *value-added* (instead of real gross output), which implies that $Materials$ is excluded as an independent variable in (1). The estimated productivity differential remains large (around 41%) and statistically significant. Notice that this variable is not constructed but given directly by the data set and available for a somewhat larger number of firms (compared to the sample size in Table 2).

Another robustness check is to explore if an how our results are affected by our definition of IOFs. So far we have defined IOFs as a residual category consisting of all firms that are not classified as cooperatives in the data. In Column 2 we report the estimated coefficients when we 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.[22] Whereas the number of firms drops by around 9%, the productivity differential between cooperatives and IOFs remains almost unchanged.

The results in Table 2 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 estimate reported in Table 2 is likely to be downward biased. In Column 3 of Table 3 we report coefficient estimates based on data from only 2010

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

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

and 2011, for which we have exact information about organizational form. The estimated coefficient for the $COOP$ variable provides some evidence for our above explained conjecture, since it gives a slightly higher estimate for the productivity differential between cooperatives and IOFs when only actual information on organizational form in 2010-2011 is used.

Finally, we 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). The results are presented in Columns 4 and 5 in Table 3 and reveal that the aggregate productivity differential is significant and large for both size categories, though somewhat smaller for micro firms.

We now turn to estimation results using the System-GMM approach, which, in principle, allows us to circumvent the notorious endogeneity problems associated with the estimation of production functions. The results from this estimation strategy, more elaborately explained above, are reported in Table 4, where Column 1 is the counterpart of Column 5 in Table 2, and Columns 2 and 3 are the counterparts of Columns 4 and 5 in Table 3.

[Table 4 here]

Interestingly, when controlling for endogeneity by using a System-GMM approach, the estimated difference in total factor productivity between the two organizational forms increases considerably, with cooperatives being, on average, 65% less productive than IOFs. Furthermore, the difference between micro firms and larger firms vanishes.

5.2.2 Industry-specific productivity differentials

We now relax the restriction of a common productivity differential across industries and run separate regressions of (1) for each of the 13 industries specified in Section 4. The results from these regressions are shown in Table 5, were we report both GLS and System-GMM estimates.

[Table 5 here]

The first general observation to make from the results in Table 5 is that, although there is considerable variation across industries, there is no industry in which cooperatives are found to be more productive than IOFs, regardless of whether the productivity differential is estimated by GLS or System-GMM. Focussing on the GLS estimates, the results in Table 5 reveal that cooperatives are significantly less productive than their investor-owned counterparts in 9 out of 13 industries (in the most general specification), with the negative productivity differential being particularly large in industries such as 'agriculture', 'electricity, water and construction', 'social work' and 'artistic and cultural associations'.

It is also interesting to note that 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 'artistic and cultural associations', whereas the vast majority of cooperatives in 'textile and clothing' are labour-managed firms. On the other hand, in 'electricity and construction', consumer cooperatives, worker cooperatives and supplier-owned cooperatives coexist.[23] The fact that the estimated productivity differential is negative and large in all these industries suggest that the productive inefficiency of cooperatives applies to all cooperative types. A similar argument can be made based on the industries in which cooperatives and IOFs are found to be equally productive. For example, cooperatives in 'beverages' and 'other associations' are predominantly supplier-owned cooperatives, whereas 'other manufacturing' and 'storage, hotels and media' have a significant presence of all types of cooperatives. Thus, whether cooperatives are equally or less productive than IOFs does not seem to depend particularly on the type of cooperative. This result 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.

The above described results are broadly confirmed by the estimated productivity differentials obtained from the System-GMM approach. Overall, the magnitude of the productivity differential changes little between the two empirical approaches, though some coefficients are less precisely estimated with System-GMM. The most important differences appear in the two industries 'textile and clothing' and 'artistic and cultural', where the coefficients are not statistically significantly different from zero.

5.2.3 Allowing for technology differences between cooperatives and IOFs

Whether estimating a single production function for the entire economy or separate production functions for each industry, we have so far assumed that cooperatives and IOFs have the same technology (apart from the production function having potentially different intercepts). However, most of the agency-based arguments for why cooperatives and IOFs might differ in terms of productive efficiency are related to incentive effects that might be embodied in the production factors of the two organizational forms. This implies that cooperatives and IOFs might simply have different technologies; i.e., their production functions might differ

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

beyond a difference in intercepts. In order to explore this possibility, we now estimate (1) for each industry, were we also allow the input parameters β_1, β_2 and β_3 to differ between cooperatives and IOFs.

When we estimate different production functions for cooperatives and IOFs, we can no longer measure differences in total factor productivity by a single coefficient. Instead, we 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).

The predicted outputs of each type of firm, when using each of the two estimated technologies, are given in Table 6 (based on GLS estimates) and Table 7 (based on System-GMM estimates). In each table, and for each of the two types of firms, the actual output is reported in the first column, whereas, in the second column, we show the predicted (counterfactual) output in case the firms (cooperatives or IOFs) use the same amount of each input, but adopt the technology of the other type of firms. A statistical comparison between these two results is obtained with a t-test and, in each table, a value displayed in *italics* indicate that output is (statistically significantly) larger when firms of a given type use their own technology.

[Table 6 here]

The overall picture that emerges from the GLS-estimates in Table 6 is very clear. The output of cooperatives is consistently lower than the predicted output if these firms would change the way they organise production by adopting the (estimated) technology of IOFs. And vice versa, for a given input use, IOFs consistently produce more with their own technology that what they would have done if they adopted the cooperative way of production. The only exception from this pattern is for 'other associations', where the cooperatives in this industry produce more with their own technology, although the difference is only weakly significant. Thus, when allowing for different technologies between the two organizational types, the previously presented results of IOFs outperforming cooperatives are very much confirmed. If anything, the results are stronger, since the relative inefficiency of cooperatives now applies to practically all industries.

[Table 7 here]

The System-GMM results (presented in Table 7) confirm to a large extent the results based on GLS estimations, although the picture is now slightly more mixed. IOFs perform significantly better with their own technology than with the cooperative technology in 10 out of 13 industries, whereas cooperatives perform significantly better with their own technology only in two industries: 'beverages' and 'other manufacturing'. In 8 out of 13 industries, cooperatives would perform significantly better if they adopted the way of production used by their investor-owned counterparts. Perfectly consistent results, in terms of symmetry, are obtained for 'agriculture', 'food', 'electricity, water and construction', 'retail trade', 'education', 'social work' and 'artistic and cultural associations'. In each of these seven industries, cooperatives (IOFs) would perform significantly better (worse) if they adopted the alternative technology. With the exception of 'artistic and cultural associations', this set of industries also corresponds perfectly to the set of industries in which IOFs have a significantly higher total factor productivity than cooperatives (based on System-GMM estimations) when the parameters of the production function (apart from the intercept) are constrained to be the same for the two types of firms (cf. Table 5). Given that the prevalence of different types of cooperatives is very different across these particular industries, these results serve as a further indication that productivity differences between cooperatives and IOFs are not systematically linked to a particular type of cooperative.

6 Concluding remarks

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 differences in total factor productivity 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 produce strong and consistent results. Cooperatives are, on average, considerably less productive than their investor-owned counterparts, and this result applies to a vast majority of the thirteen industries considered. These results are to a large extent confirmed when we estimate a System-GMM model to control for the endogeneity of the input and output variables.

Since we estimate several different specifications of two different empirical models, running separate regressions for each of thirteen different industries, it is not surprising that our results display some degree of variability across specifications and across industries. In fact, we think our results are surprisingly consistent, particularly across industries. We are able to identify six industries – 'agriculture', 'food', 'electricity, water and construction', 'retail trade', 'education' and 'social work' – where our results are perfectly consistent across all empirical specifications. In each of these industries, cooperatives would produce significantly more with their current use of inputs, if they operated as IOFs (i.e., if the cooperatives adopted the estimated production technology of IOFs). And *vice versa*, IOFs would produce significantly less with the same amount of inputs if they instead adopted the cooperative way of production. On the other hand, there is no industry were cooperatives are found to be consistently more productive than IOFs.

The consistency of our results across a wide range of industries is interesting, particularly since the predominant type of cooperative is known to be very different across these industries. This suggests that the underperformance of cooperatives is not particularly related to the type of cooperative (worker cooperative, supplier cooperative or consumer cooperative, for example), which is also consistent with the fact that several of the theoretical arguments for why cooperatives might be less productive than IOFs are rather general in nature and do not apply exclusively to a particular type of cooperative.

By way of conclusion, we must of course acknowledge that our analysis are not without weaknesses, which implies that some caution is needed when interpreting our results. Perhaps the main drawback is our short panel, with three years of data. Although the availability of some key variables for a longer time period (prior to 2010) enables us to perform System-GMM estimations based on the three-year panel, the fact that some of the productivity coefficients from these estimations are less precisely estimated can probably be attributed to the shortness of the panel. Ideally we would also like to have data on the type of cooperatives, although, as mentioned above, our results seem to give indirect evidence to the hypothesis that the productive inefficiency of cooperatives is not confined to a particular type of cooperative.

References

[1] Akridge, J.T., Hertel, T.W., 1992. Cooperative and investor-owned firm efficiency: a multiproduct analysis. Journal of Agricultural Cooperation, 7, 1–14.

[2] Arando, S., Gago, M., Jones, D., Kato, T., 2015. Efficiency in employee-owned enterprises: an econometric case study of Mondragon. Industrial and Labor Relations Review, 68, 398–425.

[3] Arellano, M., Bond, S., 1991. Some tests of specification for panel data: Monte Carlo evidence and application to employment equations. Review of Economic Studies, 58, 277–297.

[4] Arellano, M., Bover, O., 1995. Another look at the instrumental variable estimation of error-component models. Journal of Econometrics, 68, 29–51.

[5] Banerjee, A., Mookherjee, D., Munshi, K., Ray, D., 2001. Inequality, control rights and efficiency: a study of sugar cooperatives in Western Maharashtra. Journal of Political Economy, 109, 138–90.

[6] Barlett, W., Cable, J., Estrin, S., Jones, D., Smith, S., 1992. Labor-managed cooperatives and private firms in North Central Italy: an empirical comparison. Industrial and Labor Relations Review, 46, 103–118.

[7] Berman, K.V., Berman, M.D., 1989. An empirical test of the thoery of the labor-managed firm. Journal of Comparative Economics, 13, 281–300.

[8] Bontems, P., Fulton, M., 2009. Cooperatives, worker-owned enterprises, productivity and the international labor organization. Journal of Economic Behavior and Organization, 72, 322–343.

[9] Boyle, G., 2004. The economic efficiency of Irish dairy marketing co-operatives. Agribusiness, 20, 143–153.

[10] Carson, R., 1977. A theory of co-operatives. Canadian Journal of Economics, 10, 565–589.

[11] Cocolina, C.Q., 2016. The power of cooperation: Cooperatives Europe key figures 2015, Cooperatives Europe.

[12] Cook, M.L., 1995. The future of U.S. agricultural cooperatives: a neo-institutional approach. American Journal of Agricultural Economics, 77, 1153–1159.

[13] Cote, D., 1989. Firm efficiency and ownership structure: the case of the U.S. electric utilities using panel data. Annals of Public and Cooperative Economics, 60, 431–450.

[14] Defourny, J., 1992. Comparative measures of technical efficiency for five hundred French workers' cooperatives. Advances in the Economic Analysis of Participatory and Labor-Managed Firms, 4, 27–62.

[15] Doucouliagos, C., 1997. The comparative efficiency and productivity of labor-managed and capital-managed firms. Review of Radical Political Economics, 29, 45–69.

[16] Doucouliagos, C., Hone, P., 2000. The efficiency of the Australian dairy processing industry. Australian Journal of Agricultural and Resource Economics, 44, 423–438.

[17] Estrin, S., 1991. Some reflection on self-management, social choice, and reform in Eastern Europe. Journal of Comparative Economics, 15, 349–366.

[18] Estrin, S., Jones, D.C., 1992. The viability of employee-owned firms: evidence from France. Industrial and Labor Relations Review, 45, 323–338.

[19] Fakhfakh, F., Pérotin, V., Gago, M., 2012. Productivity, capital, and labor in labor-managed and conventional firms: an investigation on French data. Industrial and Labor Relations Review, 65, 847–879.

[20] Ferrier, G.D., Porter, P.K., 1991. The productive efficiency of U.S. milk processing co-operatives. Journal of Agricultural Economics, 42, 161–173.

[21] Ferrantino, M.J., Ferrier, G.D., Linvill, C.B., 1995. Organizational form and efficiency: evidence from Indian sugar manufacturing. Journal of Comparative Economics, 21, 29–53.

[22] George, D. A., 1982. Workers' co-operatives in Denmark. Managerial and Decision Economics, 3, 205–212.

[23] Hansmann, H., 1999. Cooperative firms in theory and practice. Finnish Journal of Business Economics, 4, 387–403.

[24] Harris, R., Siegel, D.S., Wright, M., 2005. Assessing the impact of management buy-outs on economic efficiency: plant-level evidence from the United Kingdom. Review of Economics and Statistics, 87, 148–153.

[25] Jones, D. C., 2007. The productive efficiency of Italian producer cooperatives: evidence from conventional and cooperative firms. In Sonja Novkovic and Vania Sena (eds.) *Advances in the Economic Analysis of Participatory and Labor-Managed Firms, Cooperative Firms in Global Markets: Incidence, Viability and Economic Performance*, Vol. 9, pp. 3–28. Oxford: Elsevier Science.

[26] Logue, J., Yates, J.S., 2006. Cooperatives, worker-owned enterprises, productivity and the international labor organization. Economic and Industrial Democracy, 27, 686–690.

[27] Monteiro, N., Stewart, G., 2015. Scale, scope and survival: a comparison of cooperative and capitalist modes of production. Review of Industrial Organization, 47, 91–118.

[28] Nilsson, J., 2001. Organisational principles for co-operative firms. Scandinavian Journal of Management, 17, 329–356.

[29] Ortmann, G. F., King, R. P., 2007. Agricultural cooperatives I: history, theory and problems. Agrekon, 46, 18–46.

[30] Pencavel, J., Pistaferri, L., Schivaardi, F., 2006. Wages, employment, and capital in capitalist and worker-owned firms. Industrial and Labor Relations Review, 60, 23–44.

[31] Pollitt, M.G., 1995. Ownership and performance in electric utilities: the international evidence on privatization and efficiency. Oxford: Oxford University Press.

[32] Porter, P.K., Scully, G.W., 1987. Economic efficiency in cooperatives. Journal of Law and Economics, 30, 489–512.

[33] Roodman, D., 2009. How to do xtabond2: an introduction to difference and system GMM in Stata. The Stata Journal, 9, 86–136.

[34] Sexton, R.J., Iskow, J., 1993. What do we know about the economic efficiency of cooperatives: an evaluative survey. Journal of Agricultural Cooperation, 4, 41–53.

[35] Sexton, R.J., Wilson, B.M., Wann, J.J., 1989. Some tests of the economic theory of cooperatives: methodology and application to cotton ginning. Western Journal of Agricultural Economics, 14, 55–66.

[36] Singh, S., Coelli, T., Fleming, E., 2001. Performance of dairy plants in the cooperatives and private sectors in India. Annals of Public and Cooperative Economics, 72, 453–479.

[37] Soboh, R. A., Lansink, A. O., Giesen, G., Van Dijk, G., 2009. Performance measurement of the agricultural marketing cooperatives: the gap between theory and practice. Review of Agricultural Economics, 31, 446–469.

[38] Soboh, R., Lansink, A. O., Van Dijk, G., 2012. Efficiency of cooperatives and investor owned firms revisited. Journal of Agricultural Economics, 63, 142–157.

[39] Staatz, J.M., 1984. A theoretical perspective on the behavior of farmers' cooperatives. Ph.D. thesis, Michigan State University.

[40] Sterner, T., 1990. Ownership, technology, and efficiency: an empirical study of cooperatives, multinationals, and domestic enterprises in the Mexican cement industry. Journal of Comparative Economics, 14, 286–300.

[41] Syverson, C., 2011. What determines productivity? Journal of Economic Literature, 49, 326–365.

[42] Wagner, J., 2007. Exports and productivity: a survey of the evidence from firm-level data. World Economy, 30, 60–82.

[43] Windmeijer, F., 2005. A finite sample correction for the variance oflinear efficient two-step GMM estimators. Journal of Econometrics, 126, 25–51.

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

	Cooperatives	IOFs	Robust t-stat.[a)]
ln real gross output	12.227	11.878	4.06***
Inputs			
ln L	2.168	1.540	10.26***
ln K	12.284	10.886	14.26***
ln M	11.920	11.403	4.29***
ln(K/L)	10.115	9.346	10.49***
Workforce composition			
Full-time workers (%)	0.924	0.955	4.18***
Unpaid workers (%)	0.088	0.087	0.14
Males (%)	0.518	0.568	3.94***
Other firm attributes			
Training (indicator variable)	0.128	0.122	0.55
R&D (indicator variable)	0.011	0.008	0.97
Firm birth indicator	0.004	0.042	18.60***
Export (indicator variable)	0.191	0.209	-1.16
Import (indicator variable)	0.256	0.323	-4.10***
Market concentration			
HHI	0.110	0.082	4.04***
Location			
North	0.324	0.321	0.15
Algarve	0.037	0.040	-0.48
Center	0.252	0.258	-0.33
Lisbon	0.122	0.211	-6,76***
Alentejo	0.182	0.132	3.09***
Azores	0.072	0.018	5.12***
Madeira	0.011	0.019	-1.83*
# of observations	1,697	22,879	
# of firms	685	10,164	

Notes: *** and * indicate that the means differences are statistically significant at the 1% and 10% levels, respectively.

[a)] Standard errors clustered at firm level.

Table 2 - Overall productivity differential; dependent variable: log (output)

	GLS random estimates				
	(1)	(2)	(3)	(4)	(5)
COOP	-0.504***	-0.490***	-0.496***	-0.475***	-0.478***
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
Inputs					
ln L	0.572***	0.560***	0.551***	0.542***	0.542***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
ln K	0.151***	0.150***	0.146***	0.144***	0.144***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
ln M	0.337***	0.333***	0.325***	0.319***	0.320***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Workforce composition					
Full-time workers (%)		0.180***	0.184***	0.184***	0.185***
		(0.048)	(0.048)	(0.048)	(0.048)
Unpaid workers (%)		-0.285***	-0.273***	-0.271***	-0.270***
		(0.046)	(0.045)	(0.045)	(0.045)
Males (%)		0.048*	0.050*	0.051*	0.050*
		(0.029)	(0.029)	(0.029)	(0.029)
Other firm attributes					
Training (indicator variable)			0.088***	0.084***	0.085***
			(0.015)	(0.015)	(0.015)
R&D (indicator variable)			0.125***	0.112**	0.111**
			(0.045)	(0.045)	(0.045)
Firm birth indicator			-0.445***	-0.441***	-0.440***
			(0.033)	(0.032)	(0.032)
Export (indicator variable)				0.175***	0.175***
				(0.016)	(0.016)
Import (indicator variable)				0.075***	0.074***
				(0.013)	(0.013)
Market concentration (HHI)					0.178**
					(0.086)
Industry FE	Y	Y	Y	Y	Y
Region FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
N (observations)	24,576	24,576	24,576	24,576	24,576
N (firms)	10,849	10,849	10,849	10,849	10,849
Chi^2	25,325	25,325	25,325	25,325	25,325

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

Table 3 - Productivity differential: robustness to alternative concepts and samples (GLS estimation)

	Value added	Narrower definition of IOFs	Using 2010 and 2011 only	Micro firms	Other firms
	(1)	(2)	(3)	(4)	(5)
COOP	-0.414***	-0.480***	-0.520***	-0.431***	-0.562***
	(0.038)	(0.040)	(0.042)	(0.052)	(0.058)
Inputs					
ln L	0.837***	0.548***	0.550***	0.487***	0.639***
	(0.011)	(0.015)	(0.015)	(0.018)	(0.028)
ln K	0.180***	0.131***	0.143***	0.139***	0.140***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.013)
ln M	-	0.329***	0.323***	0.326***	0.251***
		(0.010)	(0.010)	(0.011)	(0.022)
Workforce composition					
Full-time workers (%)	0.324***	0.174***	0.149***	0.154***	0.327***
	(0.045)	(0.049)	(0.056)	(0.051)	(0.106)
Unpaid workers (%)	-0.526***	-0.316***	-0.264***	-0.281***	-0.869*
	(0.036)	(0.046)	(0.051)	(0.043)	(0.450)
Males (%)	0.067**	0.067**	0.052	0.038	0.159***
	(0.028)	(0.029)	(0.033)	(0.031)	(0.055)
Other firm attributes					
Training (indicator variable)	0.150***	0.082***	0.121***	0.061**	0.070***
	(0.016)	(0.015)	(0.018)	(0.026)	(0.015)
R&D (indicator variable)	0.109**	0.100**	0.140**	0.073	0.057*
	(0.053)	(0.046)	(0.056)	(0.159)	(0.030)
Firm birth indicator	-0.489***	-0.436***	-0.486***	-0.434***	-0.771***
	(0.035)	(0.037)	(0.041)	(0.035)	(0.102)
Export (indicator variable)	0.164***	0.171***	0.180***	0.203***	0.056**
	(0.018)	(0.016)	(0.018)	(0.020)	(0.023)
Import (indicator variable)	0.140***	0.071***	0.086***	0.071***	0.051***
	(0.015)	(0.013)	(0.016)	(0.017)	(0.018)
Market concentration (HHI)	0.094	0.166*	0.211**	0.179*	0.225
	(0.077)	(0.086)	(0.091)	(0.099)	(0.165)
Industries FE	Y	Y	Y	Y	Y
Region FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
N (observations)	32,024	22,790	17,073	17,888	6,688
N (firms)	14,507	9,858	10,119	8,435	2,848
Chi^2	34,224	27,957	32,279	8,288	10,118

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

Table 4 - Overall productivity differential using System-GMM

	All (1)	Micro firms (3)	Other firms (4)
COOP	-0.649***	-0.625***	-0.628***
	(0.131)	(0.132)	(0.124)
Inputs			
ln L	0.248*	0.311*	0.851***
	(0.128)	(0.165)	(0.259)
ln K	0.133**	0.104*	0.091
	(0.059)	(0.054)	(0.110)
ln M	0.556***	0.557***	0.423***
	(0.082)	(0.083)	(0.145)
Workforce composition			
Full-time workers (%)	-0.504	-1,146	0.430
	(1.037)	(1.023)	(1.610)
Unpaid workers (%)	0.007	-0.274	-0.007
	(0.495)	(0.420)	(3.618)
Males (%)	-2.858*	-1,467	-1,109
	(1.711)	(1.278)	(1.568)
Other firm attributes			
Training (indicator variable)	0.241	0.177	0.039
	(0.274)	(0.263)	(0.235)
R&D (indicator variable)	0.137	-0.697	-0.470
	(0.281)	(0.673)	(0.350)
Firm birth indicator	-0.297***	-0.323***	-0.445**
	(0.101)	(0.087)	(0.173)
Export (indicator variable)	0.188	0.274**	0.026
	(0.121)	(0.130)	(0.112)
Import (indicator variable)	-0.021	-0.010	-0.047
	(0.142)	(0.133)	(0.134)
Market concentration (HHI)	0.480**	0.400*	0.223
	(0.226)	(0.207)	(0.237)
Industries FE	Y	Y	Y
Region FE	Y	Y	Y
Year FE	Y	Y	Y
N (observations)	24,576	17,888	6,688
N (firms)	10,849	8,435	2,848
N instruments	47	43	43
Hansen test, p-value	0.306	0.162	0.598
Diff Hansen_1 test, p-value	0.192	0.027	0.224
Diff Hansen_2 test, p-value	0.481	0.508	0.714
Chi^2	6,298	1,608	3,089

Notes: Significance level at which the null hypothesis is rejected: ***, 1%; **, 5%; and *, 10%.

The System-GMM is estimated with two-steps using robust standard errors corrected for finite samples. The dependent variable is log of real gross output.

Table 5 - Productivity differential by industry; dependent variable: log (output)

Industry	GLS random estimates (1) = year, region and industry fixed effects	(2) = (1) + workforce comp.	(3) = (2) + other firm attributes and market concentration	System-GMM (4) = (3)	N (obs.)	N (firms)
Agriculture and other	-0.932***	-0.853***	-0.852***	-0.988***	2111	923
	(0.141)	(0.129)	(0.130)	(0.312)		
Food	-0.253***	-0.281***	-0.287***	-0.411**	1692	731
	(0.093)	(0.095)	(0.096)	(0.167)		
Beverages	-0.172**	-0.156*	-0.106	0.564	1960	750
	(0.083)	(0.084)	(0.085)	(0.633)		
Textile, clothing and other	-1.000*	-1.024**	-1.006**	-0.784	474	196
	(0.515)	(0.517)	(0.508)	(0.989)		
Other manufacturing	-0.546	-0.507	-0.454	0.302	1306	523
	(0.419)	(0.372)	(0.369)	(0.684)		
Electricity, water and construction	-0.724***	-0.764***	-0.808***	-0.883*	1571	858
	(0.185)	(0.188)	(0.203)	(0.472)		
Wholesale trade	-0.429***	-0.420***	-0.378***	-0.583**	6398	2585
	(0.068)	(0.068)	(0.065)	(0.262)		
Retail trade	-0.319***	-0.344***	-0.389***	-0.279**	3865	1557
	(0.071)	(0.067)	(0.064)	(0.120)		
Storage, hotels, media and other	-0.147	-0.178	-0.191	0.113	573	275
	(0.151)	(0.150)	(0.143)	(0.286)		
Education	-0.545***	-0.522***	-0.548***	-0.564*	1978	959
	(0.199)	(0.200)	(0.191)	(0.323)		
Social work	-0.955***	-0.953***	-0.956***	-1.038***	850	547
	(0.119)	(0.120)	(0.128)	(0.398)		
Artistic and cultural associations	-0.851***	-0.870***	-0.836***	-0.429	860	447
	(0.313)	(0.317)	(0.324)	(0.358)		
Other associations	0.211	0.131	0.082	-0.045	1118	528
	(0.236)	(0.228)	(0.232)	(0.480)		

Notes: Significance level at which the null hypothesis is rejected: ***, 1%; **, 5%; and *, 10%.

In the GLS random estimates, the standard errors are clustered at firm level. The System-GMM is estimated with two-steps using robust standard errors corrected for finite samples. The number of instruments used in each industry-entry varies between 30 and 43. Neither the Hansen overidentification test nor the difference in Hansen tests between the System and first difference GMM reject the validity of the instruments used (further details available upon request).

Table 6 - Predicted output (GLS) using the two different estimated technologies by industry

	Cooperatives			IOFs		
	Coop technology	IOF technology	*t-test*	Coop technology	IOF technology	*t-test*
Agriculture and other	10.438	11.266	***	10.266	*11.140*	***
Food	12.186	12.447	***	12.551	*12.906*	***
Beverages	13.740	13.827	***	12.226	*12.441*	***
Textile, clothing and other	8.900	9.783	***	12.120	*12.251*	***
Other manufacturing	10.526	10.840	***	12.176	*12.587*	***
Electricity, water and construction	11.812	12.734	***	11.451	*12.267*	***
Wholesale trade	12.688	13.081	***	11.367	*11.643*	***
Retail trade	11.499	11.874	***	11.489	*11.825*	***
Storage, hotels, media and other	11.583	11.798	***	11.752	*12.227*	***
Education	12.745	13.224	***	10.855	*11.524*	***
Social work	11.759	12.909	***	10.706	*11.469*	***
Artistic and cultural associations	10.458	11.197	***	10.643	*11.139*	***
Other associations	*11.214*	11.096	*	10.757	*11.146*	***

Notes: ***,** and * indicate that means are significantly different at the 1%, 5% and 10% level, respectively. NS indicates that the means difference is not statistically different from zero.

Table 7 - Predicted output (System-GMM) using the two different estimated technologies by industry

	Cooperatives			IOFs		
	Coop technology	IOF technology	*t-test*	Coop technology	IOF technology	*t-test*
Agriculture and other	10.452	11.408	***	10.290	*11.182*	***
Food	12.279	12.532	***	12.634	*12.935*	***
Beverages	*13.757*	13.535	***	12.333	*12.508*	***
Textile, clothing and other	8.791	10.274	NS	12.888	12.280	***
Other manufacturing	*10.469*	10.089	***	13.078	12.615	***
Electricity, water and construction	11.768	12.687	***	11.845	*12.386*	***
Wholesale trade	12.672	13.194	***	11.720	11.651	***
Retail trade	11.514	11.772	***	11.528	*11.828*	***
Storage, hotels, media and other	11.525	11.457	NS	11.652	*12.225*	***
Education	12.716	13.249	***	10.939	*11.544*	***
Social work	11.690	13.206	***	11.369	*11.464*	***
Artistic and cultural associations	10.350	11.137	***	10.981	*11.156*	***
Other associations	11.404	11.093	NS	10.270	*11.219*	***

Notes: ***,** and * indicate that means are significantly different at the 1%, 5% and 10% level, respectively. NS indicates that the means difference is not statistically different from zero.

Figure 1: Distribution of cooperatives across industries