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Market Power and the Volatility of Markups in the Food Value Chain: The Role of Italian Cooperatives

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Abstract

Agricultural cooperatives have often been promoted as a way to increase their market power and to obtain stability of profit against uncertainty. This paper estimates the firm-level markups and markup volatility to identify the countervailing market power of cooperatives in the Italian fruits and vegetable sector and the dairy sector. We use the firm-level data of Italian firms for the period 2007-2014. We find that, overall, there is a tradeoff in cooperatives' role between obtaining market power and stability. Farmer cooperatives in both sectors gain stability in their markups but their markups are lower, on average, than those for non-cooperatives. For processor cooperatives, the fruits and vegetable sector obtains more market power. This appears to arise from the product differentiation strategy of the processors cooperative.

Keywords: Cooperatives, market power, firm-level markups, volatility

JEL codes: L44, Q13, D23

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1. Introduction

Agricultural cooperatives have been a key instrument for strengthening the economic position of producers. While there are several reasons for producers to form cooperatives, such as economies of scale in processing and marketing activities, exercising countervailing market power is one of the main objectives of many cooperatives (Bijman & Hendrikse, 2003; Hendrikse & Veerman, 2001; Rogers & Marion, 1990; Valentinov, 2007; Van Cayseele, 2018). Through collective marketing of their output, agricultural cooperatives can reduce transaction costs and obtain bargaining power vis-à-vis buyers. Many producers cooperatives are established in places where monopsony power is present (Hansmann, 2012).

In recognition of the role of cooperatives in improving the market power, EU Common Agricultural Policy (CAP) has been encouraging the creation of producer organizations since 2001 (Michalek, Ciaian, & Pokrivcak, 2018). This policy is motivated by the concentration of firms in the food value chain that puts farmers in a weaker position in the negotiation. Market power and concentration in downstream sectors of the EU agri-food chain, among other factors such as major volatility in global agricultural and food markets, have kept drawing attention from policymakers, stakeholders as well as academics. This concern has spawned another EU regulation in 2019 against Unfair Trade Practices to primarily protect farmers who are in a disadvantageous position relative to other actors in the food value chain. Throughout the discussion of its development, the importance of other mechanisms such as facilitating the role of cooperatives kept recurring to further improve the effectiveness of the governments' intervention. Our study attempts to evaluate the market power of cooperatives, and this paper will provide important evidence to the increasing concerns from policymakers for better functioning of the EU food chain.

We also examine the role of cooperatives in providing for the stability of markups, ultimately indicating the stability of profits. The uncertainty associated with price volatility is likely to cause inefficiencies by making it difficult for producers to formulate optimal decisions and investments ahead (Bellemare, Barrett, & Just, 2013; Dawe & Timmer, 2012). In fact, producers perceive the price volatility as one of the primary factors affecting their income (Hall, Knight, Coble, Baquet, & Patrick, 2003), and it is recognized that forming cooperatives can be a management strategy of farmers against income risks (OECD, 2000). Notably, Müller, Hanisch, Malvido, Rommel, & Sagebiel (2018) focus on the effect of cooperatives and find that high market shares of cooperatives in the EU countries reduce milk price volatility. Particularly after 2006 when there were shocks and volatility of global food prices, there has been an intense policy debate whether governments need to intervene to reduce price volatility and thus risk and uncertainty (Bureau & Swinnen, 2018; Pieters & Swinnen, 2016). Our focus on markup volatility will show whether the cooperative could function as a hedge, by providing profit stability, against the risks widely prevalent in the agricultural sector.

There are a number of studies exploring the role of agricultural cooperatives on farm's, or firm's, performance. A large part of the relevant study is from the context of developing countries, and most of those find the positive effect of agricultural cooperatives on-farm performance often evaluated in farm income, or revenue. Verhofstadt & Maertens (2014) find that cooperative membership has a positive impact on farm performance. They use several indicators for farm performance including farm income and labor productivity (farm income divided by worker). Zhang, Sun, Ma, & Valentinov (2019) identify the effect of farmers' cooperatives on technology adoption, which in turn will increase crop productivity and farmers' income. Ofori, Sampson, & Vipham (2019) do not find evidence on the impact of vegetable cooperatives on agricultural income. Ahmed & Mesfin (2017) evaluate the effect of the agricultural cooperative on the wellbeing of smallholder farmers measured by household expenditure. Other studies focus on productivity, i.e. technical efficiency as firm performance, and find mixed effects of cooperatives (Maietta & Sena, 2008; Monteiro & Straume, 2018). Most of the literature relies on performance indicators measured by income, sales, or operating profits, which is restricted to accounting profits that do not capture the whole economic rents (De Loecker & Goldberg, 2014).

While there is a long history of studying the market power of agricultural markets and the role of cooperatives in agriculture separately, there are relatively few studies on the market power of cooperatives. Myers, Sexton, & Tomek (2010) discuss the concern of imbalanced power between farmers and marketing firms raised in the early twentieth century. Most studies focus on evaluating the competitiveness and its associated performance of the agricultural market or the motivations of farmers in participating in the collective action (Sexton, 1986; Staatz, 1983). The few existing studies on the market power of cooperatives are mostly theoretical with a focus on welfare effects: Sexton (1990) models the role of cooperative processors on the pricing behavior of non-cooperative processors and finds that cooperatives of the open-membership type introduce a procompetitive effect in the market; Bergman (1997) demonstrates that cooperatives may generate different welfare effects depending on whether they have access to export markets, discriminating between prices in export and domestic markets; Prasertsri & Kilmer (2008) focus on the relative bargaining power of milk marketing cooperatives and milk processors in Florida and estimate that cooperatives have higher bargaining power.

One of the few studies that empirically address the market power of cooperatives is Cakir & Balagtas (2012) who estimate markups of dairy farmers' cooperatives in the US. They focus on the effect of the marketing order regulations that target higher milk prices for cooperatives over processors in the US. They measure market power with markups, similar to our study, but their study relies on the demand side approach to estimate markups which requires data on prices and quantities of products. We recover markups from the production side approach that is known to be more flexible without having to put restrictions on underlying consumer demand (De Loecker, 2011). Hirsch & Koppenberg

(2020) apply the same methodology introduced by De Loecker & Warzynski (2012) to estimate the market power of French retailing and include the cooperative status in their regression analysis. But their interest does not lie in its countervailing power of agricultural cooperatives, and they also do not explicitly incorporate the cooperative status in their production function estimation. Cloest to the motivation of our research is probably the work by Vigani & Curzi (2021) who use survey data of dairy cooperatives in the UK to analyse the impacts of dairy farmers' cooperatives on milk prices, production costs and markups. However, there is a major drawback in their markup measurement using production costs as the percentage of the above selling price, arising from the limit in using the survey data.

We aim to estimate the role of cooperatives on markups and their volatility with a flexible empirical framework developed by De Loecker & Warzynski (2012). After the markup estimation, a series of regression analyses and treatment effect estimators such as propensity score matching and inverse probability weight regression adjustment estimator are applied to identify the relationship between cooperatives and markups (both as to their level and volatility). There is a contentious view on the success of the cooperative to exercise countervailing power due to the potential failures to reach an agreement or free-riding (Myers et al., 2010). Our analyses will unveil the role of cooperatives in countervailing market power ultimately affecting the performance of the food supply chain, as inequalities in bargaining power and anti-competitive practices lead to market distortions and negative effects on the competitiveness (European Commission, 2009).

In our study, we use the firm-level balance sheet data of Italian firms for fruits and vegetables (F&V) as well as the dairy sector for the period 2007-2014 from the Bureau van Dijk's Amadeus database. The period 2007-2014 is important as it is characterized by major price volatility in global agricultural and food markets. With this period of analysis, we are able to capture how cooperatives could function as a management strategy against risks.

Overall, we find that there is a tradeoff for cooperatives in obtaining market power and stability. Farmers cooperatives obtain stability of markups at the expense of lower markup levels. Farmers may place higher importance on the stability of profit due to the inherent uncertainties that already exist in agricultural production. For processor cooperatives, those in the fruits and vegetable sector obtains more market power. This appears to arise from the product differentiation strategy of the processors cooperative. In the dairy sector, cooperative processors have higher stability but their market power is lower.

The remainder of the paper is organized as follows: In section 2, we first provide a brief background of cooperatives in Italy. Section 3 describes the dataset. Section 4 explains the empirical methodology applied for the markup estimation as well as the regression and treatment effect to

identify the role of cooperatives on markup and its volatility. Section 5 presents the results, with the discussion followed in section 6. Section 7 concludes.

2. Background: Cooperatives in Italy

Italy is an interesting country to study the effect of cooperatives on market power. Italy is an economy with one of the largest cooperative sectors and we aim to see how well the cooperative functions in its fully-developed form. Italy also has a long history supporting the development of cooperatives; for example, Italy is one of the few countries whose constitution recognizes the societal role of cooperatives (Bijman & Iliopoulos, 2014).

Cooperatives in Italy play an important role especially in the agri-food sector; one-fifth of the largest Italian agri-food enterprises are cooperatives (Fonte & Cucco, 2017). Most Italian agri-food cooperatives are engaged in marketing and processing and these activities amount to 37 percent of the national value of agricultural production.¹

We focus on the role of cooperatives in the fruit and vegetables and dairy sectors given their considerable share in the number of cooperatives as well as their revenue share, in addition to the interest for the two sectors in the policy.² In 2016, the 4703 agri-food cooperatives associated with the four main national federations had a turnover of around 35 billion euros and 91,584 employees (*Osservatorio della cooperazione agricola italiana*, 2017: 59). The fruit and vegetables sector is the second largest sector in terms of the number of firms in Italy, and it also accounts for a quarter of the revenue share of the cooperatives in Italy; the dairy sector constitutes 16 percent of the total number of cooperative firms and 19% of the revenue share (Table 1).

Besides the importance of cooperatives in Italy, Italy is also a key producer of agricultural products and food in the EU. Italy is the second-largest country (14%) contributing to the total EU agricultural output (European Union, 2020). When it comes to fruit production, Italy accounts for more than 25% of total EU fruit production (Eurostat, 2019).

¹ Farmers cooperatives can be specialized in different roles other than bargaining (marketing), such as directly engaging in farming activities or providing technology or machinery to the farmers (Bijman & Hanisch, 2012). Although we do not observe the detailed cooperative type, most Italian agri-food cooperatives are engaged in marketing and processing (Fonte & Cucco, 2017) and the major function of cooperatives is collective bargaining (Bijman & Hendrikse, 2003; Höhler & Kühl, 2014)

² CAP has promoted the farmers' cooperative in the F&V sector since 2001, and the dairy sector since 2011. It is only after the 2013 CAP reform that the cooperatives in all agricultural sectors are included (Michalek et al., 2018)

3. Data

We use the firm-level balance sheet data of Italy for the period 2007-2014 from the Bureau van Dijk's (BvD) Amadeus database. The data is collected based on the 4-digit code in the European NACE Rev.2 from the agricultural sector (NACE A 01) – farmers, and the food processing sector (NACE C 10) – processors, each for fruits and vegetables (F&V) and dairy sectors.³ We observe firm-level measures of turnover, input expenditure including material costs, total assets, and number of employees for estimation of the production function. Ideally, one uses data for input and output in physical quantities in production function estimation. While in practice due to data availability, one often relies on the input expenditure and total sales that contain the firm-level price variations. To control for the price bias, at least at an industry-level, production variables used in the markup estimations are deflated with national 2-digit industry deflators, following the common practice when the quantity data are not available.⁴

We eliminated all observations that report zero or negative values of production variables implementing the standard data cleaning procedure (Curzi, Garrone, & Olper, 2020), which resulted in an unbalanced dataset with 3804 firms. We classify a firm into a cooperative based on the legal form data. The observations of legal form are not always complete through-out the period of our analyses. Thus, we classify a firm as cooperative when the firm has a legal form of cooperative at least at one point in time, assuming that a firm retains the same legal form. In our sample, the share of the number of farmers' cooperatives is larger than that of processors' cooperatives in both the F&V and Dairy sector (Table 2). Table 3 reports summary statistics of the variables used in the estimation of markups.

The period 2007-2014 is significant in our study as it is characterized by major price volatility in global agricultural and food markets. With this period of analysis, we are able to capture how cooperatives could function as a management strategy against risks. In addition, it is argued that the performance of cooperatives was positive in times of crisis (2008-2012) compared to investment-oriented firms (Fonte & Cucco, 2017).

³ The following subsectors are included for F&V: *Growing of vegetables and melons, roots and tubers* (NACE 113), *Growing of tropical and subtropical fruits* (NACE 122), *Growing of citrus fruits* (NACE 123), *Growing of pome fruits and stone fruits* (NACE 124), *Growing of other tree and bush fruits and nuts* (NACE 125), *Growing of oleaginous fruits* (NACE 126), *Growing of beverage crops* (NACE 127), *Growing of spices, aromatic, drug and pharmaceutical crops* (NACE 127), *Growing of other perennial crops* (NACE 129). *Manufacture of fruit and vegetable juice* (NACE 1032), *Other processing and preserving of fruit and vegetables* (NACE 1039), *Manufacture of oils and fats* (NACE 1041). For dairy, *Raising of dairy cattle* (NACE 141), *Operation of dairies and cheese making* (NACE 1051) are included. We did not include the manufacture of any types of alcoholic beverages in Food processing sector (NACE C 10) as its elasticity of demand may depend on addictive consumption behaviors thus different from characteristics of other products.

⁴ Turnover and material costs are deflated using the gross product output and intermediate input deflators from OECD STAN. Total assets are deflated with a gross fixed capital formation deflator from Eurostat, as in Curzi, Garrone, & Olper (2020).

4. Methodology

4.1. Measuring market power

We estimate markups as an indicator for market power. Markups capture the firm's profitability (excluding fixed costs) based on identifying the firm's marginal cost. Furthermore, we are able to jointly estimate productivity and market power by employing the empirical framework of De Loecker & Warzynski (2012) through estimation of the production function. This framework allows to generate firm-level markups while addressing the simultaneity bias in estimating production function. Maietta & Sena (2010) identify the relationship between the productivity of cooperatives and their market power using the frontier approach. They estimate the parameters of production frontier to measure technical efficiency but market power is proxied with the size of the market share of each firm, i.e. a concentration index which does not necessarily translate into the higher market power (European Commission, 2018; OECD, 2014; Sheldon, 2017; Swinnen & Vandeplass, 2010).

Although concentration level can be a handy indicator of market power, the Structure Conduct Performance (SCP) paradigm has many limitations. A well-known example is the use of market concentration directly for the presence of market power. Another criticism toward the SCP is that it relies on the accounting profits when investigating the concentration-profit relationship (Sexton, 2000). Economic profits are conceptually different from accounting profits as illustrated in (Fisher & McGowan, 1983). Since we are interested in is the economic behavior of firms that depends on economic profits, rather than accounting profits, the New Empirical Industrial Organization (NEIO) paradigm is followed. Market power then is typically measured by a markup capturing the ability of firms to charge a price above marginal costs. Instead of calculating the markup directly as price over marginal cost (equivalently, without directly estimating the marginal cost), NEIO relies on the econometric estimation of a firm's demand or supply response.

4.1.1. Firm-level markups

As a first indication, without having to go through the structural econometrics, one can make use of the available accounting data by multiplying total quantity (Q) in the definition markup, i.e. price over marginal cost ($=P/MC$), and obtain markup from the available data as sales over the total cost. This simple calculation is based on the strict assumption of constant returns to scale, and the flaws of this accounting approach however have been spelled out above.

One structural econometric approach is based on the standard cost minimization of firm behavior in production. It is firstly developed by the seminal work of Hall, Blanchard, & Hubbard (1986) who estimate industry-specific markups from production data. Their key idea is that under imperfect competition, cost and revenue shares of inputs differ, and thus markup can be obtained as

the difference between the share of an input's expenditure in the total cost and total sales. Konings, Van Cayseele, & Warzynski (2001), for the first time in Europe, estimates the change in markups as the result of changes in competition policy; in subsequent work, they analyze another shift in policy making: The gradual opening of centrally planned economies (Konings, Van Cayseele, & Warzynski, 2005). Kaditi (2013) applies this method and estimates the industry average markups of the food value chain in response to the increased competitive pressure.

In our analyses, we rely on the production side approach developed by De Loecker & Warzynski (2012) that allows us to benefit from its two key advantages. One is that we can obtain markups at a firm-level.⁵ Based on the insight from Hall et al. (1986), this framework overcomes one of its major restrictions that only average sector-specific markups could be achieved with the assumption of a common markup across producers in a given market. Thus we are able to correlate the firm-level characteristics such as cooperative status with the level of markup. Another advantage of this framework is that it is more flexible in such a way that we do not need assumptions on any particular consumer demand and any specific price-setting model as compared to the demand side approach. De Loecker & Warzynski (2012) only builds on the assumption of standard cost minimization for variable inputs free of adjustment costs for the estimation of the production function.

For a production function of a firm i at time t , $Q_{it} = \Omega_{it}F(X_{it}; K_{it})$ represents a firm producing gross output Q by using a set of variable inputs X and capital K under productivity Ω . We assume this productivity to be Hicks-neutral. Across the set of producers, technology parameters are common. In deriving the markup, De Loecker & Warzynski (2012) rely on one restriction imposed on the production process: it is continuous and twice differentiable with respect to its arguments. We assume producers are cost-minimizing⁶ in the market and obtain the following first-order condition with respect to a variable input X : $P_{it}^X - \lambda_{it} \frac{\partial Q_{it}(X_{it}; K_{it})}{\partial X_{it}} = 0$, where P_{it}^X denotes a firm's input price for variable input X and λ_{it} is the Lagrangian multiplier that could be expressed as the marginal cost of production at a given level of output $\lambda_{it} = \frac{\partial L_{it}}{\partial Q_{it}}$. Rearranging and multiplying both sides by $\frac{X_{it}}{Q_{it}}$, and using the definition of markup ($\mu_{it} \equiv \frac{P_{it}}{\lambda_{it}}$) leads to the following markup expression: $\mu_{it} \equiv \frac{\theta_{it}^X}{\alpha_{it}^X}$, where θ_{it}^X is the output elasticity of the variable input X and α_{it}^X is the share of expenditure on input X in total

⁵ We estimate firm-level markups, not the product-level markups. We assume firms are single-product producers as we do not need to assume how firms allocate inputs across different products, which we cannot often observe in data. The detailed product level information of firms is often lacking.

⁶ One might argue that cooperatives may not behave as cost minimizers. However, as each member of cooperatives receives dividend pro-rata with its contribution, there is enough incentive for each of them to behave as such. Furthermore, Grau & Hockmann (2018) argue that dairies, in particular cooperatives, often adopt a cost-minimizing strategy that aims to maximally employ their production capacities.

sales ($P_{it}Q_{it}$). For uncovering markups, as the share of expenditure is directly observable in the data, we proceed to the estimation of the output elasticity of a variable input of production.

4.1.2. Estimating output elasticity

As the output elasticity of a variable input θ_{it}^X equals to $\frac{\partial \ln F}{\partial \ln X_{it}}$, we consider the following logarithmic transformation of the gross-output production function: $y_{it} = f(m_{it}, l_{it}, k_{it}) + \omega_{it} + \epsilon_{it}$, where y_{it} now is the log of gross output, m_{it} , l_{it} , k_{it} are the log of material, labor, and capital, respectively. ω_{it} represents productivity as known by the firm hence affecting input choices, but it is not observable to the researcher. Thus, it is important to control for this simultaneity bias in order to obtain a consistent estimate of output elasticity. ϵ_{it} indicates unexpected idiosyncratic shocks to production that are not observable both to firm and researcher. We also allow for measurement error in ϵ_{it} , so that $y_{it} = \phi_{it} + \epsilon_{it}$, capturing the differences between expected output and the actual realization, and purge out this measurement error as in De Loecker & Scott (2016); De Loecker & Warzynski (2012); Rubens (2019). Note that we estimate markups by each sector to allow for different technological and market conditions in different industries.

We account for the potential simultaneity bias with a control function approach following the two-step procedure developed in Olley & Pakes (1996) and Akerberg, Caves, & Frazer (2015), and use the inverse of the material demand function as a proxy for the unobserved productivity following Levinsohn & Petrin, (2003).⁷ Without controlling for productivity, OLS estimates are biased and inconsistent. Other standard methods to avoid this bias such as fixed effects or instrumental variables estimators do not perform adequately (Manjón & Mañez, 2016). A fixed-effect estimator may deal with the endogeneity of productivity but productivity shocks cannot have time variation. The instrumental variable method is often limited by finding appropriate instruments that are not correlated with productivity but correlated with the input.

For our main analyses, we use the Cobb-Douglas (CD) gross output production function⁸:

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \omega_{it} + \epsilon_{it}.$$

In the first step, we obtain estimates of $\widehat{\phi}_{it}$ and $\widehat{\epsilon}_{it}$ in the following regression:

⁷ Relying on material demand for proxy lies in the assumption of the monotonicity of intermediate inputs in productivity (De Loecker & Warzynski, 2012; Levinsohn & Petrin, 2003).

⁸ We did not include the cooperative dummy as an input in the Cobb-Douglas production function estimation because it implies that a firm can substitute any input with being a cooperative at a constant unit elasticity, which is unrealistic assumption (De Loecker, 2013). Furthermore, Natalia P. Monteiro & Straume (2018), one of very few literatures that relate cooperatives and production function estimation, do not find evidence that there are estimated technological differences between cooperatives and non-cooperatives.

$y_{it} = \phi_{it} + \epsilon_{it}$, where $\phi_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \omega_{it}$.

In the second step, estimates for all production function coefficients are obtained using the law of motion for productivity: $\omega_{it} = g_t(\omega_{it-1}, coop_i) + \xi_{it}$, where ξ_{it} is the innovation to productivity or productivity shocks. We include the cooperative status of each firm in the evolution of productivity to allow the performance improvement varying across firms as firms react differently to shocks as in Brandt, Van Biesebroeck, Wang, & Zhang (2017) and De Loecker (2013), given the particular period of our analyses.⁹ The relationship between cooperatives and productivity is documented in several pieces of the literature, although the direction of the relationship is not always clear-cut (Maietta & Sena, 2008, 2010; Monteiro & Straume, 2018).¹⁰

After the first step, we are able to use the estimated value $\widehat{\phi}_{it}$ to compute the estimate for productivity ω_{it} for each value of β as following: $\omega_{it}(\beta) = \widehat{\phi}_{it} - \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it}$

To recover $\xi_{it}(\beta)$, we use a non-parametrical regression of $\omega_{it}(\beta)$ on the third-order polynomial of its lag $\omega_{it-1}(\beta)$. The GMM technique is employed, using instruments for the inputs orthogonal to the innovation to productivity. Our moment condition follows the one suggested by Levinsohn & Petrin (2003): We rely on the assumption that capital is a state variable that is decided a period ahead, and labor and material inputs are nondynamic, thus they are chosen concurrently when the firm realizes a productivity shock (Rovigatti & Mollisi, 2017). Thus, the moment conditions are as follows: $E[\xi_{it}(\beta)Z_{it}] = 0$, where $Z_{it} = (m_{it-1}, l_{it-1}, k_{it})$ indicating that ξ_{it} is independent of the predetermined k_{it} , as well as the lagged value of material and labor input (m_{it-1}, l_{it-1}) .

In our analyses, we rely on the output elasticity of the material, a variable input that is least likely to be subject to adjustment costs. Firms may have more barriers to freely adjust labor force to minimize their costs due to restrictions on hiring or firing (Brandt et al., 2017). This is particularly important for our data concerning Italy where the level of employment protection is high, hindering the firms' adaptation to changes. Italy is one of the top countries for having the most stringent restrictions in labor markets, according to the OECD indicators of employment protection legislation (Scarpetta, 2014).

Under the Cobb-Douglas production function, the output elasticity of materials is as follows: $\theta_{it}^M = \hat{\beta}_m$. In the following analyses, the CD production function is used in an attempt to obtain the

⁹ De Loecker (2013) and De Loecker & Warzynski (2012) include export status in the evolution of productivity to capture the effect of learning by exporting. However in our analyses, including the cooperative status is to capture the firm specific reaction to productivity shocks given the correlation between productivity and cooperatives, not primarily for the learning effect because our cooperative status variable is time-invariant.

¹⁰ Under the cooperatives' effect on productivity, one may obtain biased production coefficients. But allowing the cooperative status to affect productivity does not guarantee its effect on productivity (De Loecker et al., 2016). The inclusion of cooperative status in the evolution of productivity does not a priori presume the presence of its effect.

most unbiased estimates especially for the interest on the relationship between cooperative and markups, following Brandt et al., (2017). Our approach is fully in line with Bond, Hashemi, Kaplan, & Zoch (2020) which suggest focusing on estimating the differences in mean markups across firms under the Cobb-Douglas production function.

It is worth mentioning a trade-off we face in using the CD production function. Despite the advantage of obtaining unbiased estimates, the CD production function assumes the elasticity of the input substitution to be one. The output elasticity of a variable input is constant for all firms over time, thus, the markup variation across firms will be mostly determined by the expenditure share.¹¹ Due to these restrictions, an estimation based on a Translog (TL) production function with Leontief technology is further followed. Translog specifications are more flexible than a CD production function in that they allow the output elasticity to differ across firms over time as we introduce interaction terms. We chose Leontief technology as it may be able to better reflect the production in the agri-food sector, for example, milk cannot be replaced by labor or capital for dairy processors. Under Leontief technology, materials are not allowed to be substituted with labor or capital but a fixed proportion of materials is used for producing a unit of output. The Leontief production function is used in earlier studies estimating markup with the production function approach, for the beer industry by De Loecker & Scott (2016), and the cigarette industry by Rubens (2019). However, we should be aware of the price bias that cannot be purged out thus markup and its volatility may still carry some potential bias. In consideration of the tradeoff between the flexibility and the potential bias, we also estimate markups under the Translog production function with Leontief technology for comparison.¹²

4.2. Relationship between cooperative and markup (volatility)

4.2.1. Regression

For the markup, its magnitude may be subject to potential bias but the main interest of our study on the relationship between the markup and cooperative can be correctly estimated under CD as the output elasticity is canceled out for cooperative firms and non-cooperative firms in the logarithm of markup and the cooperative in dummy variable. For markup volatility, its magnitude and accordingly the relationship can be estimated unbiasedly.

To answer the question of whether cooperatives have higher market power than non-cooperative, markups are expressed in logarithms and the cooperative status is put as a dummy

¹¹ Note that the output elasticity is adjusted for measurement error obtained in the first step of the production function estimation.

¹² With Translog Leontief production function, the output elasticity θ_{it}^l is equal to $\beta_l + 2\beta_l l_{it} + \beta_{lk} k_{it}$, and markup is calculated as follows: $\mu_{it} = (\alpha_{it}^l / \theta_{it}^l) + \alpha_{it}^m)^{-1}$ See the derivation in De Loecker & Scott (2016); Rubens (2019).

variable. We run regressions to identify the δ_1 , the percentage difference in markup between cooperatives and non-cooperatives is of our interest. For control variables (X_{it}), we include labor and capital used to account for firm size and factor intensity as in De Loecker & Warzynski (2012) and Natália Pimenta Monteiro & Stewart (2015), and productivity that is retrieved from the production function estimation. But it is not our main interest to interpret the coefficient of various control variables. The observations for cooperatives are not often fully complete across time, thus we assume that a firm is cooperative throughout when at least one point in the period of our analyses indicates a cooperative status. As cooperative status is time-invariant, we cannot employ the fixed effect model due to its inability to estimate the effect of a variable that does not vary within, neither the random effect model due to violation of its assumption.

Therefore, we rely on correlated random-effects (Mundlak, 1978; Wooldridge, 2010) and hybrid models (Allison, 2009)¹³, which allow us to estimate within effects in random-effects models. The idea of the hybrid model is to decompose a variable into a between ($\bar{x}_i = \sum_T x_{it}$) and a within ($x_{it} - \bar{x}_i$) component. The two models are closely related to each other but the correlated random-effects model relaxes the assumption of correlation between the covariates and the individual error (Schunck, 2013). This is achieved by introducing the individual error ($\alpha_i = \pi\bar{x}_i + \nu_i$), where the mean of each individual (\bar{x}_i) can capture any correlation between x_{it} and α_i . Including the cluster mean of a variable in a random-effects model can be an alternative to cluster mean centering (Halaby, 2003). We take the results from these two models, as the coefficient of our interest δ_1 , that is the effect of time-invariant cooperative status, is not different in the two models. Along with these, results from other panel estimators including pooled-OLS, fixed and random-effect models are also provided as robustness checks.

$$\log(\text{markup})_{it} = \delta_0 + \delta_1 \text{coop}_i + \delta_2 X_{it} + \text{year} + \alpha_i + \eta_{it}$$

To explore the question on the hedging effect of cooperatives against risks, we run regressions for markup volatility with the same specification as above, separately. The coefficient of our interest is θ_1 , the difference in markup volatility between cooperatives and non-cooperatives.¹⁴

$$\text{Markup volatility}_i = \theta_0 + \theta_1 \text{coop}_i + \theta_2 X_{it} + \varepsilon_i$$

We adopt a markup volatility measurement that is commonly used in the price volatility literature. Following Gilbert & Morgan (2010) and Pieters & Swinnen (2016), markup volatility is measured as the standard deviation of the logarithm changes of firm-level markups:

¹³ There also exist a between estimator, that answers the question about the effect of x when x changes between firms. However, it is seldom used since the Pooled-OLS estimator is more efficient (Cameron & Trivedi, 2009).

¹⁴ Markup volatility is not in logarithm as it is not advisable to use log when the value is between 0 and 1 (e.g. ratio) and takes on values close to zero (Wooldridge, 2012)

$$v_i = sd(r_i) = \left[\sum \frac{1}{T-1} (r_{it} - \bar{r}_i)^2 \right]^{0.5}, \text{ where } \bar{r}_i = \sum \frac{1}{T} r_{it}, r_{it} = \ln\left(\frac{\mu_{it}}{\mu_{it-1}}\right).$$

In other words, the volatility indicates the deviation of the markup changes each year to the average markup changes over time. With this measure, we can also address the issue of de-trending the series, if any.¹⁵ Under the CD production function, the logarithm changes of firm-level markups become immune to the potential bias of output elasticity. Therefore, not only the relationship between the markup (volatility) and cooperative participation but also the markup volatility itself is estimated unbiased.

4.2.2. Treatment effect

As cooperative status is likely not randomly distributed in the population, we need to account for selection bias that may influence the results. Matching techniques can control for a potential self-selection process of firms by creating control groups similar in firms characteristics (De Loecker, 2007), notably the potential self-selection bias of higher or lower market power firms becoming cooperatives. We apply propensity score matching (PSM) to estimate the average treatment effect of cooperatives on markup and markup volatility, respectively. The average treatment effect, the average markup difference between cooperatives and non-cooperatives firms of the match, allows us to obtain a reliable estimate of the effect of cooperatives on markups under the Cobb-Douglas production function despite the bias that may potentially be present in the output elasticity.

A large body of literature investigating the effects of cooperatives commonly apply PSM to account for the potential bias (Ahmed & Mesfin, 2017; Ito, Bao, & Su, 2012; Maertens, Colen, & Swinnen, 2011; Ofori et al., 2019; Verhofstadt & Maertens, 2014; Zhang et al., 2020). By matching cooperatives (treated) firms with non-cooperative (non-treated) firms similar in their observable characteristics, PSM eliminates selection bias, that may arise from the differences in treated (cooperative) firms and non-treated firms for reasons other than the cooperative status per se (Caliendo & Kopeinig, 2008).

Propensity score as the probability of being a cooperative is estimated from the probit¹⁶ model, by which the kernel matching¹⁷ is based on the propensity score. The score is constructed with the same control variables in our regression analyses as productivity, factor intensity, and size of the firms

¹⁵ See Gilbert & Morgan (2010) Minot (2014) Pieters & Swinnen (2016) for more details.

¹⁶ We prefer probit model over logit model due to the stronger assumptions of the logit model, that is not likely to be met. However the logit and probit models usually generate similar results in case of the binary treatment (Caliendo & Kopeinig, 2008).

¹⁷We chose Kernel matching as it does not require to reduce the sample size by discarding unmatched individuals from the comparison (Garrido et al., 2014; Verhofstadt & Maertens, 2014), and “it maximizes precision by retaining sample size without worsening bias (by giving greater weight to better matches)” (Garrido et al., 2014)

are potentially correlated with cooperatives (Jos Bijman & Hanisch, 2012).¹⁸ We match the firms within the sub-sectors to allow the different contexts in each sector that drives firms to become cooperatives. We calculate the average treatment effect on treated (ATT), defined as the difference between expected outcome values with and without treatment for those who actually participated in treatment.¹⁹

$$ATT = E(treatment|D = 1) = E[Y(1) - Y(0)|D = 1]$$

What we essentially do is removing the difference between the cooperative firms and non-cooperative firms that could potentially lead to differences in the outcome even in the absence of treatment. By matching firms with those in similar pretreatment characteristics, we are able to attribute the effect of cooperatives on the outcome solely to the cooperative status itself (Caliendo & Kopeinig, 2008).

There are two underlying assumptions for PSM to effectively work: common support and conditional independence. We address these assumptions with the propensity score overlap and balancing properties in appendix 1. Only the observations in the common support regions are included in the analyses, following Heckman, Ichimura, & Todd (1997). Compared to regressions, matching methods have two main advantages: The common support condition allows the comparison of comparable subjects; a semi-parametric matching technique helps avoid the problem of potential misspecification. Conditional independence is untestable directly, and it is also a key assumption in regression analyses. Thus, for a robustness check, we apply an additional treatment effect estimator, inverse probability weight regression adjustment estimator (IPWRA) for markup volatility.²⁰ IPWRA is a doubly-robust estimator that gives unbiased estimates of the treatment effect when either the propensity score or the outcome model is correctly specified. By doing this, we further account for the potential violation of conditional independence.

5. Results

¹⁸ We use the second order polynomial of the variables in order to improve the matching quality (Caliendo & Kopeinig, 2008).

¹⁹ Reason to estimate ATT, instead of average treatment effect (ATE), are twofold. One is because of the less restrictive PSM assumptions required for ATT, compared to ATE (Caliendo & Kopeinig, 2008; StataCorp, 2019). Another relates to our research question as pointed in Heckman et al. (1997), that we are primarily interested in the effect of cooperatives on the market power as those who are in need of improving their seller power.

²⁰ IPWRA is an extension of the Regression Adjustment (RA) estimator that is based on a regression model, not a matching estimator. The principle of RA is to fit a linear regression separately for the treated and non-treated groups, and takes the average difference of the two regression lines to calculate the average treatment effect (StataCorp, 2019). This cannot be applied to the analyses for markup in level because the bias present in output elasticity cannot be removed in this method. Therefore, we apply IPWRA only to the analysis for markup volatility.

We look at the effect of cooperatives in the subsector, for F&V and the dairy sector. Exploring the effect of cooperative by each sector can give more detail: Verhofstadt & Maertens (2014) find a heterogeneous effect of cooperatives by the type of crops; and Hansmann (2012) also states that the agricultural marketing cooperatives are typically organized by crops. We focus on F&V and dairy sector in our analyses because of the large market share of their cooperatives compared to other subsectors apart from the interest for the two subsectors in the policy.

Before we investigate the relationship (coefficient) between cooperative and markups, and cooperative and markup volatility, we first compare the distribution of markup under CD and TL. We can see that the distributions are different to some extent under the two different production functions, which might hint the price bias present in the estimated markups under TL (Table 4). Hereafter we explore the coefficient under the CD production function that could minimize the potential price bias.²¹

In Table 5, we provide a summary of the estimated effects of cooperatives on markup level and markup volatility.²² For the markups in the F&V sector, the estimated effect of cooperative on markup is different by actors: farmers lose, and processors gain market power from being a cooperative. The effect of cooperatives on each actor for the markup volatility is the opposite of the effect on the markup level. However, the dairy cooperative processors do not enjoy the market power gain; rather their market power is significantly smaller than for non-cooperative dairy processors. Table 6.1 and Table 6.2. present the full regression results.

For the markup volatility of the F&V sector; cooperative farmers appear to achieve markup stability but not so for the cooperatives processors, although the effects are not always significant. The significantly different effects of cooperatives on farmers and processors are also confirmed in the interaction term (*coop*processors*) for the regression that combines the whole set of observations (Table 7); the markup volatility of processors cooperatives is larger than that of farmers cooperatives. The opposite effect of cooperatives for farmers and processors is interesting because non-cooperatives processors have significantly lower volatility than non-cooperatives farmers – the negative coefficient of *Processors* in columns (3) and (4) in Table 7. For the dairy sector, not only the cooperative farmers but also cooperative processors obtain markup stability relative to the non-cooperatives.

For farmers, cooperatives have lower market power while their markup volatility decreases. with no difference found between F&V farmers and Dairy farmers. Farmers cooperatives secure the stability of their market power (seller power) at the expense of smaller seller power. The same result is found in Vigani & Curzi (2021) who use the survey data showing the stated preference for stability by

²¹ The distribution of markups by the cooperative status under different production functions, however, does not substantially differ (see appendix 2).

²² See appendix 3 for the evolution of average markups over time.

farmers. This may be explained by the ownership of cooperatives: Monteiro & Stewart (2015) differentiate the types of ownership of each cooperative and demonstrate that food processor cooperatives are mostly owned by suppliers, i.e. farmers. There is no need for farmers' cooperatives to exert the seller power toward processors if they themselves are the members of the processors' cooperatives (Van Cayseele, 2018).

For processors, the effect of cooperatives is different for F&V and dairy sectors. Regarding market power, processor cooperatives of the F&V sector increase their market power, while the cooperative processors of the dairy sector have less market power. For markup volatility, in the F&V sector, cooperative processors seem to have higher markup volatility than non-cooperative processors. This can be explained by cooperatives who vertically integrate relieve the farmers from volatility by absorbing it.

6. Discussion

The different effects of cooperatives on farmers, compared to processors, may be attributed to the inherent uncertainties that already exist in agricultural production, for example, due to varying weather conditions (Nilsson, 2001).²³ Farmers may place higher importance on the stability of their profits. Mérel, Saitone, & Sexton (2015) also show that risk-averse farmers enjoy the insurance aspect of the cooperatives' pooling practices against the quality shocks of their produce because this type of risk is not guaranteed by the standard crop-insurance scheme.

Now, we elaborate more about the higher market power, i.e. higher profitability (excluding fixed cost), of cooperatives processors in the F&V sector. This market power gain is in addition to controlling for productivity, which indicates that they achieve higher markups also from the demand side.²⁴ One possible explanation is the product differentiation, e.g. through branding, of the F&V cooperative processors.²⁵ This significantly positive effect is more notable because the estimated productivity that we include as a control variable does not only exclusively represent physical productivity but the revenue productivity that already carries the price effect, given that we had to rely

²³ In a slightly different perspective, Grashuis (2018) states that vertical integration is one of their common strategies of farmers' cooperatives.

²⁴ Note that it is not our interest to interpret other coefficients including productivity. It is particularly for productivity that cannot be precisely measured for physical productivity due to data restrictions.

²⁵ Modern agri-food value chains are characterized by the rise in importance of quality (Caswell & Mojduszka, 1996) and credence attributes (Darby & Karni, 1973), because of changing circumstance in the agricultural markets. Several studies find that adopting standards as part of producers' strategy for product differentiation may assign them pricing power (Bonnet & Bouamra-Mechemache, 2016; Bonroy & Constantatos, 2015; Caswell & Mojduszka, 1996).

on revenue data instead of physical output in production function estimation (De Loecker & Goldberg, 2014).

The success of cooperatives' product differentiation is also supported by the literature. Höhler & Kühn (2014) find that branding is one of the major differentiation strategies of cooperatives in the food value chain. Cooperatives, particularly at the processing stages of the food value chain, are more easily invest in specialized assets that are required in differentiation such as brand names (Hendrikse & Veerman, 2001). Producer organizations play a role in promoting product differentiation (e.g. grading schemes) and certifying quality (Myers et al., 2010; Verhaegen & Van Huylbroeck, 2001). More than one-third of cooperatives' turnover in Italy is from processed products sold with the cooperative's own brand (Fonte & Cucco, 2017).

The result could be also attributed to the EU regulation for the common organization of agricultural markets in the EU (No. 1308/2013), which initially targeted the F&V sector of the development of producer organizations since 2001. The dairy sector has been supported by this regulation only since 2011 (Michalek et al., 2018). This regulation not only aims to support the producer organizations but also to increase the marketing standard enhancing the quality of the product. For example, F&V are among the most often registered category for geographical indication product in Europe and Italy has the highest number of products registered as a GI country of origin (Török & Moir, 2018).

Lastly, we would like to emphasize the importance of our measure of market power which precisely represents the profitability in terms of economic cost, on the contrary to the accounting profit that does not take into account the opportunity costs. It is possible that the higher markup for cooperatives could be the result of the higher fixed inputs as firms need to increase the price just to cover the higher fixed inputs, thus higher markup might not come from the higher market power, as argued in De Loecker, Eeckhout, & Unger (2020). To that effect, we plot Figure 1 to identify whether there are any systematic differences between cooperatives and non-cooperatives in the relationship between markup and fixed input.²⁶ It is shown that higher fixed input will lead to a higher markup, as expected because higher prices relative to marginal cost are required to offset the fixed cost in order to avoid making losses (De Loecker et al., 2020). However, most importantly, we do not find any patterns specific to cooperatives. We can conclude that it is not due to the higher fixed input that we find higher markup for F&V processors but it is the higher market power, hence the profitability of the cooperatives.

²⁶ We also run simple regressions to clear out the different effect of capital share on markup by the cooperative dummy. However, there is no evidence of the higher markups of cooperatives arising from the higher capital of cooperative, compared to non-cooperative. Rather, the coefficient of capital share on markup is even larger for non-cooperatives.

7. Conclusion

The article encompasses 2 theories regarding the formation of cooperatives: on the one hand IO theory explains cooperatives as emerging from the goal to create countervailing market power. This explanation is rejected in the Italian data. On the other hand, and in line with a policy target of EU CAP, the reduction of the volatility is the goal. By relying on the instrument of cooperatives however, the reduction of volatility comes at the expense of a reduction in markup levels, not rejecting the well-known risk return tradeoff in finance. The implications for policy making are extremely important: if EU CAP solely promotes the reduction of volatility by forming cooperatives, this will imply a reduction of farm income. Other, complementary policies then may be needed to guarantee both a sustainable and stable income for farmers.

Table 1 Share of cooperatives in Italy by subsectors

Subsector	Number of firms	Revenue
Fruits and vegetables	22%	25%
Dairy	16%	19%
Meat	7%	26%
Services	29%	14%
Wine	10%	13%
Olive	6%	1%
Land management and forestry	6%	1%
Other sectors	5%	2%
Cooperatives in Total	100%	100%

Source: *Osservatorio della cooperazione agricola italiana* (2017)

Table 2 Share of cooperatives in our data

	Fruits and Vegetables		Dairy	
	Farmers	Processors	Farmers	Processors
Share of coop	43.8%	13.4%	38.6%	28.1%
Total no. of firms	1507	987	280	1030

Table 3 Descriptive statistics of production variables

	Unit in million €	F&V			Dairy		
		Mean	S.D.	Obs.	Mean	S.D.	Obs.
Farmers	Turnover	1459	5445	4697	3077	6701	1118
	Total assets	2057	5302	4697	5330	9155	1118
	Material costs	828	3307	4697	2123	4529	1118
	No. of employee	15	65	4697	14	61	1118
Processors	Turnover	12667	37928	4593	16489	65885	5231
	Total assets	11593	30940	4593	18286	131474	5231
	Material costs	8480	28236	4593	10999	40852	5231
	No. of employee	29	74	4593	33	117	5231

Table 4 Markup distribution under different production functions

	Cobb-Douglas		Translog value added	
	F&V	Dairy	F&V	Dairy
Farmers	1,67 (1.401)	1,18 (0.419)	1,44 (0.650)	1,33 (0.240)
Processors	1,12 (0.668)	0,80 (0.177)	1,52 (0.672)	1,32 (0.220)

Note: Mean(S.D). The distributions are censored at 3rd and 97th percentiles, following the common practice, notably De Loecker, Goldberg, Khandelwal, & Pavcnik (2016). Further analyses are based on this distribution of firm-level markups.

Table 5 Summary of estimated effects of cooperatives on markup and markup volatility

	Estimator	Fruits and Vegetables		Dairy	
		Farmers	Processors	Farmers	Processors
Markup	OLS	-0.158*** (0.025)	0.049 (0.030)	-0.120*** (0.029)	-0.014 (0.009)
	CRE	-0.149*** (0.030)	0.083** (0.036)	-0.064* (0.034)	-0.020* (0.012)
	PSM	-0.091*** (0.024)	0.047* (0.019)	-0.108*** (0.030)	-0.041*** (0.007)
Markup volatility	OLS	-0.011 (0.018)	0.026 (0.016)	-0.033** (0.016)	-0.007 (0.006)
	PSM	0.006 (0.023)	0.020 (0.020)	-0.042 (0.030)	-0.014 (0.008)
	IPWRA	0.005 (0.019)	0.017 (0.017)	-0.044** (0.020)	-0.012 (0.007)

Note: The same observations are used across different estimators. For PSM, the number of observations slightly differs because of the observations that do not satisfy the common support assumption. Nonetheless, the observations dropped in PSM are very few: eight in F&V and four in dairy sectors.

Table 6.1 Regression analyses for Markup and cooperatives by actor (Fruits and vegetable sector)

	Farmers					Processors				
	(1) Pooled OLS	(2) Hybrid	(3) CRM	(4) FE	(5) RE	(6) Pooled OLS	(7) Hybrid	(8) CRM	(9) FE	(10) RE
Labor	0.092*** (0.016)		0.172*** (0.008)	0.173*** (0.008)	0.140*** (0.008)	0.148*** (0.011)		0.126*** (0.006)	0.126*** (0.006)	0.125*** (0.006)
Labor_b		0.022 (0.018)	-0.149*** (0.020)				0.130*** (0.018)	0.004 (0.019)		
Labor_w		0.172*** (0.008)					0.126*** (0.006)			
Capital	0.052*** (0.011)		0.031** (0.015)	0.031** (0.015)	0.030*** (0.008)	-0.162*** (0.010)		-0.120*** (0.011)	-0.120*** (0.011)	-0.158*** (0.007)
Capital_b		0.063*** (0.010)	0.032* (0.018)				-0.179*** (0.012)	-0.058*** (0.016)		
Capital_w		0.031** (0.015)					-0.120*** (0.011)			
Coop dummy	-0.158*** (0.025)	-0.149*** (0.030)	-0.149*** (0.030)		-0.184*** (0.029)	0.049 (0.030)	0.083** (0.036)	0.083** (0.036)		0.108*** (0.036)
Productivity	-1.919*** (0.060)		-1.601*** (0.062)	-1.610*** (0.062)	-1.849*** (0.047)	-1.294*** (0.055)		-0.748*** (0.043)	-0.748*** (0.043)	-0.859*** (0.038)
Productivity_b		-1.901*** (0.076)	-0.299*** (0.098)				-1.208*** (0.088)	-0.461*** (0.098)		
Productivity_w		-1.601*** (0.062)					-0.748*** (0.043)			
Constant	3.143*** (0.105)	3.223*** (0.116)	3.223*** (0.116)	2.540*** (0.141)	3.148*** (0.087)	2.040*** (0.069)	2.161*** (0.109)	2.161*** (0.109)	1.297*** (0.100)	1.718*** (0.063)
Observations	4,697	4,697	4,697	4,697	4,697	4,593	4,593	4,593	4,593	4,593
R-squared	0.399			0.253		0.354			0.167	
No. of firms		1,507	1,507	1,507	1,507		981	981	981	981

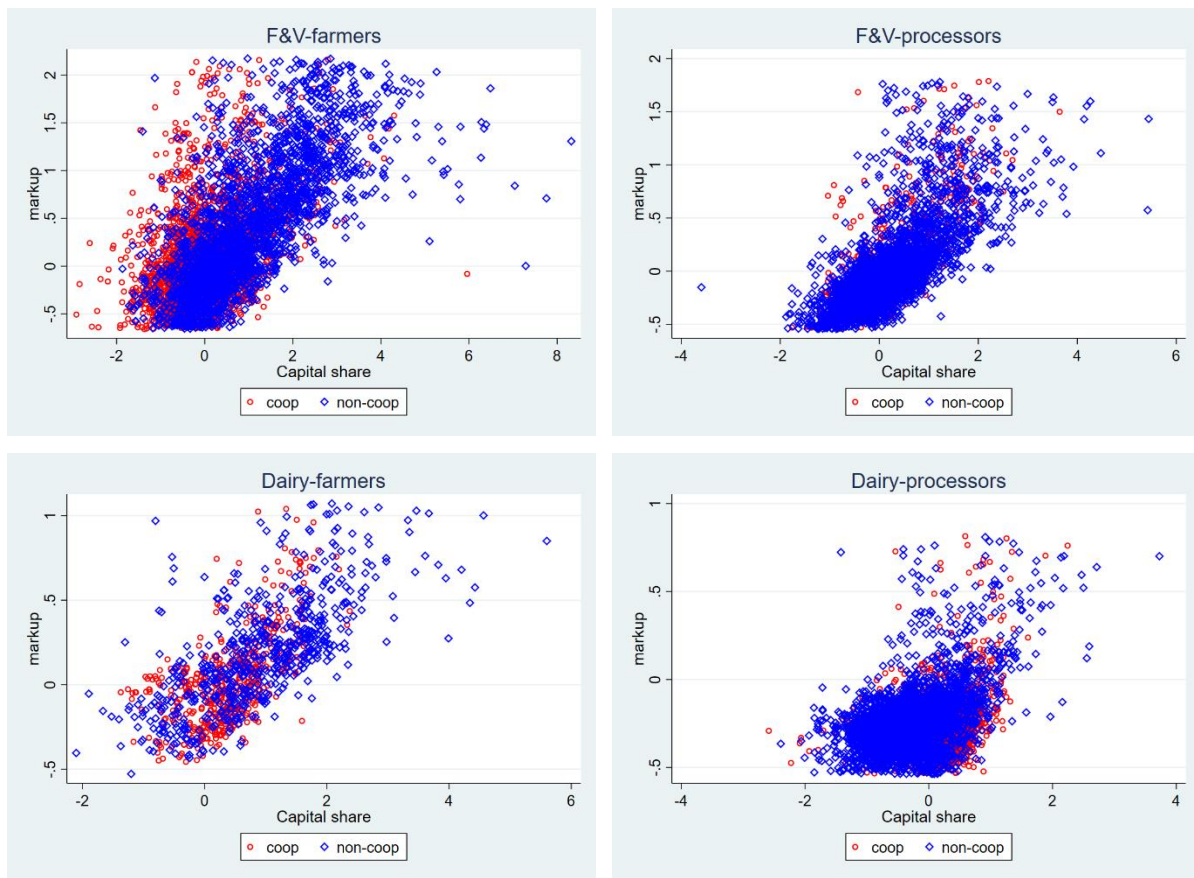
Table 6.2 Regression analyses for Markup and cooperatives by actor (Dairy sector)

	Farmers					Processors				
	(1) Pooled OLS	(2) Hybrid	(3) CRM	(4) FE	(5) RE	(6) Pooled OLS	(7) Hybrid	(8) CRM	(9) FE	(10) RE
Labor	0.085*** (0.018)		0.091*** (0.011)	0.093*** (0.011)	0.081*** (0.010)	0.139*** (0.007)		0.150*** (0.004)	0.150*** (0.004)	0.142*** (0.004)
Labor_b		0.061*** (0.023)	-0.030 (0.026)				0.110*** (0.009)	-0.040*** (0.010)		
Labor_w		0.091*** (0.011)					0.150*** (0.004)			
Capital	-0.061*** (0.012)		0.050*** (0.015)	0.050*** (0.015)	-0.017 (0.010)	-0.045*** (0.004)		-0.062*** (0.006)	-0.063*** (0.006)	-0.054*** (0.003)
Capital_b		-0.057*** (0.014)	-0.108*** (0.021)				-0.036*** (0.005)	0.027*** (0.007)		
Capital_w		0.050*** (0.015)					-0.062*** (0.006)			
Coop dummy	-0.120*** (0.029)	-0.064* (0.034)	-0.064* (0.034)		-0.095*** (0.035)	-0.014 (0.009)	-0.020* (0.012)	-0.020* (0.012)		-0.006 (0.011)
Productivity	-1.223*** (0.119)		0.381*** (0.102)	0.384*** (0.102)	-0.145 (0.088)	-0.749*** (0.038)		-0.693*** (0.022)	-0.693*** (0.022)	-0.702*** (0.019)
Productivity_b		-1.206*** (0.165)	-1.586*** (0.195)				-0.715*** (0.040)	-0.022 (0.046)		
Productivity_w		0.381*** (0.102)					-0.693*** (0.022)			
Constant	1.376*** (0.110)	0.381*** (0.174)	1.381*** (0.175)	-0.776*** (0.157)	0.217* (0.113)	0.950*** (0.054)	0.909*** (0.057)	0.909*** (0.057)	0.970*** (0.058)	0.947*** (0.033)
Observations	1,118	1,118	1,118	1,118	1,118	5,231	5,231	5,231	5,231	5,231
R-squared	0.276			0.159		0.383			0.344	
No. of firms		280	280	280	280		1,030	1,030	1,030	1,030

Table 7 Regression analyses for markup volatility and cooperatives by actor

	F&V				Dairy			
	Farmers	Processors	All	All	Farmers	Processors	All	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ols	ols	ols	ols	ols	ols	ols	ols
Labor	-0.026*	-0.010	-0.032***	-0.030***	-0.004	-0.011**	-0.010**	-0.009**
	(0.014)	(0.009)	(0.007)	(0.007)	(0.006)	(0.005)	(0.004)	(0.004)
Capital intensity	0.015**	-0.019***	0.002	0.001	-0.019***	0.008***	0.004*	0.003
	(0.007)	(0.007)	(0.005)	(0.005)	(0.006)	(0.003)	(0.002)	(0.003)
Coop dummy	-0.011	0.026	-0.010	-0.033*	-0.033**	-0.007	-0.010*	-0.026*
	(0.018)	(0.016)	(0.013)	(0.017)	(0.016)	(0.006)	(0.005)	(0.015)
Processors			-0.282***	-0.297***			0.054***	0.039*
			(0.029)	(0.029)			(0.017)	(0.023)
Coop* Processors				0.071***				0.021
				(0.024)				(0.017)
Productivity	-0.269***	-0.211***	-0.212***	-0.211***	-0.204***	-0.135***	-0.127***	-0.121***
	(0.046)	(0.036)	(0.026)	(0.026)	(0.050)	(0.023)	(0.020)	(0.021)
Constant	0.656***	0.478***	0.651***	0.666***	0.452***	0.245***	0.211***	0.219***
	(0.067)	(0.044)	(0.050)	(0.050)	(0.063)	(0.032)	(0.020)	(0.022)
Observations	781	726	1,507	1,507	180	818	998	998
R-squared	0.083	0.133	0.156	0.160	0.138	0.084	0.120	0.122

Figure 1 Relationship between the markup and the fixed input



Note: Firm-level markups and the fixed input as a share of expenditure are both expressed in logarithms.

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Appendix 1: Assumption checks for PSM estimations

A. PSM for markup level

A.1 Overlap and distribution of estimated propensity score

Figure A1.1 Propensity score distribution of farmers and processors (fruits and vegetable sector)

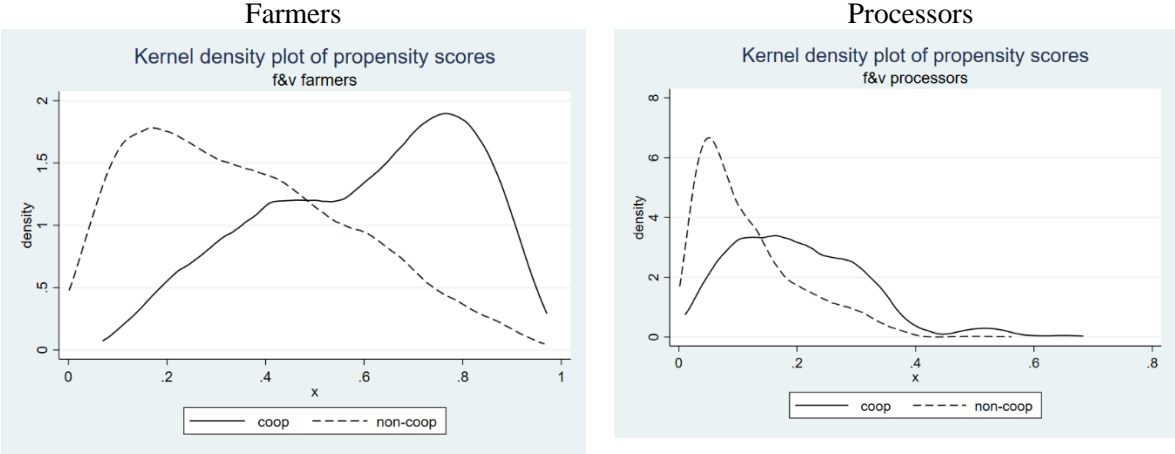
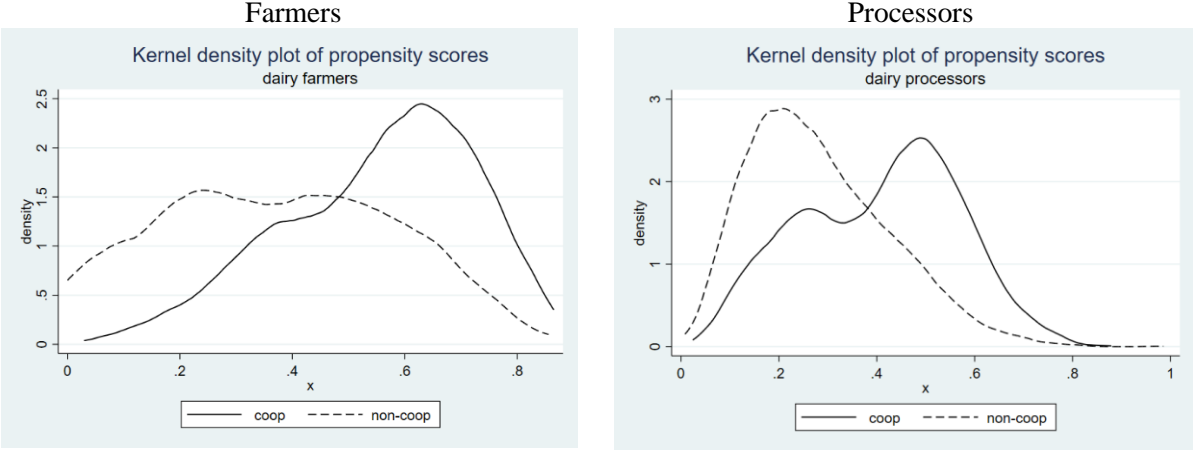


Figure A1.2 Propensity score distribution of farmers and processors (dairy sector)



A.2 Balancing properties

Figure A2.1 Propensity score histograms of farmers and processors (fruits and vegetable sector)

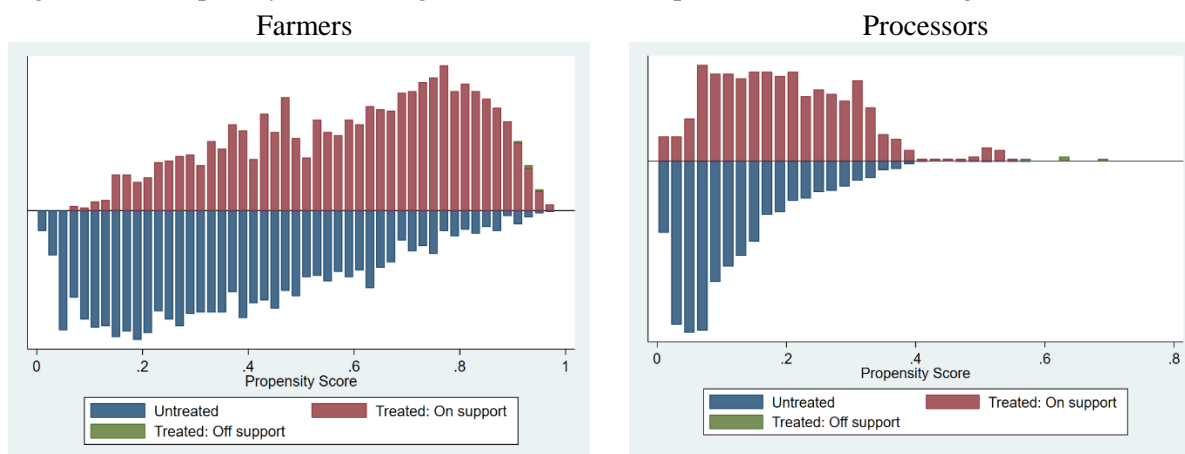


Figure A2.2 Propensity score histogram of farmers and processors (dairy sector)

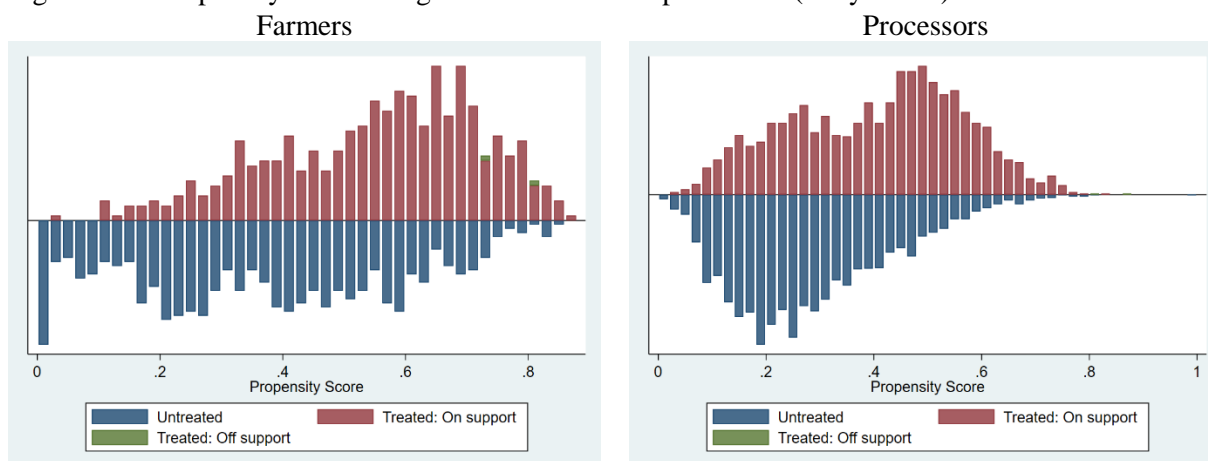


Table A2.1 Balancing properties of covariates of cooperatives and non-cooperatives for kernel matching on propensity scores

			Pseudo R2	LR chi2	p>chi2	MeanBias	MedBias	B	R
FV	Farmer	Unmatched	0.189	1230.53	0.000	39.0	19.4	110.7*	0.82
		Matched	0.004	27.24	0.000	6.8	6.0	15.6	0.67
	Processor	Unmatched	0.100	350.90	0.000	32.7	23.8	85.8*	0.91
		Matched	0.002	3.94	0.685	5.7	5.8	11.6	0.84
Dairy	Farmer	Unmatched	0.129	198.87	0.000	20.0	24.7	65.6*	0.12*
		Matched	0.002	3.01	0.807	2.7	2.6	10.9	0.94
	Processor	Unmatched	0.098	646.08	0.000	28.4	33.4	78.1*	1.02
		Matched	0.003	15.35	0.018	4.8	4.3	13.3	0.47*

B. PSM for markup volatility

B.1 Overlap and distribution of estimated propensity score

Figure B1.1 Propensity score distribution of farmers and processors (fruits and vegetable sector)

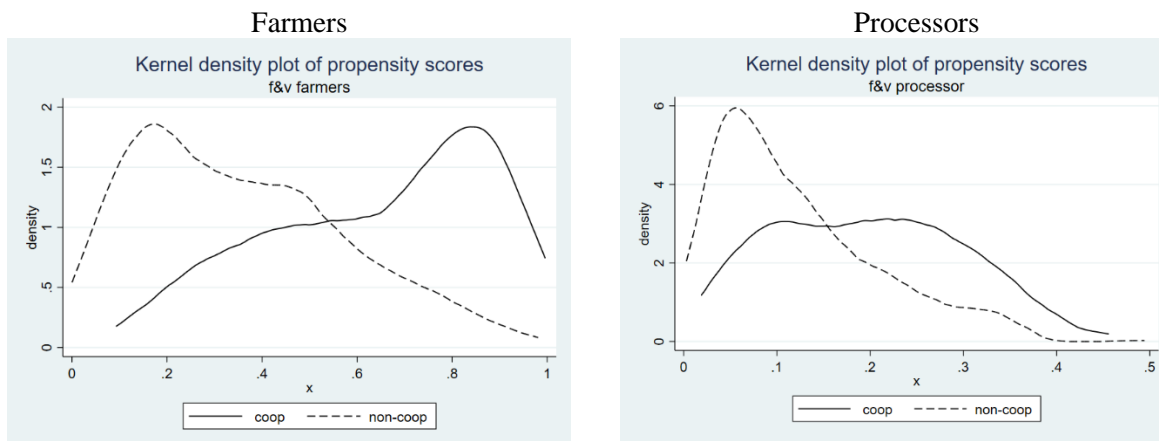
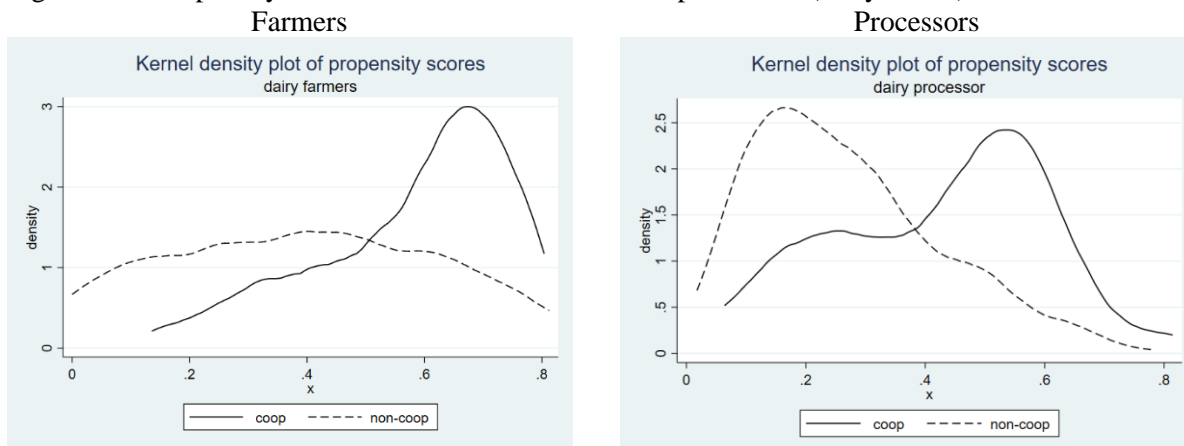


Figure B1.2 Propensity score distribution of farmers and processors (dairy sector)



B.2 Balancing properties

Figure B2.1 Propensity score histograms of farmers and processors (fruits and vegetable sector)

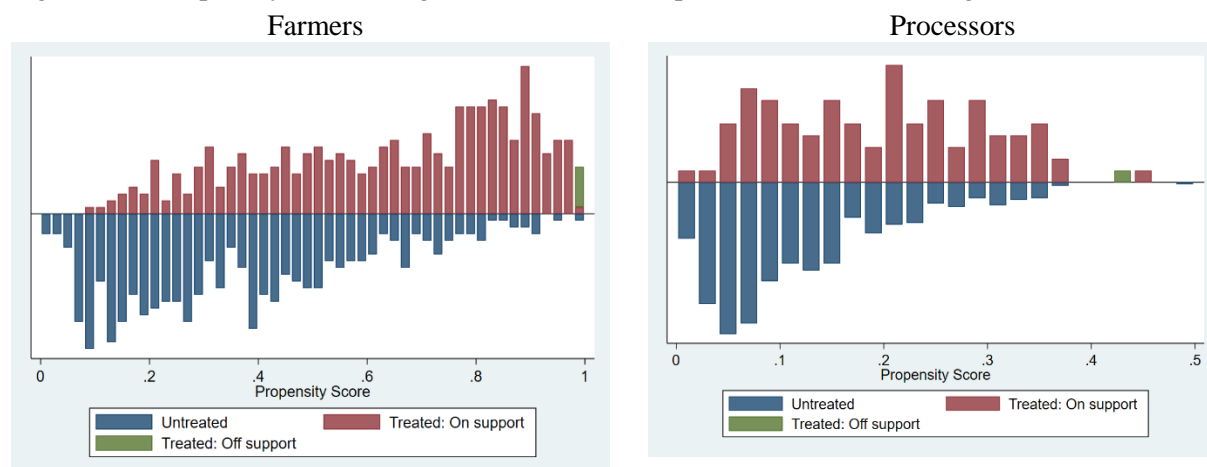


Figure B2.2 Propensity score histogram of farmers and processors (dairy sector)

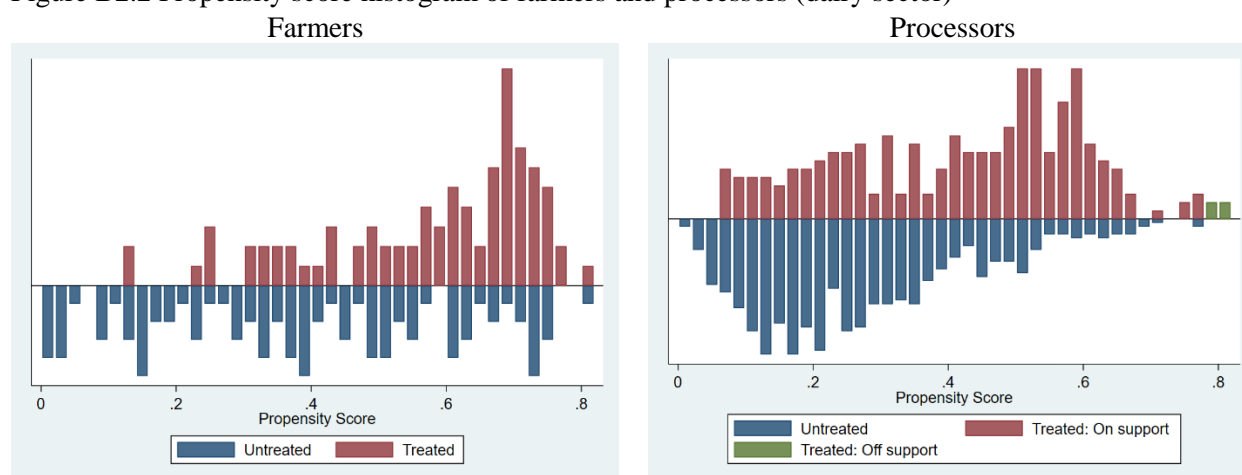
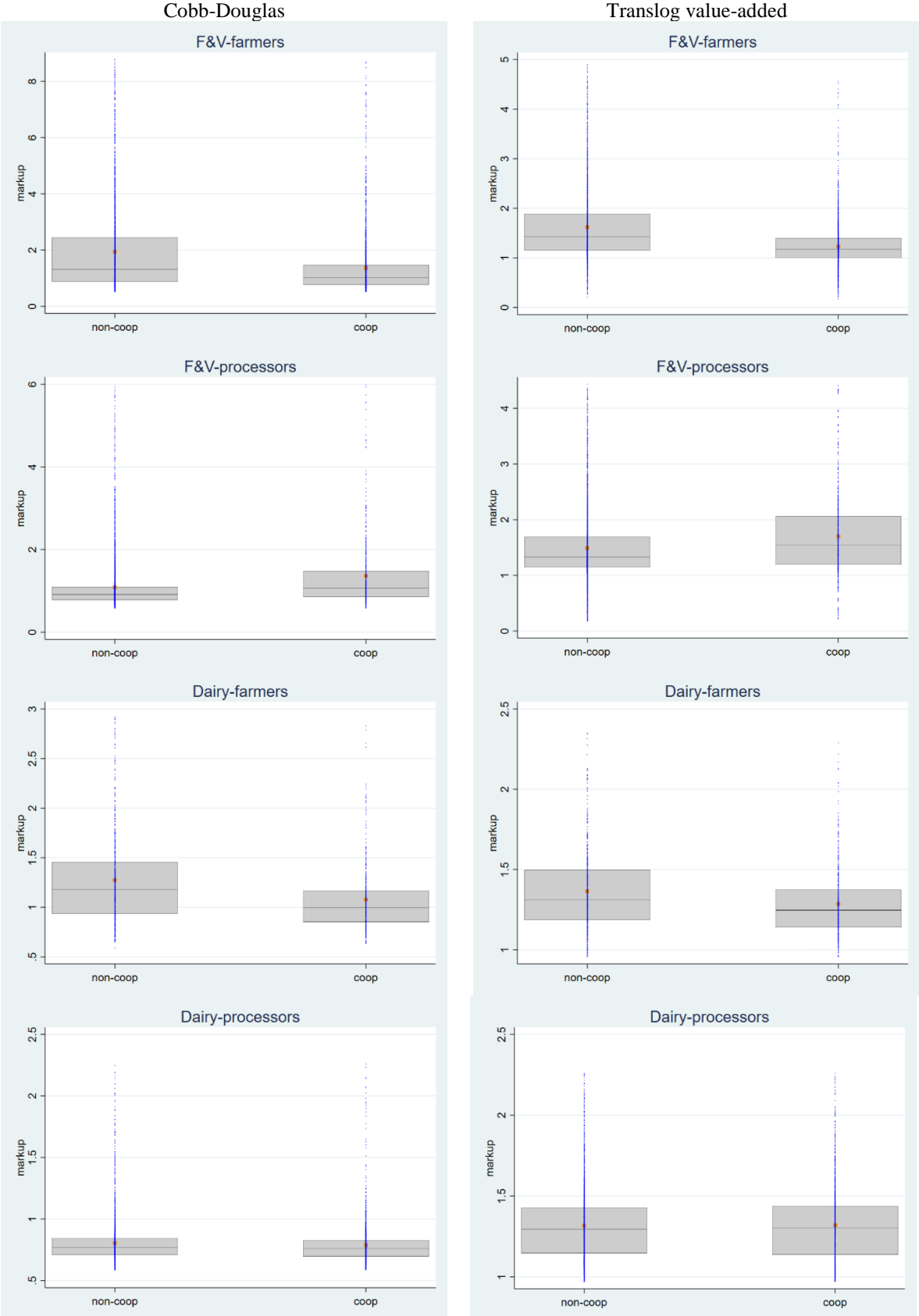


Table B2.1 Balancing properties of covariates of cooperatives and non-cooperatives for kernel matching on property scores

			Pseudo R2	LR chi2	p>chi2	MeanBias	MedBias	B	R
FV	Farmer	Unmatched	0.237	256.39	0.000	46.0	29.0	124.7*	1.09
		Matched	0.008	8.24	0.221	8.0	8.4	20.4	0.67
	Processor	Unmatched	0.095	53.56	0.000	36.9	28.6	83.7*	0.81
		Matched	0.002	0.41	0.999	4.8	5.3	9.3	0.89
Dairy	Farmer	Unmatched	0.129	198.87	0.000	20.0	24.7	65.6*	0.12*
		Matched	0.002	3.01	0.807	2.7	2.6	10.9	0.94
	Processor	Unmatched	0.098	646.08	0.000	28.4	33.4	78.1*	1.02
		Matched	0.003	15.35	0.018	4.8	4.3	13.3	0.47*

Appendix 2: Markup distribution by cooperative under different production functions



Note: The figure presents boxplots for each sector by cooperative status. All data points corresponding to the estimated firm-level markups are shown in blue. The orange dot denotes the average markup.

Appendix 3: Evolution of average markups

