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ORIGINAL ARTICLE

Markups, organic agriculture and downstream concentration at the example of European dairy farmers

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Abstract

A competitive environment, highly concentrated processing and retailing sectors as well as increasing decoupling of direct payments from production volumes and the area under cultivation incentivizes farmers to find alternative ways to improve their bargaining position towards downstream companies. This article explores the possibilities of organic agriculture to enhance the bargaining power of farmers along with the role of concentration in downstream industries. Using a dataset with more than 200,000 observations from approximately 40,000 dairy farms, I estimate markups of price over marginal cost in dairy farming as a measure of market power in the EU. The results show that organic farmers achieve a significant markup premium over conventional farmers. With increasing market shares of organic milk in total milk production markups of conventional farmers diminish whereas those of organic farmers are unaffected. Farm-level markups decrease with increasing market shares of medium-sized dairy processors and increase with increasing market shares of large processors. The presence of large multinational retail chains shows an adverse impact on farmers' markups.

KEYWORDS
dairy farming, market power, markups, organic agriculture

JEL CLASSIFICATION
D22, L11, L66, Q11, Q12, Q18

1 | INTRODUCTION

Farmers are often seen as being exposed to market power exercised by downstream companies in food supply chains (Sexton, 2013; Sexton & Xia, 2018). This may cause farm-gate prices to be below the competitive level, thereby reducing farmers' income. While the financial support of farmers still accounts for 36% (=€59 billion) of the overall EU budget, the subsidies get stepwise decoupled from production volumes and the area under cultivation, and are increasingly bound to the provision of ecosystem services (European Commission, 2020a). This development reinforces the incentive for farmers to seek ways achieving higher prices and circumvent downstream market power. One of these ways is organic agriculture generating price premia over conventional products (Crowder & Reganold, 2015). However, organic agriculture also entails higher average costs of production compared with conventional agriculture (European Commission, 2013; Uematsu & Mishra, 2012). Hence, whether organic farmers have an improved bargaining position towards downstream companies or higher prices only result from increased production costs, remains an open question.

I investigate farm-level seller market power of dairy farmers and its determinants in Europe to shed light on the relationship between market power and organic production. Milk production represents a good case study since dairy processors have been accused repeatedly to abuse market power in raw milk procurement (Di Marcantonio et al., 2020; Grau & Hockmann, 2018). I calculate farmers' markups of price over marginal cost as an indicator of market power estimating a translog cost function. Further, I identify determinants of markups with a particular emphasis on markup differences between conventional and organic farms. My data cover the years 2004–2017 and 18 European countries with more than 200,000 observations comprised by approximately 40,000 farms. My results are of particular interest for farmers who seek improving their bargaining position in price negotiations with downstream companies, or achieving higher prices in direct marketing to consumers. Moreover, the insights generated by this study may guide policy makers in adapting the Common Agricultural Policy towards more targeted measures in supporting farmers.

The theory of niche markets suggests that firms operating in small markets realize higher margins as they offer differentiated products (Ilbery & Kneafsey, 1999; Smallbone et al., 1999). Despite the fact that sales of organic food products along with the area under production have experienced a steep incline during the past two decades (Reganold & Wachter, 2016), the area under organic production has contributed less than 10% to the total farm area in approximately 70% of the European countries in 2017 (Eurostat, 2020c). The shares of organic in total milk production are even smaller (Eurostat, 2020b, 2020d) such that the market for organically produced milk must still be considered as a niche market. In that regard, Bonnet and Bouamra-Mechemache (2016) find that an organic label improves the bargaining position of dairy processors towards retailers compared to unlabeled products in the French fluid milk market, resulting in margins of organic milk exceeding those of conventional milk by 25 percentage points.

Nevertheless, this does not necessarily imply that organic farmers also have a better bargaining position towards processors since processors have been found to exercise input market power in raw milk procurement from farmers. Čechura et al. (2014) estimate an average markdown of the input price below the marginal value product of raw milk of 6.6% (2003–2012). Grau and Hockmann (2018) estimate conjectural elasticities[1] of dairy processors in purchasing raw milk from farmers between .04 and .07 in Germany for 2010–2011 indicating a mild departure from perfect competition. Therefore, it may be that processors absorb a certain share of the organic price premium, and organic farmers' bargaining position may be the same as for conventional farmers.

First, I contribute to the literature on market power in food supply chains by estimating farm-level markups of output price over marginal cost of milk production in 18 European countries. Second, estimating markups on the farm-level enables me to identify farm-specific drivers of markups. In that respect, organic production is of key interest. Third, I examine whether markups vary for changing market shares of organic milk in total milk. Thereby, I provide evidence of whether the increased margins in niche markets are robust when the size of the niche varies. Further, I analyze how markups relate to farm size, which helps to understand farm structural change in Europe. Last, I explore the impact of concentration in downstream industries on farm-level markups since concentration in food processing and retailing is widely perceived as being responsible for declining prices of agricultural outputs (e.g., Crespi et al., 2012; Sexton & Xia, 2018).

The rest of the paper is structured as follows. In the next section, I illustrate the theoretical basis for the markup estimation. This is followed by the empirical strategy to uncover markups. Subsequently, I derive my hypotheses with respect to the relationship of markups and farm characteristics. Thereafter, I present the data used in the analysis and discuss the results. Finally, I conclude by deriving the implications of my findings.

2 | THEORETICAL CONSIDERATIONS

Under perfect competition in output markets, an output's price (P) equals its marginal cost (MC). The prevalent measure to capture deviations from competitive pricing is markup (μ) defined as the ratio of P over MC (e.g., Bonanno et al., 2018; De Loecker et al., 2020; Kumbhakar et al., 2012). μ ranges from zero to infinity while $\mu = 1$ indicates perfect competition. For $\mu > 1$, the farmer possesses oligopolistic or monopolistic market power.

I obtain an estimate of MC by estimating a cost function.[2] I follow previous studies on dairy farming in Europe and assume that dairy farmers minimize cost as

[1] The conjectural elasticity ranges from zero to one. A value of zero indicates perfect competition and a value of one a monopsony.

[2] There are several other methods to estimate markups. The production function approach introduced by De Loecker and Warzynski (2012) is one of them where one uses input expenditures, revenue, and an estimate of the output elasticity to recover markups. However, for joint production

they take milk output quantities as given (e.g., Alem et al., 2019; De Frahan et al., 2011; Pierani & Rizzi, 2003; Wieck & Heckelei, 2007).[3] The restricted possibilities of milk output adjustments by farmers are due to the EU milk quota system (1984–2015).[4] For cost minimization, farmers choose quantities of variable inputs for given levels of output and quasi-fixed inputs such that cost are minimum. The farmers' short-run variable cost function (C) is given by:

$$C = \mathbf{W}'\mathbf{X} + \mathbf{R}'\mathbf{K} \; s.t. \; f\ (\mathbf{X}, \mathbf{K}) = \mathbf{Q} \tag{1}$$

where $\mathbf{W}$ is a vector of prices for the variable inputs and $\mathbf{X}$ denotes the vector of the quantities of variable inputs. $\mathbf{R}$ and $\mathbf{K}$ are price and quantity vectors of quasi-fixed factors, respectively. Quasi-fixed factors cannot be adjusted in the short-run, that is, farmers minimize cost conditional on the quantities of $\mathbf{K}$. $\mathbf{Q}$ is a vector of output quantities. The technology by which inputs are transformed into outputs is represented by $f(.)$. The cost function is non-decreasing in $\mathbf{Q}$ and $\mathbf{W}$, and is linearly homogeneous in $\mathbf{W}$[5] (Coelli et al., 2005). C is concave in each $\mathbf{W}$ implying that, for a given relative increment in some $\mathbf{W}$, costs will increase to a lesser extent due to input substitutability. The Lagrangian (L) for the cost minimization problem is:

$$L \ = \ \mathbf{W}'\mathbf{X} + \mathbf{R}'\mathbf{K} - \ \lambda\left(f\left(\mathbf{X}, \mathbf{K}\right) - \mathbf{Q}\right) \tag{2}$$

where λ denotes the Lagrange multiplier. Taking the first derivatives with respect to $\mathbf{X}$ along with λ and setting them equal to zero yields the first-order conditions (FOC) of the optimization problem. Solving the system of equations for the variable input quantities, I obtain the contingent input demand functions. These can be substituted into Equation (1) to obtain the farmers' short-run minimum cost function $C(\mathbf{Q},\ \mathbf{W},\ \mathbf{K})$, which is the target function to estimate.

2.1 | Empirical implementation

I approximate the true minimum cost function using a multi-input, multi-output translog cost function, which provides high flexibility (e.g., Christensen et al., 1973) and is widely applied (Alem et al., 2019; Renner et al., 2014; Wimmer & Sauer, 2020).[6] The cost function is given by

$$\begin{aligned} lnC = \kappa_0 \ &+ \sum_{l=1}^{L} \alpha_l lnQ_l + 0.5 \sum_{l=1}^{L} \sum_{m=1}^{M} \alpha_{lm} lnQ_l lnQ_m \\ &+ \sum_{j=1}^{J} \beta_j lnW_j + 0.5 \sum_{j=1}^{J} \sum_{k=1}^{K} \beta_{jk} lnW_j lnW_k \\ &+ \sum_{l=1}^{L} \sum_{j=1}^{J} \gamma_{lj} lnQ_l lnW_j + \sum_{r=1}^{R} \upsilon_r lnK_r \\ &+ 0.5 \sum_{r=1}^{R} \sum_{s=1}^{S} \upsilon_{rs} lnK_r lnK_s + \sum_{l=1}^{L} \sum_{r=1}^{R} \eta_{lr} lnQ_l lnK_r \\ &+ \sum_{j=1}^{J} \sum_{r=1}^{R} \omega_{lr} lnW_j lnK_r + \sum_{t=1}^{T} \delta_t Tech_t \ + \ \varepsilon. \end{aligned} \tag{3}$$

α, β, γ, δ, υ, η, ω and κ_0 are parameters to estimate, and l and m (j and k, r and s) are subscripts for outputs (variable inputs, quasi-fixed inputs). In the selection and definition of outputs, quasi-fixed and variables inputs, I largely follow previous literature on EU dairy farming (De Frahan et al., 2011; Renner et al., 2014; Skevas et al., 2018; Wieck & Heckelei, 2007; Wimmer & Sauer, 2020). The $L = 3$ outputs are (1) milk, (2) meat, and (3) crop output other than feedstuff[7]. The $J = 3$ variable inputs are (1) purchased feed, (2) energy, and (3) seeds, fertilizer and plant protection products. Last, the $R = 6$ quasi-fixed inputs comprise

processes with multiple outputs such as agriculture, it is not possible to display the technology using single production functions as they are not able to depict the dependencies of the different outputs (Hall, 1973; Lence & Miller, 1998). Alternatively, it would be possible to use the stochastic frontier approach introduced by Kumbhakar et al. (2012) which comes at the cost of assuming markups being strictly larger than or equal to one. But, since farmers receive a considerable number of subsidies, they may continue their operations even though they incur markups being smaller than one (Caselli et al., 2018; Koppenberg & Hirsch, 2022a, 2022b). Last, demand side approaches to estimate markups (Berry et al., 1995; Nevo, 2001) are not possible to apply in my case since the necessary data are not available. Therefore, I abstained from using one of the other approaches.

[3] Note that this assumption is to be relaxed when studying other geographical areas since farmers could adjust their output strategically as a response to outputs of other farmers or as a reaction to price changes in international markets.

[4] In the quota system, farmers had to pay a levy, if they produced more than their allocated quota volume. Despite the possibility to trade quota certificates, the certificates have been very costly for the buyer (Wieck & Heckelei, 2007).

[5] Linear homogeneity entails a b-fold increase in costs for an increase in all variable input prices by factor b.

[6] Even though some studies also have used simpler specifications, for example, by assuming linear marginal cost curves , the majority of earlier research on dairy farming has found that simple technology specifications such as Cobb-Douglas are to be rejected against more complex functions forms Alem et al. (2019); Atsbeha et al. (2012); Moreira and Bravo-Ureta (2010); Tauer (2016).

[7] An aggregation into one single output is not feasible for the scope of my study as I am particularly interested in the markups for milk production. Creating a compound output measure would lead to an overall markup across all outputs, that is, milk, meat, and crops. I would then not be able to separate the different markups for each output. A further aggregation of outputs is hence inappropriate (Mosheim & Knox Lovell, 2009).

(1) unpaid labor[8], (2) paid labor, (3) land, (4) capital, (5) dairy cows, and (6) other livestock. Note that I use a panel data set but omit subscripts for farm (i) and year (t) to keep the equations concise. $Tech$ is a set of year dummies accommodating for Hicks-neutral technical change and ε is an error term capturing optimization and measurement error.

The translog cost function is symmetric meaning that $\alpha_{lm} = \alpha_{ml}$, $\beta_{jk} = \beta_{kj}$ and $\upsilon_{rs} = \upsilon_{sr}$ for all l, m, j, k, r and s (Coelli et al., 2005). With respect to the regularity conditions, linear homogeneity of the cost function requires the following parametric restrictions: $\sum_{j=1}^{J} \beta_j = 1$, $\sum_{k=1}^{K} \beta_{jk} = \sum_{l=1}^{L} \gamma_{lj} = \sum_{r=1}^{R} \omega_{jr} = 0$ (Alem et al., 2019; Liu et al., 2014; Ray, 1982). I impose the restrictions a priori by normalizing Equation (3) by one variable input price, that is, I divide C and the variable input prices by one variable input price such that Equation (3) turns into:

$$\begin{aligned} ln\left(\frac{C}{W_J}\right) &= \kappa_0 + \sum_{l=1}^{L} \alpha_l lnQ_l \\ &+ 0.5 \sum_{l=1}^{L} \sum_{m=1}^{M} \alpha_{lm} lnQ_l lnQ_m + \sum_{j=1}^{J-1} \beta_j ln\tilde{W}_j \\ &+ 0.5 \sum_{j=1}^{J-1} \sum_{k=1}^{K-1} \beta_{jk} ln\tilde{W}_j ln\tilde{W}_k \\ &+ \sum_{l=1}^{L} \sum_{j=1}^{J-1} \gamma_{lj} lnQ_l ln\tilde{W}_j + \sum_{r=1}^{R} \upsilon_r lnK_r \\ &+ 0.5 \sum_{r=1}^{R} \sum_{s=1}^{S} \upsilon_{rs} lnK_r lnK_s + \sum_{l=1}^{L} \sum_{r=1}^{R} \eta_{lr} lnQ_l lnK_r \\ &+ \sum_{j=1}^{J-1} \sum_{r=1}^{R} \omega_{jr} ln\tilde{W}_j lnK_r + \sum_{t=1}^{T} \delta_t Tech_t + \varepsilon \end{aligned} \tag{4}$$

where $\tilde{W}_j = W_j / W_J$. Monotonicity in **Q** and **W** as well as concavity in **W** cannot be imposed a priori but are tested a posteriori. For monotonicity, it suffices that all partial first derivatives of C with respect to the elements of **Q** and **W** are non-negative. C will be concave in **W**, if the Hessian of second derivatives with respect to the elements of **W** is negative semi definite (Diewert & Wales, 1987).[9] I follow the previous literature and exclude all observations from further analysis that do not adhere to the regularity conditions (Salvanes & Tjøtta, 1998).

From Equation (3), I can derive the cost share equations for each variable input in total cost. Shepard's lemma yields that the partial first derivative of C with respect to a variable input's price yields the contingent demand for that input (Nicholson & Snyder, 2008):

$$\frac{\partial C}{\partial W_j} = X_j \tag{5}$$

By substituting $\partial C = \partial lnC \cdot C$ and $\partial\, W_j = \partial lnW_j \cdot W_j$ in Equation (5), I obtain the cost share equation of each variable input as

$$\begin{aligned} \frac{\partial lnC}{\partial lnW_j} = \frac{W_j X_j}{C} &= \beta_j + 0.5 \sum_{k=1}^{K} \beta_{jk} lnW_k + \sum_{l=1}^{L} \gamma_{lj} lnQ_l \\ &+ \sum_{r=1}^{R} \omega_{lr} lnK_r \end{aligned} \tag{6}$$

where $W_j X_j / C$ is the expenditure share of variable input j in total variable cost. This adds further information to the model without inflating the number of parameters to be estimated. To estimate Equation (4) and the share equations jointly, I use the seemingly unrelated regression (SUR) model proposed by Zellner (1962). I within-difference the data to account for farm-specific effects, that do not change over time and are correlated with costs and output quantities, input prices and/or quantities of quasi-fixed factors, such as managerial ability of the farmer and quality of inputs and outputs (e.g., Alem et al., 2019; Wieck & Heckelei, 2007). After estimation of the system of equations, I can derive MC of milk production by taking the first derivative of Equation (4) with respect to the natural log of milk quantity, and multiply this with the ratio of total variable cost over the milk quantity.

An issue arising is the occurrence of zero values for any of the variables contained in the cost function because the natural log is not defined at zero. Battese (1997) proposes to include a dummy variable for each variable in the estimable equation. This dummy variable will be equal to one, if the respective variable equals zero, and equal to zero, if the respective variable is larger than zero. The value of the original variable is replaced by a value of one, if the original value was zero. I follow this approach which is also frequently used in current applications (e.g., Rasmussen, 2010; Renner et al., 2014; Villano et al., 2015; Wimmer & Sauer, 2020).[10]

In addition, I test for differences in technology between different farm types. Technological differences are observed as soon as some of the coefficient estimates

[8] If unpaid labor were a variable input, I would have to assign a shadow price to unpaid labor since it would also have to suffice the equality in Equation (6).

[9] This will be fulfilled, if all Eigenvalues of the Hessian are non-positive.

[10] Another possibility consists in substituting the zero values by a positive number that is arbitrarily close to zero (e.g., Alem et al., 2019; Morrison et al., 2000). However, this procedure will probably generate biased parameter estimates, if the number of zero observations is large and depends on the units of measurement of the variables.

of Equation (4) deviate for certain groups of farms, that is, the transformation process of inputs into outputs is different. Falsely assuming the same technology for all farms can lead to biased estimates of the cost function (Bottasso et al., 2011; Triebs et al., 2016; Wenninger, 2003). First, I test whether conventional and organic dairy farmers produce under different technologies. Organic farms are confronted with many legal restrictions in their production process which do not apply to conventional farms, for example, the prohibition of using chemically synthesized inputs, a maximum amount of livestock per hectare or permanent access for livestock to outside areas (European Commission, 2007). Second, Alem et al. (2019) reject a common technology across specialized dairying, mixed farms and specialized crop farms in the case of Norwegian agriculture (1991–2014). Therefore, I test whether the technologies differ between farms that only produce milk (specialized dairying), and farms that produce milk and crops (mixed farms). I explain the test procedure in the Appendix.

3 | DETERMINANTS OF MARKUPS

After estimating farm-level markups, I investigate the link between markups and farm characteristics, in particular the role of organic production. It is well known that organic products provide a price premium over conventionally produced food on the retail level (e.g., Ankamah-Yeboah et al., 2016; Connolly & Klaiber, 2014; Nieberg & Offermann, 2003). For fresh milk in the United States, Kiesel and Villas-Boas (2007) find an organic price premium of approximately 40% whereas Smith et al. (2009) estimate the premium to be between 60% and 109% depending on the fat content. In the case of European dairy processing, Bonnet and Bouamra-Mechemache (2016) show that organic milk prices are higher than those of conventional milk, and dairy processors exhibit higher bargaining power towards retailers for organic vis-à-vis conventional milk in France. As yet however, there is no evidence of the effects of organic production on the market power of farmers in terms of markup as a direct measure of market power.

The theory of niche markets suggests that firms operating in small specialized markets realize higher margins (Ilbery & Kneafsey, 1999; Smallbone et al., 1999). Given a mean volume share per country of organic in total milk production of approximately 4% in Europe in 2018 (Eurostat, 2020b, 2020d), organic milk can still be considered as a niche product.

In addition, an important difference between organic and conventional dairy farming is the role of international competition. In 2019, less than .1% of total dairy imports were certified as organic (European Commission, 2021b, 2022). In contrast, considerable quantities of conventional dairy products are traded internationally entailing spatial price transmission between countries (Fousekis & Trachanas, 2016; Newton, 2016). When it comes to organic food products, consumers prefer short transport distances (Pedersen et al., 2018), and there is a lack of demand for products with longer shelf life made from organic milk such as milk powder hindering trade of organic dairy products (European Commission, 2019). That is, competition from imports plays a negligible role. Therefore, organic prices are not directly affected by import competition implying that organic dairy farmers should generate higher markups (Curzi et al., 2021).

However, previous studies find positive cross-price elasticities between organic and conventional dairy products (Alviola & Capps, 2010; Bernard & Bernard, 2009; Jonas & Roosen, 2008; Lindström, 2022; Schröck, 2012). This entails price decreases of organic milk when the price of conventional milk decreases, for example, due to increased import competition. The effect will be weaker for organic farms as the cross-price elasticities in the aforementioned studies are all below one.

Compared with conventional agriculture, organic farming entails a larger share of land, labor and capital costs in total costs due to restrictions on the use of synthetic fertilizer and the ban of synthetic pesticides leading to a larger importance of mechanical weed control and higher requirements regarding land to produce feed (European Commission, 2013; Heinrichs et al., 2021; Uematsu & Mishra, 2012). The extensive production system of organic dairy farming entails milk yields that are 4%–30% smaller than for conventional dairying depending on the country (European Commission, 2019). Removing the organic price premium, a meta-analysis on 55 crops on five continents has found that organic farming performs 10% worse than conventional farming in terms of gross premium (Crowder & Reganold, 2015) since organic farming leads to higher average cost than conventional farming (Uematsu & Mishra, 2012).

I expect that organic dairy farms achieve higher markups compared to conventional dairy farms (Hypothesis 1) as previous literature has found evidence for a significant price premium of organic food, and organic products are less affected by import competition such that the niche product organic milk generates a markup premium over conventional milk. I capture the characteristic of organic production by a dummy which is equal to zero for conventional farms and equal to one for organic farms.

While the average market share of organic milk is small, these market shares show considerable heterogeneity across the EU. In 2018, the share of organic in total milk production varied from below 1% (e.g., Bulgaria, Poland, and Spain) to more than 10% (e.g., Latvia, Denmark, and

Sweden) with a maximum of approximately 20% in Austria (Eurostat, 2020b, 2020d). This dispersion allows to further shed light on the theory of niche markets in the given context. First, the distinguishing attribute of specialty decays with increasing market shares of organic milk. Second, organic dairy farmers face difficulties in finding processors and retailers to sell their milk to in countries where organic production plays a minor role (European Commission, 2019). I expect that an increasing market share of organic milk leads to improvements regarding the infrastructure of the organic dairy supply chain. This leads to decreasing asset specificity and uncertainty related to organic milk, thereby decreasing transaction costs (Williamson, 1979), prices, and markups. Of course, increasing/decreasing demand may also lead to increasing/decreasing markups outweighing the aforementioned mechanisms. However, supply of organic milk is restricted in the short-term since farmers are bound to a conversion time of 18–24 months before they can market their products as organic. Hence, prices for organic milk may vary in the short-term due to changing demand while the market share of organic milk is predetermined largely by the supply quantity.

Assuming that supply and demand shifters are exogenous, that is, not determined simultaneously[11], increasing market shares of organic milk will ceteris paribus lead to a downward shift of the supply curve due to increasing supply quantities and decreasing transaction costs, lower prices and lower markups. I hypothesize that markups of organic farmers decrease with an increasing market share[12] of organic milk since the distinguishing attribute decays (Hypothesis 2a).

Moreover, I expect that markups of conventional farms decrease with an increasing market share of organic milk. The total demand for dairy products in the EU has been almost constant with growth rates slightly below 1% per year (2004–2017) (OECD, 2022). Projections predict that that the demand for dairy products in the EU will remain on a constant level (European Commission, 2021a). Hence, conventional and organic dairy products compete in a market with almost fixed size. I hypothesize that markups of conventional dairy farmers diminish with increasing market shares of organic milk (Hypothesis 2b).

Third, I examine the link between farm size and markups. Previous literature has found that large firms exhibit higher markups than small firms (Autor et al., 2020; Barla, 2000). For agri-food supply chains, most researchers investigate the role of cooperatives on the bargaining power of farmers. Cooperatives negotiate the prices with downstream companies for all their members jointly, and thereby, achieve higher prices due to scale advantages over single farmers who deliver their milk to investor-owned firms (Hendrikse, 2009). Numerous studies have found that cooperatives improve the bargaining power of cooperative members compared with non-members (e.g., Cakir & Balagtas, 2012; Fałkowski et al., 2017; Liang & Wang, 2020; Prasertsri & Kilmer, 2008). I expect that larger farms yield higher markups because their bargaining power towards dairy processors or food retailers is higher (Hypothesis 3). I proxy farm size by the natural logarithm of milk output since milk output will be the only size variable of interest concerning price negotiations with downstream companies.

Last, I investigate whether concentration in downstream sectors negatively affects farmers' markups as the traditional view on market power and concentration suggests (Sexton & Xia, 2018; Wijnands et al., 2007). Earlier research has detected that price and price volatility transmission from farmers to processors and retailers are hampered in agri-food sectors with highly concentrated downstream stages (Assefa et al., 2017; Cutts & Kirsten, 2006). As downstream sectors, I consider the dairy processing industry and the food-retailing sector. For each of those two sectors, I introduce two variables to measure concentration. I use the cumulative market share (in total sales) of firms with 50–249 employees (medium-sized firms), and the cumulative market share of firms with more than 249 employees (large firms) to proxy concentration (Eurostat, 2020e).[13] I conjecture that farmers' markups decrease with increasing market shares of medium-sized and large-sized food processors (Hypothesis 4a) as well as food retailers (Hypothesis 4b).

I control for the share of fixed in total cost and the deployment of unpaid labor. De Loecker et al. (2020) argue that larger markups might not necessarily be a result of welfare decreasing market power but could origin from an increased share of quasi-/fixed in total cost. In my case, these would be, inter alia, costs of capital, paid labor or land. If a positive link between the share of quasi-/fixed

[11] Reviews by Aertens et al. (2009) and Kushwah et al. (2019) show that most of the determinants for organic food purchases are not related to factors determining the conversion to organic agriculture on the supply side.

[12] An issue regarding the measurement of the market share of organic milk is that statistics of organic milk production are only partially available Eurostat (2020d). To alleviate this problem, I use the share of agricultural area under organic production in the total agricultural area as a proxy. An ordinary least squares regression of organic milk output in total milk output on the agricultural area under organic production in the total agricultural area and a set of country dummies yields an R^2 of .985 for the periods available. Thus, the share of area under organic production in total farming area as a good proxy for the market share of organic milk.

[13] The inclusion of the market share of small firms (<50 employees) would lead to issues with respect to collinearity.

in total cost and markups was absent, this would be evidence for the presence of welfare decreasing market power (De Loecker et al., 2020; Hirsch & Koppenberg, 2020). Similarly, I test whether farms with higher use of unpaid labor charge higher markups. Family members provide most of the unpaid labor on farms. Due to foregone earnings from an alternative employment, I anticipate that farms with higher deployment of unpaid labor have higher markups.

To test the hypotheses derived, I apply the following linear model:

$$\mu_{ict} = \beta_0 + \beta_1\, ORG_{it} + \beta_2\, OSHORG_{ict} + \beta_3\, OSHCON_{ict} + \beta_4\, ln\left(MILK_{it}\right) + \beta_5\, PRSHM_{ict} + \beta_6\, PRSHL_{ict} + \beta_7\, RETSHM_{ict} + \beta_8\, RETSHL_{ict} + \beta_9\, SHFC_{it} + \beta_{10}\, UNPLAB_{it} + \sum_{t=1}^{T} \beta_{10+t} D_t \tag{7}$$

where μ is markup and $\boldsymbol{\beta}$ are the parameters to estimate. I use i, c and t as subscripts for farm, country and year, respectively. ORG is a dummy variable being equal to one for organic farms, and zero otherwise (Hypothesis 1). $OSHORG$ ($OSHCON$) denote the share of organic milk in total milk production for organic (conventional) farms and is equal to zero for conventional (organic) farms in the respective country. I use $OSHORG$ to identify the effect of an increasing market share of organic milk on markups of organic farms (Hypothesis 2a) and $OSHCON$ for the effect of an increasing market share of organic milk on markups of conventional farms (Hypothesis 2b). $ln(MILK)$ denotes the natural log of the quantity of raw milk [million tons] produced by the farmer (Hypothesis 3). $PRSHM$ and $PRSHL$ depict the market share of medium and large dairy processors in the dairy processing industry of each country, respectively (Hypothesis 4a). $RETSHM$ and $RETSHL$ represent the corresponding variables for the food retail sector (Hypothesis 4b). The control variables are represented by the share of quasi-/fixed in total cost ($SHFC$), the number of hours of unpaid labor deployed on the farm [hundred hours] ($UNPLAB$) and a set of year dummies ($\mathbf{D}$) which control for changes in world market prices and other macroeconomic factors.

I estimate (8) by pooled ordinary least squares regression (OLS) and a fixed effects regression (FE). The pooled OLS identifies the gross difference in markups between organic and conventional farms. The pooled OLS includes country fixed effects to control for regional differences on the supply- and demand-side. To account for unobserved factors, which may influence markups as well as the independent variables of the model raising concerns of endogeneity, I estimate FE where I add farm-specific constants α_i to (7). For instance, the farmers' negotiation skills are unobserved which would have an impact on markup and probably on the hours of unpaid labor on the farm since higher negotiation skills would lead to higher markups incentivizing the deployment of unpaid (family) labor.

4 | DATA

The data used in the analysis are provided by the European Farm Accountancy Data Network (FADN). My dataset covers the years 2004–2017 and 24 of 27 EU countries plus the United Kingdom (Cyprus, Luxembourg and Malta are missing). The FADN data include information on farm-level inputs, outputs and other financial data of the holding per year. Besides, I retrieve several country- and year-specific price indices from Eurostat (2020a). For six countries, the price indices were insufficiently available such that I omit them from the analysis: Bulgaria, Croatia, Estonia, Ireland, Lithuania, and Romania. Table A1 in the Appendix gives an overview of the variable specifications used for the estimation of the translog cost function and the second stage regression. Table A2 displays the descriptive statistics of all variables.

While the use of price indices is common in recovering a technology's parameters (e.g., Alem et al., 2019; De Frahan et al., 2011; Gullstrand et al., 2013; Wieck & Heckelei, 2007), it potentially introduces a bias in the estimation of the cost function parameters as soon as there is unobserved cross-farm variation in input and/or output prices (De Loecker et al., 2016; Morlacco, 2020). Factors that cause such variation are, for example, location as well as quality differences of inputs and outputs. Examples in the farming context are quality of land, climatic conditions or access to infrastructure. However, as long as this cross-farm variation is farm-specific and changes little over time, introducing fixed effects or conducting within-differencing will resolve this issue (De Loecker et al., 2016; Jafari et al., 2022). Since I within-difference the data before the estimation, I assume that the bias due to the use of price indices is negligible.

Moreover, I only observe ex-post outputs while the farmer minimizes cost based on expected output which can lead to biased estimates of the cost function (e.g., Chambers & Serra, 2019; Chavas, 2008; Moschini, 2001). In agriculture, deviations of realized from expected output typically result from weather conditions that differ from the farmers' expectations (e.g., Finger et al., 2018; Key & Sneeringer, 2014; Schlenker & Roberts, 2009). Supposing that the weather conditions for a given year are less favorable than expected by farmers, realized output falls short of expected output such that the estimated parameters for output in the cost function will be overestimated. Hence, MC estimates will be biased as well.

However, since my geographical scope is large, there will be some locations where weather conditions will be better than expected, some locations where weather conditions will be worse than expected and some locations where the weather conditions will be as expected. Hence, some farmers will overestimate expected output, some farmers will underestimate expected output and some farmers realize their expected output. I expect that, on average, expected output is close or equal to realized output such that only standard errors of the estimates are inflated. Systematic pessimism/optimism of a farmer will be eliminated by the within-differencing that I apply to the data. Besides, in the absence of good instruments for output, two-stage least squares or three-stage least squares are performing much worse than SUR (Johnston, 1963; Wieck & Heckelei, 2007). Anyway, my main interest does not lie in the absolute size of markups but the results of the second stage regressions, which will be unaffected by potential biases in the estimation of the technology as long as the bias is the same for all farms (De Loecker & Warzynski, 2012).

I identify the sample farms by the FADN TF14 farming types 45 ("specialist milk"), 49 ("specialist cattle") and 80 ("mixed crops and livestock") (see European Commission, 2020b for the complete list of farming types). The sample contains 203,979 observations[14] comprised by 39,786 farms producing cows' milk between 2004 and 2017. The sample contains 11,378 (5.58%) observations comprised by 2878 farmers for organic production and 192,601 (94.42%) observations comprised by 37,761 farmers for conventional production (2004–2017). For 115,333 (28,106) observations (farms), farmers produced milk and meat as well as crops and for 88,646 (22,079) observations (farms), farmers did not produce crops. The descriptive statistics are given in Table A2 in the Appendix. A detailed comparison of the constitution of the sample and the population for farming type 45 in 2016 is given in Table A3 in the Appendix. Overall, the sample slightly overrepresents larger farms in eastern countries and slightly underrepresents larger farms in western and northern countries.

5 | RESULTS AND DISCUSSION

The test for a joint technology across the four farm types (conventional specialized dairying, conventional mixed, organic specialized dairying and organic mixed) reveals that a common technology is to be rejected (see Appendix for details). Therefore, I estimate one cost function for each farming type. With respect to the properties of the cost function, 1379 observations do not fulfil monotonicity in output (.68% of all observations) which I drop in the further analysis.

Table 1 shows the descriptive statistics of MC of milk production and output for conventional and organic farmers. Mean and median MC are slightly larger for conventional (.13€/kg and .08€/kg) compared with organic (.11€/kg and .07€/kg) milk farmers (Table 1). For both farming types the MC density curves exhibit a positive skew which is more pronounced for conventional than for organic farmers as indicated by the 99th percentile (1.12€/kg vs. .81€/kg) (Table 1).

My MC estimates are in line with those of Wieck and Heckelei (2007) who estimate MC of dairy farmers for selected regions in Denmark, France, Germany, the Netherlands, and the UK (1989–2000). Regional averages of MC range from .12€/kg to .18€/kg in 1991 and from .084€/kg to .15€/kg in 1999. Given that my data cover the period from 2004 to 2017 and farmers realized further technical progress, my MC estimates are plausible.

I compute markups (μ) by dividing the milk price (P) by the estimates of MC, that is, P/MC, where a value of one indicates marginal cost pricing. Table 2 contains the descriptive statistics of markups for conventional and organic farmers. The mean of conventional farmers' markups is 4.11, that is, the milk price exceeds MC by 311% (Table 2). This value equals 5.95 for organic farmers suggesting a markup premium for organic farmers of 1.84 over conventional farmers without controlling for other factors. The difference in median markups between conventional (3.78) and organic (5.27) farmers equals 1.49 (Table 2). The density and cumulative distribution functions of markups show that organic farmers' markups dominate those of conventional farmers (Figure 1).[15]

It is noteworthy that my mean and median markup estimates far exceed those of earlier studies estimating markups for other sectors (e.g., Autor et al., 2020; De Loecker et al., 2020).[16] Recent applications in the food sector find mean markups ranging from 1.07 to 2.57 for the food manufacturing industry (Curzi et al., 2021; Jafari et al., 2022; Koppenberg & Hirsch, 2022b; Lopez et al., 2018) and from 1.18 to 3.57 for the food retailing sector (Hirsch & Koppenberg, 2020; Koppenberg & Hirsch, 2022a; Sckokai

[14] Note, that the market shares of downstream companies are not available for all countries and years such that the number of observations reduces to 81,490 for the second stage regressions. Concentration data are completely missing for the Czech Republic, Denmark, Finland, Slovakia, Slovenia, and Sweden. However, the coefficients of the other variables do not change signs when I omit the concentration measures and run the analysis on the full sample with the limited set of independent variables.

[15] A comparison of markups between countries is provided in the Appendix.

[16] For instance, as well as find median markups between 1 and 1.6. While use data on all firms in manufacturing, wholesale trade, retail trade, services, utilities, transportation, and finance in the US, De Loecker et al. (2020) only include publicly traded US-firms but without restrictions regarding the sectoral activity.

TABLE 1 Descriptive statistics of marginal cost of milk production and milk output

		Mean	Median	1st percentile	99th percentile
Marginal cost (€/kg)	Conventional	.13	.08	.03	1.12
	Organic	.11	.07	.02	.81
Output (tons)	Conventional	494.66	212.58	.22	4555.90
	Organic	331.55	153.60	.24	2423.40

Source: Own calculations based on data of the European Farm Accountancy Data Network.

TABLE 2 Descriptive statistics of markups for conventional and organic dairy farmers

		Mean	Median	Minimum	1st percentile	99th percentile	Maximum
Markup	Conventional	4.11	3.78	.00	.20	1.99	1205.09
	Organic	5.95	5.27	.01	.27	19.12	349.43

Source: Own calculations based on data of the European Farm Accountancy Data Network.

et al., 2013). However, two pivotal differences between manufacturing and service industries and the farming sector drive this result. First, unlike most of the companies in manufacturing and service industries, the farming sector is characterized by a very large share of sole proprietors running their farms without external work force.[17] Second, the share of quasi-/fixed cost is much larger in farming than in other sectors. I provide an in-depth discussion on the relationship between unpaid labor, quasi-/fixed costs and markups when I present the results of the regression analysis.

Turning to the determinants of markups, Table 3 contains the results of the pooled OLS and the FE regressions. Since Figure 1 and Table 2 indicate that the distribution of the markup estimates is skewed and contains extreme values, the results of the linear regressions could be distorted. Therefore, I reestimate the pooled OLS and the FE model once omitting observations below the 1% and above the 99% percentile of markups and once omitting observations below the 5% and above the 95% percentile of markups.[18] Moreover, I apply a robust median regression, which is well suited in the presence of extreme values (Powell, 2022).[19] Columns 4–8 of Table 3 show the results of the pooled OLS and FE models excluding the bottom and top markup percentiles and those of the median regression.

The results of the pooled OLS using all observations suggest a gross markup premium for organic over conventional dairy farmers of 2.579 ($p < .01$), that is, on average markups of organic farmers exceed those of conventional farmers by 257.9 percentage points (cf. column 2 of Table 3). The FE model using all observations, which accounts for time-invariant unobserved farm characteristics, yields a markup premium of .924 ($p < .01$) (cf. columns 2 and 3 of Table 3). Omitting extreme values which potentially distort the linear models, the predicted markup premium of the pooled OLS models shrink to 1.664 ($p < .01$) and .898 ($p < .01$) for organic over conventional farmers while the FE model estimates amount to .778 ($p < .01$) and.586 ($p < .01$) (columns 4–7 of Table 3). The robust median regression predicts a premium of 1.034 ($p < .01$) (column 8 of Table 3). Hence, I find evidence in favor of Hypothesis 1, that is, that organic farmers generate higher markups compared with conventional farmers in European milk production. That is, the supply of organic products allows farmers to drive a larger wedge between output price and MC compared to conventional farmers.

With respect to the effects of increasing market shares of organic milk in total milk production, the results are inconclusive. Some models (pooled OLS and median regression) yield negative and significant estimates (cf. columns 2, 4, 6, and 8 of Table 3). The FE models yield positive estimates which are not significant (cf. columns 3, 5, and 7 of Table 3). I re-estimate the models and control for MC to elicit the impact of varying shares of organic milk in overall milk production on the milk price component of markups.

The results in Table 4 show that pooled OLS predicts that markups controlled for MC decrease with increasing market shares of organic milk ($p < .01$). Accounting for unobserved farm heterogeneity, the FE model excluding markups below the 5% and above the 95% percentile identifies a negative and significant relationship between the share of organic milk in total production and the markup controlled for MC (cf. Table 4, column 7). However, the

[17] In my sample, approximately 62% of the observations do not employ any paid labor whereas 93.8% deploy unpaid labor of at least one full-time equivalent (assuming an annual workload of 1600 h per year and person).
[18] As a robustness check, I estimate (8) using pooled OLS, FE, and the median regression using all observations but log markup as the dependent variable. These estimations are shown in Table A10 in the Appendix since they are mostly in accordance with the other regressions.
[19] As suggested by a referee, I also estimate the quantile regression at the 10%, 25%, 75%, and 90% quantile. The results and their discussion can be found in the Appendix (Table A11).

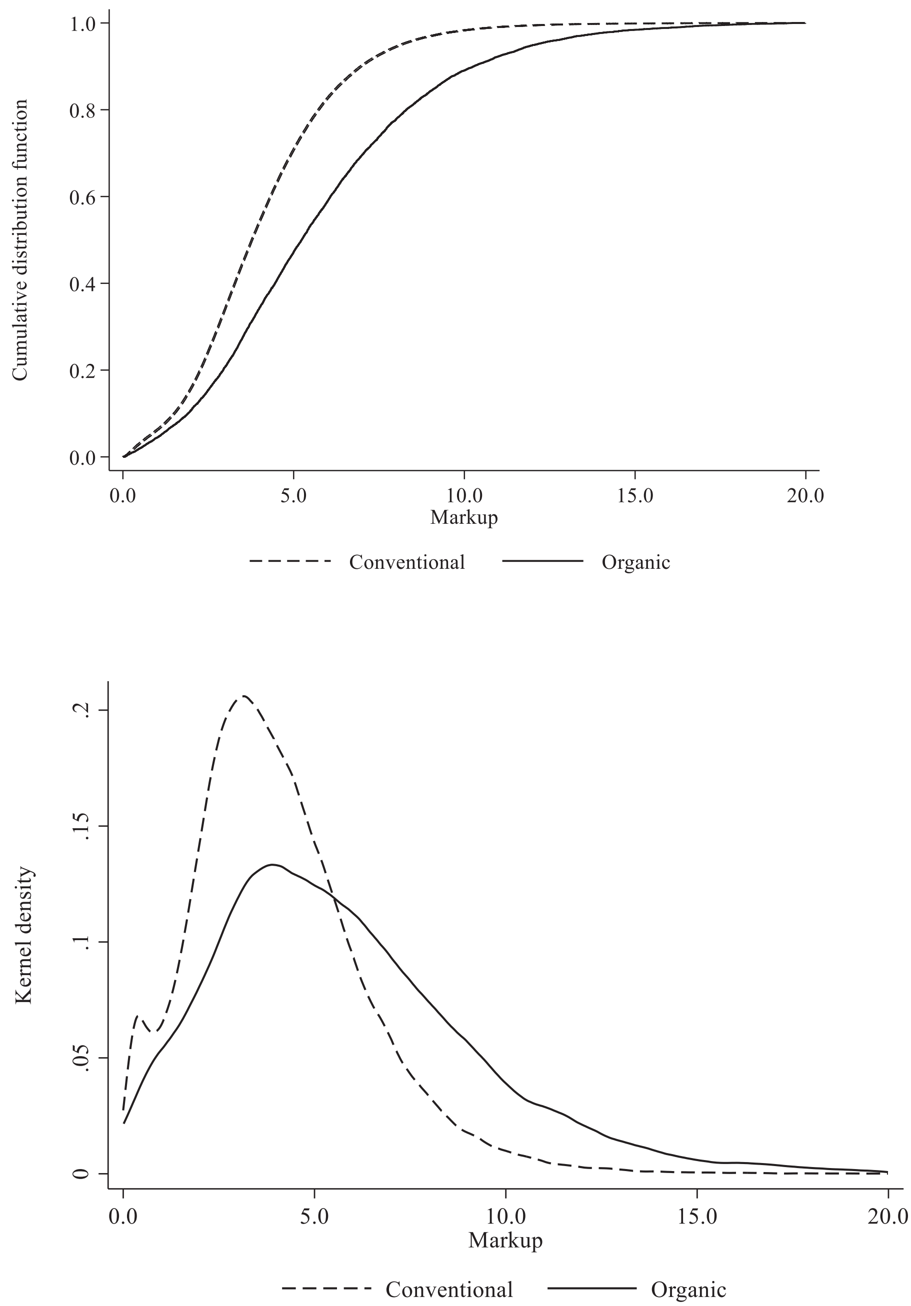

FIGURE 1 Kernel density and cumulative distribution function of markups for conventional and organic farmers

Note: About 206 observations > 20 omitted to ensure readability.
Source: Own illustration based on data of the European Farm Accountancy Data Network.

other FE models (columns 3 and 5 of Table 4) as well as the median regression (column 8 of Table 4) do not find a significant relationship between the share of organic in total milk production and markups. Increased supply, that is, increasing market shares of organic in total milk production, seems to be offset by increased demand such that prices do not change, and hence markups are not impacted by varying market shares of organic milk (Willer et al., 2019).[20] Consequently, I do not find clear evidence for Hypothesis 2a (*Markups of organic farms decrease with an increasing market share of organic milk in total milk production).*

[20] Note that for approximately 80% of the observations the market shares of organic milk increase. Therefore, my argumentation refers to increasing supply/demand.

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TABLE 3 Markups and their determinants in european dairy farming: Pooled OLS, FE and median regression

Variables	Pooled OLS	FE	Pooled OLS (Excluding markups below 1% and above 99% percentile)	FE (Excluding markups below 1% and above 99% percentile)	Pooled OLS (Excluding markups below 5% and above 95% percentile)	FE (Excluding markups below 5% and above 95% percentile)	Median regression
ORG	2.579***	.924***	1.664***	.778***	.898***	.586***	1.034***
	(.191)	(.213)	(.110)	(.157)	(.089)	(.141)	(.119)
OSHORG	−.122***	.018	−.073***	.008	−.027**	.007	−.022**
	(.019)	(.026)	(.015)	(.018)	(.012)	(.016)	(.010)
OSHCON	−.069***	−.026***	−.051***	−.024***	−.024**	−.018**	−.049***
	(.013)	(.010)	(.011)	(.009)	(.010)	(.008)	(.004)
ln(MILK)	.662***	.773***	.600***	.787***	.431***	.809***	.763***
	(.015)	(.025)	(.014)	(.023)	(.013)	(.025)	(.007)
UNPLAB	.011***	.003***	.010***	.002***	.009***	.002**	.004***
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
PRSHM	−.108***	−.092***	−.109***	−.088***	−.086***	−.075***	−.088***
	(.009)	(.005)	(.006)	(.004)	(.005)	(.004)	(.004)
PRSHL	.011***	.013***	.014***	.012***	.011***	.008***	.026***
	(.004)	(.002)	(.002)	(.002)	(.002)	(.002)	(.003)
RETSHM	−.024	.002	−.005	.002	−.004	−.003	−.008***
	(.018)	(.006)	(.007)	(.006)	(.006)	(.005)	(.003)
RETSHL	.015**	−.022***	.012***	−.021***	.011***	−.019***	−.011***
	(.007)	(.003)	(.004)	(.003)	(.003)	(.002)	(.003)
SHFC	.069***	.096***	.050***	.083***	.039***	.074***	.077***
	(.005)	(.002)	(.001)	(.001)	(.001)	(.001)	(.002)
Constant	2.814***	.850***	3.521***	1.510***	3.198***	1.968***	
	(.441)	(.179)	(.282)	(.133)	(.247)	(.114)	
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	No	Yes	No	Yes	No	No
Farm fixed effects	No	Yes	No	Yes	No	Yes	Yes
Observations	81,490	81,490	80,092	80,092	74,622	74,622	81,490
R^2	.232	.200	.330	.289	.264	.222	

Note: Standard errors clustered by farm in parentheses; Significance indicators: *** $p < .01$, ** $p < .05$, * $p < .1$; definition of variables and descriptive statistics can be found in the Appendix (Tables A1 and A2).
Source: Own calculations based on data of the European Farm Accountancy Data Network.

For Hypothesis 2b (*Markups of conventional farms decrease with an increasing market share of organic milk in total milk production*), all models show negative parameter estimates which are significantly different from zero (cf. Table 3). Thus, demand for conventional milk decreases and, thereby, entails shrinking markups for conventional farmers. The estimates for *OSHCON* range from −.018 for FE excluding markups below the 5% and above the 95% percentile to −.069 for pooled OLS (cf. Table 3). Given a mean increase across countries over the entire sample period in the market share of organic milk of 4.19 percentage points, this would imply a markup decrease of.08 and.29 for FE excluding the bottom and top 5% and pooled OLS, respectively. Consequently, in addition to the organic markup premium the effect of increasing market shares of organic milk on conventional dairy farmers' markups also incentivizes the conversion to organic farming.

Regarding farm size, the coefficient of log milk output [thousand tons] amounts to .787 and is significantly different from zero (cf. Table 3, column 5). That is, markups rise by .079 for a ten -percent increment in milk output, which supports the expectation that markups increase with increasing output (Hypothesis 3). The effect size and its significance are robust across all models. It is also interesting to note how the estimates change when I control for *MC* (Table 4). The models excluding upper and lower markup percentiles and controlling for *MC* predict a markup change between −.020 and .025 when milk output increases by 10%, which points to the presence of economies of scale for conventional as well as organic farmers because farmers with higher output realize a high

TABLE 4 Markup determinants: Pooled OLS, FE and median regression controlling for marginal costs

Variables	Pooled OLS	FE	Pooled OLS (Excluding markups below 1% and above 99% percentile)	FE (Excluding markups below 1% and above 99% percentile)	Pooled OLS (Excluding markups below 5% and above 95% percentile)	FE (Excluding markups below 5% and above 95% percentile)	Median regression
ORG	2.454***	.915***	1.349***	.699***	.867***	.372***	.816***
	(.193)	(.213)	(.100)	(.154)	(.062)	(.118)	(.137)
OSHORG	−.115***	.016	−.065***	−.008	−.085***	−.053***	−.012
	(.019)	(.026)	(.014)	(.017)	(.009)	(.015)	(.008)
OSHCON	−.067***	−.028***	−.052***	−.040***	−.077***	−.075***	−.056***
	(.013)	(.010)	(.011)	(.009)	(.007)	(.006)	(.004)
ln(MILK)	.546***	.693***	.238***	.251***	.040***	−.198***	.214***
	(.036)	(.039)	(.018)	(.058)	(.012)	(.025)	(.021)
UNPLAB	.011***	.003***	.010***	.003***	.005***	.001*	.003***
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
PRSHM	−.106***	−.090***	−.103***	−.080***	−.065***	−.057***	−.091***
	(.009)	(.005)	(.005)	(.004)	(.004)	(.003)	(.005)
PRSHL	.010***	.013***	.015***	.012***	.010***	.008***	.017***
	(.004)	(.002)	(.002)	(.002)	(.001)	(.001)	(.001)
RETSHM	−.028	.001	−.020***	−.011**	−.045***	−.036***	−.015***
	(.018)	(.006)	(.007)	(.005)	(.005)	(.004)	(.004)
RETSHL	.012*	−.022***	−.003	−.019***	−.016***	−.024***	−.012***
	(.007)	(.003)	(.003)	(.003)	(.002)	(.002)	(.002)
SHFC	.070***	.094***	.049***	.066***	.023***	.024***	.065***
	(.005)	(.002)	(.001)	(.002)	(.001)	(.001)	(.001)
MC	−1.316***	−.611**	−7.834***	−6.993***	−25.088***	−26.883***	−6.979***
	(.435)	(.242)	(.403)	(.821)	(.993)	(.566)	(.032)
Constant	2.615***	.918***	3.646***	2.401***	6.971***	6.040***	
	(.442)	(.181)	(.253)	(.165)	(.233)	(.129)	
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	No	Yes	No	Yes	No	No
Farm fixed effects	No	Yes	No	Yes	No	Yes	Yes
Observations	81,490	81,490	80,092	80,092	74,622	74,622	81,490
R^2	.247	.211	.460	.425	.651	.536	

Note: Standard errors clustered by farm in parentheses; Significance indicators: *** $p < .01$, ** $p < .05$, * $p < .1$; definition of variables and descriptive statistics can be found in the Appendix (Tables A1 and A2).
Source: Own calculations based on data of the European Farm Accountancy Data Network.

share of their markup gains from lower *MC*. My result is in line with other studies who find that marketing cooperatives and producer organizations help farmers to enhance their bargaining power towards downstream companies (e.g., Cakir & Balagtas, 2012; Fałkowski et al., 2017; Prasertsri & Kilmer, 2008). But, while the previous literature investigates this effect for organizations with multiple farms, I am able to show that the enhancing effect of size on market power is also present at the level of a single farm.

For the concentration in downstream industries, the results are equivocal. For the dairy processing industry, an increase in the market share of medium-sized processors of one percentage point entails a decrease in farmers' markups of .108 (pooled OLS; $p < .01$) and .092 (FE; $p < .01$) (cf. columns 2 and 3 of Table 3). However, the pooled OLS and the FE models both yield positive estimates for large processors' market share that are significantly different from zero (cf. columns 2 and 3 of Table 3). The models excluding the lower and upper markup percentiles and the median regression confirm this finding (cf. Table 3, columns 4–8). A possible explanation for this outcome is the spatial nature of competition in dairy processing (Graubner, Balmann et al., 2011; Graubner, Koller et al., 2011; Perekhozhuk et al., 2015). Because milk is highly perishable and costly to transport due to its high water content, it is infeasible for farmers to deliver their milk to far dairy processors (Rogers & Sexton, 1994). Therefore, already medium-sized processors may countervail farmers' bargaining power and engage in price discrimination (Graubner, Balmann et al., 2011). In contrast, large processors need higher raw milk quantities to exploit their processing capacities, and pay higher prices to ensure raw milk supply. In that regard, Mérel and Sexton (2017) show that high market concentration in the processing sector may not necessarily entail milk prices below the competitive level but the long-run incentive to secure milk supply dominates the short-run incentive to undercut the perfectly competitive milk price which would lead to farm-exit in the long-run.

Last, neither pooled OLS nor FE results identify any significant impact of medium-sized retailers' market shares ($RETSHM$) on dairy farmers' markups in the base models (cf. columns 2–3 of Table 3), even when omitting extreme markup values (cf. columns 4–7 of Table 3). Only for the median regression, I find a negative coefficient for $RETSHM$ which is also significantly different from zero ($p < .01$; column 8 of Table 3). When controlling for MC and excluding the bottom and top markup percentiles, all models predict a negative relationship between $RETSHM$ and markup ($p < .01$; cf. columns 4–8 of Table 4).

For the market share of large retailers ($RETSHL$), the FE and median regression estimates are negative and significantly different from zero (cf. Tables 3 and 4). Only some of the pooled OLS models yield a positive and significant estimate ($p < .05$) (cf. column 2 of Tables 3 and 4). As pooled OLS ignores unobserved farm-specific heterogeneity, its results should be interpreted with caution such that I rely on the outcome of the FE and median regressions, which present evidence in favor of Hypothesis 4b (*Dairy farmers' markups decrease with increasing concentration in the food retail sector*). My result is in accordance with studies on the bargaining power of retailers (e.g., Bonnet & Bouamra-Mechemache, 2016; Draganska et al., 2010; Richards et al., 2018) which find that multi-/national food retail chains are able to push prices below the competitive level in procurement of food products from processors. Consequently, the processors' marginal value product of raw milk diminishes leading to lower prices of agricultural outputs and, finally, to smaller markups for farmers.

Regarding the relationship between the control variables and markups, all coefficients have the expected signs, that is, the share of quasi-/fixed costs and the amount of unpaid labor are positively related with markups. An increase in $SHFC$ by one percentage point is associated with an increase in markups of .039–.096 depending on the model (cf. Table 3). The same applies to the amount of unpaid labor spent on the farm [hundred hours]. The parameter estimates range from .002 to .011 and are significantly different from zero in all models (cf. Table 3).

The markups obtained in this study are much larger than those of earlier studies on manufacturing and service sectors. This is mainly driven by the fact that the fixed cost share, that is, the share of quasi-/fixed in total costs, is much larger in agriculture compared to other sectors. For instance, Koppenberg and Hirsch (2022b) investigate markups in three European dairy processing sectors (France, Italy, and Spain) where firms have a mean fixed cost share of approximately 20% whereas the fixed cost share in my sample amounts to 54%. Using the lower (.039; cf. Table 3, column 6) and upper (.096; cf. Table 3, column 3) boundaries of the respective coefficient estimates ($SHFC$), a reduction of the fixed cost share from 54% to 20% would entail a decrease in markup by 1.33 and 3.26, respectively. Besides, the vast majority of industrial companies does not use unpaid labor in contrast to farmers. Decreasing the amount of unpaid labor from the sample mean (36.10) to zero would lead markups to diminish by further .07 or .40 depending on whether we use the lower boundary of the coefficient estimates for unpaid labor (.002; cf. Table 3, column 3/7) or the upper boundary (.011; cf. Table 3, column 2). Hence, a large share of the discrepancy in markups between my study and those of earlier studies on industrial and service sectors can be explained by differences in the share of fixed cost and the use of unpaid labor.

6 | CONCLUSION

I estimate farm-level markups of output price over marginal cost of milk production for a sample of approximately 40,000 European dairy farmers using a translog cost function. Second, I investigate the role of farm- and country-level characteristics to explain the heterogeneity of markups across farms with particular emphasis on the role of organic farming.

Mean marginal cost are slightly larger for conventional compared to organic farmers while mean output is almost 50% larger for conventional farmers. My results indicate that the vast majority of farmers charges markups above one such that milk prices exceed marginal costs of milk production.

The regressions of markups on farm- and country-level characteristics show a significant markup premium for organic over conventional dairy farmers. When controlling for marginal costs, the advantage is slightly smaller such that organic farmers produce at lower marginal costs and achieve higher prices than conventional farmers do. Interestingly, markups of organic farmers do not vary with increasing market shares of organic milk in total milk production even when I control for marginal costs. Given that market shares of organic milk rise in approximately 90% of the cases, potential price decreases for organic milk due to increased supply are offset by rising demand. In contrast, markups of conventional farmers decrease with increasing market shares of organic milk as the demand for conventional milk decreases which is robust across all model specifications.

In addition, markups increase significantly with milk output across all models. This is in line with studies that identify the impact of producer organizations and cooperatives on the milk price bargaining power of farmers, and find that cooperative members achieve significantly higher prices compared to non-members. However, the incline diminishes when I control for marginal costs which points to the presence of economies of scale, that is, cost advantages that large farms benefit from, thereby boosting their markups.

Regarding the concentration in downstream sectors, my findings point to adverse effects of the presence of large national food retail chains on farm-level markups. For concentration in dairy processing, I find a robust negative relationship between the market share of medium-sized processors and farm-level markups in all models. Contrary, my analysis reveals a positive link between the market share of large dairy processors and farmers' markups, which is consistent across all models. This seems counterintuitive given the large body of literature on the relationship of market structure and conduct predicting that processors will pay below-competitive raw milk prices with rising concentration. But, the assurance of long-run milk supply from farmers may dominate the short-run incentive to exercise bargaining power in raw milk procurement (Mérel & Sexton, 2017) such that large dairy processors could pay higher prices than medium-sized processors.

From a farmer's perspective, my results show that the conversion to organic agriculture is highly beneficial when looking at markups as a target measure. Besides, continuously increasing demand for organic milk outweighs potential price decreases due to increasing supply in the past years so that the conversion is still to be considered attractive for conventional farmers. This is even reinforced by the fact that markups of conventional farmers decrease with increasing market shares of organic milk. While my analysis illustrates the case of organic farming and dairy farmers' markups, the outcomes are likely transferable to other niche products such as organic meat production or locally produced plant-based milk. By successfully discovering or creating new niche markets farmers can enhance their bargaining power towards downstream companies, and thereby, sustain long-term competitiveness. For the Common Agricultural Policy, policy makers may contemplate the creation of innovation funds that may help farmers to design new products or redesign the production process to generate price premia in new niche markets.

Further, my analysis indicates that large dairy farms exploit economies of scale and have higher bargaining power towards downstream companies. This is in line with earlier research stating that larger farms are less likely affected by asymmetric price transmission to and from downstream companies compared to smaller farms (Bakucs et al., 2014). Consequently, farm growth is a favorable strategy from a farmer's perspective reinforcing the structural change of European agriculture towards larger farms, which plays an important role in debates on the Common Agricultural Policy of the European Union (European Union, 2016).

The robust negative relationship between farmers' markups and the market share of large food retailers, which are mostly driven by the presence of large multi-/national retail chains, raises concerns with respect to adverse effects of the continuing consolidation in food retailing on farmers in Europe. While competition authorities mainly look at the impact of mergers and acquisitions on downstream competition in their evaluation process, my study highlights the need to consider the influence on upstream companies as well.

Despite my study is informative about the differences in markups between organic and conventional farmers, other farm and product characteristics and the potential presence of interactive effects on farm-level markups are worthwhile to examine. For instance, labels of local production, extensive non-organic livestock farming or increased transparency sheds may provide synergies in generating a markup premium. With the given data however, it is not possible to elicit such mechanisms so that I encourage future research to investigate this question.

Milk is highly perishable. The effect of organic production on markups might change as international trade of raw products becomes more important when perishability declines, for example, for cereals. With increased international competition, the markup premia for organic farmers may abate. Therefore, future studies should investigate the effect of international competition on markups of organic and conventional farmers across different farming types.

Riskiness is another important issue since prices and yields in dairy farming are volatile (D'Antoni & Mishra, 2012; Finger et al., 2018; Henry et al., 2016). How riskiness affects markups and markup volatility presents an important question for future research.

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