

Imami, Drini; Xhoxhi, Orjon; Babayan, Davit; Herzfeld, Thomas; Rakhmetov, Rustam

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ORIGINAL ARTICLE OPEN ACCESS

Treatment Effect Heterogeneity of Farmers Participating in Cooperatives

Drini Imami^{1,2}  | Orjon Xhoxhi¹  | Davit Babayan³ | Thomas Herzfeld^{4,5}  | Rustam Rakhmetov⁴ 

¹Agricultural University of Tirana, Tirana, Albania | ²CERGE-EI Prague, Prague, Czech Republic | ³Centre for Agricultural Research and Certification (SNCO), Merdzavan, Armenia | ⁴Leibniz Institute of Agricultural Development in Transition Economies (IAMO), Halle (Saale), Germany | ⁵Martin-Luther-Universität Halle-Wittenberg, Halle (Saale), Germany

Correspondence: Drini Imami (dimami@ubt.edu.al) | Thomas Herzfeld (herzfeld@iamo.de)

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ABSTRACT

Despite the many studies providing evidence of the benefits of cooperatives, most small farms and farm households, particularly in transition economies, do not participate in them. This study analyses the effect of cooperative activity on farm performance using a large-scale farm survey conducted in Armenia. In addition, it addresses the issue of heterogeneity, which is often overlooked in the literature. It looks at heterogeneity in terms of observed effect modifiers, which are measured covariates that can modify the causal effect of cooperation on a specific farm performance indicator. This is the first study that pays special attention to heterogeneity and uses the causal forest approach in the context of cooperative membership to characterise the drivers of treatment heterogeneity (i.e., variation in the causal impact of cooperative membership across farmers with different observable characteristics). Participation in cooperatives is associated with greater perceived farm performance among farmers with limited access to market information and low financial literacy. Similarly, higher benefits are observed for less experienced and older farmers, suggesting that cooperatives play a particularly important role in supporting more vulnerable subgroups.

JEL Classification: D22, O13, Q13

1 | Introduction

There is broad consensus in the literature that small farms face a range of challenges, from lower producer prices to limited access to production inputs. Although consolidating them into larger farms is often suggested as a potential solution (e.g., German et al. 2020; Ma and Sexton 2021), greater cooperation and collective action can also, under specific conditions, help integrate smallholders into value chains (Blandon et al. 2009; Tadesse et al. 2019). Through collective action, farmers can improve their access to services and inputs as well as their position with regard to processors and other actors in the supply chain, and thus optimise their performance (Ayouba et al. 2025). Studies show that cooperatives, for example, enable farmers to obtain better prices (Bernard et al. 2008), improve their technical efficiency (Abate et al. 2014), and use better inputs and achieve

higher yields (Blekking et al. 2021). In addition, cooperatives could enhance farmers' awareness of and demand for vaccination services in the Global South (Maina et al. 2024). This underscores the potential role of cooperatives in improving access to essential services in emerging and developing economies, where such access remains a major challenge.

However, in many post-communist economies, aversion to cooperative action in marketing or production decisions is widespread (Balint and Wobst 2006; Lissowska 2013; Möllers et al. 2018; Zhou 2004). One reason for this is the historical legacy of forced collective action. Additionally, rapid social transformations have contributed to an erosion of trust within rural communities. In this context, effective village leadership can be important in rebuilding social cohesion, fostering trust among community members, and coordinating collective

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efforts (Skreli et al. 2024). This, in turn, can lower transaction costs and help individual farmers manage risks more effectively and positively contribute to farm performance. Furthermore, farmers' (perceived) benefits offered by cooperatives can play a crucial role in shaping their willingness to participate (ibid).

Identifying a causal relationship between cooperation and its potential benefits is not straightforward, as simple linear econometric models do not account for the risk that more capable farms might also be more likely to participate in cooperatives. Previous research has pointed to a non-linear or even u-shaped relationship when it comes to cooperative behaviour. For example, Wollni and Fischer (2015) find a u-shaped relationship between farm size and the share of produce farmers deliver to their marketing cooperative. Therefore, difference-in-difference approaches using panel data are often considered the most appropriate econometric method (Bachke 2019). Most studies analysing the impact of participation in cooperatives¹ on farm performance focus in general on estimating the average treatment effect (ATE) on a specific outcome (e.g., income, prices) and neglect the heterogeneity within the sample (Abate et al. 2014; Bernard et al. 2008; Ito et al. 2012). However, the more heterogeneous the general farming population is, the more heterogeneous the marginal effect of joining a cooperative might be. Thus, in order to understand the impact of participation in cooperatives on farmers' business performance, it is important to consider how it might vary within a given population—that is, the potential treatment effect heterogeneity.

In this paper, we focus on treatment effect heterogeneity within the potential outcomes framework (Imbens and Rubin 2015). In other words, we look at systematic variation in the causal impact of cooperative membership across farmers with different observable characteristics. Rather than assuming uniform benefits from joining a cooperative, we examine how these effects differ depending on variables, such as age, farming experience and farm size. This approach allows us to identify which types of farmers benefit most from cooperative participation, offering important insights to design more tailored and effective support strategies. It is important to note that our use of 'heterogeneity' is distinct from (i) preference heterogeneity among cooperative members, and (ii) intra-cooperative power asymmetries or conflict, both of which are outside the scope of this analysis.

This study addresses the issue of treatment effect heterogeneity in terms of observed effect modifiers. These are measured covariates that can modify the causal effect of cooperation on a specific farm performance indicator. The expectation is that participation in a cooperative may increase all elements of farm performance. We estimate the average causal treatment effects for these outcomes using a unique dataset based on a structured dairy farm survey, which includes variables that allow us to control for observed confounders of the causal relationship between farmers' participation in cooperatives as the treatment and farm performance outcomes as the effects.

The dairy sector is a cornerstone of Armenia's agricultural economy, with dairy cattle playing a key role in rural livelihoods. As in many post-communist emerging economies, the sector is predominantly composed of small-scale farms, which emerged after the sharp decline of large-scale operations during the early

post-reform period (Rozstalnyy and Kuipers 2014). These smallholder farms face multiple structural challenges, including limited access to affordable, high-quality feed, costly and unevenly available veterinary services and weak farm management capacities. These constraints contribute to low productivity, substandard milk quality, and difficulties in meeting export standards (Dries et al. 2014). In this context, farmer cooperation through producer organisations or cooperatives can be a potentially powerful mechanism to overcome market and institutional failures. Armenia, thus, provides a highly relevant setting to explore whether and for whom cooperative membership can enhance farm performance, offering insights that are transferable to similar transition and developing economies with fragmented farm structures and (value chain) coordination failures.

Previous research on the Armenian dairy sector shows that cooperation between farmers significantly increases the likelihood of investment, whereas farm size does not significantly impact investments (Dries et al. 2012). Gorton et al. (2015) show that marketing cooperatives strengthen the bargaining power of suppliers and reduce buyer opportunism in the context of the Armenian dairy sector.

This paper makes two main contributions. First, it demonstrates the value of applying causal machine learning—specifically the causal forests approach (Athey et al. 2019)—to evaluate the impact of cooperation on farm performance and identify drivers of treatment effect heterogeneity. We address key methodological challenges, including confounding from observed covariates under the assumption of no unobserved confounding. Second, the study provides novel, policy-relevant evidence on how the effects of cooperative membership vary across different types of farmers, offering insights for more targeted support strategies.

Our empirical results show that the causal forests approach—a machine learning method designed to estimate heterogeneous treatment effects—can generate valuable insights for policymakers, development agencies, and practitioners aiming to support smallholders through cooperation. By identifying which types of farmers benefit most from cooperative membership, this method enables more targeted and effective interventions. These findings align with and extend previous applications of causal forests in development and health economics (Athey et al. 2019; Kreif and DiazOrdaz 2019; Miller 2020; Rehill 2025; Wager and Athey 2018).

Specifically, we apply causal forests to explore the treatment effect heterogeneity of cooperation in regard to selected farm performance indicators—namely business growth, yields, prices and farmers' perceived performance. In this study, we employ both objective indicators (milk price, milk yield, and change in cow numbers) that affect farm turnover and profitability and subjective indicators (farmers' perceived performance) to comprehensively assess farm performance. Including perceived performance complements the objective measures by capturing farmers' own evaluations of their progress and well-being, which are crucial for understanding behavioural outcomes such as their willingness to continue farming and participate in cooperatives.

The remainder of the paper is set out as follows. Section two briefly describes the structure of the Armenian dairy sector and

reviews the literature on treatment effects from a methodological perspective. Section three introduces the methodology applied in this study, and section four presents the results. Section five discusses our findings and concludes.

2 | Contextual Background

Since gaining independence in 1991, Armenia has experienced substantial growth in its dairy sector, with milk production peaking in 2016–17. In Armenia, dairy cattle are mainly kept by household farms, which, according to the most recent data (2023), account for 99% of the country's cows and 98.9% of its milk production, with the rest coming from larger companies or enterprises (legal persons). However, the average milk yield is substantially lower for households (2800 kg per cow and year) than for legal persons (3100 kg per cow and year) (ArmStat 2024). Regions contributing relatively large shares to the national production of approximately 573 million kg per annum in 2023 are Gegharkunik (17%), Lori (14%), Shirak (13.5%) and Aragatsotn (12%). However, the distribution of dairy cows across farm types reveals regional differences. Although in Gegharkunik and Aragatsotn dairy cows are almost exclusively kept by households, legal persons hold an above-average share of the herds in the regions Kotayk, Syunik and Tavush.

The post-communist development of Armenia's agricultural sector—including livestock—and its early documentation have been closely linked to donor involvement, particularly through initiatives supported by USDA and USAID. USDA's marketing assistance programme was in place between 1996 and 2005, and aimed at establishing farmer-owned marketing cooperatives (Cocks et al. 2003). Later, its activities were transferred to the Center for Agribusiness and Rural Development (CARD), an independent Armenian foundation (<http://www.card.am/en>). Since the early 2010s, the World Bank provided financial support to a programme targeting pasture-based livestock farms, including dairy supply chain investments (Millns 2013).

Given the structure of its dairy production, Armenia is comparable to many other emerging and developing economies, which have experienced a substantial increase in milk production over the last four decades (Gerosa and Skoet 2012). From a regional perspective, this growth has been particularly fast in South Asia (+4% per year in the period 1989–2009) and East and Southeast Asia (+8% per year in the period 1989–2009). However, during the same period, dairy production declined by 1.8% per year among former centrally planned economies, making Armenia an exception (Gerosa and Skoet 2012). Compared to other agricultural products, traditional dairy production is labour-intensive, and the perishability of raw milk presents a major challenge in maintaining product quality. Furthermore, the more fragmented nature of the sector means that processors face higher collection costs and greater uncertainty when it comes to quality.

In Armenia, the development of agricultural cooperatives post-independence occurred in three stages. The first saw the creation of autonomous, voluntary farmers' organisations, which did not last for long. The second was defined by the donor-driven establishment of project-supported cooperatives in the 2000s. Finally, since 2010, the development of cooperatives has been promoted

by domestic policy (Gyulgyulyan and Bobojonov 2019). Indeed, in 2015, Armenia passed the law on agricultural cooperatives (Poleshkina and Peplozyan 2016), which has spurred their development in recent years. In terms of proliferation, Gyulgyulyan and Bobojonov (2019) identify approximately 270 agricultural cooperatives active in collecting milk, fruit and vegetables, and providing services. As of 1 January 2024, according to data from the State Register Agency of Legal Entities under the Ministry of Justice, a total of 497 cooperatives operating in various agricultural sectors are registered in the country. Of these, 153 (31%) are agricultural cooperatives, whereas 344 (69%) are consumer cooperatives engaged in agricultural activities.

3 | Methodology

3.1 | Data and Key Variables of Interest

The dataset is based on a survey of dairy farmers in Armenia conducted in 2018. Starting from a national list of dairy farms compiled using a combination of sources, including the national agricultural database, industry associations and government registries, the sample size per region was defined in proportion to the total number of farms. Armenia's subnational administrative division consists of 10 provinces (marz) and the capital city. As there is at least one active dairy cooperative in each of these 10 regions, the sample targeted all of them except the capital (namely Aragatsotn, Ararat, Armavir, Gegharkunik, Kotayk, Lori, Shirak, Syunik, Tavush and Vayots Dzor). The sample was drawn randomly from the list of dairy farmers within each region. In total, 353 dairy farmers were surveyed, of which 68 participated in cooperatives or farmer groups and 285 did not participate.²

To analyse the impact of cooperatives on farm performance, we define farmers who participate in cooperatives as treated and those who do not as the control group. More specifically, observed participation in cooperatives is measured by merging the three main elements of cooperative activities. The variable takes a value of one if a farmer responded 'yes' to the question 'Do you take part in any joint activity with other farmers related to agricultural production?' and at least one of the following questions: 'Are you part of a group of farmers who paid for the service of an agricultural specialist together?', 'Are you part of a group of farmers who bought and applied together for agricultural and/or mechanical means of transportation?' and 'Are you a member of any association of agricultural cooperation in purchasing inputs or selling products?' Due to historical sensitivities related to forced collectivisation under socialism, similar to other post-communist countries, we avoided the term 'cooperative'. As such, some may engage in collective activities that functionally resemble cooperative membership, either informally or through alternative organisational forms. Our questionnaire and analysis reflect this contextual complexity, and references to 'cooperative participation' should be understood in this broader sense.

A common concern in evaluating the impact of cooperatives is that individuals self-select into them based on preferences and potential gains unobserved by the researcher. To address potential bias from unobserved differences between cooperative members and non-members, we control for farmer and household characteristics. This helps us better account for the factors

that influence farmers' decisions to join cooperatives and ensures more reliable comparisons of outcomes. In selecting these covariates, we focus on traits identified in the literature as determinants of cooperative membership—such as demographics—that are plausibly exogenous to farm performance. Because none of these variables directly affect milk price, yield per cow, herd growth or subjective performance ratings, they fulfil the 'independent of farm performance' criterion required for our unconfoundedness assumption. Thus, in line with previous studies, we include farmers' experience, age, gender, number of family members working on the farm, land area cultivated with animal feed, share of income from the dairy business, number of dairy processors within a 1-h drive, and share of feed produced on the farm.

In addition, five variables of the study—namely, (1) farmer's willingness to cooperate (Will_coop), (2) farmer's perceived farm performance (Farm_perf), (3) farmer's access to information (Acc_info), (4) farmer's financial literacy (Fin_lit) and (5) farmer's perceived presence of leadership in the village (Leadership)—are latent variables. These are measured using a five-item Likert scale where lower values indicate lower levels of farm performance, lower willingness to cooperate, and so on. The procedure suggested by Churchill (1979), and Gerbing and Anderson (1988) is employed to create a composite score from the different items measuring a latent factor. To operationalise the five perception-based constructs (willingness to cooperate, perceived farm performance, access to information, financial literacy and leadership presence), we conduct a confirmatory factor analysis (CFA).³ Model fit is excellent ($\chi^2/\text{df}=1.64$; CFI=0.981; SRMR=0.042; RMSEA=0.043; PCLOSE=0.79). Composite reliability (CR) exceeds 0.70 for all constructs, and average variance extracted (AVE) exceeds 0.50 for four of the five constructs (access to information AVE=0.485). Discriminant validity criteria (AVE > MSV; square root of AVE > inter-construct correlations) are also satisfied. For full CFA loadings, reliability and validity statistics, and bias tests, see [Appendix](#).

3.2 | Treatment Effect Heterogeneity: Conceptual Background

In this paper, 'heterogeneity' refers exclusively to treatment effect heterogeneity in the potential outcomes framework (Imbens and Rubin 2015)—that is, systematic variation in the causal impact

$$\tau(x) = E[(Y(1) - Y(0)|X = x)]$$

of cooperative membership across farmers with differing observable covariates X . We study three key dimensions of this heterogeneity:

1. Magnitude—the size of $\tau(x)$ relative to zero;
2. Direction—whether $\tau(x)$ changes sign for different X ;
3. Drivers (effect modifiers)—which covariates most strongly explain variation in $\tau(x)$.

In standard impact evaluations utilising observational data, researchers often explore effect modifiers through subgroup

analyses, comparing treatment effects across distinct population segments, such as those defined by socioeconomic characteristics (List et al. 2016). However, when assessing the impact of cooperative action, such an approach may produce misleading conclusions. The decision to join a cooperative is not randomly assigned and may be influenced by the same subgroup attributes under investigation, complicating causal inference. Traditional methods for estimating treatment effect heterogeneity often rely on incorporating interaction terms in regression models, which impose parametric assumptions that may not hold or are difficult to verify (Hainmueller et al. 2019).

To overcome these limitations, machine learning (ML) techniques have gained popularity due to their ability to systematically investigate treatment effect heterogeneity without relying on subjective subgroup definitions or parameterisation. These methods leverage advancements in causal ML, employing supervised learning algorithms to estimate key causal parameters (Chernozhukov et al. 2018; Kreif et al. 2022). Some approaches aim to identify subgroups that experience the strongest or weakest treatment effects (e.g., Chernozhukov et al. 2018; Imai and Strauss 2011), whereas others estimate the conditional average treatment effect (CATE) function in a flexible, data-driven manner to capture how treatment effects vary across observed covariates (Fan et al. 2022). These methods combine the adaptability of ML with the rigour of semiparametric statistical theory, enabling robust inference even after adaptive estimation processes.

In this study, we adopt the causal forest approach (Athey et al. 2019; Wager and Athey 2018) to estimate treatment effects at the individual level, which can be aggregated to derive average effects for specific subgroups. This method offers several key benefits compared to conventional techniques. First, it eliminates the need to pre-specify subgroups or assume particular forms of covariate–treatment interactions, thereby reducing dependence on restrictive parametric models. Second, the causal forest framework provides statistical tests to evaluate the significance of treatment effect heterogeneity driven by observed covariates and identifies the variables most strongly associated with this variation. Third, it is well-suited for cross-sectional data, making it particularly valuable in contexts where longitudinal data are limited or unavailable.

Simulation studies have demonstrated the strong performance of the causal forest estimator and its extensions (e.g., Fan et al. 2022; Knaus et al. 2021; Lechner 2023). Although widely applied in medical research, its use in program evaluation is growing, particularly in labour economics (Davis and Heller 2017). However, the application of causal forests to evaluate cooperative participation, especially in non-randomised settings, remains underexplored. In such contexts, robust statistical methods are essential to address potential confounding and ensure reliable causal inference.

3.3 | Estimation of Average Treatment Effect

This study aims to evaluate the causal effect of cooperative membership on multiple dimensions of farm performance. We focus on four key performance indicators: (1) milk price, (2) change in

herd size (number of cows) between 2015 and 2017, (3) annual milk yield per cow, and (4) perceived farm performance. For analytical consistency, each outcome is examined independently, with any given outcome denoted as (Y) , and cooperative participation represented by (W) . For an individual farmer (i) , the potential outcome under treatment status (w) is expressed as $(Y_i(w))$, where $(w \in \{0, 1\})$. The individual treatment effect for farmer (i) is thus defined as $[\tau_i = Y_i(1) - Y_i(0)]$.

Our identification strategy hinges on the unconfoundedness assumption, which posits that, conditional on a comprehensive set of observed covariates (X) , the assignment to treatment [cooperative participation, (W)] is independent of the potential outcomes $[Y(1), Y(0)]$. Formally, this is expressed as $[Y(1), Y(0) \perp W | X]$. Combined with the assumptions of no interference between units, consistency, and overlap (i.e., a positive probability of being in either the treatment or control group for all values of X), this framework enables estimating key causal estimands: the ATE, the average treatment effect on the treated (ATT), and the average treatment effect on the controls (ATC).

These estimands address distinct policy-relevant questions. The ATE, defined as $\{E[Y(1) - Y(0)]\}$, quantifies the expected difference in outcomes if all farmers participated in cooperatives compared to if none did, averaged across the entire population. The ATT, given by $\{E[Y(1) - Y(0) | W = 1]\}$, evaluates the benefit of cooperative participation for those farmers who actually joined, relative to the counterfactual scenario where they did not participate. Conversely, the ATC, expressed as $\{E[Y(1) - Y(0) | W = 0]\}$, estimates the potential benefit for non-participating farmers had they chosen to join a cooperative.

In addition to these population-level effects, we examine the CATE, expressed as $\{\tau_x = E[Y(1) - Y(0) | X = x]\}$. The CATE captures how treatment effects vary across specific covariate profiles, reflecting the expected treatment effect for farmers

with a given set of characteristics (x) . Given the likelihood that multiple observed factors influence the size and direction of the treatment effect in the context of cooperative participation, investigating heterogeneity across covariate strata is critical.

To estimate the causal effects, we employ both a traditional and ML approach. The traditional approach calculates an inverse propensity weighted (IPW⁴) estimator, a doubly robust (DR) estimator that estimates the propensity score of treatment and incorporates this information to conduct a weighted OLS regression (Imbens 2004). We implement this method using the R package WeightIt to get the weight for the different estimates (i.e., ATE, ATT and ATC), and run weighted regressions for each of them to obtain the estimated ATE, ATT and ATC. These more traditional estimates are later contrasted with the causal forest estimates for ATEs (see next section). All models use the same set of covariates for confounder adjustment. The estimated effects are specific to our study sample, and any inferences extending beyond this sample represent preliminary indications of generalisability, which should be validated using a truly randomised sample.

4 | Results

4.1 | Descriptive Statistics

Figure 1 illustrates the differences in observed characteristics between farmers who are members of cooperatives (the treated group) and those who are not (the control group). The figure reports both the mean values and standardised mean differences for a set of covariates across these two groups. As shown, the unadjusted sample reveals considerable imbalances, with numerous covariates displaying standardised mean differences $> 10\%$.

Table 1 gives the descriptive statistics of farm performance outcomes for the control group (farmers who do not participate in

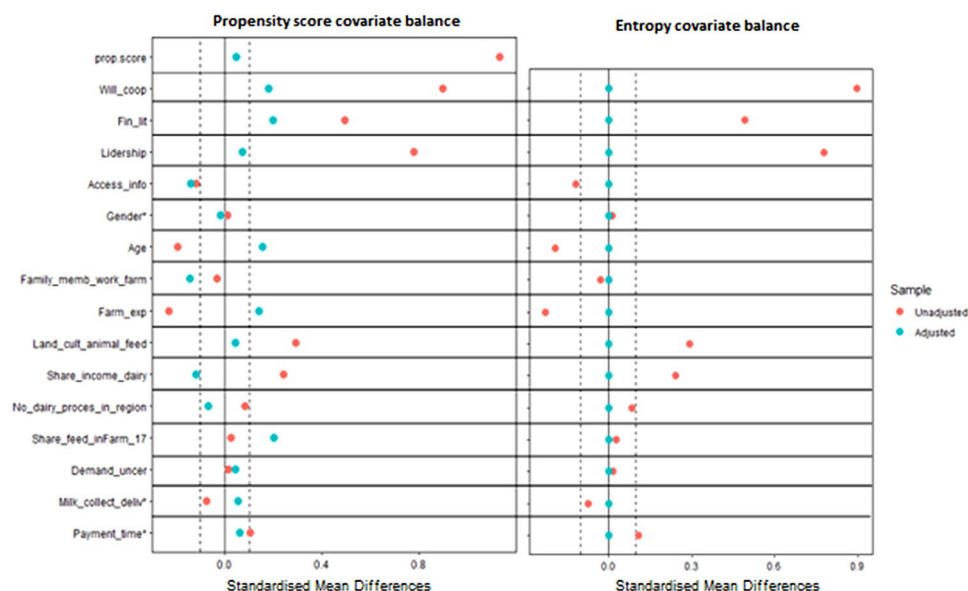


FIGURE 1 | Covariate balance with propensity score weighting and entropy balance. [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 1 | Descriptive statistics of farm performance outcomes.

Farmer performance outcomes	Units	Control (n = 285)		Treated (n = 68)	
		Mean	SD	Mean	SD
Change in number of cows 2015–17	Heads	0.05	3.13	1.35	2.94
Perceived farm performance	Continuous	−0.13	1.08	0.53	0.77
Milk price	AMD/kg	164.89	57.86	145.25	32.81
Milk yield	kg/cow/year	1765.65	534.24	1746.68	493.07

cooperatives) and the treated group (farmers who participate in cooperatives). From the descriptive statistics, we can see that, on average, both groups have a similar milk yield per cow per year of about 1748 kg. This yield is substantially lower than the average calculated from national statistics. Surprisingly, farmers who do not participate in cooperatives receive AMD⁵ 155 per kg of milk sold, whereas farmers who participate in cooperatives receive AMD 137 per kg. On the other hand, farmers who participate in cooperatives increased their herd size between 2015 and 2017 by about 1.35 heads, whereas there was no change on average for farmers not participating in cooperatives. However, the larger standard deviation points to a higher within-group heterogeneity among the control group compared to the treated group.

The composite score of the five perception-based variables yields a value of 0.53 for farmers engaged in cooperative activities and a value of −0.13 for non-participating farmers. Thus, two out of four performance variables tend to suggest a worse performance for members of cooperatives. In the following, we will test whether these differences result from a random process or point to structural differences.

4.2 | Average Treatment Effects

Figure 1 describes the covariate balance achieved after inverse probability weighting (IPW) using two approaches: (1) IPW based on propensity scores (PS) generated from logistic regression, and (2) IPW estimated from entropy balancing (ebal). Furthermore, it contrasts these estimates with the unweighted balance. The PS method improves the balance, but there are still covariates that have standardised differences larger than 10%, whereas the ebal method achieves a good balance with all covariates reaching standardised differences close to 0.

Table 2 presents the ATEs for all outcomes of interest by using the DR inverse probability weighting regression estimates and causal forest (CF) estimates. From the table, we can see that farmers participating in cooperatives receive a slightly lower price than farmers who do not participate. Those who participate in cooperatives increased their herd size between 2015 and 2017 by more than one cow (in all estimates). Farmers who are members of cooperatives perceive a higher farm performance score than farmers who are not members. Lastly, the differences in milk yields between the two groups are small relative to the variation within the two groups.

TABLE 2 | Estimates of average treatment effects.

	DR estimator	DR estimator	Causal
	IPW-PS	IPW-ebal	forest
	Estimate (SE)	Estimate (SE)	Estimate (SE)
Milk price			
ATE	−7.815 (4.165)*	−1.348 (6.365)	−8.572 (3.533)**
ATT	−7.96 (4.063)*	−4.68 (4.581)	−7.197 (3.234)**
ATC	−7.686 (4.423)*	1.017 (11.5)	−8.922 (3.938)**
Change in no. cows 2015–2017			
ATE	1.492 (0.377)***	1.761 (0.575)***	1.135 (0.387)***
ATT	1.298 (0.409)***	1.618 (0.501)***	1.014 (0.388)***
ATC	1.582 (0.387)***	1.509 (0.71)**	1.171 (0.428)***
Milk yield per cow per year			
ATE	−17.204 (54.706)	92.042 (84.562)	−11.851 (47.737)
ATT	−79.153 (69.711)	−49.953 (79.696)	−19.794 (55.183)
ATC	−11.656 (54.283)	147.575 (94.658)	−8.943 (50.983)
Farmer’s perceived farm performance			
ATE	0.501 (0.109)***	0.567 (0.167)***	0.409 (0.091)***
ATT	0.356 (0.108)***	0.468 (0.113)***	0.328 (0.093)***
ATC	0.554 (0.114)***	0.497 (0.226)**	0.431 (0.1)***

Note: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.
 Abbreviations: ATC, average treatment effect among the controls; ATE, average treatment effect; ATT, average treatment effect among the treated; DR estimator, Doubly robust estimator; IPW-ebal, inverse probability weighting from entropy balancing; IPW-PS, inverse probability weighting from propensity scores; SE, standard error.

Each cell in Table 2 shows an estimate and a standard error in parentheses.⁶ The rows refer to three causal contrasts:

- ATE: difference if everyone participated versus no one.
- ATT: effect among actual cooperative participants.
- ATC: hypothetical effect if non-participants had joined.

The three columns correspond to different estimators:

1. DR estimator IPW-PS—DR regression weighted by PS.
2. DR estimator IPW-ebal—same regression weighted by entropy balance weights.
3. CF—flexible ML estimate of the average effect.

For example, the -7.815 (4.165) entry under ‘Milk price’ and ‘ATE’ (DR IPW-PS) means that, on average, cooperative members receive AMD 7.8 less per litre than non-members. Likewise, the 1.492 (0.377) entry under ‘Change in no. cows’ and ‘ATE’ indicates that cooperative members increased their herd size by 1.5 cows more than non-members. Comparing across columns demonstrates the robustness of each effect to different weighting schemes and to the CF approach.

4.3 | Heterogeneous Treatment Effect

The formal test for treatment effect heterogeneity indicates the slight presence of heterogeneity for perceived farm performance

($p=0.07$), but not for milk price ($p=0.54$), change in the number of cows between 2015 and 2017 ($p=0.76$), and milk yield ($p=0.98$). Table 3 presents the ranking of covariates in terms of their importance in predicting treatment effect heterogeneity for each outcome.

For milk price, the most influential variables are the farmer’s financial literacy and demand uncertainty, followed by access to information and the share of animal feed that is produced on the farm. For the change in the number of cows between 2015 and 2017, the most important variables are the farmer’s perceived presence of leadership in the village, the farmer’s age and the land cultivated with animal feed. On the other hand, for the milk yield, the most important covariates in explaining treatment effect heterogeneity are the farmer’s access to information, the farmer’s willingness to cooperate, the share of family income that comes from the dairy activity, and the land cultivated with animal feed. Lastly, for the perceived farm performance, the top three covariates are the farmer’s perceived presence of leadership in the village, the farmer’s access to information and the farmer’s financial literacy.

We then present the CATE (Figure 2) for each outcome for subgroups constructed based on the variables suggested by the final CFs’ variable importance (Table 3). The *top left corner* of Figure 2 presents the subgroup ATEs for milk price; the *top right corner* shows the subgroup ATEs for change in the number of cows between 2015 and 2017; the *bottom left corner* presents the subgroup ATEs for milk yield; and the *bottom right corner* shows the perceived farm performance. To create subgroups, each continuous variable is categorised into three levels (i.e., low, mid and high).

TABLE 3 | Importance of covariates in explaining treatment effect heterogeneity for each outcome.

Rank	Milk price		Change in no. cows 2015–2017		Milk yield per cow		Farmer's perceived farm performance	
	V.IMP	Variable	V.IMP	Variable	V.IMP	Variable	V.IMP	Variable
1	0.192	Financial literacy	0.174	Leadership	0.101	Access to information	0.199	Leadership
2	0.165	Demand uncertainty	0.172	Age	0.100	Willingness to cooperate	0.184	Access to information
3	0.147	Access to information	0.166	Land cultivated with animal feed	0.095	Share of income from dairy	0.162	Financial literacy
4	0.119	Share of feed produced on farm	0.166	Willingness to cooperate	0.093	Land cultivated with animal feed	0.145	Willingness to cooperate
5	0.103	Leadership	0.166	Financial literacy	0.093	Financial literacy	0.110	Land cultivated with animal feed
6	0.098	Milk_collect_deliv	0.157	Access to information	0.092	Farm experience	0.103	Farm experience
7	0.090	Land cultivated with animal feed			0.091	Age	0.096	Age
8	0.086	Age			0.088	Leadership		

Note: The V.IMP (variable importance measure) is based on the count of the proportion of splits on the given variable.

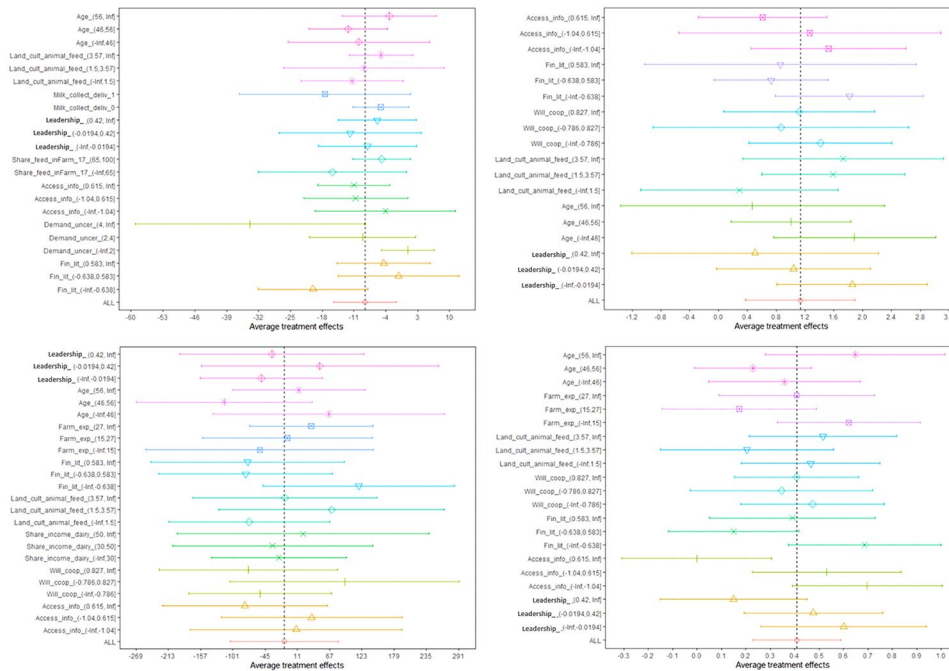


FIGURE 2 | Estimated subgroup average treatment effect for each outcome. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com)]

As suggested by the treatment effect heterogeneity test, we expect to observe heterogeneity in treatment in perceived farm performance and no heterogeneity in treatment among the other outcomes. In this context, in the bottom right corner of Figure 2, the largest differences are observed for the presence of leadership in the village, the farmer's access to information, the farmer's financial literacy, the land cultivated with animal feed and the farmer's age.

Thus, farmers who perceive that there is leadership in the village have a lower ATE (on perceived farm performance) compared to farmers who do not perceive the presence of leadership in the village (brown-coloured triangle in Figure 2 bottom left).

Farmers with less access to market information systems and farmers with low financial literacy appear to benefit the most (in terms of perceived farm performance) from participating in cooperatives compared to farmers who have more access to market information and higher levels of financial literacy (i.e., higher ATE from participation in cooperatives is observed for the subgroup with limited access to market information and low financial literacy).

Lastly, participation in cooperatives appears to provide greater benefits (in terms of perceived farm performance) to inexperienced and older farmers (i.e., higher ATE from participation in cooperatives is observed for the subgroup with < 15 years of experience and farmers older than 56 years).

5 | Discussion and Conclusions

Many studies highlight the benefits of cooperation for farmers; however, most neglect the heterogeneity within the sample. This study addresses this issue using a large-scale farm survey conducted in Armenia. The results offer a nuanced picture of

cooperative action in the Armenian dairy sector. Although milk yields are broadly similar between cooperative members and non-members, the lower milk price observed for cooperative members is surprising and warrants further investigation. Even if dairy cooperatives pay lower prices, members might receive non-monetary benefits such as lower variability of prices, lower transaction costs, or even equipment and additional services. Indeed, the literature shows that farmers' perceptions of transaction costs can outweigh lower revenues (Hernández-Espallardo et al. 2013). From 2015 to 2017, farmers who were part of cooperatives expanded their herds, while those who weren't members did not. This supports the idea that membership offers farmers more advantages than just price improvements.

Although the ATEs suggest that farmers who engage in cooperatives perform worse than farmers who do not, our findings show that subgroup-specific effects could well be positive. When comparing the ATEs across subgroups, the results indicate that farmers with less access to market information systems and farmers with low financial literacy benefit the most (in terms of perceived farm performance) from participation in cooperatives compared to farmers who have more access to market information and a higher level of financial literacy. This result supports the hypothesis that cooperatives often provide critical support and resources to otherwise relatively disadvantaged farmers, significantly enhancing their capabilities and performance. Similarly, participation in cooperatives provides greater benefits (in terms of perceived farm performance) to farmers with less than 15 years of experience and farmers older than 56. Older farmers may benefit more from cooperatives, as they may rely on them for access to inputs, services, and markets due to lower digital skills or financial literacy. From a policy perspective, these results highlight the need to provide a supporting environment for collective action and the potential benefits to rural development. In particular, if less advantaged farmers benefit more from cooperatives, government actors and donor agencies

should stimulate their emergence, as it is likely that these farmers will otherwise leave the sector. Thus, cooperatives soften the social costs of structural change by keeping disadvantaged groups in the sector but not at the cost of farm growth, as shown by the increase in herd size among cooperative members.

The above findings align with the literature on the inclusiveness of cooperatives. Scholars have long acknowledged that cooperatives are uniquely positioned to empower vulnerable or marginalised actors (Bijman and Wijers 2019). Our results reinforce this claim, suggesting that cooperatives can act as redistributive mechanisms—disproportionately supporting those who face barriers to market participation or lack social capital—and thereby help redress structural inequalities. However, these marginalised farmers may also be the least likely to join cooperatives. As organisations shift from a community orientation towards a market orientation, inclusivity often declines (Wassie et al. 2019). It is therefore crucial to actively promote and support the cooperative membership of marginalised farmers, since they stand to gain the most.

At the same time, the literature warns that inclusion-driven heterogeneity, whereas socially desirable, also increases coordination and decision-making costs, raising the risk of conflict or organisational degeneration unless governance is innovated accordingly (Iliopoulos and Valentinov 2022). As cooperatives expand their inclusivity, they must also adapt their governance structures to manage greater complexity. Accordingly, support interventions should recognise not only average effects but also the distinct ways cooperatives serve different member groups, and ensure governance evolves to meet those varied needs.

Although the dataset dates back to 2018, its core relevance remains intact, as the structural barriers to cooperation, such as low trust and limited experience with collective action, persist in Armenia's agricultural sector. In recent years, there have been policy efforts to modernise agriculture and promote cooperation, including subsidies and support for forming cooperatives. These developments signal a gradual shift, but the underlying social and institutional constraints captured in the 2018 data still provide valuable insights into the enduring challenges and dynamics of farmer cooperation.

Although this study is specific to the dairy sector in Armenia, several findings have broader relevance for similar settings. The observed heterogeneity in the impact of membership—particularly the greater benefits for farmers with lower market access, limited financial literacy, or less farming experience—is relevant for other countries, especially for post-transition or emerging economies where structural barriers limit farmers' access to resources. Furthermore, the variation in impact by characteristics such as age, financial literacy, trust in leadership, and access to information provides empirical evidence of real-world member diversity with significant organisational consequences (Valentinov and Iliopoulos 2021).

This study makes several important methodological contributions. First, by assessing the effect of cooperative membership on farm performance, we illustrate the advantages of employing innovative causal ML methods. Notably, this is the first investigation to apply the CF approach to evaluate cooperative

participation, enabling a nuanced characterisation of the sources of treatment effect heterogeneity. We draw attention to the methodological challenges inherent in such analyses, particularly the necessity of adequately addressing confounding by observed covariates that influence both cooperative participation and farm outcomes, whereas acknowledging the strong assumption of no unobserved confounding.

Second, we provide novel and policy-relevant empirical insights on the overall impact of cooperation by examining the heterogeneous effects of cooperatives on various aspects of farm performance. Our findings demonstrate that the CF methodology can yield valuable information for policymakers, development practitioners, and agencies seeking to support the development of smallholder enterprises and livelihoods through cooperative initiatives. Specifically, we leverage CFs to investigate the heterogeneity of cooperative effects across selected farm performance metrics, including business growth, productivity, prices and farmers' subjective assessments of performance.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Endnotes

¹ In this manuscript, the term 'collective action' is used interchangeably with 'cooperative (action)' and 'cooperative participation'. This is done to reflect the country and cultural context (described later in the paper).

² Information on the number of active members in agricultural cooperatives is not available.

³ Confirmatory Factor Analyses (CFAs) were conducted using AMOS 25, following the reliability threshold proposed by Nunnally (1978) for the minimum acceptable Cronbach's alpha (α), and assessing construct validity in line with the criteria outlined by Bagozzi et al. (1991) and Hair et al. (2010). For further details, see Appendix (Tables A1–A4).

⁴ <https://github.com/yqzhong7/AIPW>.

⁵ AMD: Armenian dram. The average exchange rate at the time of the survey has been AMD 1 = EUR 0.001757.

⁶ Although the sample does not represent a perfect random sample of the underlying (unknown) full population of dairy producers, *p* values are reported. However, they should be interpreted as providing graded strength of evidence (Hirschauer et al. 2019).

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Appendix

Confirmatory factor analyses (CFAs) were conducted in AMOS 25. The items for each of the five latent constructs were derived from a combination of literature review and qualitative in-depth interviews with farmers. To get measures for the latent constructs, the items of each construct are included in CFA, which generates measures and psychometric properties of each construct. Thus, construct reliability is assessed by estimating CR and maximum reliability MaxR(H). According to Nunnally (1978), the minimum acceptable value for α is 0.70. Table A1 shows that each construct has a CR greater than the suggested threshold value of 0.7.

Beyond reliability, each construct should be valid. A construct is considered valid when it fulfils two main conditions: convergent validity (i.e., items loading significantly on the factor they are measuring) and the condition of discriminant validity (ensuring that these factors are distinct and have a low covariance among each other) (Bagozzi et al. 1991). Convergent validity can be assessed through AVE (Average Variance Extracted). The suggested threshold value for AVE is 0.5 (Hair et al. 2013). From B1, only the Access to information variable has an AVE slightly smaller than 0.5.

TABLE A1 | Validity and reliability.

	CR	AVE	MSV	MaxR(H)	Farm_perf	Access_info	Will_coop	Fin_lit	Leadership
Farm_perf	0.829	0.567	0.125	0.936	0.753				
Access_info	0.78	0.485	0.036	0.849	-0.015	0.697			
Will_coop	0.78	0.563	0.15	0.869	0.091	-0.086	0.75		
Fin_lit	0.74	0.593	0.125	0.807	0.353***	0.082	0.112 [†]	0.77	
Leadership	0.87	0.771	0.15	0.924	0.192**	-0.189**	0.388***	0.155*	0.878

Note: In bold the square root of the AVE, below this diagonal factor correlations; significance of correlations: [†] $p < 0.100$; * $p < 0.050$; ** $p < 0.010$; *** $p < 0.001$. Abbreviations: AVE, average variance extracted; CR, composite reliability; MaxR(H), maximum reliability; MSV, maximum shared squared variance.

Regarding discriminant validity, Hair et al. (2013) suggest two threshold values: (1) Average Variance Extracted (AVE) should be larger than the Maximum Shared squared Variance (MSV) and (2) the square root of AVE should be greater than inter-construct correlations. Based on the results of Table A1, it can be seen that all the threshold values suggested by Hair et al. (2013) are satisfied. Thus, it can be concluded that the constructs fulfil the conditions of convergent and discriminant validity.

TABLE A2 | CFA standardised factor loadings.

Items←Latent factor	Estimate
FP1←Farm_perf	0.949
FP2←Farm_perf	0.910
FP5←Farm_perf	0.525
FP3←Farm_perf	0.517
INF3←Access_info	0.838
INF4←Access_info	0.848
INF2←Access_info	0.555
INF1←Access_info	0.461
WC2←Will_coop	0.892
WC3←Will_coop	0.846
WC1←Will_coop	0.420
ST8←Fin_lit	0.639
ST7←Fin_lit	0.882
LD2←Lidership	0.794
LD1←Lidership	0.955

Note: All loadings ≥ 0.40 , meeting conventional thresholds for practical significance (Hair et al. 2013).

TABLE A3 | CFA—measurement model goodness of fit.

Measure	Threshold	Model values
Chi-square/df	< 3	1.640
CFI	> 0.95 great; > 0.90 moderate	0.981
SRMR	< 0.09	0.042
RMSEA	< 0.05 good, 0.05–0.10 moderate	0.043
PCLOSE	> 0.05	0.791

Note: Chi-square/df is the chi-square value of the model divided by model degrees of freedom; p value for the model—tests whether the departure of the data from the model is significant and a p value ≤ 0.05 means the difference between the data and the model is significant.

Abbreviations: AGFI, Adjusted Goodness of Fit Index; CFI, Comparative Fit Index; PCLOSE, tests the null hypothesis that the population RMSEA is no > 0.05 ; RMSEA, the root mean square error of approximation; SRMR, standardised root mean square residual.

We conducted two χ^2 -difference tests to assess potential bias:

TABLE A4 | Zero constraints test.

Test	χ^2 (unconstrained)	df	χ^2 (constrained)	df	$\Delta\chi^2$	p
Zero-constraints model	106.618	65	195.283	80	88.665	<0.001
Equal-constraints model	106.618	65	195.283	79	88.665	<0.001

Note: The chi-square test for the zero constrained model was significant (i.e., measurable bias was detected). Therefore, a bias distribution test was made (of equal constraints). The chi-square test is significant on this test as well (i.e., unevenly distributed bias). Thus, the SB construct was retained for subsequent causal analyses.