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Yield effects of agricultural cooperative membership in developing countries: A meta-analysis

Wanglin Ma[1] | **Sanghyun Hong**[2] | **W. Robert Reed**[2] | **Jianhua Duan**[3] | **Phong Luu**[4]

[1]Department of Global Value Chains and Trade, Faculty of Agribusiness and Commerce, Lincoln University, Christchurch, New Zealand

[2]Department of Economics and Finance, UC Business School, University of Canterbury, Christchurch, New Zealand

[3]Stats NZ, Christchurch, New Zealand

[4]Department of Financial and Business Systems, Faculty of Agribusiness and Commerce, Lincoln University, Christchurch, New Zealand

Correspondence
Wanglin Ma, Department of Global Value Chains and Trade, Lincoln University.
Email: wanglin.ma@lincoln.ac.nz

Abstract

This study uses a meta-analysis to synthesize the effects of agricultural cooperative membership on the yield of crops and livestock. It collects 158 estimated yield effects from 42 studies, covering 19 developing countries. Our analysis finds evidence that there exists positive publication bias in the empirical literature, confirming that researchers and journals have a preference to publish articles that report positive and significant results. After correcting for publication bias, we find that cooperative membership has a small-sized and insignificant effect on the yield. The meta-regression analysis reveals that variation in the reported yield effects can be largely explained by the study attributes such as the sample type (full sample vs. subsample), membership ratio, econometric approaches (instrumental-variable based parametric approach, non-parametric approach or ordinary least square regression), effect size types (average treatment effects on the treated, average treatment effects, or coefficient), agro-product type (grain or others), and climate zones (tropical or non-tropical).

KEYWORDS
cooperative membership, developing countries, meta-analysis, yield effects

JEL CLASSIFICATION
J54, Q12

1 | INTRODUCTION

Improving the yield of crops and livestock in agricultural production is a key to ensuring global food security, relieving hunger and poverty, and encouraging sustainable development. However, the growth in farm yield and food production is challenged by many factors such as climate change, higher input prices, degradation of natural resources, the loss of biodiversity, and the spread of transboundary pests and diseases of plants and animals (Asfaw et al. 2020; Challinor et al. 2014; Lachaud et al. 2022; Varma & Bebber 2019). A further challenge is ensuring that crop and livestock yields keep pace with population growth. The United Nations predicts that the global population is expected to reach around 10 billion by 2050, an increase of 2 billion people from 2019 levels. This growth means that food production needs to increase by around 60% for consumable calories per capita to remain constant.

Different programs have been proposed and developed in recent decades to tackle the challenges facing smallholder farmers in developing countries, helping sustain or increase farm production. Agricultural cooperatives are one of them. Agricultural cooperatives have been touted as a way to improve farm-level performance across a variety of dimensions such as improving crop yield, farm income, production efficiency, input use, product quality, and sales price (Grashuis & Su 2019; Lin et al. 2022; Tran et al. 2021; Zhang et al. 2020).

Efficient cooperatives can also empower their members economically and socially (Dohmwirth & Liu 2020; Engel 2012; Ferguson & Kepe 2011; Lin et al. 2022; Ma et al. 2022b; Mojo et al. 2015; Sebhatu et al. 2021). For example, cooperatives can create sustainable employment through equitable and inclusive business models that are more resilient to external shocks. They can also help build smallholder farmers' skills by providing them with information and knowledge, helping them to adapt to fluctuating markets, and building their capacity to adopt the appropriate practices and technologies. Candemir et al. (2021) found that agricultural cooperatives also play a non-negligible role in promoting smallholder farmers' adoption of environmentally friendly practices.

While numerous studies have made efforts to investigate the relationship between cooperative membership and farm performance, as evidenced by two review studies (Bizikova et al. 2020; Grashuis & Su 2019), no consensus has been reached regarding how cooperatives influence farm sustainability. Grashuis and Su (2019) reviewed 56 peer-reviewed publications and found that cooperative membership positively affects sales price, farm income, crop yield, product quality, market access, technology adoption, and input-output efficiency. They also pointed out that the benefits received by small and large producers are unevenly distributed. Based on 239 studies from 24 countries, Bizikova et al. (2020) reviewed the contributions of farmers' organizations (e.g., associations, cooperatives, self-help, and women's groups) to smallholder agriculture in developing countries. They showed that 57% of the reviewed studies report positive impacts of farmers' organizations on farm income, but only 19% of reviewed studies report positive impacts on crop yield. Although these two studies provide important insights, they fail to account for publication bias. Publication bias occurs when researchers and journals have preferences for estimates that are statistically significant or have a certain sign (Anwar & Mang 2022; Xue et al. 2021). These preferences work to filter out less preferred estimates so that the literature presents a distorted picture of reality. Taking estimates in the literature at face value, without correcting for publication bias, can mislead policymaking.

In this study, we synthesize existing research to estimate the "average" yield effects of agricultural cooperative membership. We focus on farm yield because crops and livestock yields affect food security, dietary diversity, and the nutrition intake of human beings (Kassaye et al. 2021; Khonje et al. 2022; Rahman & Connor 2022). In addition, farm yield is an important component of farm revenue. To date, the literature in this field reports mixed findings. Most studies show that cooperative membership increases yield (Ahado et al. 2021; Bairagi & Mottaleb 2021; Chagwiza et al. 2016; Ingutia & Sumelius 2022). In contrast, some find that cooperative membership has little (Hun et al. 2018; Kashiwagi 2020; Mwaura 2014; Shumeta & D'Haese 2016) or even a negative impact on yield (Fischer & Qaim 2012; Neupane et al. 2022).

Meta-analysis is a statistical tool that allows researchers to appropriately weight contrasting estimates while accounting for the influence of publication bias (Anwar & Mang 2022; Ogundari 2022; Ogundari & Bolarinwa 2018; Ridhwan et al. 2022). The goal is to produce an estimate of the overall, average effect of a given treatment or intervention. We bring the analytical tools of meta-analysis to the empirical literature on the effect of cooperative membership on crop and livestock yields. To do that, we collect 158 estimates from 42 published studies that estimate the yield effects of cooperative membership in developing countries. The findings from this study can provide guidance to policymakers tasked with developing public policies towards agricultural cooperatives.

A further contribution of our study is that we investigate why different studies produce different estimates. Different study attributes (e.g., econometric approaches, effect types, sample types, and climate zones) may help explain different estimated yield effects of cooperative membership. For example, cooperative membership is widely considered to be an endogenous variable. Scholars have addressed the endogeneity issue of cooperative membership using both instrumental variable-based parametric approaches such as the endogenous switching regression model (Kehinde & Ogundeji 2022; Kumar et al. 2018; Ma et al. 2022a) and non-parametric approaches such as the propensity score matching (PSM) technique (Hoken & Su 2018; Mishra et al. 2018; Ortega et al. 2019; Shumeta & D'Haese 2016). These different estimation procedures may produce systematically different estimates of yield effects. Another example relates to climate. Agricultural production in tropical regions or African countries may have different yield effects compared with production in temperate regions or Asian countries. Meta-analysis can help to identify this. Being able to associate conditions under which agricultural cooperatives have a greater impact can help policymakers to design better policy instruments.

The rest of this paper is structured as follows: Section 2 discusses the mechanism of how cooperative membership affects farm yield. Section 3 presents the meta-dataset, methods, and variables. The results are presented and discussed in Section 4. The final section concludes the paper and recommends policy implications.

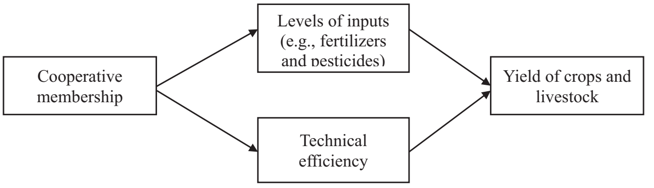

FIGURE 1 Influencing pathways on the relationship between cooperative membership and farm yield

2 | THE MECHANISM OF HOW COOPERATIVE MEMBERSHIP AFFECTS FARM YIELD

Agricultural cooperatives can help increase farm yield mainly through two channels: increasing the levels of inputs (e.g., fertilizers, pesticides, machinery, and labour) and improving the levels of technical efficiency (Figure 1). Several studies have found that cooperative membership increases the probability of agricultural technology adoption and the levels of input use (Abebaw & Haile 2013; Addai et al. 2022; Blekking et al. 2021; Manda et al. 2020; Sarkar et al. 2022; Zhang et al. 2020). In their investigations of maize farmers in Zambia, Manda et al. (2020) found that cooperative membership significantly increases the probability of adopting improved variety and inorganic fertilizer and Blekking et al. (2021) showed that cooperative members use more fertilizer and hybrid seeds than non-members. A study for Ghana reveals that rice farmers who have membership in farmer-based organizations are 38% more likely to adopt machinery than those without membership (Addai et al. 2022). The increased usage of inputs contributes to an improvement in farm yield.

Technical efficiency refers to the effectiveness with which a given set of inputs is used to produce an output (Carrer et al. 2022; McFadden et al. 2022; Zheng et al. 2021). An improvement in technical efficiency also helps increase the yield of crops and livestock. Relative to improving farm yield by increasing input levels, improving technical efficiency is a more ideal way because the latter strategy does not require additional investment in inputs. It only requires better farm management and readjustments in utilizing the existing inputs in more efficient ways, which ultimately saves production costs. Prior evidence also reveals that cooperative membership plays a significant role in improving the technical efficiency of crop and livestock production. (Abate et al. 2014; Addai et al. 2022; Ahado et al. 2021; Lin et al. 2022; Neupane et al. 2022; Olagunju et al. 2021; Qu et al. 2020).

Ahado et al. (2021) analyzed the impact of cooperative membership on the technical efficiency of potato farmers in Mongolia and found that cooperative members are more technically efficient with an average technical efficiency between 64% and 71%, in comparison to 54%–57% for non-members. This is further confirmed by Olagunju et al. (2021), who investigated maize production in Nigeria and found that the technical efficiency of cooperative members is 49% higher than that of non-members. Neupane et al. (2022) estimated the production efficiency of goat production in Nepal. They found that the average technical efficiency scores of cooperative members and non-members are 93.2% and 90.7%, and the difference is statistically significant. By estimating the technical efficiency of apple production in China, Addai et al. (2022) found that the technical efficiency for cooperative members ranges from 79% to 86% and that for non-members ranges from 74% to 84%.

In light of the important role of agricultural cooperatives in supporting sustainable agricultural development, quantifying the nexus between agricultural cooperatives and farm yield using the meta-analysis approach can deepen our understanding in this field. The study's findings can help decision-makers to revisit the existing cooperative development policies and improve appropriately, making cooperative organizations better assistors for sustainable rural and agricultural development.

3 | META-DATASET, METHODS, AND VARIABLES

3.1 | Meta-dataset

3.1.1 | Data strategy and selection criteria

The first step in meta-analysis is to search and collect the existing studies that empirically examined the effects of agricultural cooperative membership on the yield of crops and livestock and then extract required information such as effect size, *t*-statistics, degree of freedom, and study attributes. To be included in our meta-analysis, a study must contain an estimation that explores how cooperative membership affects yield. We collect the required studies from different databases, including Google Scholar, Scopus, JSRTOR, RePEc, Web of Science and ScienceDirect and others. The selected studies include journal articles, working and conference papers, master's theses, and PhD dissertations.

When searching the databases, we combined three groups of keywords: "cooperative", "yield", and "agriculture". The "cooperative" group consisted of "cooperatives", "cooperative membership", "producer association", "farmer association", "farmer group", "farmer-based organization", "farmer organization", and "collection action". We consider "association", "farmer group", "farmer organizations", and "collective action" in our search because they are similar forms of cooperatives and expected to improve smallholder farmers' production performance in developing countries (Bizikova et al. 2020; Fischer & Qaim 2012; Grashuis & Skevas 2022; Minah 2022). The "yield" group consisted of "yield", "productivity", "household welfare", and "farm performance". In some studies (Kumar et al. 2018; Ma & Abdulai 2016), the yield of crops and livestock is used as one of the dependent variables that capture household welfare and farm performance. The "agriculture" group consisted of "agriculture", "farm", "rural", "crop", and "livestock". Our search produces 994 studies.

We apply the following inclusion criteria to select the studies used for our meta-analysis. First, the study must empirically estimate the effects of cooperative membership. Thus, qualitative studies are excluded. Second, the study must consider the yield of crops or livestock as a dependent variable. Third, the study must contain sufficient information to calculate *t*-statistics. Therefore, the studies that did not report standard errors or *t*-statistics are excluded. Fourth, we further compared published journal articles and the theses and removed the theses that overlap with the journal articles. Fifth, we excluded the literature on developed countries because we are only interested in exploring the yield effects of cooperative membership in developing countries. As a result, our original dataset consists of 42 studies (see Table A1 in the Appendix), covering 19 developing countries (see Table A2 in the Appendix). The selected studies record 158 estimated yield effects. The mean number of estimates from these studies is 3.45, ranging between 1 and 12.

3.1.2 | Distributions of *t*-statistics

Figure 2 depicts the distribution of *t*-statistics used in our dataset. It can be seen that the distribution is right-skewed with many studies reporting positive estimates. The descriptive statistics of

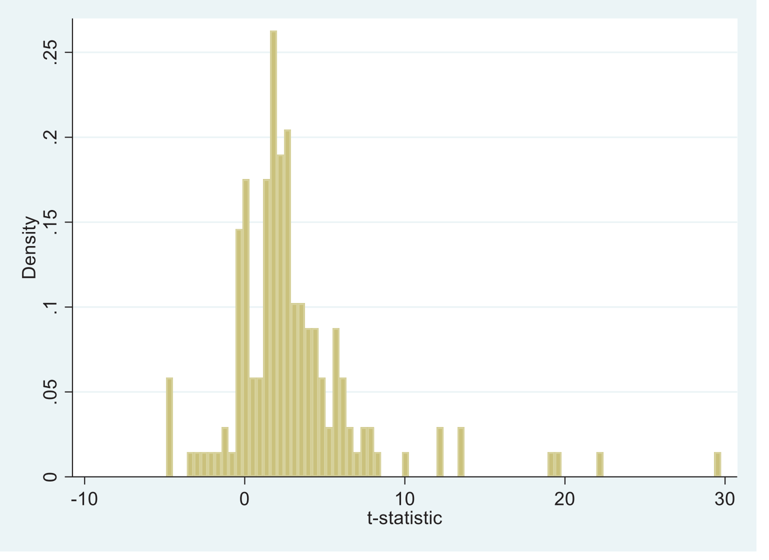

FIGURE 2 Distribution of *t*-statistic values. Notes: The *x*-axis represents the effect size captured by the PCC values; the *y*-axis represents the inverse of the standard errors of the effect size. The solid vertical line denotes the mean of the sample [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 1 Descriptive *t*-statistics

	t-statistics	
	Full sample (1)	**Truncated sample (2)**
Mean	3.037	2.900
SD	4.446	3.928
Median	2.220	2.220
Minimum	−4.917	−4.903
Maximum	29.76	29.76
1%	−4.903	−4.623
5%	−1.995	−1.158
10%	−0.280	−0.245
90%	6.733	5.92
99%	22.25	19.30
Skewness	2.633	2.869
Kurtosis	14.04	18.16
Number of estimates	158	154

the *t*-statistics (column 1 of Table 1) show that the mean and median *t*-statistics for the full sample are 3.037 and 2.220, respectively. The minimum and maximum *t*-values are –4.917 and 29.76.

We follow Duan et al. (2020) and truncated the top and bottom 1% of partial correlation coefficient values to eliminate potential outliers. This approach removed only four estimates. The associated *t*-statistics are reported in column 2 of Table 1. The mean *t*-statistic for the truncated sample decreases slightly to 2.9 and the median *t*-statistic stays the same (i.e., 2.220). In sum, the *t*-statistics between the full and truncated samples are not substantially different. As a robustness check, we estimated our meta-analysis models using both the full sample and the truncated sample and found that they generated similar results. Consequently, we subsequently only report the results for the full sample.

3.2 | Methods

3.2.1 | Measuring the effect sizes

A common approach to estimating the impact of cooperative membership on the yield of crops and livestock assumes a linear specification for yield as a function of a vector of a dummy cooperative membership choice variable, a vector of control variables that capture farmer- and household-level variables, as well as an error term. The yield regression can be expressed as:

$$Y_i = \alpha_i + \beta_i C_i + \gamma_i \sum X_i + \varepsilon_i \tag{1}$$

where Y_i refers to the yield of crops or livestock; C_i identifies the cooperative membership status of a farming household (1 = members; 0 = non-members); X_i represents a vector of control variables (e.g., age, gender and education of farmers, household size, asset ownership, farm size, and geographical locations) that affect the farm yield; α_i is a constant and ε_i is an error term; β_i and γ_i are parameters to be estimated.

In a meta-analysis, the estimated parameter $\hat{\beta}_i$ from Equation (1), which represents the yield effect of cooperative membership, becomes the dependent variable. However, $\hat{\beta}_i$ is not directly comparable across studies for at least two reasons. First, studies estimate yields for a variety of farm products such as apple (Ma & Abdulai 2016), potato (Ahado et al. 2021), maize (Olagunju et al. 2021), rice (Bairagi & Mottaleb 2021), banana (Ma et al. 2022a), coffee (Ortega et al. 2019), dairy (Chagwiza et al. 2016), and goat (Neupane et al. 2022). Accordingly, different units (e.g., tons, kilograms, and litres) are employed to measure yields. Even when the studies examine the same crop, some may capture the log-transformed form of the yield whereas others use a linear or some other form. Second, scholars have used different estimation procedures such as ordinary least squares regression (Sellare et al. 2020), endogenous treatment regression model (Ingutia & Sumelius 2022), propensity score matching method (Blekking et al. 2021; Desai & Joshi 2014), and endogenous switching regression model (Kehinde & Ogundeji 2022; Kumar et al. 2018) when estimating the yield effects of cooperative membership. Because the estimated "effects" are captured by average treatment effects on the treated (ATT), average treatment effect (ATE), and coefficients, they are interpreted in different ways. To make these different studies comparable, the estimated yield effects of cooperative membership must be transformed into a standard unit.

The standard approach to dealing with this problem is to convert the estimated yield effects to a partial correlation coefficient, or PCC (Ogundari 2022; Ogundari & Bolarinwa 2018; Xue et al. 2020). The PCC is a scale-free metric, providing a unified interpretation across different studies (Anwar & Mang 2022; Ogundari & Bolarinwa 2018; Ridhwan et al. 2022). It is calculated using the following equation:

$$PCC_i = \frac{t_i}{\sqrt{t_i^2 + df_i}} \tag{2}$$

where t_i and df_i refer to the t-statistic and degrees of freedom associated with the respective yield effect. The PCC bears a close mathematical relationship to the standardized beta coefficient. From Equation (2) it can be seen that PCC ranges between –1 and 1. The associated standard error for the PCC, that is, SE_PCC_i, is given by:

$$SE\_PCC_i = \sqrt{\frac{1 - PCC_i^2}{df_i}} \tag{3}$$

Following Doucouliagos (2011), we interpret the absolute values of PCC equal to 0.07 as "small", equal to 0.17 as "moderate", and "0.33" as large.

3.2.2 | Testing the publication bias

A simple way to estimate the overall mean effect of cooperative membership on the yield of crops and livestock is to average the sample of PCC values. This is equivalent to regressing PCC_i on a constant using the ordinary least squares (OLS) regression model as follows:

$$\widehat{PCC}_i = \mu + \psi_i \tag{4}$$

where $i = 1, 2, \ldots, N$ refers to the number of estimated yield effects in the meta-analysis sample, μ captures the overall mean effect of cooperative membership on yield, and ψ_i is an error term.

In Equation (4), μ should be interpreted with caution because the estimates do not account for publication bias. The existence of publication bias may outweigh the real effect size, skewing the distributions of the reported effect size, and leading to biased policy implications. One important application of meta-analysis is to identify the existence of publication bias and correct it.

Two approaches can potentially be used to check whether there exists the presence of publication bias in meta-analysis: funnel plots and the funnel asymmetry test (Hong et al. 2021; Ogundari & Bolarinwa 2018; Ridhwan et al. 2022; Xue et al. 2021). The funnel plot is a scatterplot of study-specific effect sizes on the x-axis against a measure of study precision such as standard errors or inverse standard errors (in our case) on the y-axis. It provides an intuitive way to detect publication bias.

If the distributions of the inverse standard errors are symmetrically distributed around the mean line, this suggests there is no publication bias (Xue et al. 2021). If there existed upward publication bias, the scatter-dots would be clustered on the right of the mean line. Because funnel plots are always vulnerable to subjective interpretations, people usually also employ the funnel asymmetry test to check the publication bias (Xue et al. 2020). The funnel asymmetry test is carried out by including the standard error as an additional regressor in Equation (4). We use both funnel plots and the funnel asymmetry test to check for the existence of publication bias in this study.

The specification for the funnel asymmetry test (Egger et al. 1997) is:

$$PCC_i = \varpi + \xi_i SE\_PCC_i + V_i \tag{5}$$

where PCC_i and SE_PCC_i refer to the PCC and its corresponding standard error for the ith estimate in the created samples, respectively. ϖ is a constant; ξ_i is an estimated parameter; V_i

represents the error term of the regression model. If the estimated coefficient for ξ_i is statistically significant, this indicates the presence of publication bias (Duan et al. 2020; Xue et al. 2021).

It is worth noting that OLS estimation of Equations (4) and (5) is inefficient because of heteroscedasticity.[1] Heteroscedasticity arises because the estimated yield effects have different standard errors in the original studies. This carries over to the PCC values having different standard errors. This, in turn, induces the error term in the respective equations to be heteroscedastic.

Following previous studies (Anwar & Mang 2022; Duan et al. 2020; Ogundari 2022; Ridhwan et al. 2022; Xue et al. 2021), we employ two weighted least squares (WLS) estimators to address this problem: WLS-Fixed Effects (FE) and WLS-Random Effects (RE).[2] The WLS-FE model assumes that there is a single underlying true effect and the reason for different estimates across studies is solely due to sampling error. The corresponding weight is given by the inverse of the variance of the estimated effect, that is, $1/[SE(PCC_i)^2]$ (Xue et al. 2021).

Alternatively, the WLS-RE model assumes true effects are heterogeneous. As a result, the variance in the estimated effects is determined by both sampling error and heterogeneity in the true effects (Xue et al. 2021). The corresponding weight for the WLS-RE model is $1/[SE(PCC_i)^2 + \tau^2]$, with τ^2 capturing the variance of the true effects. There is no consensus as to whether WLS-FE is superior to WLS-RE. Accordingly, we follow Duan et al. (2020) and proceed by using both models.

3.2.3 | Investigating sources of heterogeneity

To investigate the factors that lead to variation in effect sizes, we perform a meta-analysis by estimating the following equation:

$$PCC_i = \alpha_0 + (1 - \varrho)\,\varphi_i SE\_PCC_i + \sum_{=1}^{k} \alpha_k X_{ik} + \vartheta_i \tag{6}$$

where PCC_i is the ith estimate capturing the yield effect of cooperative membership; α_0 is a constant; X_k is a vector of data, study, and estimation characteristics, φ_i and α_k are parameters to be estimated, and ϑ_i is an error term.

The parameter ϱ represents a "rule" identifying whether SE_PCC_{ij} should be included as a regressor or not. Specifically, SE_PCC_i is included if publication bias is identified by the results of Equation (5), in which case $\varrho = 0$. If no evidence is found for publication bias, we exclude SE_PCC_{ij} as a regressor in Equation (6), in which case $\varrho = 1$.

3.3 | Description of variables

To understand the factors causing systematical differences among the reported yield effects, we code 13 variables for X_k in Equation (6) (see Table 2), capturing sample characteristics,

[1] Both White's test and Breusch and Pagan's test are utilized to test the potential heteroscedasticity; both reject the null hypothesis of homoscedasticity and confirm the presence of heteroscedasticity.

[2] It is worth mentioning here that the WLS-FE and WLS-RE models used for meta-analysis are different from the FE and RE models used for panel-data analysis in nature, although the names are quite similar.

TABLE 2 Description of variables

Variables	Description	Mean	SD
Dependent variable			
PCC	Effect size captured by the partial correlation coefficient	0.210	0.270
Independent variables			
SEPCC	Standard error of PPC	0.070	0.050
Sample characteristic			
Full sample	1 if the effect is estimated by full sample, 0 otherwise	0.790	0.410
Membership ratio	Ratio of the number of members to total sample size	0.460	0.190
Econometric approaches			
IV-based parametric approach	1 if primary study used instrumental variable-based parametric approach, 0 otherwise	0.170	0.380
Non-parametric	1 if primary study used non-parametric approach, 0 otherwise	0.590	0.490
OLS	1 if primary study used ordinary least square (OLS) regression, 0 otherwise.	0.340	0.480
Effect types			
ATT	1 if the effect is captured by the average treatment effect on the treated (ATT), 0 otherwise	0.530	0.500
ATE	1 if the effect is captured by an average treatment effect (ATE), 0 otherwise	0.130	0.340
Coefficient	1 if the effect is captured by a coefficient, 0 otherwise	0.240	0.420
Agro-product type			
Grain	1 if grain yield is used in the analysis, 0 otherwise	0.390	0.490
Publication characteristics			
Publication year	The year that the primary paper was published	2018	2.970
Journal article	1 if the work is published in a peer-reviewed journal article, 0 otherwise	0.880	0.330
Climate zone			
Tropical	1 if primary study is carried out in a tropical region, 0 otherwise	0.700	0.460
Geographical location			
Africa	1 if primary study is carried out in an African country, 0 otherwise	0.530	0.500

TABLE 3 Study weights

	WLS-FE model (1)	WLS-RE model (2)
Mean (%)	2.381	2.381
Std. dev.	4.735	2.057
Median (%)	0.972	1.628
Minimum (%)	0.016	0.141
Maximum (%)	25.727	5.894
1%	0.016	0.141
5%	0.051	0.243
10%	0.205	0.288
90%	4.339	5.830
95%	6.155	5.854
99%	25.727	5.894
Top 3 (%)	49.885	17.637
Top 10 (%)	76.303	55.750
Number of studies	42	42

econometric approaches, effect types, agro-product type, publication characteristics, climate zone, and geographical location.

Table 2 presents the definitions and descriptive statistics of the variables used in the meta-analysis. For example, we show that the average cooperative membership ratio is 0.46. Most of the yield effects (59%) are estimated by the non-parametric models such as PSM, and just more than half of the estimates (53%) are captured by the ATTs. Around 53% of yield effects are estimated by samples from African countries. Before we proceed, we checked the potential multicollinearity issue using the variance inflation factor (VIF). The VIF value for the individual variable is all below 3 and the mean VIF is below 2, confirming there is little multicollinearity among the explanatory variables we have chosen.

4 | RESULTS AND DISCUSSIONS

4.1 | Study weights

Table 3 presents the study weights for each study in our sample, calculated by the WLS-FE and WLS-RE models. They weigh the individual estimates of a study by the respective weighting scheme and then aggregate the weights at the study level. Study weights are calculated by $w_i / \sum w_i$, in which $w_i = 1/(SE\_PCC_{ij})^2$ for the WLS-FE model and $w_i = 1/[(SE_{PCC_{ij}})^2 + \tau^2)]$ for the WLS-RE model (Duan et al. 2020; Ringquist 2013). In this way, each study receives a weight, and the sum of weights equals 100%. Because 42 studies are included in our meta-analysis, each study would receive a weight of 2.381% if the weights were divided equally across studies.

Column 1 of Table 3 shows the study weights of the WLS-FE model. The median weight is 0.972%, and the maximum weight for a single study is 25.727%. The top 3 studies account for 49.885% of the total weights, and the total top 10 studies account for 76.303%. Why is this a potential problem? If we believe that there is a distribution of true effects, not just one true effect, then having the overall average dominated by just a few studies means that we run the risk of attaching

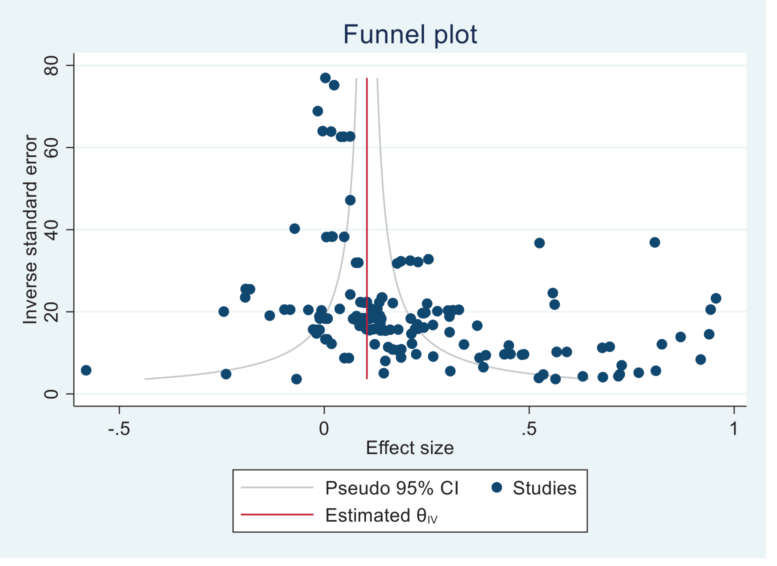

FIGURE 3 Funnel plot of effect size [Colour figure can be viewed at wileyonlinelibrary.com]

undue influence to these studies. Figure A1 in the Appendix gives a closer look at the respective studies.

Column 2 of Table 3 presents the study weights of the WLS-RE model. Three results are worth noting. First, the difference between the mean and median values is much smaller for the WLS-RE model compared to the WLS-FE model (0.753 vs. 1.409). Second, the maximum weight among the 42 studies for the WLS-RE model is 5.894%, compared to 25.727% for the WLS-FE model. Third, the top 3 studies account for 17.637% of the total weights for the WLS-RE model, and the total top 10 studies account for 55.75%. This is again much smaller than the corresponding values for the WLS-FE model (49.885% and 76.303%). Compared with the WLS-FE model, the WLS-RE model weights the estimates more uniformly while still allowing different weights based on estimate precision. The contrast between Figures A2 and A1 in the Appendix further highlights the differences in the weights used by the two models. Based on these results, our subsequent analysis emphasizes the WLS-RE results, though we also report results for the WLS-FE model for comparison.

4.2 | Publication bias and mean yield effects of cooperative membership

As indicated previously, we use both funnel plots and funnel asymmetry tests to check for publication bias. Figure 3 presents a funnel plot. In the centre is a vertical line indicating the estimate of the overall mean. On either side of that line are curved lines indicating a 95% confidence region. Under the assumption of no publication bias, we would expect 95% of the estimates to lie within this region. In fact, Figure 3 shows that a disproportionate number of studies lie outside the 95% confidence interval on the positive side, to the right of the vertical. This indicates positive publication bias. This is consistent with researchers and/or journals selectively reporting results that find a positive relationship between cooperative membership and farm yield.

Table 4 presents the results of the funnel asymmetry test. "Panel A" of Table 4 presents the estimates of the overall mean effect of cooperative membership on yield without correcting for

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TABLE 4 Overall mean effect of cooperative membership on the yield and publication bias

	WLS-FE model (1)	WLS-RE model (2)
Panel A: Without correction for publication bias		
Constant (μ)	0.104 (0.038)***	0.192 (0.037)***
Panel B: With correction for publication bias		
SEPCC (ξ)	2.867 (0.772)***	1.963 (0.784)***
Constant (ϖ_i)	0.008 (0.039)	0.062 (0.055)

Standard errors are clustered on studies and reported in parentheses; *** p < 0.01

publication bias (cf. Equation 4). The estimates are all positive and statistically significant at the 1% level. Based on these results, one would conclude that cooperative membership, on average, significantly increases the yield of crops and livestock. Focusing on the WLS-RE estimate of 0.192 in column 2 and using the Doucouliagos (2011) size classifications, this estimate fits squarely in the "moderate" size category. Importantly, however, it does not account for publication bias.

Panel "B" of Table 4 presents estimates of the overall mean effect after correcting for publication bias (cf. Equation 5). In this specification, the variable SEPCC (ξ) captures the effect of publication bias; whereas the constant term (ϖ_i) estimates the overall mean effect after correcting for publication bias. There are two findings of note here.

First, the estimated coefficients of SEPCC are positive and statistically significant at the 1% significance level. This provides further confirmation of the presence of publication bias. According to Doucouliagos and Stanley (2013) and Ogundari (2022), estimated coefficients larger than one in absolute value for the standard error variable indicate substantial selectivity bias. The respective estimate in Table 4 for the WLS-RE model is 1.963 (2.867 for the WLS-FE model), indicating strong publication bias. In other words, our analysis provides evidence that the current literature on the effect of agricultural cooperatives on crops and livestock yield is not representative of the true effect. Rather, it is distorted by publication bias.

Second, based on the WLS-RE model, our best estimate of the overall mean effect of cooperative membership on yield is 0.062 (0.008 for the WLS-FE model). In terms of the Doucouliagos (2011) size classifications, this represents a "small" effect. In other words, after correcting for publication bias, our estimate of the yield effect of cooperative membership decreased from "moderate" to "small". Even more, the estimated effect is no longer statistically significant, even at the 10% significance level.

In other words, our estimates cannot reject the hypothesis that agricultural cooperatives yield no benefits, on average, to smallholder farmers in developing countries. This echoes the findings of studies that report an insignificant relationship between cooperative membership and farm yield (Hun et al. 2018; Kashiwagi 2020; Mwaura 2014; Shumeta & D'Haese 2016). With respect to the subsequent analysis, the finding of publication bias indicates that we should include the SEPCC variable in Equation (6) when investigating the sources of effect heterogeneity in the literature.

Although the findings of this study show that cooperatives are not very effective, on average, in boosting farm yield in developing countries, this does not mean that they are useless. Besides yield improvement, cooperatives may help farmers on other dimensions such as serving as a marketing channel (Hao et al. 2018; Liu et al. 2019) and empowering rural women (Dohmwirth & Liu 2020; Meador et al. 2019).

If cooperatives provide little yield benefit in developing countries, why are they so widely adopted? Agricultural cooperatives are widespread and longstanding organizations in most

TABLE 5 Sources of heterogeneity in effect sizes

Variables	WLS-FE model (1)	WLS-RE model (2)
SEPCC	1.854 (1.031)*	1.664 (0.858)*
Full sample	0.102 (0.051)*	0.087 (0.050)*
Membership ratio	0.287 (0.183)	0.306 (0.180)*
IV-based parametric approach	0.148 (0.079)*	0.238 (0.082)***
Non-parametric	−0.031 (0.055)	−0.023 (0.050)
ATT	0.187 (0.083)**	0.172 (0.062)***
ATE	0.228 (0.089)**	0.182 (0.077)**
Grain	0.117 (0.062)*	0.162 (0.068)**
Publishing year	−0.004 (0.012)	−0.020 (0.011)*
Journal article	−0.071 (0.089)	0.004 (0.070)
Tropical	−0.143 (0.090)	−0.176 (0.078)**
Africa	−0.012 (0.085)	0.066 (0.073)
Constant	7.440 (24.850)	40.656 (21.769)*
Number of estimates	158	158

Standard errors are clustered on studies and reported in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; The reference group of IV-based parametric approach and non-parametric approach is OLS; The reference group of ATT and ATE is coefficient.

developing countries. According to Francesconi and Wouterse (2019, 2022), every other village in rural Africa hosts at least one member-owned organization of some sort and their prevalence has been growing consistently since the beginning of colonialism. We discuss two possible explanations here.

First, the proliferation of cooperatives across the developing world has been mostly driven by national governments and international donors. These find it convenient to use cooperatives to distribute subsidies and aid to large numbers of small and scattered rural farmers (Francesconi & Wouterse 2019). Although this may not be the most effective and efficient use of cooperatives, it is nonetheless an important service, especially to poor and vulnerable farmers. Second, cooperatives may contribute to building social cohesion and thus improve the effectiveness and efficiency of mutual support among farmers in times of need (Deng et al. 2021; Valentinov & Iliopoulos 2021).

It is possible that cooperatives play more of a social protection or resilience-enhancing role in developing countries rather than a productive and income-generating role. With respect to the latter, not all cooperatives function as well as they should. Hu et al. (2017) surveyed 50 cooperatives in China and found that some of them fail to deliver the expected benefits to smallholder farmers and do not meet the standards outlined in China's Cooperative Law. Nevertheless, the longevity and popularity of cooperatives cannot be overlooked, as it represents evidence that farmers need and want cooperatives.

4.3 | Meta-regression analysis

Table 5 reports the results of a meta-regression analysis. We continue to focus on the estimates from the WLS-RE model (cf. column 2), though we also report WLS-FE estimates for the sake of comparison. The estimated parameters show that the SEPCC variable remains positive, indicating positive publication bias, but is now only significant at the 10% level.

The coefficient of the full sample is positive and statistically significant at the 10% level, suggesting that the yield effects estimated using the full sample are larger than those estimated using subsamples such as subsamples by farm sizes or survey locations. The membership ratio variable has a positive and statistically significant coefficient at the 10% level. This suggests that a higher membership ratio in a survey sample is associated with a higher estimated yield effect.

The coefficient of the IV-based approach is positive and significantly different from zero at the 1% level, suggesting that studies estimating IV-based models report larger effect sizes than those estimated using the OLS regression model as the reference. The IV-based models such as the ESR model and ETR model help correct for selection bias arising from both observed and unobserved factors (Dong et al. 2019; Ingutia & Sumelius 2022; Kehinde & Ogundeji 2022; Kumar et al. 2018), while the OLS model does not correct for selection bias. Thus, our finding underscores the importance of estimating models that correct for both observed and unobserved selection bias for better-informed policy implications.

The coefficients of ATT and ATE are positively and statistically significant at the 1% and 5% levels, respectively, suggesting that studies estimating treatment effects report larger effect sizes than those estimating "normal" coefficients. Both IV-based parametric models (Dong et al. 2019; Ingutia & Sumelius 2022; Kumar et al. 2018) and non-parametric approaches such as the PSM model and IPWRA model (Blekking et al. 2021; Kehinde & Ogundeji 2022; Ortega et al. 2019) could help calculate ATT and ATE by accounting for selection bias; the simple coefficients are usually estimated without addressing selection bias. The findings further highlight the importance of correcting selection bias (either observed or unobserved selection bias or both) in estimating the yield effects of cooperative membership.

The coefficient of grain is positive and statistically significant at the 5% level. The finding suggests that studies focusing on the yield of grain production report larger effects than those focusing on other crops such as fruits and vegetables. The finding verifies that cooperative membership generates uneven benefits for farmers cultivating different crops and livestock.

The publishing year variable has a negative and statistically significant coefficient at the 10% level. The finding suggests that more recent studies find a smaller effect than older studies. The significant and negative coefficient of the tropical variable suggests that studies focusing on tropical countries report lower yields than those focusing on non-tropical countries. Previous studies find that crop yield in tropical regions is generally lower than in temperate regions (Challinor et al. 2014; Lesk et al. 2021).

5 | CONCLUSIONS AND POLICY IMPLICATIONS

Increasing the yields of crops and livestock plays an integral part in ensuring global food security, improving the nutrition intake of human beings, and promoting sustainable agricultural production. Although agricultural cooperatives have been considered an important institutional innovation that helps farm performance, the findings for the yield effects of cooperative membership are difficult to synthesize, both because of estimates widely, and because of concerns that publication bias distorts the published literature. Accordingly, this study provides a meta-analysis of that literature, utilizing 158 estimates from 42 studies across 19 developing countries. Our analysis produces several important findings.

First, we find evidence of positive publication bias in the literature. This is consistent with the hypothesis that researchers and/or journals prefer estimated yield effects that are positive and statistically significant. After correcting for publication bias, we estimate an overall mean effect of cooperative membership on crops and livestock yield that is small in size. Further, we cannot reject the hypothesis that, on average, agricultural cooperatives do not produce yield benefits for smallholder farmers in developing countries. Second, our analysis identifies a number of data, study, and estimation characteristics that are systematically related to differences in estimated yield effects across studies. Specifically, estimates depend on factors such as whether the effects are estimated by full sample or subsample, membership ratio, the econometric models used, effect types, type of agro-product, and climate zone (tropical or non-tropical).

Although we find that membership in agricultural cooperatives does not, on average, generate a significant impact on farm yield, this does not imply that policymakers in developing countries should reject cooperative organizations as a tool for economic development. Many institutions and organizations do not function as well as they should. If not yield benefits, cooperatives must be generating other benefits for farmers or they would not be so prevalent. Instead, we interpret our findings to indicate that policymakers should focus on how to make cooperatives work better, especially through improving their provisions of yield-improving services, rather than on how many cooperatives they should build. In other words, there should be greater emphasis on quality rather than quantity.

Although many cooperatives collectively purchase farm inputs (e.g., fertilizers, pesticides, and improved seeds) to help lower their members' production costs, they should train their members on how to use those inputs efficiently and manage cropland appropriately to boost farm productivity and incomes. Our findings suggest the importance of the government's role in carefully evaluating the qualifications of the applicants before approving the establishment of new agricultural cooperatives. Governments and non-governmental agencies should also check the functioning of existing cooperatives before providing financial and material subsidies to them. These efforts can help ensure that cooperatives assist rural farmers in securing benefits from agricultural production and marketing.

We note that this study only focused on yield as a farm performance indicator. Future research could employ meta-analytic investigations to study other farm performance indicators such as farm income, sales price, technical efficiency, and adoption of farm technologies (e.g., fertilizers and pesticides). This would improve the discipline's understanding of the effects of agricultural cooperatives in developing countries. Future research could use meta-regression to explore the pathways through which cooperative membership affects farm economic performance. This could help us comprehensively understand the roles and functions of agricultural cooperatives in contributing to sustainable agricultural development and rural income growth.

Finally, like any empirical analysis, estimation becomes more reliable with larger and more representative samples. Because the empirical literature on the effects of cooperative membership is still relatively young, our study was only able to include 158 estimated yield effects from 42 studies. As the literature expands over time, further meta-analyses using larger samples can improve our understanding of the role of agricultural cooperatives in improving farm performance.

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ORCID

Wanglin Ma https://orcid.org/0000-0001-7847-8459

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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