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Impacts of improved agricultural technology adoption on welfare in Africa: A meta-analysis

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ABSTRACT

A large body of researches have widely examined the impact of adopting improved agricultural practices and technologies on general welfare of smallholder farmers. The results of deep literature review show that varies agricultural technologies have significant impacts on different welfare measures identified in the primary studies. However, the estimated effects of technology adoption differ among studies. The current study presents a meta-analysis of empirical estimates using a sample of 52 studies that investigated the impact of improved agricultural technologies in Africa on three key sets of outcome variables: output or expenditure, food security, and poverty. The study also conducted tests for publication bias to see if researchers tend to report results in similar or different ways for the same outcome variable. The findings the study shed light on the ways of identifying potential factors explaining the differences in the effects of estimated technology adoption. Results of the meta-regression analysis revealed that differences in the reported impact of technologies is explained by factors like data type, model specification, sample size, region of the study, and journal type. It was also observed that no publication bias in the studies reviewed for the effect size measures of output (expenditure) and poverty models, but in the food security model there is some evidence of publication bias. One of the core implications of the current study is that, based on the sensitivity of effect sizes to study attributes (i.e. data type, econometric methods, sample size, region of the study, and journal type), interested researchers and academicians need to pay attention to these attributes to provide more reliable estimates for policy interventions. We believe this study provides information useful to interested decision-makers in designing policy intervention measures that could encourage the adoption of improved agricultural practices and technologies in the African context. Finally, the study also highlighted future research directions.

1. Introduction

Adopting improved innovation and technologies in agriculture are important ways of increasing productivity of smallholder farmers in Africa as this fosters economic growth and improved well-being of millions of poor households. In contrast to many other parts of the world, many African governments do not collect or explore/report important data in a relevant form and in the required time. Without basic and descriptive information about who is adopting improved agricultural technologies and who is not, it is difficult

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to formulate effective policies aimed at increasing agricultural productivity [1].

Studies that focus on agriculture and welfare issues evidenced that adopting improved agricultural innovations and technologies can reduce poverty and food insecurity and increases farm household incomes and overall social welfare [2–26]. Many studies have also replicated, extended, and explored the impact of adopting agricultural technologies in different parts of the globe.

A literature review shows that many studies have been published on the impact of agricultural technologies over several years, with mixed results. There are large variations in the magnitude of the impact across studies which lead to questioning whether there is unambiguous evidence in the existing empirical literature on the link between technology adoption and welfare outcomes. Given the impact studies in the agriculture sector which have been done independently by different authors at various times and in various locations using different designs, methods, and datasets, it is very likely that they capture considerable heterogeneity and mixed effects in their impact evaluations. A traditional meta-analysis accumulates as broad a pool of cases as is possible from which inferences are made under the assumption that a sufficient population of cases will balance out individual methodological flaws [27]. It is also argued that the magnitude of the impact depends on the nature of the technology (for example, improved seeds, livestock technology, and improved practices), data type, research designs (experimental or non-experimental), methods of estimation, and the like. Thus, these differences can contribute to the mixed results and to variation in the reported impact of agricultural technologies in the various studies [28].

A meta-analysis is a powerful methodology that collates research findings from previous studies and distils them for broader conclusions. It is, therefore, termed an 'analysis of analyses.' A meta-analysis can be helpful for policymakers who may be confronted by a mountain of conflicting conclusions [29]. According to Stanley and Jarrell [30], "meta-analysis is the statistical analysis of statistical analyses – the application of statistical methods to analyze, measure, and verify the varied statistical results from the empirical study of a particular phenomenon." Meta-analyses have become quite common in the fields of psychology and education. Although a meta-analysis does not supplant the expert judgments of specialists in the field, it does furnish a strategy to minimize the need for more subjective judgments while selecting studies for study, how to weigh the chosen studies, and when to dismiss apparently aberrant findings. A meta-regression analysis (MRA) is a helpful framework for integrating, cumulating, and explaining disparate empirical economic literature.

The meta-analytical framework consists of a set of statistical and econometric methods which allow synthesizing outcomes from empirical studies carried out on a particular research question; it also helps in investigating their heterogeneity and mixed effects [30–33]. It is a statistical procedure that integrates and up-scales numerous spatially and temporally distributed combinable micro-level studies to distil logical macro-level policy inferences. The inferences drawn based on a meta-analysis are often more objective and authentic [34]. The methodology also allows a combination of all relevant literature in a particular research area using statistical methods for evaluating, synthesizing, and testing existing evidence [35].

Some studies also state that a proper meta-analysis goes beyond a literature review in two ways. First, a meta-analysis includes all the studies that meet the review criteria and is thus comprehensive and forms a pool. Second, with a large sample, a meta-analysis can make use of statistical techniques for summarizing and reviewing quantitative research to overcome limits of size or scope in individual studies and obtain more reliable information about the impact of a treatment. Because of these advantages a meta-analysis has become increasingly popular in recent decades. The methodology has been applied with increasing frequency, especially with randomized controlled trials in health, medicine, and psychology where randomized controlled trials are the research norm [36].

The basic meta-analytical metric, namely the effect size, indicates the magnitude and the direction of the relationship between two variables. However, an issue of the non-equivalence of the effect size may arise here [32,37]. The differences in effect size are a result of the fact that a variable is measured in different units in different studies and there are also disparities in the empirical specifications of the relationship. For instance, output may be measured as total production, aggregate income, and percentage growth of annual income in most adoption literature. The question of why the magnitude of regression coefficients differs across studies, however remains unanswered.

Despite this wide array of applied work in various studies, the extent to which empirical measures of the impact of agricultural technologies are sensitive to the choice of methodology remains a matter of controversy.

In practical research, a meta-analysis helps to uncover the actual effect size of interest and identification of sources of heterogeneity/variation across primary studies under review. In the current study, we address the appropriate statistical tools needed to estimate the effect size in a meta-analysis, given its relevance for policy purposes.

The current study conducts a meta-analysis based on a sample of 52 improved technology adoption studies focusing on the agriculture sector in the entire Africa. To the best of our knowledge, this represents the first meta-analysis of the welfare impact of improved agricultural technology adoption focusing on the entire parts of Africa. The single notable exception in the literature is the study by Ogundari and Bolarinwa [38] that conducted a meta-regression analysis on 92 studies published between 2001 and 2015 in the SSA region, however the study focuses only in the case of SSA. The present research, thus, contributes to the existing literature by synthesizing those studies to assess impacts of agricultural technologies on welfare in Africa in which previous studies rarely explored. Thus, the study attempts to narrow some gaps and shed light on systematic reviews by performing a meta-analysis of literature on the welfare impact of improved agricultural technology adoption in Africa. Hence, the study employs a meta-regression analysis to address the following research questions:

- Do agricultural technologies have impacts on the potential outcomes considered in the primary studies?
- Are the reported impacts in the primary studies sensitive to study-specific characteristics?

Thus, the result of the current study will bring important insight for different stakeholders such as policy makers, agricultural extension experts and agricultural officers who have a stake in further expanding the adoption of improved agricultural practices and technologies and enhancing the welfare of the farmer households in the continent in general.

The rest of the paper is structured as follows. Section 2 presents the application of a meta-analysis in economics. Section 3 discusses the material and methods used; it specifically presents the key elements of the sample studies and discusses the data and variables. Section 4 discusses the meta-regression analysis, while Section 5 gives the regression results. Section 6 assesses the possible presence of a reporting bias by giving the publication bias tests conducted, and finally section 7 gives the concluding remarks of the study.

2. A review of meta-analysis in economics

A meta-analysis is quite popular in medical, educational, pharmaceutical, and marketing research [39]. As Stanley [33] argues, a meta-analysis has been successfully employed in hundreds of applications throughout the social and medical sciences and in some limited cases in economics researches as well. However, a review of literature shows that it has also been extended to a wide range of areas in economic research other than the impact of improved agricultural technologies. The methodology's application has been further extended to some more areas in recent times.

However, Gorg and Strobl [32] argue that while meta-analysis has been frequently applied in educational, psychological and medical research, its application in economics has been limited to a relatively small number of studies. They explain the possible reasons for this as most of the time the nature of the data used in economic research is non-experimental while data in the fields of education, psychology, and medicine is mainly experimental in nature. Stanley and Jarrell [30] argue that the problem of dependence on observations is likely to be no more important for meta-analyses than for primary econometric studies as these are not the result of controlled experiments either.

The first studies on meta-analysis in economics and specifically in the farming sector include the works of Thaim et al. [39] who evaluated 34 farm studies in developing countries. Bravo-Ureta et al. [40] conducted an extended analysis using 167 farm level studies in developed and developing countries. Later Lopez and Bravo-Ureta [41] used the meta-analysis in the dairy sector. Their meta-analysis included 65 parametric and non-parametric published frontier studies. Ogundari [42] examined Nigerian agriculture sector's efficiency performance from 1999 to 2008 by considering 64 published research articles. As argued in the vast literature (see for instance 39–40, 42], meta-analyses have particular flaws on farm efficiency because these studies integrated the sample of developed and developing countries as a single population and set the average technical efficiency as a conjoint benchmark. A meta-analysis based on the overall technical efficiency performance of the farm sector, specifically in a single country case, gives a broader and meaningful picture. In addition, Bravo-Ureta and Pinheiro [43] and Ogundari and Brümmer [44] used a meta-analysis to investigate how technical efficiency scores from a primary study of agriculture and food production differed across studies.

Pattanayak et al. [45] used a meta-analysis to examine agricultural technology use and analyzed 32 studies on the adoption of agro-forestry practices. Their study concluded that, "credit, savings, prices, market constraints and plot characteristics are potentially important determinants of adoption behavior that have not been studied adequately." Similarly, Alston et al. [29] conducted a meta-analysis of returns to agricultural R&D. They found that the characteristics of the analyst, research, and research evaluation all had important implications for the results. Rose and Stanley [46] investigated the effects of common currencies on international trade. Iwasaki and Tokunaga [47] did a meta-analysis of technology transfers and foreign direct investment (FDI) spillovers in transition economies.

More recently, some economists have used the meta-analysis technique but there appears to be no application of this methodology in an analysis of the impact of improved technology adoption on staple crop agricultural production in Africa. Some of the studies are related to agriculture but are different from the focus area of our study. These include the impact of genetically modified (GM) crops [48]; farm-level cost and benefit analysis of GM crops [49]; economic and agronomic impact of commercialized genetically modified crops [50]; impact of agricultural subsidies on farm technological efficiency [51]; impact of microfinance interventions [52]; an efficiency and productivity analysis of Pakistan's farm sector [53]; assessing the returns to water harvesting [54]; willingness to pay for reducing pesticide risk exposure [55]; and nutrient management in African sorghum cropping systems and an assessment of yields and profitability [56].[1]

Applications of meta-analyses in diverse areas include the effects of immigration on wages [57]; income and calorie intake [58]; income inequality and economic growth [59]; the impact of technical barriers to trade [60]; effect of aid on economic growth [61]; energy consumption and economic growth [62]; effect of currency unions on trade [63]; price and income elasticity of demand for meat [64,65]; price and income elasticity of demand for alcohol [66]; income elasticity of demand for cigarettes [67]; assessing the impact of interventions in fisheries' co-management in developing countries [68]; exchange rate volatility and trade [69]; and debt and economic growth [70]. Recently, Ogundari and Bolranwa [38,71] used MRA to provide insights into agricultural extension services' impact. Ruzzante et al. [72] also used MRA to investigate variables that regularly explain adoption across technologies in a related development. The present study differs by extending the application of the MRA of welfare impact of improved agricultural technology adoption on the entire parts of Africa.

There are vast theoretical and empirical reasons while meta-analysis is applied in practical research. A typical meta-analysis allows researchers and academicians to combine results from diverse homogenous studies into a comprehensive estimate for better policy discussions and implementation [73].

[1] See Stanley [33], pp.132-134 for more applications of meta-analysis in economics.

3. Material and methods

3.1. Literature search

A meta-analysis is a statistical procedure that collates research findings from previous studies and distils them for a broader analysis and conclusions. As such it can be a major source of concise up-to-date information. It is a helpful framework for integrating and explaining disparate empirical economic literature. The overall conclusions of a meta-analysis, however, depend heavily on the quality of the meta-analytical process and an appropriate evaluation of the quality of the meta-analysis which can be challenging. To meet the required conditions, we performed extensive searches of adoption literature datasets. To begin with, we used a set of combined keywords search (meta-analysis, agriculture, staple crops, technology adoption, productivity, welfare, and Africa) in specific and important economics literature databases such as the Web of Science, the Web of Knowledge (WoK), Research Papers in Economics (RePEc), JSTOR, Science Direct, Research in Agricultural and Applied Economics (AgEcons), Econlit, Econpapers, and Google Scholar. The flowchart of the entire procedure of literature searching and compilation is presented in Fig. 1 below.

3.2. Description of the sample and variables

Originally, a total of 607 technology adoption studies were identified across the globe, however through a step-by-step screening process only limited of them were selected and put in to a list for a meta-analysis (refer to Fig. 1). To be included in our meta-analysis, a study had to be an empirical study which assessed the impact of agricultural technologies on any of the three welfare indicator outcome variables – output or expenditure, food security, and poverty indices – conducted in Africa (we use output and income interchangeably). Consequently, we excluded studies that were not empirical and/or used any other outcome variables. The study thus addressed the above raised questions using 52 studies that yielded 78 effect size estimates conducted in the case of Africa.

The majority of meta-analysis literature document that the widely used effect sizes in the meta-analysis include elasticities, Cohen's d, Hedges' g, partial correlation coefficient (PCC) and odds ratio [28,74]. But the choice of which effect size to use depends on the primary studies in focus.

Among others, elasticities are the popular measures of effect size in meta-analysis. However, they are largely unsuitable when primary studies do not provide sufficient information to calculate elasticities or when they use a variety of non-comparable scales and different functional forms [38,71]. Stanley [33] also states that the effect size is usually measured as an elasticity estimate, a partial correlation coefficient, or a regression coefficient that is thought to measure some important underlying economic phenomenon.

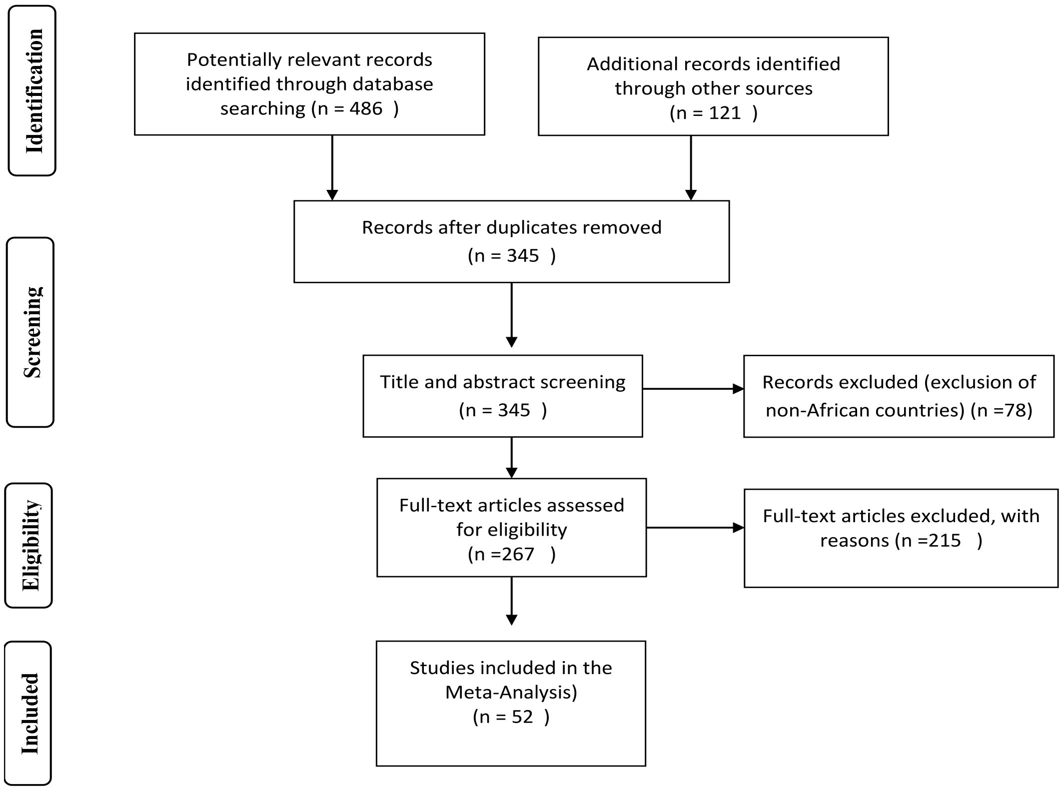

Fig. 1. Results of the paper selection flowchart.

On the other hands, the literature discusses common prevalence of non-equivalence of effect size [32,37]. The differences in effect size are a result of the fact that a variable is measured in different units. Many of the studies we used did not report a measure of mean values for output or expenditure, as well as average consumption and mean poverty levels we needed to construct a common scale. In the primary studies if the reported effect size was not comparable or if the results were in different measurements or scales, especially when those studies used variables with different scales and when such variables could not be transformed to a common scale the results become non-comparable. Due to such facts, we have constructed a value in common scale, elasticity form. For the results reported in non-comparable form in the primary studies to find the desired and comparable effect size.

Appendix Table A and B present the list of studies included in the Meta-Analysis. These studies were obtained after inspecting recent studies on the wider area of the impact of agricultural technology adoption covering different regions of the African continent. A majority of the papers included in our study from East African countries (Ethiopia, Kenya, Uganda, and Tanzania). The remaining papers are from West and South Africa. The relatively large sample size of 52 studies allowed us to include a large number of meta-independent variables and unlike other studies our study is not constrained by problems related to low degrees of freedom.

The independent variables called 'moderator variables' by Stanley [33] are those study characteristics that are thought to be consequential. There is some latitude for identifying what these key characteristics should be based on factors like the nature of the study, sample size and quality, methods used, and relevant theories. At a minimum, a meta-analyst will wish to code dummy variables for the use of different datasets and econometric modeling choices. However, because the number of studies is limited, and most studies entail a unique combination of theory, estimation methods, explanatory variables, data, time periods, and other research related choices, not every uncommon study characteristic can be coded and analyzed. Variations due to minor modeling choices may be treated as part of the random study-to-study background. We selected and defined several potential moderator variables which primarily represent differences in econometric specifications in our technology adoption studies.

These moderator variables include accounting for the nature of the data for which we used a dummy variable, whether the data is a cross-section or panel data (DATA). In addition, we also used a regional dummy: East Africa, North Africa, Southeast Africa, Central Africa, and West Africa (REGION = 1 if the study was in East Africa, 0 if it was elsewhere). We also used dummy variables to account for differences in estimation techniques, PSM (propensity score matching), ESR (endogenous switching regression), and OLS (ordinary least squares), etc. (MODEL = 1 if the study used the PSM/ESR method, 0 otherwise) and if the study used any theory (THEORY = 1, if the study has used specific theory, and 0 if no theory was specified). There were also dummy variables for whether the type of technology was improved seeds (TECHNO = 1, 0 otherwise). Further, we calculated a set of dummy variables to account for different journal types (JOURNAL = 1 if it was published in a peer-reviewed journal, 0 for studies published elsewhere). Other variables include year of publication (YEAR) and sample size (SAMPLE). The full list of dependent and independent variables used in the meta-regression is given in Table 1 below.

Fig. 2 shows the distribution of the outcome of raw data and some of the moderator variables from the primary studies plotted against regions and the types of technology adopted. The observed variations in the distribution of these outcome variables (Fig. 2a) shows that there were clear regional differences in the impact of the various agricultural technologies in different parts of the continent. In addition, Fig. 2b also reveals the distribution of the 25 percentile values of outcomes and total values of the four explanatory variables disaggregated by regions and technology type considered in the review, a possible difference is also confirmed again with this Figure. Apart from the above results, some additional information is also presented on Fig. 2c below.

4. An analysis of the meta-regression

To explore and assess the variations in the results across the sample studies concerning the welfare impact of improved agriculture technology adoption in the African context we did a meta-regression analysis (MRA) suggested by many literatures in the areas of meta-analysis [30,32,33,35,75]. As stated earlier, our study used the three outcome variables to capture the reported impact of adopting improved agricultural technologies on welfare in Africa from the primary studies. In doing so, we estimated an equation for integrating the empirical results across different studies:

Table 1
Definitions of dependent and independent variables used in the meta-analysis.

Variable	Definition
Dependent/outcome:	
Total income or expenditure (Y/E)	Total amount of income (output) or expenditure reported in the primary studies
Food security (FS)	Food security levels reported in the primary studies
Poverty (PO)	Poverty index (headcount ratio in %) reported in the primary studies
Independent:	
YEAR	Year of publication
DATA	1 if the data used was cross-sectional, 0 otherwise
REGION	1 if the study was in East Africa, 0 elsewhere
THEORY	1 if the study used a specific theory, 0 otherwise
MODEL	1 if the study used PSM/ESR methods, 0 otherwise
TECHNO	1 if the technology was improved seeds, 0 otherwise
SAMPLE	The sample size used in the selected studies
JOURNAL	1 if the study was published in a peer-reviewed journal, 0 otherwise

Source: Authors' definitions

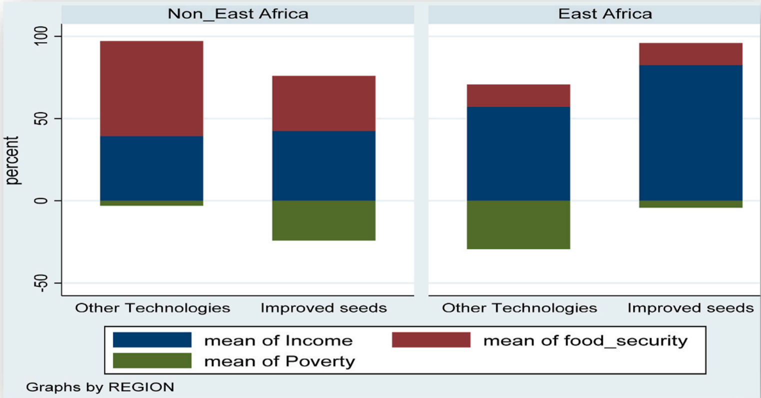

Fig. 2a. Distribution of Outcomes by regions and types of technology adopted.

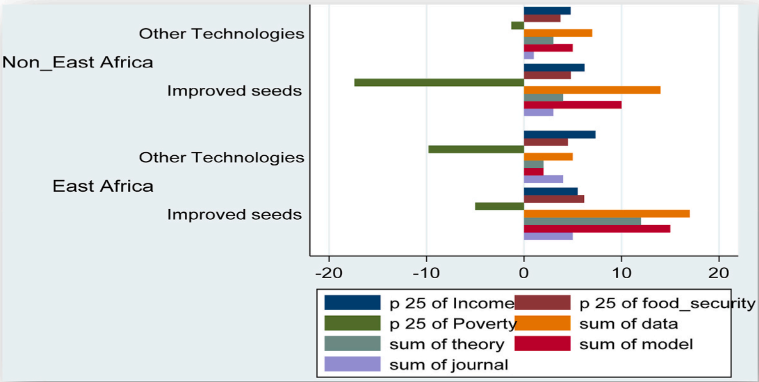

Fig. 2b. Distribution of the 25 percentile values of outcomes and total values of the four explanatory variables by regions and technology type.

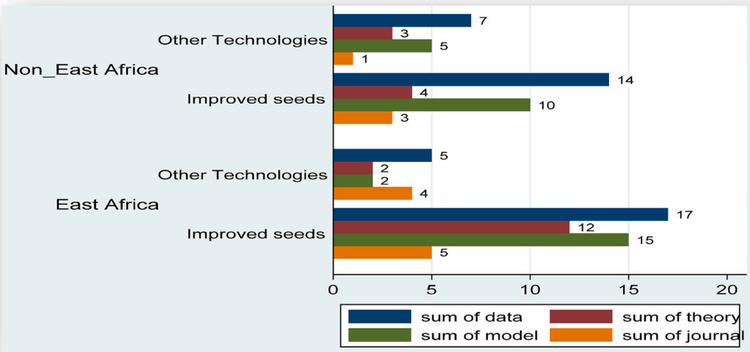

Fig. 2c. Distribution of the explanatory variables by regions and technology type.

$$Y_j = \beta_0 + \sum_{k=1}^{K} \beta_k Z_{jk} + e_j j = 1, 2, ..., N \tag{1}$$

where Y_j is the reported impact estimate of the outcome in study j from a total of N studies (effect size measures, elasticities in our case) and Z_{jk} is a vector of meta-independent variables which measure relevant characteristics of an empirical study that might explain effect variations in Y_j *s* across studies in the meta sample, β_k is a vector of unknown parameters to be estimated, and e_j represents the unexplained variations in the dependent variable or the random error term. The estimated effect β_k indicates the effect of specific sample characteristics on the outcome variable.

5. Estimation results

5.1. Model 1: output or expenditure

We estimated a linear regression model separately for the three outcome variables. Table 2 presents the OLS' estimates with robust standard errors of the meta-regression analysis. For comparison purpose a weighted least square (WLS) was estimated, but the results are a bit similar to robust OLS estimation results and these are not reported here. The OLS results show that included factors heterogeneously influenced different outcomes in the sample studies.

The dependent variable for the first model estimated (Model 1, Table 2) is output or expenditure from the sample studies. The intercept term, or β_0 from Equation (1) is an estimate of technology adoption on output or expenditure given zero effects from the slope determinants. The estimated intercept is statistically insignificant interpreted as not being different than zero. The parameter estimates of the publication year of the study, while negative, are not statistically significant. This suggests that reported percentage points of output or expenditure decreased over time, but this reduction is not statistically significant across periods. The results show that recent studies reported lower impacts of agricultural technology adoption on welfare represented by output or expenditure and measured in percentage points (elasticity or percentage changes in output effect with respect to a change in the time period).

Studies based on cross-sectional data exhibit significantly lower percentage points of output or expenditure estimates than those using panel or time series data. In other words, the effect of improved agriculture technology adoption appears to be lower in cross-sectional studies. Models relying on panel data are likely to yield more accurate efficiency estimates given that there are repeated observations of each unit [76] and one can account for long run or dynamic effects of technology adoption. However, no *a-priori* expectations of the impact of data type (cross-sectional versus panel data) on the magnitude of percentage points of output or expenditure values are developed in our study. Other studies also state that this difference across data types may arise because of problems associated with unobserved time invariant heterogeneity effects. Specifically, if there are time-invariant effects across the individual units then the cross-sectional studies may produce biased and inconsistent estimates. Such time-invariant effects may, however, be eliminated by within-mean transformations or changes over time if panel data is used [32,76].

Our results confirm that studies that use East African countries in their analyses report higher output or expenditure values as compared to other regions of the African continent. This suggests that improved agricultural technology adoption in East Africa has a bigger effect on families' output or expenditure than those used elsewhere on the continent. Estimates of whether a primary study used any theory or not and the sample sizes of those studies do not significantly affect the output or expenditure elasticity estimates across the sample studies. Given that a substantial number of studies, 59% of the studies considered did not specify the standard theories employed, we suggest that future researchers should attempt to strengthen the theoretical foundations in this research field.

Our study also analyzed whether the estimation method used played a role in affecting the relationship between adoption and different outcome measures. Studies that used propensity score matching (PSM) or the endogenous switching regression (ESR) approach or both yielded significantly higher output or expenditure effect values than those that used OLS, logit, probit, or tobit estimation methods. This result is striking in that recent studies excessively employ estimation techniques like the PSM or ESR approaches that take into account issues such as sample selection bias and heterogeneity of sample units while many of the earlier studies

Table 2
Meta-regression analysis results: OLS with robust standard errors.

Variables	**Model 1**	**Model 2**	**Model 3**
	Output/Expenditure	Food security	Poverty index
YEAR	−2.16 (1.51)	0.799*** (0.12)	−2.34** (1.08)
DATA	−143.90*** (45.48)	_	−13.18** (5.98)
REGION	59.63** (28.43)	−8.995** (3.72)	−8.72** (3.55)
THEORY	−13.18 (40.64)	9.665* (4.77)	_
MODEL	84.65** (38.56)	_	7.10* (3.70)
SAMPLE	0.002 (0.011)	−0.005** (0.001)	−0.005** (0.002)
JOURNAL	−18.85 (24.63)	_	−10.79* (5.27)
CONSTANT	4436.86 (3018.79)	−1587.48*** (246.87)	4737.44** (2175.54)
No. of obs.	46	13	19
Adjusted R^2	0.214	0.613	0.466

Notes: ***, ** and * are significant at 1%, 5% and 10% levels, respectively. Robust standard errors in parentheses below the coefficients.
Source: Authors' computations

partly or totally failed to account for such aspects affecting the properties of the estimated effects. Most importantly, the differences in effect size estimates across studies that control selection bias and those that did not show that evaluation design significantly matters which is important to understand the true impact of programs being evaluated for policy.

This finding underscores the importance of issues such as accounting for selection bias, study location (region), study design etc., to better understand and propose relevant policy implications. Such concerns are important aspects in meta-analysis and each attribute is highly relevant to researchers and academicians. Researchers and academicians may need to pay attention to these attributes to provide a more reliable estimate of the impact of improved agricultural technologies to use for policy-making and implementation.

Additionally, our study examined whether the type of publication matters in the variations in technology adoption effects among the studies investigated. Keeping the other factors fixed, the regression coefficients for the variable journal reported in Table 2 show that studies published in peer-reviewed journals had lower estimated gains in output or expenditure as compared to studies published elsewhere, but this was not statistically significant. When only observations from studies that were published in peer-reviewed journals are included, the mean effect size is larger than when all observations are included. In this regard, one can suspect the presence of a bias in the publication of those studies, which implies that only studies that report substantial effects are more likely to be accepted for publication in a journal [77]. Second, even if there is publication bias, our mean results will be estimated correctly (this issue is dealt with in greater detail in Section 6).

5.2. Model 2: food security

For the second outcome variable, food security levels, Model 2 is estimated with only four of the most important independent variables due to fewer observations and also to not lose the degree of freedom. Thus, the small size of our sample prevents the inclusion of additional moderator variables. The results of the meta-regression using OLS are reported in Table 2, Model 2. The parameter estimate of the year of the study is positive and statistically significant. This implies that reported probabilities of being food secure (percentage gain of food security levels) increased significantly over time. This suggests that recent studies have reported higher gain of improved technology adoption as measured by food security.

The variable REGION indicates whether the study was based in East African countries or not. It allows us to test for the differences in the regional effects of technology adoption. The results show that studies that covered East African countries in their analyses reported lower food security gains as compared to studies elsewhere in the continent. Our findings also suggest that it actually matters whether a study uses a specific theory or not. Studies that used theories reported higher percentage gains of food security as compared to studies that were ad-hoc and built without a specific theory; this was also statistically significant. Another way of explaining this result is that primary studies that employed theory in their work reported a significant impact of improved agricultural technologies when the potential outcome variable was food security levels.

When it comes to sample size of the studies included in our analysis, our results show that studies with smaller sample sizes reported higher percentage gains of food security. This implies that reported probabilities of being food secure differed across studies with different sample sizes. A larger sample is expected to result in more stable and accurate technology adoption effects on food security, but our results went the other way.

5.3. Model 3: poverty index

The OLS estimation results with robust standard errors for the third outcome variable (headcount poverty index) are reported under Model 3 in Table 2 where the dependent variable is poverty indices from the sample studies.

An estimation of the model shows that the year of the study for the poverty index estimation was negative and statistically significant. This implies that the reported poverty indices decreased significantly over time and confirms that earlier studies reported higher reduction in poverty and hence a higher impact of agricultural technologies on. Our results also show that studies based on cross-sectional data had significantly lower poverty reduction in percentage points than those using panel or time series data. In other words, the impact of improved agriculture technology adoption was estimated to be lower in cross-sectional studies. Panel data captures the dynamic and accumulated learning by studying the effects of technology adoption.

Our results confirm that when it comes to regional effects of technology adoption, studies that used data from East African countries reported lower poverty reduction as compared to other regions. Our study also shows that studies using propensity score matching or endogenous switching regression approaches or both yielded higher poverty reduction than those that used other estimation techniques. This result is statistically significant at the 10% probability level. Studies that used a larger sample size reported lower reduction in poverty. Hence, our results indicate a negative and statistically significant link between poverty reduction and sample size.

Lastly, our study examined whether the type of publication mattered for the technology adoption effect. In this case the regression coefficient for the variable journal publication of Model 3 indicates that studies published in peer-reviewed journals reported lower reduction in poverty as compared to similar studies published elsewhere; this was also statistically significant.

From a policy perspective, we provide information useful to decision-makers interested in designing policy initiatives or intervention measures that encourage the adoption of improved agricultural technologies and modern practices in the African context. However, it should be noted that the effects of the stated technologies vary when different outcome variables are used. This by itself has relevant policy implication. Another important policy concern is whether empirical evidence supports the effectiveness of adoption of improved agricultural technologies and modern practices in African context, and our study has revealed this concern clearly.

6. Test of publication bias

In research, academic journals have a tendency to publish papers with '*statistically significant*' results and those which are consistent with expectations determined by the theory used [78,79]. In several studies, publication bias has been generally recognized as yet another threat to the relevance of applied economics. Concerning publication bias. De Long and Lang [[79], p. 1258], state that, "… even a careful review of the existing published literature will not provide an accurate overview of the body of research in an area if the literature itself reflects selection bias." This may be especially true in cases in which the research concerns are a parameter that is predicted to have a certain sign using the conventional economic theory. In this case, insignificant or 'wrong-signed' results may be substantially under-reported in the published research.

According to Stanley [[80], p. 104], "econometric estimates can easily be overwhelmed by publication selection because there are so many plausible econometric models to choose from. Conventional literature reviews and econometric techniques are powerless to address publication bias." Nowadays the econometric methodology cannot reliably assess the empirical merit of any economic hypothesis. Issues of publication selection and its identification and circumvention are crucial for genuine empirical economics.

More recently, researchers have also investigated the issue of publication bias. These include Abreu et al. [81], Ashenfelter et al. [82], Card and Krueger [35], Doucouliagos [83], Doucouliagos et al. [84], Doucouliagos and Stanley [85], Gorg and Strobl [32], Nijkamp and Poot [86], Rose and Stanley [46], and Stanley [33,87,88], among others.

However, it should also be noted that publication bias need not arise from some deliberate motive to deceive. Authors may be less likely to submit statistically insignificant results because of the 'rational' expectation that they will have a lower probability of being accepted. Or referees and editors may disproportionately select significant results believing them to be more informative. In either case, insignificant empirical findings will be under-represented and any unadjusted summary of research literature will be biased in favor of the investigated effects irrespective of the motivation of the researchers. Needless to say, a prior commitment to a given ideological or theoretical position can greatly compound the publication bias.

There are some common methods for testing publication bias. For example, Card and Krueger [35] suggest two types of tests for publication bias. Unfortunately, we could not perform either of these tests or follow common methods for testing publication bias because a majority of our sample studies employed non-linear functional forms which make the tests inappropriate using specified methods as they do not provide information on sample means of income or expenditure, average food consumption, or poverty level adopters and non-adopters. Very few studies in our sample have employed a linear specification which does not allow us to run a meaningful regression on the sample.

Another alternative and common way of assessing possible publication bias in a meta-analysis is a funnel plot (see Fig. 3a through 3c) and a funnel asymmetry test (FAT)-MRA approach. The first method, a funnel plot, is a simple scatter plot of intervention effect estimates (effect size) from individual studies against some measure of each study's size or precision. A funnel plot is a graph that shows the relationship between effect size and a measure of precision such as a standard error or inverse of standard error of the effect size. Literature on meta-analysis states that funnel plots are more likely to be vulnerable to subjective interpretations [87] and consequently, alternative methods like FAT-MRA are used in combination with funnel plots to validate the existence of publication bias in the sampled primary studies.

Here we follow the second publication bias test method proposed by Card and Kruger [35] of regressing the effect size estimate on

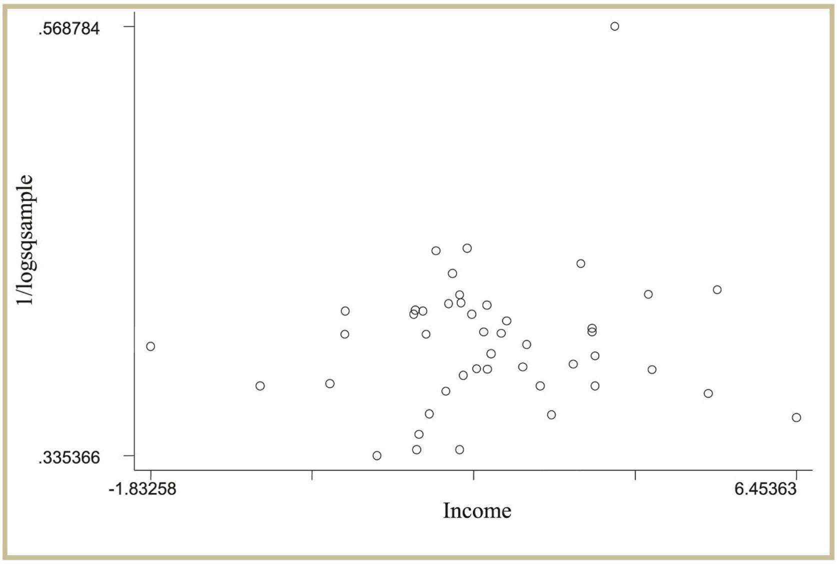

Fig. 3a. Funnel plot of Income effect size against inverse of logsqsample
Source: Authors' computations.

its standard error (logsqsample, log of square root of sample size, is used as a proxy in our case). Begg and Berlin [78] also argue that sample sizes are usually not planned and instead depend mainly on the availability of data and computing powers. Thus, it may be reasonable to assume that the sample size is determined without any meaningful association with its underlying true random effect. This assumption then allows us to investigate a publication bias by analyzing whether there is indeed no meaningful relationship between sample size and our three outcome variables.

Concerning the empirical approaches of publication bias, Egger et al. [89] proposed a method of FAT-MRA by regressing a measure of precision on the effect size of interest, and based on this we adopted equation (2) for the current study specified as:

$$Effect_{ij} = \beta_0 + \beta_1 P_{ij} + \varepsilon_{ij} \tag{2}$$

where *Effect* is the measure of effect size of each study, *P is* the study's size or precision, β_0 and β_1 are estimated parameters, and ε_{ij} stands for the random error term.

Publication bias exists when the correlation between the study's effect size (*Effect*) and the study's size gives a statistically significant result. This suggests that a large proportion of the primary studies with significant effect size perhaps dominate the literature under review. In the absence of publication bias, the effect size of the primary studies is less likely to correlate significantly with the study's size.

The first test for the existence of publication bias is the funnel plots reported for all the three outcome variables in Fig. 3a through 3c. Fig. 3a shows the relationship between output (expenditure) effect size and the log of the square root of the sample size (logsqsample) in the included studies. We would expect a positive relationship between output estimates and sample size but this does not appear to be the case for our data shown in the graph and it is not obvious from Fig. 3a whether there is any relationship or not between the two, and thus the plot does not provide any evidence of association of the two variables. The same thing can be seen in Fig. 3c where the relationship is not clear, but in Fig. 3b there seems to be a weak relationship between food security and sample size; and thus, publication bias exists in the second model.

Confirming the meta-regression-analysis' results, the funnel plot also shows that there is no publication bias in the first and third models of our sample studies, but a publication bias exists in the second model. The absence of a publication bias (in the two models), is perhaps due to the inclusion of more studies that were not published in peer-reviewed journals.

A visual inspection of the funnel plots can be subjective so that we also estimated the FAT-MRA as an empirical test to further investigate the existence of publication bias. The results are presented in Table 3.

The results in Table 3 show that the study's size or precision (sample size in our case) for the first and third outcomes is statistically insignificant supporting the funnel plot presented earlier and confirm that there is no publication bias in those models. In the second model, however, the results of the estimate of sample size are statistically significant at 10% probability level providing evidence of the existence of a moderate publication bias. This confirms the results of the funnel plots and thus shows that publication bias exists in the food security model.

7. Conclusion

A large body of literature has analyzed the impact of adopting improved agricultural technologies on welfare. However, these studies have many variations and report different effects across different parts of the African continent. A meta-analysis is one of the best ways of shedding light on unexplained variations across studies. The basic objective of conducting a meta-analysis in this study is to understand the large variations across the results of selected studies in the case of Africa.

Several studies in the literature have evidenced that adopting improved agricultural innovations and technologies can reduce poverty and food insecurity and increases farm household incomes and overall social welfare. However, an important policy concern is

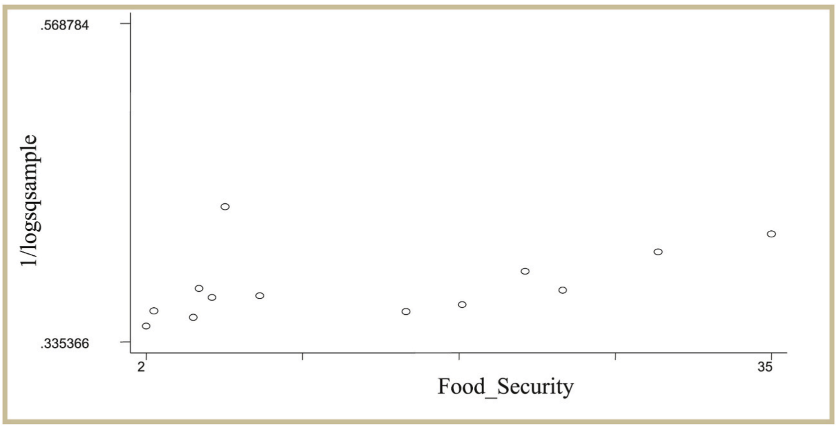

Fig. 3b. Funnel plot of food security effect size against inverse of logsqsample
Source: Authors' computations.

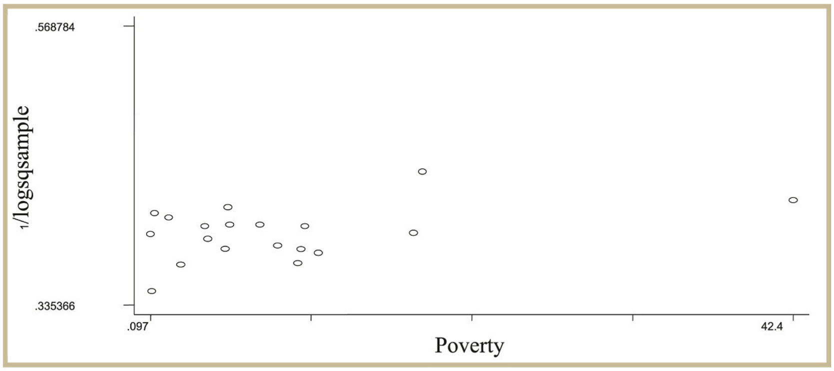

Fig. 3c. Funnel plot of poverty index effect size against inverse of logsqsample
Source: Authors' computations.

Table 3
Estimated funnel asymmetry test (FAT)-MRA.

	Output (Expenditure)	Food security	Poverty index
Sample size	−0.13 (0.21)	−6.33*(3.23)	−5.22 (3.00)
Constant	3.35**(1.35)	58.74**(23.16)	42.25*(19.16)
N	46	13	19

Notes: ** and * are significant at 5% and 10% levels, respectively. Standard errors in parentheses.
Source: Authors' computations.

whether empirical evidence supports the effectiveness of adoption of improved agricultural technologies and modern practices, given the mixed results across studies, in African context.

The findings of our study revealed that the estimated impact of varies improved agricultural technologies on welfare represented by the effect sizes of elasticity forms of the considered outcome variables is strongly influenced by study periods, location (region), the research design, use of a specific theory, data types and choice of econometric methods used in the primary studies.

Based on the results we obtained for all the three outcomes, the differences in effect size estimates across those studies have some common trends. For example, dominant of the studies considered did not specify the theories employed, suggesting that upcoming studies should attempt to strengthen the theoretical foundations in area. Another important issue is the way that studies deal with impact evaluation techniques, studies that employed better impact evaluation methods like PSM/ESR or both significantly varies as compared to studies that used common estimation approach like OLS implying that evaluation design matters. This is important to instrument the actual impact of programs being evaluated for policy purposes.

Employing a funnel asymmetry test (FAT)-MRA and funnel plots, the study has also examined the possibility of publication bias in the selected studies. The analysis revealed that there was no evidence of publication bias in the effect size measures of output (expenditure) and poverty models, but in the food security model the test's results showed that moderate publication bias existed.

The results of the current study have also some important implications. Based on the meta-analysis, our results highlight the important role of a study's attributes of factors that explain variations in the reported impact of agricultural technologies and improved practices on selected outcome variables in Africa, which is very useful for advancing such an approach in the agriculture sector; and motivate researchers in identifying study-specific attributes essential for modeling the impact of different agricultural technologies and modern practices in the sector. One of the core implications of the current study is that, based on the sensitivity of effect sizes to study attributes (i.e. data type, econometric methods, sample size, region of the study, and journal type), interested researchers and academicians need to pay attention to these attributes to provide more reliable estimates for policy interventions. The findings have also improved our understanding of the various impacts of modern agricultural innovations and technology adoption which enhances the application of appropriate policy analyses in the agriculture sector. Thus, policy makers can use this finding as an input to design future agricultural-related interventions in the region.

In general, we believe that our current research can provide better insight into the estimated impact of varies improved agricultural technologies on welfare and paves ways for future research. However, as is usually the case when it comes to research, the study faced a single limitation and this could suggest lines for subsequent research works. The study is based on studies conducted in African context. Thus, to fully understand the estimated impact of varies improved agricultural technologies on social welfare globally, we recommend further researches to be conducted at global context and compare the difference in effect sizes between the developed and developing countries case.

Author contribution statement

Both authors listed have significantly contributed to the development and the writing of this article.

Declaration of competing interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Additional information

No additional information is available for this paper.

Ethics approval

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Consent to participate

Not applicable.

Consent for publication

Not applicable.

Author contribution statement

Both authors listed have significantly contributed to the development and the writing of this article.

Data availability statement

Data will be made available on request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. List of studies included in the Meta-Analysis with country of the study and data used

No	Author(s)	References (Publication Year)	Data Type	Country of Study
1	Kassie et al.	[6]	CS	Uganda
2	Ahmed et al.	[90]	CS	Ethiopia
3	Faltermeier and Abdulai	[91]	CS	Ghana
4	Khonje et al.	[92]	CS	Zambia
5	Teklewold et al.	[93]	CS	Ethiopia
6	Wiredu et al.	[94]	CS	Ghana
7	Adekambi et al.	[2]	CS	Benin
8	Asfaw et al.	[23]	CS	Malawi
9	Mulugeta and Hundie	[10]	CS	Ethiopia
10	Nyangena and Juma	[95]	PD	Kenya
11	Tesfaye et al.	[24]	CS	Ethiopia
12	Asfaw et al.	[3]	CS	Tanzania and Ethiopia
13	Dercon et al.	[96]	PD	Ethiopia
14	Teklewold et al.	[97]	CS	Ethiopia
15	Asfaw and Shiferaw	[98]	CS	Ethiopia and Tanzania
16	Asfaw et al.	[99]	CS	Tanzania
17	Shiferaw et al.	[22]	CS	Ethiopia
18	Abdulai and Huffman	[100]	CS	Ghana
19	Hailu et al.	[101]	CS	Ethiopia
20	Melesse	[102]	PD	Ethiopia
21	Hundie and Admassie	[5]	CS	Ethiopia
22	Bezu et al.	[103]	PD	Malawi
23	Mango et al.	[104]	CS	Zimbabwe, Malawi and Mozambique
24	Zeng et al.	[105]	CS	Ethiopia

(continued on next page)

(*continued*)

No	Author(s)	References (Publication Year)	Data Type	Country of Study
25	Braun	[106]	CS	The Gambia
26	Vigani and Magrini	[107]	CS	Tanzania.
27	Kinuthia and Mabaya	[108]	PD	Uganda and Tanzania
28	Pan et al.	[109]	CS	Uganda
29	Afolami et al.	[110]	CS	Nigeria
30	Awotide et al.	[111]	CS	Nigeria
31	Challa and Tilahun	[112]	CS	Ethiopia
32	Adebayo and Olagunju	[113]	CS	Nigeria
33	Wossen et al.	[114]	CS	Nigeria
34	Verkaart et al.	[16]	PD	Ethiopia
35	Mojo et al.	[115]	CS	Ethiopia
36	Ogunsumi et al.	[116]	TS	Nigeria
37	Omilola	[117]	CS	Nigeria
38	Benedito	[118]	CS	Mozambique
39	Amare et al.	[119]	PD	Nigeria
40	Cunguara and Darnhofer	[120]	CS	Mozambique
41	Nguezet et al.	[121]	CS	Nigeria
42	Danso-Abbeam et al.	[122]	CS	Ghana
43	Adenuga et al.	[123]	CS	Nigeria
44	Sserunkuuma et al.	[124]	CS	Uganda
45	Abate et al.	[125]	CS	Ethiopia
46	Anissa	[126]	CS	Cameroon
47	Jaleta et al.	[127]	CS	Ethiopia
48	Gebrehiwot	[128]	CS	Ethiopia
49	Awotide et al.	[129]	CS	Nigeria
50	Kijima et al.	[130]	CS	Uganda
51	Beyene et al.	[131]	CS	Ethiopia
52	Coulibaly et al.	[132]	CS	Malawi

Notes: Cross-sectional (CS), time series (TS), and panel data (PD).
Source: Compiled by the authors.

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