Factors Shaping Farmer's Innovative Behavior: A Meta-Analysis of Technology Adoption Studies in Agriculture

K. Chatzimichael[*], C. Daskalaki[†], G. Emvalomatis[†], M. Tsagris[†] and V. Tzouvelekas[†]

January 21, 2023

Abstract

Despite extensive empirical research on the drivers of technology adoption in agriculture, there is only little agreement among researchers over how improved agricultural technologies can be effectively promoted among individual farmers. In this paper, we employ a meta-regression analysis approach to synthesize empirical evidence on the average partial effects of eleven adoption determinants that regularly appear in empirical studies examining farmer's adoption behavior worldwide. Our analysis considers a total of 122 studies from the adoption literature using discrete choice models that are published in 24 peer-reviewed journals since 1985, covering farmer's adoption behavior around the world and for a wide variety of agricultural technologies. Using this unique and broad meta-dataset, we investigate whether each of the eleven determinant factors has a true average partial effect on technology adoption rates. Moreover, we identify the sources of heterogeneity across reported estimates on average partial effects, and examine whether publication bias is one of the drivers of observed asymmetries in estimates. Our meta-regression model is estimated using a Weighted Least Squares (WLS) estimator that allows capturing observed heterogeneity arising from differences in population characteristics across studies or study attributes.

Keywords: Agricultural technology; Technology adoption; Average partial effect; Meta-regression analysis; Publication bias
JEL Codes: C21, D22, Q16, Q18.

[*]Department of Agricultural Economics and Rural Development, Agricultural University of Athens, Greece.
[†]Department of Economics, University of Crete, Greece.

Introduction

Over the past decades, food insecurity and environmental degradation issues have been placed at the top of the global political agenda. With the agricultural sector being the largest economic sector in many regions of the developing world where food insecurity is prevalent (FAO et al., 2022) and a major contributor to environmental pollution (FAO, 2020), political attention has been arguably placed on agriculture as a key driver for jointly achieving food security and environmental goals (Lipper et al., 2014; Sayer and Cassman, 2013).[1] As a result, the sector has been extensively targeted for policy interventions aiming to raise agricultural productivity while preserving natural resources and the environment. Efforts have concentrated on the development of policy programs and initiatives directed to accelerate the transition to sustainable farming systems, enhance agricultural innovation, and promote the adoption and diffusion of new agricultural technologies, particularly among smallholder farmers (Kebebe, 2017; Ogundari and Bolarinwa, 2018). Yet, despite the policy interventions, a steady increase in food insecurity and agricultural pollution levels is witnessed in recent years (FAO, 2020; GNAF, 2022), questioning the effectiveness of past agricultural policy measures.

Although there is a general consensus among researchers that the widespread adoption of improved technologies is essential for ensuring sustainable growth in agricultural production (Ruzzante et al., 2021; Ogundari and Bolarinwa, 2018), an important debate remains in the relevant literature over how such technologies can be effectively promoted among farmers, particularly in developing regions (Takahashi et al., 2020). Following the early contributions of Griliches (1957) and Rogers (1962) and the influential work of Feder et al. (1985), a large number of studies has emerged after the middle 80's seeking to explore empirically the drivers of adoption behavior in agriculture and map farmers' preferences towards innovation. However, this empirical literature is often characterized as inconclusive, providing mixed results on the impact of commonly investigated factors on adoption rates (Sunding and Zilberman, 2001; Ruzzante et al., 2021). For instance, although the majority of studies stress the importance of farmer's education in adoption decisions (Koundouri et al., 2006; Khanna, 2001; Lin, 1991), a few other studies find insignificant or negative effects of education on adoption rates (Kassie et al., 2013; Martin et al., 2008). Similar controversies and asymmetries in results are documented for other determinants that have been a common preoccupation of adoption studies in agriculture, such as farm size, access to credit, farmer's age, and others (Koundouri et al., 2006; Dinar and Yaron, 1992; Batz et al., 1999). Needless to say, this diversity in research findings can yield flawed information to policy makers, explaining, in part, the

[1] Land degradation and shortages of farmland and water resources under climate change have posed serious threats to global agricultural production, making the goal of feeding the world's rising population particularly challenging. The recent pandemic crisis and increase in energy prices have further aggravated food insecurity issues, particularly in the developing world (FAO et al., 2022).

ineffectiveness of past agricultural policies.

The lack of robustness in reported estimates can be partly attributed to differences in characteristics among adoption studies. Existing empirical work examines adoption behavior in a variety of settings and for a variety of technology types, relies on different empirical approaches and specifications, and uses various datasets from a wide range of regions around the globe, observed at different periods of time. This great heterogeneity in study attributes is undoubtedly important and may result in significant variations in study outcomes (Balima et al., 2020). In addition, observed asymmetries in reported estimates can be due to an artifact related to certain research choices made by researchers driven by the interest to obtain results consistent with the conventional view or results with higher statistical significance, *i.e.*, publication selection bias (Stanley, 2005; Balima et al., 2020). However, to assist evidence-based policy-making, a comprehensive synthesis of the diverse findings in the adoption literature is necessary, that could enable identification of the sources of heterogeneity beyond research choice biases.

Meta-regression analysis (MRA) is a powerful statistical method with many applications in the economic literature (Stanley, 2001, 2005, 2008; Oczkowski and Doucouliagos, 2015; Ogundari and Bolarinwa, 2018; Balima et al., 2020), which allows researchers to summarize and synthesize diverse findings in a comprehensive and objective manner.[2] MRA enables tracing excess study-to-study variations in reported estimates attributable to differences in study characteristics while, at the same time, isolating potential effects associated with research choices (Stanley, 2005; Stanley and Jarrell, 2005). Within the context of the literature on technology adoption in agriculture, MRA can serve as a valuable tool for synthesizing the diverse findings related to the impact of various determinants on technology adoption rates and identify sources of heterogeneity across adoption studies beyond publication bias. Therefore, by its very nature, it may enable, not only the estimation of the "genuine" effects of the various determinants on adoption decisions,[3] but also the identification of significant sources of heterogeneity in findings attributable to differences in research methods, sample characteristics, geographical areas, and types of agricultural technologies. As such, it can provide valuable information both to policy makers and researchers.

In this paper, we employ an MRA approach to meta-analyze the average partial effects of eleven factors that regularly appear in empirical studies examining farmer's adoption behavior worldwide. In particular, the following variables identified in our meta-dataset as the most commonly investigated determinants of farmer's adoption decision were anayzed: *farmer's age, education and gender, household size, membership in groups, unions or associations, access to extension services, access*

[2]The development of MRA is mistakenly attributed to Glass (1976, 1977). Studies with similar aims, mentioning the associated challenges and developing similar concepts, had appeared much earlier in the literature (Simpson and Pearson, 1904; Pearson, 1933).

[3]The term "genuine effect" refers to the true effect of a variable after correcting for publication bias.

to credit and off-farm income, farm and herd size, and farm's distance from the market. Our analysis considers 122 observational studies from the literature related to technology adoption in agriculture, which are published in 24 peer-reviewed journals since 1985, covering farmer's adoption behavior around the world and for a diverse range of agricultural technologies. Using this unique and broad meta-dataset, we investigate whether the above-listed determinants have a "genuine" effect on adoption rates. Moreover, we identify the sources of heterogeneity across reported estimates on average partial effects, and examine whether publication bias is one of the drivers of observed asymmetries in estimates. The MRA model is estimated using the Weighted Least Squares (WLS) estimator suggested by Stanley and Doucouliagos (2015, 2017), which allows capturing observed heterogeneity arising from differences in research design or population characteristics across studies

Our study adds to the existing body of knowledge mainly through three routes. First, it develops a unique meta-dataset consisting of all published studies using a Probit, Logit or Tobit model to analyze the probability of adoption in 37 developed and developing countries around the world, covering the period from 1985 to 2021. Second, unlike previous studies in the area, our study meta-analyzes the average partial effects of eleven variables agreed among researchers to affect the probability of adoption. As such, it entails rich information on the "genuine" average partial effects of the most important adoption determinants and, therefore, may serve as a valuable source of information for evidence-based policy-making, as well as for future research in the field. Third, it provides first empirical evidence on the sources of heterogeneity across adoption studies in agriculture with respect to the average partial effects of various determinants. Previous work in the field has been based mainly on normative appraisals of the adoption literature, thus, providing less objective assessments on the sources of heterogeneity, while neglecting to account for research choice biases. Needless to say, accurate and up to date information on the sources of heterogeneity can be highly useful for researchers seeking best research practices and methods.

The remainder of the paper is structured as follows. Section 2 introduces the econometric framework. Section 3 discusses the meta-sample construction and the definition of the moderator variables, as well as the approaches used to resolve issues related to the availability of required information. Section 4 presents the MRA results, while the last section concludes the paper.

Econometric Framework

The goal of any MRA study is to estimate the combined effect, which is, at least mathematically, a weighted average of the parameters of interest obtained from n collected studies. In the context of our application, the parameter of interest is the average partial effect (APE) of a pre-specified group of explanatory variables, traditionally used to explain the probability of technology adoption among farmers in both developed and developing countries. In this instance, the associated *combined APE* of the j adoption determinant factor included in our MRA, is formally given by

$$\mu_j = \frac{\sum_{i=1}^{n} w_{ij} y_{ij}}{\sum_{i=1}^{n} w_{ij}}$$

where y_{ij} is the calculated APE of the j^{th} determinant retrieved from the i^{th} study included in the meta-dataset and w_{ij} is the associated weight. Different ways of determining the weights lead to different estimates of the combined APE and intuitively, the value of y_{ij} reported in studies which also report higher precision in the estimation of y_{ij} should receive a greater weight in the calculations.

Traditionally, fixed- (FE) and random-effects (RE) estimators are employed for the approximation of the combined APE, which make different assumptions regarding its nature and, consequently, lead to different ways of defining the associated weights. The FE estimator assumes that all studies in the meta-dataset share a common true effect across all study populations. As a consequence, the observed APE varies between studies only because of a normally distributed random term, inherent in each empirical application. On the contrary, the RE estimator assumes that the studies were drawn from populations that differ from each other in ways that could affect the estimated APE. As a result, the combined APE will vary among studies for two reasons: first, due to random disturbances within studies (as in the FE model), and second, due to true variation in APE size among studies.

A more recent approach developed by Stanley and Doucouliagos (2015, 2017), that appears to be more appealing in the context of MRA as it combines the merits of both FE and RE models, suggests the use of a *Weighted Least Squares* (WLS) estimator. Specifically, the WLS estimator employs the same weights as the FE model, which in turn implies that the combined APE obtained from the estimation of the simple regression model

$$y_{ij} = \mu_j + \epsilon_{ij}$$

is the same as that obtained from the FE model,

$$\hat{\mu}_j^{WLS} = \frac{\sum_{i=1}^{n} \frac{y_{ij}}{\sigma_{ij}^2}}{\sum_{i=1}^{n} \frac{1}{\sigma_{ij}^2}} \left(= \hat{\mu}_j^{FE}\right)$$

but with a larger variance:

$$\text{Var}\left(\hat{\mu}_j^{WLS}\right) = \hat{\phi}_j \times \text{Var}\left(\hat{\mu}_j^{FE}\right) \quad \text{and} \quad \hat{\phi}_j = \frac{1}{n-1}\sum_{i=1}^{n} \frac{\left(y_{ij} - \hat{\mu}_j^{WLS}\right)^2}{\sigma_{ij}^2}$$

Using simulated data, Stanley and Doucouliagos (2015) have shown that the WLS estimator performs well, combining the nice theoretical properties of both FE and RE model specifications providing smaller bias in the estimated combined effect and wider confidence intervals. It is the main apparatus used in MRA studies in several fields and for different types of meta-data, and therefore it is adopted herein.

Because the units of analysis in an MRA are the published empirical studies or results from alternative empirical designs, a major issue of concern is the possibility of publication bias: statistically significant results are more likely to be published or are affected by different survey designs and/or estimation frameworks and this may lead to a non-representative sample being used in the meta-analysis. This issue can be initially examined visually using a conventional funnel plot, which typically depicts the point estimates of APE against their standard errors or the inverse of their standard errors (square root of estimated precision). In the absence of publication bias the points on the plot should be arranged in a shape that resembles a funnel, where the reported estimates with high precision should be closer to the overall mean of the estimates and the dispersion of points around this mean should increase symmetrically as the reported precision declines. Asymmetry in the funnel plot, or excessive clustering around the overall mean, even for low values of the precision, are indications of possible publication bias.

Publication bias is likely to occur when there is a strong preference in the literature over a certain type of result concerning typically the sign of an estimate (Type I publication bias) or the statistical significance of an estimate independently of its sign (Type II publication bias). Within the context of the empirical literature on technology adoption in agriculture, publication bias is likely to take either of the two forms, depending partly on the determinant factor under investigation. Common reasoning suggests that for certain determinants, empirical findings may have been guided by early theoretical arguments or well-established theories in the field that explain or predict, on a theoretical basis, the direction of their relationship with adoption rates, implying a possible presence of Type I bias for these determinants. For example, empirical work on the impact of human capital variables on adoption rates is likely to have been driven by early arguments stemmed from human capital theory suggesting a positive relation between human capital and probability of adoption.[4] On the contrary, the relation of some other determinants with adoption rates might be less grounded in

[4]Positive APEs for human capital, as commonly documented in empirical literature, does not necessarily imply the presence of publication bias. We simply argue that the APE of certain determinants are likely to suffer from type I publication bias and therefore it is necessary to test if publication bias exists.

economic theory (i.e., household size), thus constituting an open question of empirical nature, or alternative theoretical arguments may exist providing a dual explanation on the direction of their relationship (i.e., farmer's age). For these factors, APE estimates are likely to be subject to Type II publication bias, as researchers seeking to uncover the drivers of adoption may tend to document significant relationships.

More formally, the existence of publication bias can be statistically tested using the *Funnel Asymmetry Test* (FAT) suggested by Egger et al. (1997), which examines the existence of asymmetry in the estimated combined APE. For doing so, we formulate the following regression equation for each one of the j determinants analyzed in our MRA study:

$$y_{ij} = \mu_j + \gamma SE_{ij} + \epsilon_{ij} \tag{1}$$

where SE_{ij} denotes the associated standard error of the APE of the j^{th} determinant factor. If the reported estimates are free of Type I publication bias, then the estimated combined APE will not be correlated with its standard error (Stanley, 2005, 2008) and hence the γ coefficient will be statistically insignificant. However, if publication bias is present, researchers' efforts to find an econometric specification that leads to results that conform to the "conventional view" will induce a statistically significant relationship between the reported APEs and their standard error (Stanley, 2008). Even in the presence of publication bias, a true effect may exist in the empirical evidence. The constant term, μ_j in eq. (1), also known as *genuine effect*, is an estimate of the true effect corrected for publication bias. Testing for the null hypothesis of no genuine effect ($H_0 : \mu_j = 0$) in equation (1) is called the precision effect test (PET). Hence, the MRA specification in (1) is also known as the *Funnel Asymmetry Test-Precision Effect Test* (FAT-PET).

A more recent conditional meta-regression approach has been shown to further reduce the effect of publication selection bias (Stanley and Doucouliagos, 2014). This approach is a hybrid between the conventional Egger regression, in eq. (1), and a meta-regression that uses the estimate's variance as a moderator variable in place of its standard error (Stanley and Doucouliagos, 2014, 2017):

$$y_{ij} = \mu_j + \delta(SE_{ij})^2 + \epsilon_{ij} \tag{2}$$

It has been shown that the MRA model in eq. (1) has smaller bias when the Precision Effect Test (PET) finds no genuine empirical effect (*i.e.*, fails to reject $H_0 : \mu_j = 0$), while the MRA model in eq. (2) has smaller bias when PET finds a genuine empirical effect (*i.e.*, rejects $H_0 : \mu_j = 0$). Therefore, when the conventional t-test of $H_0 : \mu_j = 0$ from the model in eq. (1) is rejected, the model in eq. (2), also dubbed as "PET-PEESE" model, is used to estimate μ_j. Otherwise, the estimate of the genuine effect from the MRA model in eq. (1) is retained.

To accommodate Type II publication bias, a simple revision of the previous FAT-PET model in (1) is required (Stanley and Jarrell, 2005). Publication selection might be indifferent to the direction of the empirical effect but it may relate to the statistical significance of the relationship (i.e., Type II publication bias). In this case, the magnitude of the reported effect is expected to depend on SE. Thus, to test for the possible presence of Type II publication bias, we reformulate eq. (1) as follows

$$|y_{ij}| = \mu_j + \gamma SE_{ij} + \epsilon_{ij} \tag{3}$$

Testing the null hypothesis of $\gamma = 0$ in eq. (3) allows assessing the presence of Type II publication selection bias.

Variability in the reported magnitude of APE can be attributed, apart from statistical noise, also to different research designs, functional specifications and, in general modeling choices, as well as to varying characteristics of the datasets used in the original studies. As Stanley and Jarrell (2005) argue, even if each individual study suffers to some extend from misspecification issues, their findings *"represent the best information that we have about actual economic phenomena and events"*. An MRA provides a way of quantifying the average or systematic biases introduced in empirical studies by modeling choices or the characteristics of the data and leads to the model

$$y_{ij} = \mu_j + \gamma SE_{ij} + \sum_{k=1}^{K} \beta_k x_{ijk} + \epsilon_{ij}, \tag{4}$$

where $x \in \Re^K$ is a vector of moderator variables capturing different aspects of study characteristics. This general framework incorporates two components: first, it allows the evaluation of the potential impact of heterogeneity among studies on calculated APEs, and second, it permits the examination of whether any observed asymmetry in the funnel plots can be attributed to publication bias (Stanley, 2005, 2008).[5]

An additional issue is that, if multiple estimates of the APEs reported within a study, coming, possibly, from different sub-samples, different specifications or estimation methods, are used as separate observations in the meta-regression sample, then the errors in the MRA models are not independent. Evidently, it is necessary to employ a cluster robust standard error estimation of the regression coefficients in the MRA model. However, there is no clear consensus on how clustering should be treated in cases of very unbalanced data sets (a frequently occurring phenomenon) used in MRA (Oczkowski and Doucouliagos, 2015). Following Oczkowski and Doucouliagos (2015), we

[5] Empirical effects beyond publication bias within the MRA model in eq. (4) are captured by the summation term $\mu_j + \sum_k \beta_k x_{ijk}$, which can be used to test for the existence of an underlying effect after correcting for any publication selection bias (Oczkowski and Doucouliagos, 2015).

estimate the error of the regression coefficients in the most general model in eq. (4) using the wild bootstrap cluster robust methodology (Cameron et al., 2008), which has been shown to perform well in cases where there is severe inequality between cluster sizes (MacKinnon and Webb, 2017), as in our case. Throughout, we employ the WLS estimator, where the weights are the inverse of the reported or calculated variances (squared standard errors) of the APEs.[6]

Meta-Data on Farm Technology Adoption

Sample Studies

In the agricultural economics literature, the impact of factors that affect the decision to adopt an innovation is typically quantified with the use of discrete choice models. Assuming rational behavior and well defined preferences for individual farmers, these models attempt to provide an *ex-post* evaluation of their profit maximizing decisions under different economic, social and environmental conditions and farm innovations. Since our purpose is to analyze the determinants of farmers' adoption behavior, we focus on studies that provide comparable and consistent estimates of APEs for different drivers of the technology adoption decision by rational producers. Predominantly, binary *Probit* and *Logit* models are used for the specification of the probability of adoption, with the standard practice being the assignment of the value of one to the response variable for the cases of adoption and the value of zero for non-adoption of the innovation under consideration. In addition, *censored regression* models (typically, type I Tobit) are employed to model the degree of adoption of an innovation, whereas, non-adoption is still an option for the decision maker, thus providing APEs that are comparable to the ones produced by Probit models.[7] Finally, in some instances, where more than one innovation is considered, multivariate Probit models are used providing, however, again APEs equivalent to the univariate case.[8] Hence, these four variants of the discrete choice models, which cover the vast majority of published papers in the agricultural economics literature, were included in our meta-dataset. We do not consider *multinomial* Probit/Logit models because

[6]On a different direction, Stanley and Jarrell (2005) argue that if multiple effects are examined at the same time, then one could use the system of simultaneous equations equivalent to the model in eq. (4), where the equation for one effect includes the estimates of the remaining effects as additional regressors. An alternative, less demanding approach, which does not require restrictive *ad hoc* assumptions to guarantee that the system is identified, is to employ a seemingly unrelated regression model and allow only the error terms across equations to be correlated. However, we choose to not follow such a system approach because the independent variables used in the primary studies overlap very rarely, thus leading to a dramatic reduction in the number of data points we could use.

[7]The first stage of the type I Tobit model, where the probability of non-adoption is modeled, is similar to a binary Probit model. Therefore, the obtained APEs are equivalent to the corresponding APEs obtained by the univariate Probit.

[8]Multivariate Probit models deviate from univariate Probit models in terms of the likelihood function, by allowing the error terms across equations in the latent-variable representation to be correlated. However, because the marginal distribution of each error term is univariate normal, the marginal effect on the adoption of a single innovation is similar to the case of a binary Probit.

the specifics of each technology option can alter the estimated parameters and APEs, as well as, their meaning to a great extent.[9]

To gather the meta-data of technology adoption studies, we performed an extensive search in all major academic outlets in the broader area of agricultural economics using the keywords *technology adoption + agriculture + Probit/Logit/Tobit model*.[10,11,12] Additionally, we considered only papers written in English, published prior to February 2021. During the initial screening process, we excluded papers that did not provide estimates of APEs and their associated standard errors for all independent variables or did not provide the parameter estimates along with descriptive statistics to allow their *ex-post* computation. The application of the above selection criteria resulted in a sample of 163 empirical studies, published in 32 different academic outlets between 1985 and 2021 (see Table 1).[13] Several of these studies included more than a single dataset from different areas or for different farm innovations. Reviewing these studies, we identified 33 different explanatory variables employed by scholars to explain farmers' innovative behavior using different units of measurement or proxies.[14] The extensive list of variables is reported in Table A.2 in Appendix A. However, a proper meta-analysis requires a meta-dataset with a significant number of studies (Balima et al., 2020). Therefore, from this set of explanatory variables, we retained only those with more than 50 observations under a common measurement scheme. Hence, we ended up with the 11 explanatory variables listed in Table 2 (highlighted in Table A.2). This process, however, restricted our meta-dataset to 139 papers, as 24 papers did not employ the pre-selected explanatory variables with comparable units of measurement (second column of Table 1).

Next, for studies that do not report APEs and their standard errors, we calculated them for each of the 11 explanatory variables using the formulas appearing in Appendices B and C.[15] During this process, we found 17 papers producing standard errors close to zero for some or all of the explanatory variables used in their analysis.[16] This further restricted our dataset to 122 papers (last column in Table 1) with different number of observations for each explanatory variable (Table 2). Farmer's age, together with farm size, are the most frequently used explanatory variables among studies (185 and 161 observations, respectively). Extension services and farmer's educational level are also common variables, but are operationalized using different units of measurement or discrete categories across

[9]Searching in the same journals, multinomial models account for less than 2% of the published papers.

[10]The literature search and the subsequent analyses are in line with the guidelines by the *Meta-Analysis for Economics Research Network* (Stanley et al., 2013).

[11]The list of journals, together with their abbreviations, appears in the body and footnote of Table A.1 in Appendix A.

[12]Additionally, we searched in web search engines, such as *Google Scholar*, *Web of Science* and *Scopus* using the same keywords, without any difference in the final outcome.

[13]The full reference list of those studies is presented in Appendices F and G.

[14]This figure refers to the number of different adoption determinants appearing in at least five adoption studies.

[15]In the cases where both APEs and their standard errors are reported in a study, we use the reported values.

[16]Standard errors lower than 10^{-12} are considered to be zero and they are excluded from our analysis.

studies, which prevents further analysis, as the APEs themselves have non-comparable units of measurement. Tables A.3, A.4, and A.5 in Appendix A provide a general description of our final meta-dataset. Agricultural Economics, Food Policy, Agricultural Systems, American Journal of Agricultural Economics, and Journal of Agricultural Economics are the outlets that collectively published approximately 50% of the studies. It is worth mentioning that 78 out of the 122 studies were published after 2010, while it is also evident that more recent studies follow a common set of explanatory variables to explain adoption behavior among farmers. Finally, US agriculture together with the African continent are the main focus of this vast literature in agricultural economics.

Outcome Variable and Standard Errors

Various effect size measures have been proposed as outcome variables by MRA studies, with the most often used ones in economic literature being the correlation coefficient and the marginal effect or elasticity (Oczkowski and Doucouliagos, 2015). Among these two classes of effect size measures, the partial correlation coefficient is commonly preferred by researchers, mainly because it requires information only on the *t-ratio* and the degrees of freedom associated with the estimate under examination. As a result, computational complexities and data requirements are considerably lower and more estimates are commonly available for meta-analysis than if using marginal effect or elasticities. Moreover, the correlation coefficient has a common interpretation that renders it comparable across studies. On the other hand, marginal effect and elasticity measures, albeit computationally costly, can provide more precise information on the quantitative effect of the variable under investigation and therefore, may be of greater relevance to policy makers and practitioners.

Because our focus is on synthesising existing scientific evidence on the drivers of technology adoption in agriculture with the primary aim to inform evidence-based policy-making, we choose to use the APE measure as the outcome variable of our analysis, at the expense of bearing the computational cost associated with the estimation of the APEs and their standard errors for each study in our meta-sample for which APE estimates are not reported. Because the basic variants of the discrete choice models used by studies provide equivalent APEs covering the vast majority of published papers in the field, APE estimates are directly comparable across adoption studies and the number of estimates omitted from our meta-dataset because of this choice is relatively low.[17] Hence, within the context of our analysis, the APE measure seems to exhibit some of the desirable properties of the correlation coefficient measure (common interpretation and high availability of estimates), while, at the same time, provides information on the magnitude of policy-relevant effects.

[17] Broadly speaking, comparisons of marginal effect or elasticity estimates may prove challenging, mainly because empirical studies are likely to employ different functional forms, i.e. production function approaches. However, such differences in functional forms are not common in adoption studies relying on discrete choice models.

Figure 1 presents the distribution of APEs in the form of box-plots for the eleven determinants examined in our MRA study, as those were either reported in the primary studies or calculated using the formulas presented in Appendix B. Because most of these variables are measured in different units, the corresponding box-plots are not comparable between them, with the exceptions of the five determinants specified as binary variables (i.e., farmer's gender, membership in association, extension visits, access to credit, and off-farm income) for which comparisons of APEs are meaningful. Starting with these five determinants, the visual examination of the box-plots indicates a positive and relatively high median APE for membership in associations and extension visits variables and a median APE close to zero for farmer's gender, access to credit, and off-farm income variables. The APE estimates for membership in associations and extension visits appear to have wider inter-quartile spreads, with the middle 50% of estimated APEs in our meta-sample being positive for these two determinants. Estimated APEs for access to credit and off-farm income variables appear to have similar variability and following a right-skewed distribution, while the distribution of APE estimates for farmer's gender appears to be fairly symmetric. Although the statistical significance of estimated APEs is ignored in these box-plots, they may provide a preliminary summary of the existing scientific evidence revealing a tendency in the literature for positive marginal effects of membership in associations and extension visits variables on farmer's probability to adopt an innovation. In general, these effects tend to be higher and more variable in magnitude relative to the corresponding effects of farmer's gender, access to credit, and off-farm income.

Concerning the remaining six determinants considered in our MRA, the visual inspection of the box-plots indicates that approximately 75% of estimated APEs in our meta-sample are positive for farmer's education and herd size, implying a positive median for these variables, and negative for farmer's age and distance to the market variables. Moreover, roughly 50% of estimated APEs are positive for household and farm size variables, presenting a median close to zero. The distribution of APE estimates is skewed to the left for farmer's age and distance to market variables and right-skewed for the remaining four determinants. These results provide preliminary evidence that existing empirical work tends to document a positive impact of education on farmer's probability to adopt, with the relative long right tail indicating the presence of positive APEs of high magnitude. On the contrary, existing studies tend to identify a negative impact of farmer's age on adoption rates, with the longer left tail suggesting the presence of negative estimates of high magnitude.

Because differences in APE estimates across countries or over time are commonly of interest to policy makers and researchers, we further examine the mean values of estimated APEs for each country and for every time period for which estimates are available (See Tables D.1 and D.2 in Appendix D). As expected, the mean values of estimated APEs vary across countries and over time periods in our meta-sample. However, the simple comparison of the means does not reveal any clear patterns for the majority of the eleven determinants under investigation. Yet, four interesting observations can be made. First, the APE of extension services on the probability to adopt is non-negative in all countries (apart from Mexico) and in almost all years for which estimates are available.[18] This robustness in the sign of estimates is not met for the other determinants considered. Second, the impact of education on the probability to adopt is non-negative in every period until 2016, but negative, on average, afterwards. This pattern may reflect either a possible presence of publication bias in the early (or recent) years or the presence of heterogenous genuine effects. Third, the effect of farmer's age on the probability to adopt is non-positive in developed countries, while results can be characterized as mixed in developing countries. Lastly, farmer's gender, membership in associations, and access to credit are not included as explanatory variables in adoption studies focusing on developed counties, but they are commonly considered as potential drivers of adoption in studies focusing on developing countries.

Figure 2 presents the distribution of the standard errors of the APEs in the form of box-plots as those were estimated using the formulas presented in Appendix C. Comparing the distribution of the standard errors with the distribution of their corresponding APEs in Figure 1 for each determinant factor provides insights for the relative statistical significance of the eleven variables, as this is documented in existing studies in our meta-sample. The inter-quartile range of standard errors for farmer's education, herd size, and membership in associations variables appear to be narrower compared to the inter-quartile range of the associated APEs, indicating that existing empirical work tends to identify a statistically significant effect of these variables on the probability to adopt. On the contrary, the inter-quartile range of standard errors for farmer's age and gender variables appear wider than those of their corresponding APEs, suggesting a tendency for statistically insignificant effects of these variables on adoption rates.

Sources of Heterogeneity: Moderator Variables

We now discuss various moderator variables capturing different aspects of study characteristics that may explain the observed heterogeneity in APE estimates across studies. As in any regression model, failing to account for important variables is likely to result in omitted variable bias, leading to mis-estimation of the genuine APE of a factor on the probability of adoption. On the contrary, if the number of moderator variables is large relative to the number of observations in the meta-sample, estimates may become unstable and collinearity issues are more likely to arise. It is essential, therefore, to retain a balance when it comes to the choice of the moderators included in our analysis.

[18] Tables D.1 and D.2 report the mean values for estimated APEs without taking into account their statistical significance. Therefore, these observations may be misleading and should be treated with caution.

Following the relevant literature in the field (Ruzzante et al., 2021; Havranek et al., 2018), we group the characteristics of the studies into four broad categories, namely: *Data and Model Characteristics*, *Sample Composition*, *Type of Farm Technology*, and *Publication Characteristics*. Data and model characteristics are commonly assumed to play a key role in any empirical study. We account for differences in such attributes in four dimensions. First, heterogeneity in APE estimates may reflect differences in the time spans covered by adoption studies, as the impact of the various determinants on the probability to adopt is likely to alter over time depending on the changing socio-economic conditions under which farm households make their adoption decisions (Feder and Umali, 1993). To test the sensitivity of estimated APEs to time, we introduce the year of data collection of the studies as a moderator variable in our analysis, tagged as *Year of Survey*. Second, it is commonly agreed that larger samples provide more reliable estimates with greater precision and power and, therefore, sample size differences may constitute a significant source of variation in APE estimates. To account for this type of heterogeneity, we include the number of observations in the dataset of the studies as an additional moderator in our MRA model, labelled as *Sample Size*. Third, heterogeneity in estimates may be further attributed to differences in the specification of the vector of explanatory variables considered by adoption studies, as this choice may influence the extent to which the estimates are free of omission bias (Ruzzante et al., 2021). We factor in the role of model specification by considering the number of explanatory variables used in the regression model of the studies as a moderator variable, labeled as *No of Variables*, assuming that the higher the number of the covariates included, the more likely it is that the most important variables have been considered. Lastly, although the different variants of discrete choice models provide equivalent APEs, the possibility that the choice of the model influences APE estimates cannot be ruled out since this choice may reflect certain preferences of the authors towards specific research designs. To factor in the role of model choice, we introduce a binary variable in our analysis, tagged as *Probit Model*, that takes the value one for studies using a binary Probit, multivariate Probit or Type I Tobit model, and zero otherwise.[19,20]

With the term *sample composition*, we refer to the characteristics of the country in which empirical research on adoption behavior is conducted. Country's economic attributes, such as the level of economic development and the degree of openness of the economy, along with human

[19] Initially, three binary variables were included in the vector of moderator variables to account for differences in the four variants of discrete choice models, with the reference category being the Logit model. However, the number of studies in our meta-dataset using multivariate Probit and Tobit models was considerably low. Therefore, we grouped binary Probit, multivariate Probit and Type I Tobit in one category.

[20] It is common in MRA studies in economics to accommodate additional moderators aiming to account for differences between studies related to: 1. the way a study handles potential endogeneity and selectivity bias issues, and 2. the nature of dataset used, i.e., time-series, cross sectional, or panel datasets. However, within the context of our analysis, it was not possible to model the impact of such moderators because the number of studies in our meta-sample dealing with endogeneity issues or utilizing panel or time-series data was considerably low.

capital levels are known to be critical factors for the diffusion of new innovations, especially at the early stages of the adoption process. Therefore, estimated APEs are expected to vary across studies depending on the socio-economic characteristics of the country in which research is applied. Because such differences in country's attributes may have important policy implications, we pay special attention on this potential source of heterogeneity by investigating various dimensions of countries' characteristics. Differences in the levels of economic development across countries is probably the most often cited source of variation in APE estimates across studies (Feder et al., 1985; Feder and Umali, 1993). To account for differences in development levels, we include real *GDP per capita* and the *Share of Agricultural Sector in GDP* in the vector of moderator variables, both as observed at the year of the survey, assuming that the economic environment in a country, as captured by real income and the degree of industrialization, may affect rural households' adoption behavior.[21] In addition, hererogeneity in APE estimates may be explained in part by differences in human capital levels across countries. Human capital is known to improve the resource allocation skills and the informational set of farm operators and, therefore, may enhance the efficiency of adoption decisions (Nelson and Phelps, 1966; Huffman, 1977). To examine whether the APE estimates of the various determinants depend on human capital levels, we include in our analysis the average years of total schooling at the country level, as observed at the year of the survey, tagged as *Human Capital*. Finally, factors related to the openness of the economy could also explain the variations in APE estimates across studies since the transfer of new technologies and the knowledge related to the new technologies is commonly associated with the degree of economic extraversion of a country (Almeida and Fernandes, 2008). We factor in the role of economic openness by introducing two moderator variables: the foreign direct investments inflows as a share of GDP (tagged as *Share of FDI in GDP*) and the sum of exports and imports as a share of GDP (tagged as *Trade Openness*), both as they are observed at the year of the survey.

A rather interesting research question that has received less attention in the relevant literature is whether the impact of the various determinants on the probability to adopt depends on the type of agricultural technology under investigation. Common reasoning suggests that, for certain determinants, APE estimates are likely to vary between different agricultural technologies, while for others, APE estimates may be less dependent on the type of technology. For instance, the APE of education on the adoption of IC Technologies (*i.e.*, precision farming, smart agriculture etc) may be higher compared to other technology types, since both the tacit elements and software aspects of such technologies may prove to be more demanding in terms of human capital require-

[21]It is common in MRA studies to factor in the impact of level of development as a binary variable for developing or developed economies. However, because important differences may be present in development levels even within the same group of countries, we chose to use real GDP per capita as a more precise and informative measure of economic development.

ments (Evenson and Westphal, 1995; Rogers, 1995), constituting additional barriers to adoption.[22] Likewise, for many technologies, installation costs can be proportional to the size of the farm (*i.e.*, irrigation technologies), implying that the APE of farm size on adoption rates may be different for these technologies in comparison to technologies for which installation costs are irrelevant to the size of the farm or installation costs are relatively low. Therefore, it is necessary to examine whether there are variations in the estimated APEs that are explained by the type of technology considered in the primary studies.

Nevertheless, accounting for the type of innovation is challenging, mainly due to the great variety of technologies analyzed by adoption studies in our meta-sample, including more than 25 narrowly defined categories of agricultural technologies. Typically, the type of technology is modeled with the use of binary variables. However, including a large number of binary variables in the vector of moderators would result in overfitting problems and would exacerbate multicollinearity issues in our MRA model. Therefore, we opt to group the different types of technologies into broader categories. Towards this end, we initially considered a relatively high number of narrowly defined categories and then started experimenting with different meaningful aggregations of the various categories, while always trying to retain a significant number of observations in each category. To choose between the different aggregated categories developed, we relied then on goodness of fit measures. Following this strategy, we ended up with the following four broad categories: improved seeds tagged as *AgTech1*, soil conservation, protection and fertilization technologies tagged as *AgTech2*, ICT, feeding, breeding, organic and water-related technologies tagged as *AgTech3*, and other crop and livestock technologies tagged as *AgTech4*, with AgTech4 being used as the reference category.

Finally, publication characteristics are also likely to constitute an important source of heterogeneity in APE estimates, since qualitative differences across studies may have an impact on APE estimates. We account for differences in the quality of journals and the authors between studies in three dimensions. First, we include in the vector of moderators the Scimago Journal Rank Indicator of the journal in which the study has been published, as the index is observed at the year of publication, tagged as *SJR Index*. The SJR index is a commonly accepted measure of a journal's quality and prestige accounting for both the number of citations received by a journal and the quality of the journals where the citations come from. We use the SJR index to account for differences in journal quality because it covers virtually all journals in the field of economics while, at the same time, information for the index is available for different periods of time, thus enabling us to evaluate the quality of the journal at the year of publication of the study.[23] Second,

[22]The term *software aspects* of a new technology was introduced by Rogers (1995) and refers to the information base needed to use it efficiently.

[23]Using RePec impact factor or other indicators as a proxy for journal's quality is not expected to affect significantly the results of our study, since the construction of impact factor indexes is commonly based on the number of citations received, implying that the resulting indexes will tend to be highly correlated. More importantly, most indexes such

we account for the role of U.S. affiliation, a common practice in many MRA studies, by introducing a binary variable in our analysis, tagged as *US Co-author*, that takes the value one if one or more co-authors of the study are affiliated with a US institution, and zero otherwise. Lastly, we account for the scientific reputation of the authors by introducing the average h-index of the authors of the study obtained from Scopus, tagged as *Authrors' H-index*.

The afore-mentioned 15 variables discussed in this section are included in the vector of moderators, $\mathbf{x}$, in eq. (4). The same vector of variables is used in the regression analysis of each of the 11 determinants considered in our study.[24] Summary statistics of these variables are presented in Table 3. Some interesting findings emerge from the summary statistics. First, 58.5% of the studies in our meta-sample rely either on a Probit or a Type I Tobit model to empirically analyze the determinants of adoption decisions in agriculture, implying that Probit and Logit models are almost equally used in the empirical literature on adoption behavior. In terms of type of innovation, 27.1% of the studies analyze *improved seeds* technologies, while 31.7% and 27.5% of the studies focus on technologies related to *soil conservation, protection and fertilization*, and *ICT feeding, breeding, organic, and water*, respectively. Lastly, adoption studies utilize relatively large samples (including 1,217 observations on average), and tend to examine a quite high number of determinant factors (17 on average). Detailed information on the construction of the moderator variables and the data sources used are presented in Appendix E.

Results

Publication Bias and Genuine Effects

Figure 3 presents funnel plots of the distribution of APEs for the eleven adoption determinants considered in our MRA study. These scatter plots depict the relationship between effect size on the horizontal axis (APE estimate) and the precision of the estimate on the vertical axis as measured by the inverse of the associated standard error, i.e., $1/SE$. The visual inspection of the funnel plots may serve as an initial informal test for the possible existence of publication bias. In the absence of publication bias, APE estimates are expected to vary randomly and symmetrically around the true effect denoted by the vertical dashed red line. If publication bias of Type I is present, APE estimates are expected to be skewed to the left or right, suggesting that estimates consistent with the conventional view tend to be published more often. Moreover, if the bias is related to the statistical significance of the APE estimates, then funnels are expected to be wider and hollower. The funnel plots in figure 3 present rather skewed distributions pointing to the presence of type I publication

as the RePec impact factor is not available for earlier years.

[24]Figures D.1-D.8 in Appendix D present the distribution of estimated APEs across moderator variables in the form of box-plots.

bias for the majority of the determinants analyzed, and most notably for membership in associations (Y5), access to credit (Y7), and farm and herd size (Y9, Y10) outcome variables. Moreover, funnel plots appear rather wide and hollow for farmer's gender (Y4) and distance from the market (Y11) variables pointing to the likelihood of publication bias of Type II for these determinants. Overall, based on the visual inspection of the funnel plots, the presence of publication bias cannot be ruled out for the strong majority of determinants factors considered in our MRA study.

Because visual examination might be subjective, we further estimate the FAT-PET regression model in eq. (1) as a more formal way to empirically test for the possible presence of Type I publication bias. The coefficient estimates of this model are presented in the second-upper panel of Table 4. Results indicate that the coefficient of standard error variable is statistically insignificant in farmer's education (Y2), household size (Y3), and off-farm income (Y8) regression equations, and statistically significant in the remaining 8 regression models, thus pointing to the presence of type I publication bias for the strong majority of determinants considered in our MRA analysis. This finding is consistent with the results obtained from the visual inspection of the funnel plots, indicating that publication selection bias is present in the literature on technology adoption. Concerning the direction of the publication bias, our results indicate that the coefficient of standard error variable is positive in farmer's age (Y1), membership in associations (Y5), access to extension services (Y6), access to credit (Y7), and herd size (Y10) regression equations, indicating that the corresponding APEs are positively skewed, which in turn implies that negative APE estimates for these determinants tend to be under-reported in the adoption literature. On the contrary, the coefficient of standard error is negative and statistically significant in farmer's gender (Y4), farm's size (Y9), and distance from the market (Y11) regression equations suggesting that positive APE estimates for these determinants tend to be under-reported by adoption studies in our meta-sample.

To investigate whether publication bias of Type II is present in the adoption literature, we estimate the MRA model in eq. (3) for each determinant considered in our analysis. This model is the same with the FAT-PET model using though the absolute value of APE as dependent variable. The coefficient estimates of this model are presented in the fourth-upper panel of Table 4. Results indicate that household size (Y3), and access to off-farm income (Y8) variables which were found earlier to be free of type I publication bias, are subject to type II publication bias as the coefficient of standard error variable is found to be statistically significant in the regression equations of these determinants. The same result holds for all determinants considered in our MRA study with the exception of farmer's education variable for which no statistical evidence was found in favor of Type II publication bias. However, this strong evidence in favor of the presence of publication bias might simply reflect heterogeneity in genuine effects which may induce asymmetries into the funnel plots even in the absence of publication selection bias.

Regardless of whether publication selection is directional or relates to the statistical significance, the MRA model is expected to properly filter out systematic biases in empirical findings. The statistical significance of the constant term of the FAT-PET regression model reported in the second-upper panel of Table 4 can serve as a formal test for the presence of a global genuine effect for each determinant factor. Comparing the genuine effects obtained from this model (FAT-PET Model) with the uncorrected effects reported in the first-upper panel of Table 4 provides insights on how publication bias might have distorted empirical findings in the adoption literature. Results from the uncorrected model indicate that all determinants apart from farmer's age have a significant effect on adoption rates. Nonetheless, after correcting for publication bias (FAT-PET Model), insignificant constant terms are also documented for membership in associations (Y5), access to credit (Y7), farm's size (Y9), and distance from the market (Y11) outcome variables, pointing to the absence of a global genuine effect of these determinants on adoption rates.

For the determinants for which the constant term is found to be statistically significant in the FAT-PET model, the PET-PEESE model in eq. (2) is also estimated using the the square of standard error as independent variable in place of standard error. More specifically, when there is evidence of a genuine effect (statistically significant constant terms in FAT-PET model), the constant term of the PET-PEESE model is used as a more precise estimate of the genuine effect. The estimation results of the PET-PEESE model are presented in the third upper-panel of Table 4. Results indicate that the constant terms in farmer's education (Y2), household size (Y3), access to extension services (Y6), and herd size (Y10) regression equations are positive and statistically significant providing clear evidence of a positive genuine effect of these determinants on the probability to adopt. On the contrary, the constant term of farmer's gender (Y4) and access to off-farm income (Y8) variables is negative and statistically significant suggesting that male farmers with access to off-farm income are less likely to adopt new innovations. Overall, our findings suggest that at the global level educational and training programmes offering farm advice and extension services for individual farmers along with promotional programmes encouraging women's engagement in farming activities or women's representation in farm managerial positions may serve as effective policy instruments towards stimulating the adoption of new agricultural technologies. On the other hand, policy programs directed to younger farmers along with programs aiming to encourage farmers' participation in associations, or provide financial assistance to farmers in the form of facilitating access to credit might not be as effective as previously thought in boosting the diffusion of new agricultural technologies, at least at the global level.

Given the focus of MRA study, it is important to examine potential heterogeneity in the genuine effects of the various determinants between groups of countries and time periods, by analyzing separately findings from studies in our meta-dataset that use relatively comparable samples. To this end, we split collected studies in our meta-sample into more homogenous groups based on *(i)* the continent in which empirical research on adoption behavior is conducted and *(ii)* the time-span covered considering two periods: 1985-2009 and 2009-2021. Because the resulting groups are relatively homogenous, we rely on the estimation of the FAT-PET regression model in eq. (1) to investigate the presence of heterogeneity in genuine effects between continents and time-periods. The constant terms of the FAT-PET regression model for each sub-sample of studies are presented in the lower two panels of Table 4. Results reveal significant differences in genuine APEs across continents for all eleven determinants considered in our analysis, implying that, in order to be effective, policy actions need to be taken on a case-by-case basis.

More specifically, our findings suggest that policy programmes aiming to promote women's engagement in farming, enhance farmer's membership in associations, and facilitate farmers' access to credit, along with programs offering farm advice directed to larger farmers are all effective policy instruments towards accelerating the diffusion of new agricultural innovations in African countries. However, results provide a quite different picture for countries in Asia and Oceania suggesting that distance from the market is a significant barrier of adoption in these countries and pointing to farmer's education, and access to credit as the only significant drivers of technology adoption. Concerning South and Central American countries, results suggest that policy programmes directed to older and larger households along with training programs aiming to enhance farmer's human capital are the most fruitful pathways to increase farmer's probability of adoption in these countries. On the contrary, policy programmes focusing on larger livestock farmers who do not have access to off-farm income are more likely to serve as effective means towards boosting technology adoption rates in countries of North America. Regarding findings on the heterogeneity in the genuine effects of the various determinants between time periods, two notable observations can be made. First, the genuine APE of farmer's age on the probability of adoption is negative in early years, and zero after 2009. Second, the genuine APE of education, membership in associations, extensions services, and access to credit is zero in the early year but turn out to be positive in the recent years, suggesting that current policies focusing on these determinants may serve as effective policy instruments towards accelerating diffusion rates.

Study Attributes - Sources of Heterogeneity

Table 5 presents the WLS estimates of the MRA model in eq. (4) accounting for heterogeneity in study attributes. P-values for the reported coefficients have been computed using cluster robust wild bootstrapping techniques. Because nonzero continuous variables have been included in the vector of covariates (such as the real GDP per capita), the coefficient of the constant term does not have a meaningful interpretation in this model and therefore should not be treated as an estimate of the APE corrected for selection bias. Starting with the coefficient of standard error variable, results indicate statistically significant parameters for the strong majority of determinants considered in our MRA study. This implies that selection bias persists even after heterogeneity in study characteristics is modelled. Hence, we may conclude that the asymmetries observed in the funnel plots for the strong majority of determinants can be attributed both to publication bias and heterogeneity in study characteristics. It is also worth mentioning that the coefficient of standard error in farmer's education model (Y2) turns out to be positive and statistically significant once accounting for differences in study attributes. Recall that the APE of farmer's education was found to be free of publication bias based on the funnel asymmetry test (FAT).

Estimates in the second panel of Table 5 show that data and model characteristics are important factors in explaining heterogeneity in APE estimates across studies. More specifically, we find that the year of survey of the studies is positively correlated with the magnitude of APE in farmer's age (Y1), and farm and herd size (Y9 and Y10) equations, while exhibiting a negative correlation with estimated APE in farmer's education (Y2), farmer's gender (Y4), membership in associations (Y5), access to extension services (Y6), and off-farm income (Y8) equations, suggesting that the impact of the former (latter) set of determinants on adoption rates increases (declines) over time. As expected, sample size emerges also as an important explanatory variable of observed heterogeneities in APE estimates in fairly all regression models (apart from distance from the market-Y11), implying that the size of the sample has a significant impact on the APE estimates of the various determinants. Likewise, the number of variables considered in primary studies is found to be negatively correlated with the magnitude of APE estimates for five determinants, namely, household size (Y3), farmer's gender (Y4), membership in associations (Y5), access to extension services (Y6), and herd size (Y10), implying that adoption studies considering a relatively low number of explanatory variables may over-estimate the impact of these determinants on farmer's probability to adopt. Finally, results show that the choice of the econometric model used in primary studies matters for the magnitude of estimated APEs for the majority of determinants factors.

Estimation results presented in third panel of Table 5 point to the existence of systematic differences in APE estimates between adoption studies focusing on countries with different economic attributes. Most notably, we find that the APE of farmer's age (Y1) and farmer's education (Y2) on the probability to adopt decreases as the level of development of a country increases, implying that the magnitude of APE for these two outcome variables on adoption rates is higher in less developed regions. For most of the remaining determinants, results suggest a positive relation between APE estimates and country development levels as the latter is captured by real GDP per capita variable. Moreover, controlling for human capital levels decreases the magnitude of APE estimates for most determinants, implying that the magnitude of APE estimates for the majority of outcome variables is lower in countries with high levels of human capital. On the contrary, controlling for the trade openness and the degree of industrialisation of the country increases the magnitude of the APE estimates for the strong majority of determinants considered, suggesting that the degree of economic extraversion and industrialisation of a country is non-negatively correlated with the magnitude of APE estimates.

Differences in the types of agricultural technologies analyzed by primary studies is not found to make any significant difference to the magnitude of estimated APEs on adoption rates, at least for the majority of determinants considered (see fourth panel of Table 5). Nonetheless, two important conclusions can be drawn based on the WLS estimates. First, studies analyzing ICT, feeding, breeding, organic and water technologies (AgTech3) report higher effects of farmer's education and off-farm income variables on adoption rates. Second, the APE of extension services on adoption rates is higher in studies analyzing improved seeds technologies (AgTech1) and soil conversation, protection and fertilization technologies (AgTech2).

Finally, publication characteristics are also found to play an important role in the magnitude of the estimated APEs for the strong majority of determinants analyzed (lower panel of Table 5). In particular, estimation results suggest that studies published in high-quality journals (higher SJR score) tend in general to report APE estimates of lower magnitude, while studies co-written with at least one US author find higher effects of farmer's education and farm size on adoption rates and lower APEs for the majority of the remaining determinants. Moreover, authors' h-index is found to constitute a significant source of heterogeneity in the APE estimates of the various determinants (apart from access to credit-Y7, farm size-Y9, and distance from the market-Y11) with the direction of its effect on APE estimates depending on the determinant analyzed.

Conclusions

In this paper, we employed an MRA approach to synthesise the diverse and often conflicting findings of the empirical literature on the drivers of technology adoption behavior in agriculture. Focusing on the average partial effects of the eleven adoption determinants that most often appear in empirical studies, we constructed a broad dataset of estimated APEs from 122 adoption studies published in 24 peer-reviewed journals since 1985, covering farmer's adoption behavior around the world and for a wide variety of agricultural technologies. Using this broad meta-dataset, we investigated whether each of the eleven determinant factors considered in our meta-analysis has a genuine effect on technology adoption rates. Moreover, we examined whether publication selection bias is one of the drivers of observed asymmetries in APE estimates and identified the sources of heterogeneity in reported estimates.

We found that the empirical literature on the technology adoption in agriculture suffers from two types of publication bias. First, researchers in the field have a preference towards reporting APE estimates with expected signs (Type I publication bias). This finding is verified for the strong majority of determinants analyzed. Second, researchers tend to promote results with higher statistical significance (Type II publication bias). This finding is verified for fairly all determinants considered in our MRA study. Moreover, we found that publication selection bias persists even after controlling for heterogeneity in study attributes, indicating that selection bias is an important issue in the literature on technology adoption accounting for observed asymmetries in APE estimates.

Once filtering out systematic biases in empirical findings, we found insignificant genuine effects for membership in associations, access to credit, farm's size, and distance from the market variables, pointing to the absence of a global genuine empirical effect of these variables on adoption rates and suggesting that policies aiming to these variables might not be as effective as previously thought in boosting the diffusion of new agricultural technologies, at least at the global level. In addition, we found clear evidence that farmer's education, household size, access to extension services, and herd size have positive genuine effects on farmer's probability to adopt, while farmer's gender and access to off-farm income exhibit negative genuine effects on adoption rates.

We next examined whether differences exist in the genuine APEs of the various determinants between groups of countries and time periods by analyzing separately findings from studies in our meta-dataset that use relatively comparable samples in terms of countries and time periods analyzed. We found evidence in favor of the presence of significant differences in genuine APEs across continents for all eleven determinants considered in our analysis, implying that, in order to be effective, policy actions need to be taken on a case-by-case basis. In addition, we found that the genuine effects of farmer's education, membership in associations, access to extensions services, and access to credit variables are positive in the recent years, suggesting that current policies focusing on these determinants may serve as effective policy instruments towards accelerating diffusion rates.

Finally, we examined whether observed asymmetries in APE estimates can be further attributed to differences in the characteristics of the primary studies, by introducing four set of covariates in our MRA analysis, namely, data and model characteristics, sample composition, type of farm technology, and publication characteristics. We found that sample size differences across studies play an important role in explaining heterogeneity in APE estimates in fairly all determinants, and that adoption studies considering a relatively low number of explanatory variables may overestimate the impact of certain determinants on adoption rates. Moreover, we found that as the level of development of a country increases, the APE of farmer's age and farmer's education on the probability to adopt decreases while the APE of the majority of the remaining determinant increases as well. In addition, our results indicated that controlling for the trade openness and the degree of industrialisation of the country increases the magnitude of the APE estimates for the strong majority of determinants considered, suggesting that the degree of economic extraversion and industrialisation of a country is non-negatively correlated with the magnitude of APE estimates.

We did not find strong evidence that the type of agricultural technology analyzed by primary studies matters for the magnitude of estimated APEs on adoption rates, at least for the majority of determinants considered. Nonetheless, we found that studies analyzing ICT, feeding, breeding, organic and water technologies report higher effects of farmer's education and off-farm income variables on adoption rates while the APE of extension services on adoption rates is higher in studies analyzing improved seeds technologies and soil conversation, protection and fertilization technologies. Lastly, we found that publication characteristics are critical factors affecting the magnitude of the estimated APEs for the strong majority of determinants analyzed. Most notably, we found that studies published in high-quality journals tend in general to report APE estimates of lower magnitude, while studies co-written with at least one US author find higher effects of farmer's education and farm size on adoption rates and lower APEs for the majority of the remaining determinants.

Tables and Figures

Table 1: Number of Papers Using Probit, Tobit or Logit Adoption Models Included in the Meta-Regression Analysis

Outlet	No of Papers:[1] providing necessary data to compute APE&SE[2]	reporting the pre-selected variables[3]	with non-zero APE&SE estimates[4]
ABF	10	9	9
AGK	2	2	2
ARER	7	4	3
AE	26	22	20
AS	10	10	10
AHV	1	1	1
AFS	2	2	2
AJAE	15	12	9
CJAE	1	1	1
DSA	1	1	1
EDCC	2	2	2
EINT	2	2	0
ERE	1	0	0
ERAE	2	2	2
FP	18	17	13
IJAE	5	5	5
IFAMR	1	0	0
JAgB	1	0	0
JAAE	7	6	6
JARE	3	3	3
JAE	11	9	9
JDE	2	1	1
JDS	4	4	3
JSA	4	2	1
LE	1	0	0
PA	1	1	0
QJIA	3	3	3
RAE	1	1	0
RDE	4	3	3
TFSC	1	1	0
AJARE	6	6	6
WD	8	7	7
Total	163	139	122

[1] We initially search for papers using only (univariate or multivariate) Probit, Logit or type I Tobit models.
[2] Includes papers that provide either APE and SE for all explanatory variables or provide parameter estimates together with descriptive statistics to compute them.
[3] Includes papers that among their explanatory variables are all or some of those included in our MRA shown in Table 2.
[4] Includes papers that the computed APE and SE were non-zero as presented in Table 2.

Table 2: List of Variables Included in the Meta-Regression Analysis

Variable		Units of Measurement	Obs	Papers
Y1	Farmer's age	in years	185	95
Y2	Farmer's education	in years of schooling	83	55
Y3	Household size	No of household members	85	48
Y4	Farmer's gender	dummy indicating male	95	50
Y5	Membership in groups, unions or associations	dummy indicating membership	61	37
Y6	Access to extension services	dummy indicating access	62	33
Y7	Access to credit	dummy indicating access	70	47
Y8	Access to off-farm income	dummy indicating access	70	29
Y9	Farm size[1]	in Ha, Acres, Mu, etc	161	86
Y10	Herd size[1]	in TLU or No of animals	80	33
Y11	Distance to the market	in km	88	38

[1] Converted to a common unit of measurement.

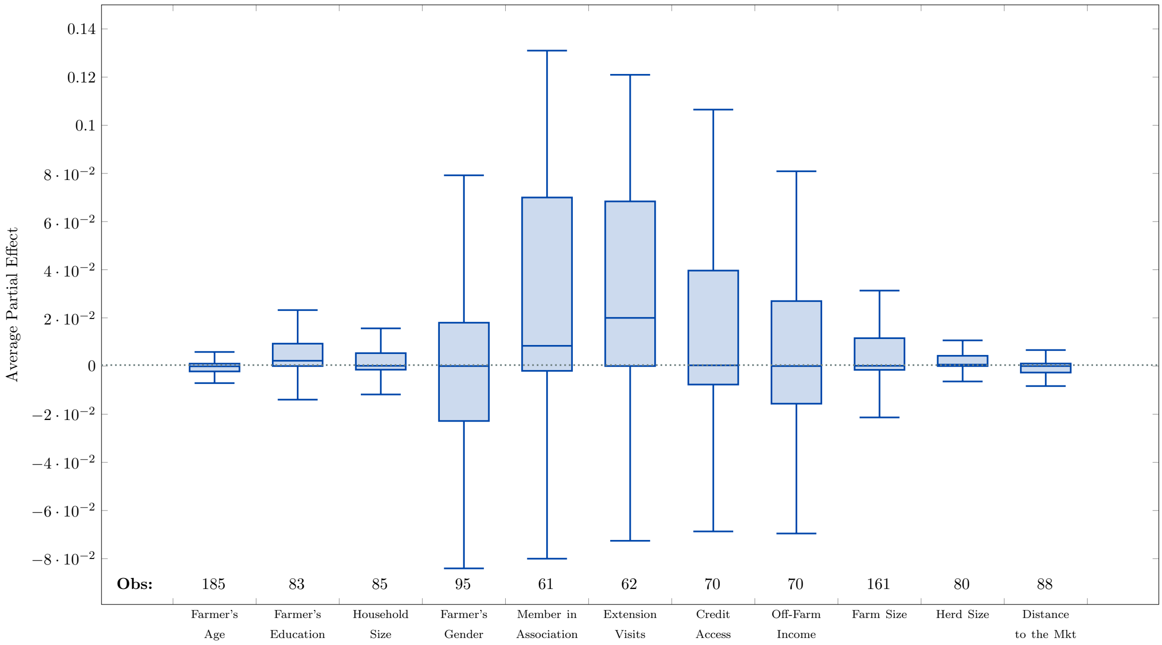


Figure 1: **Calculated APE**. Average partial effects for each variable were estimated using the formulas presented in Appendix B for each study included in the meta-regression analysis. Separate box plots on average partial effects are shown for each variable.

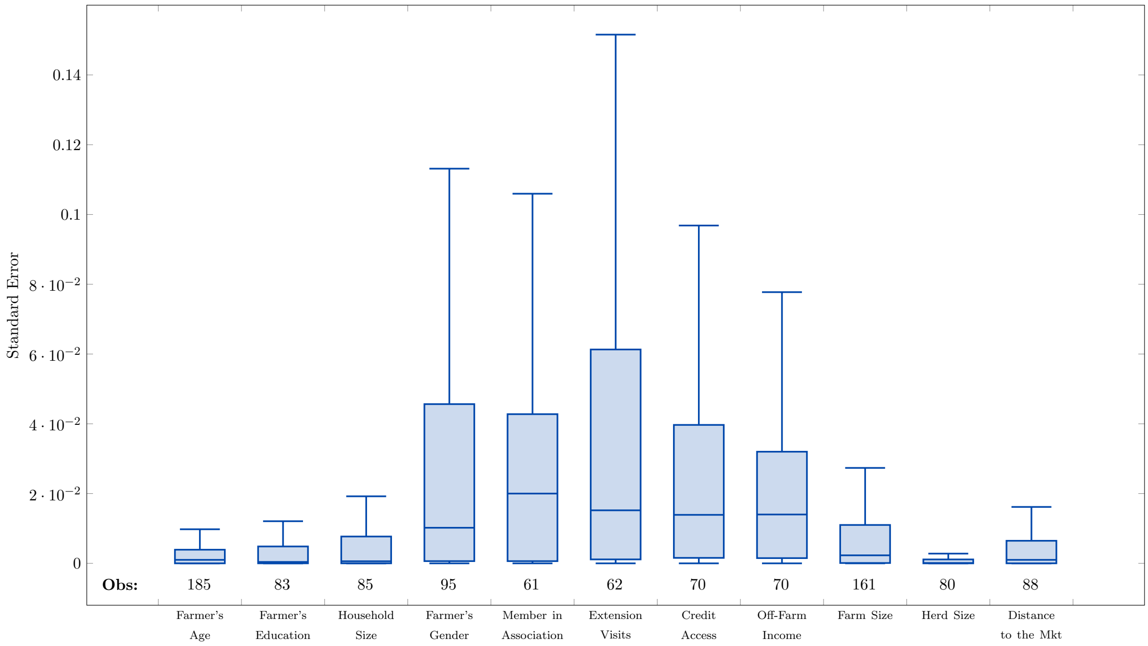


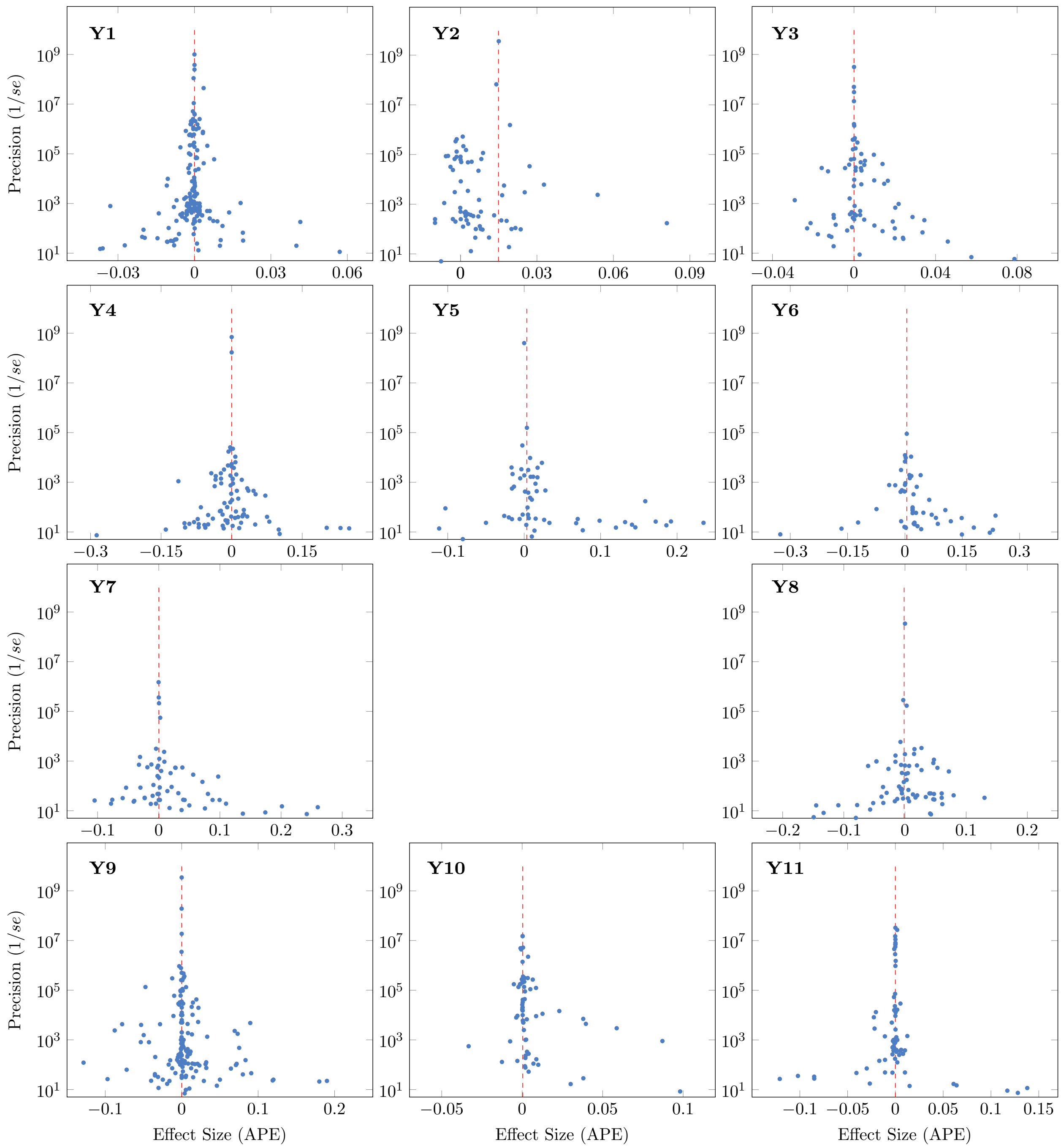
Figure 2: **Calculated Standard Errors**. Standard errors for each variable were estimated using the formulas presented in Appendix C for each study included in the meta-regression analysis. Separate box plots on these standard errors are shown for each variable.

Table 3: Summary Statistics of the Moderator Variables used in the Meta-Regression Equation

Variable	Statistics			
	Mean	Minimum	Maximum	StDev.
Data & Model Characteristics				
Year of Survey	2007	1979	2019	7
Sample Size	1,217	114	11,051	1,987
No of Variables	17	4	37	7
Probit Model[1]	the 58.5% of the observations			
Sample Composition				
GDP per capita	17,418	659	58,860	21,862
Share of Agricultural Sector in GDP	17.3	1.0	60.2	13.8
Human Capital	7.6	1.0	13.3	3.8
Share of FDI in GDP	2.7	-0.5	25.5	2.7
Trade openness	50.7	19.8	165.1	26.0
Type of Farm Technology				
Improved seeds	the 27.1% of the observations			
Soil conservation, protection & fertilization	the 31.7% of the observations			
ICT, feeding, breeding, organic & water	the 27.5% of the observations			
Other crop and livestock techs	the 13.8% of the observations			
Publication Characteristics				
SJRank Index	0.972	0.144	2.189	0.555
US Co-author	the 23.1% of the observations			
Authors' H-index	15.1	1.0	48.0	8.1

[1] It includes type I Tobit and multivariate Probit models.

Figure 3: Funnel Plots of Calculated APE



Note: **Y1:** farmer's age, **Y2:** farmer's education, **Y3:** household size, **Y4:** farmer's gender, **Y5:** membership in groups, unions or associations, **Y6:** access to extension services, **Y7:** access to credit, **Y8:** access to off-farm income, **Y9:** farm's size, **Y10:** herd size, and **Y11:** distance from the market.

Table 4: Uncorrected Combined and Genuine APE and Publication Selection Bias Tests

Variable	Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8	Y9	Y10	Y11
Uncorrected Combined APE [a]											
Constant	-0.00003	1.48786*	0.00057*	-0.00388*	0.33703*	0.47892*	0.01337*	-0.13907*	0.00022*	0.02901*	-0.00661*
Type I Publication Bias and Genuine APE: FAT-PET Model [b]											
Constant	-0.00006	1.55689*	0.00057*	-0.00388*	0.33565	0.47606*	0.01231	-0.14207*	0.00022	0.02771*	-0.00645
Standard Error	672.834*	-498.369	-5.08412	-4.92001*	1.51213*	1.63504*	2.93106*	6.83214	-61.0032*	140.909*	-12999.2*
Genuine APE: PET-PEESE Model [c]											
Constant		1.48786*	0.00057*	-0.00389*		0.47892*		-0.13906*		0.02901*	
(Standard Error)^2		-0.82549	0.54965	-0.02816*		0.43566*		-0.10977		0.96605*	
Type II Publication Bias [d]											
Constant	0.00013	1.58771*	0.00079*	-0.00388*	0.34971	0.47292*	0.01104	0.27809	0.00021	0.03132*	0.00645
Standard Error	1466.527*	-434.405	94.5654*	14.0209*	8.69303*	5.37924*	6.90925*	8.18477*	163.089*	247.498*	13005.8*
Genuine APE per Continent: PET Model [b]											
Africa	-0.00003	-0.03360	0.00058	-0.00388*	0.35427*	0.47706*	0.23175	0.26838*	0.00022*	0.04221*	-0.00642
Asia and Oceania	0.00953	1.94381*	-0.00351*	-0.15817	-0.24545	2.55547	0.03817*	0.34248	0.00043	-0.08413	-0.02805*
S.&C. America	0.02020*	0.25421**	-0.20817*						0.00269		
North America	-0.00071							-0.28398*	0.00089	0.02669*	
Genuine APE per Time Period: PET Model [b]											
1985-2009	-0.03508*	0.01294	0.00001*	-5.13744*	-0.43659	-8.33637	0.00167	0.58522	0.00003	0.35931*	-0.24908
2010-2021	-0.00052	1.57277**	0.00058*	-0.00388*	0.33536*	0.47563*	0.03744*	-0.14240	0.00022	0.02551*	-0.00641
No of papers	95	55	48	50	37	33	47	29	86	33	38
Obs	185	83	85	95	61	62	70	70	161	80	88

Note: **Y1:** farmer's age, **Y2:** farmer's education, **Y3:** household size, **Y4:** farmer's gender, **Y5:** membership in groups, unions or associations, **Y6:** access to extension services, **Y7:** access to credit, **Y8:** access to off-farm income, **Y9:** farm's size, **Y10:** herd size, and **Y11:** distance from the market. All values in the table apart from those referring to the coefficient estimates of standard errors are in $\times 10^{-2}$. P-values were computed using cluster robust wild bootstrapping except of those referring to the uncorrected combined APE. Genuine effects per continent and time periods were estimated only if a sufficient number of observations was available in our meta-sample. Europe was not included because only 3 observations were available.

$^{a}y_i = \mu + \epsilon_i$, $^{b}y_i = \mu + \gamma SE_i + \epsilon_i$, $^{c}y_i = \mu + \delta\,(SE_i)^2 + \epsilon_i$, $^{d}|y_i| = \mu + \gamma SE_i + \epsilon_i$.

$^{***}p < 0.1$, $^{**}p < 0.05$, $^{*}p < 0.01$.

Table 5: Parameter Estimates of the Meta-Regression Equation on Technology Adoption Models.

Variable	Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8	Y9	Y10	Y11
Constant	0.00904*	0.15840*	0.01786*	0.34287	0.22455*	0.80740*	0.00292	0.12924*	0.01842	-0.00943*	94.1052
Standard error	-59.1224*	26.1733*	25.2486	-0.59918*	6.34171*	2.89730	1.30619*	4.97940*	0.35931*	-39.7916*	-23.0667*
Data & Model Characteristics											
Year of Survey	0.00013***	-0.00056*	-0.00002	-0.00093*	-0.01366*	-0.00861*	-0.00151	-0.01086*	0.00051***	0.00247*	0.02723
Sample Size	-4.1E-07*	-1.7E-07***	1.6E-06*	-2.3E-06*	0.00001*	1.8E-06*	7.9E-06*	0.00002*	4.3E-06***	0.00001*	0.00052
No of Variables	0.00001	-0.00046	-0.00034*	-0.00091*	-0.00171*	-0.00023*	-0.00160	0.00072*	0.00062	-0.00137*	0.28414
Probit Model	0.00085**	0.01026*	-0.00554*	0.01471	-0.01220*	0.07234*	0.00370	0.04170*	-0.04490**	0.02644*	-39.3783
Sample Composition											
GDP per capita	-0.00003*	-0.00306*	0.00041*	0.00011	0.01256*	0.00899*	0.00234***	0.00699*	0.00088*	0.00178*	1.40996
Agr (% of GDP)	-0.01804*	0.03213	-0.02767*	-0.03522***	-0.39651*	-1.45228*	0.21098	-0.40676*	-0.01591	-0.02578*	-82.7071
Human Capital	-0.00064**	0.00404	-0.00266*	-0.00411*	-0.03901*	-0.09817*	0.00319	-0.03601*	-0.00571***	-0.00763*	-6.94670
FDI (% of GDP)	-0.00019***	-0.00011	0.00109*	-0.00008	-0.00397*	-0.01654*	0.00359*	-0.01793*	0.00050	0.00924*	1.02600
Trade Openness	-0.00080	-0.00649	0.00636**	0.02255*	0.29703*	0.39373*	-0.02748	0.18050*	0.00088	0.04742*	-5.23749
Type of Farm Technology											
AgTech1	0.00138	-0.15081*	5.3E-05	-0.26769	0.01659	0.01081*	-0.01224	0.12391*	-0.00245	-0.00064	0.00296
AgTech2	0.00069	-0.15346*	0.00033	-0.26963	-0.00763	0.00501*	-0.03277	0.10539*	0.00620	-0.00253	0.00330
AgTech3	0.00163	0.15000*	0.00000	-0.27559	0.00000	0.00000	0.00000	0.10574*	0.00411	-0.00431*	0.00000
Publication Characteristics											
SJR Index	-0.00090**	-0.00821*	0.00046	-0.02412**	-0.07760*	-0.05282*	-0.01825	-0.02332*	0.00910**	-0.03553*	-7.10857
US Co-author	0.00010	0.00956*	-0.00134	-0.00981*	-0.02323	-0.06176*	0.02111	-0.02540***	0.02138*	-0.04678*	-0.20982
Authors' H-index	-0.00009*	-0.00020*	0.00027*	0.00048*	0.00726*	-0.00044*	-0.00024	0.00104*	0.00023	0.00034*	-0.01101
$\bar{R}^2$	0.99711	0.99314	0.89819	0.52555	0.84631	0.67338	0.91982	0.98144	0.78383	0.75660	0.22600
No of papers	95	55	48	50	37	33	47	29	86	33	38
Obs	185	83	85	95	61	62	70	70	161	80	88

Note: **Y1:** farmer's age, **Y2:** farmer's education, **Y3:** household size, **Y4:** farmer's gender, **Y5:** membership in groups, unions or associations, **Y6:** access to extension services, **Y7:** access to credit, **Y8:** access to off-farm income, **Y9:** farm's size, **Y10:** herd size, and **Y11:** distance from the market. **AgTech1:** improved seeds, **AgTech2:** soil conservation, protection and fertilization, **AgTech3:** ICT, feeding, breeding, organic and water. P-values were computed using cluster robust wild bootstrapping.
$^{***}p < 0.1$, $^{**}p < 0.05$, $^{*}p < 0.01$.

References

Almeida, R. and A. M. Fernandes (2008). Openness and technological innovations in developing countries: evidence from firm-level surveys. *The Journal of Development Studies 44*(5), 701–727.

Balima, H. W., E. G. Kilama, and R. Tapsoba (2020). Inflation targeting: genuine effects or publication selection bias? *European Economic Review 128*, 103520.

Batz, F.-J., K. Peters, and W. Janssen (1999). The influence of technology characteristics on the rate and speed of adoption. *Agricultural Economics 21*(2), 121–130.

Cameron, A. C., J. B. Gelbach, and D. L. Miller (2008). Bootstrap-based improvements for inference with clustered errors. *The Review of Economics and Statistics 90*(3), 414–427.

Dinar, A. and D. Yaron (1992). Adoption and abandonment of irrigation technologies. *Agricultural Economics 6*(4), 315–332.

Egger, M., G. D. Smith, M. Schneider, and C. Minder (1997). Bias in meta-analysis detected by a simple, graphical test. *British Medical Journal 315*(7109), 629–634.

Evenson, R. E. and L. E. Westphal (1995). Technological change and technology strategy. *Handbook of Development Economics 3*, 2209–2299.

FAO (2020). Emissions due to agriculture: Global, regional and country trends 2000-2018. Technical report, FAOSTAT, Analytical Brief Series No 18 (Rome).

FAO et al. (2022). The state of food security and nutrition in the world 2022: Repurposing food and agricultural policies to make healthy diets more affordable. Technical report, FAO, Rome.

Feder, G., R. E. Just, and D. Zilberman (1985). Adoption of agricultural innovations in developing countries: A survey. *Economic Development and Cultural Change 33*(2), 255–298.

Feder, G. and D. L. Umali (1993). The adoption of agricultural innovations: a review. *Technological Forecasting and Social Change 43*(3-4), 215–239.

Glass, G. V. (1976). Primary, secondary, and meta-analysis of research. *Educational Researcher 5*(10), 3–8.

Glass, G. V. (1977). Integrating findings: the meta-analysis of research. *Review of Research in Education 5*(1), 351–379.

GNAF (2022). Global report on food crises: Joint analysis for better decisions. Technical report, Global Network Against Food (Rome).

Griliches, Z. (1957). Hybrid corn: An exploration in the economics of technological change. *Econometrica 25*(4), 501–522.

Havranek, T., Z. Irsova, and O. Zeynalova (2018). Tuition fees and university enrolment: a meta-regression analysis. *Oxford Bulletin of Economics and Statistics 80*(6), 1145–1184.

Huffman, W. E. (1977). Allocative efficiency: The role of human capital. *The Quarterly Journal of Economics 91*(1), 59–79.

Kassie, M., M. Jaleta, B. Shiferaw, F. Mmbando, and M. Mekuria (2013). Adoption of interrelated sustainable agricultural practices in smallholder systems: Evidence from rural tanzania. *Technological Forecasting and Social Change 80*(3), 525–540.

Kebebe, E. (2017). Household nutrition and income impacts of using dairy technologies in mixed crop–livestock production systems. *Australian Journal of Agricultural and Resource Economics 61*(4), 626–644.

Khanna, M. (2001). Sequential adoption of site-specific technologies and its implications for nitrogen productivity: A double selectivity model. *American Journal of Agricultural Economics 83*(1), 35–51.

Koundouri, P., C. Nauges, and V. Tzouvelekas (2006). Technology adoption under production uncertainty: theory and application to irrigation technology. *American Journal of Agricultural Economics 88*(3), 657–670.

Lin, J. Y. (1991). Education and innovation adoption in agriculture: Evidence from hybrid rice in china. *American Journal of Agricultural Economics 73*(3), 713–723.

Lipper, L., P. Thornton, B. M. Campbell, T. Baedeker, A. Braimoh, M. Bwalya, P. Caron, A. Cattaneo, D. Garrity, K. Henry, et al. (2014). Climate-smart agriculture for food security. *Nature Climate Change 4*(12), 1068–1072.

MacKinnon, J. G. and M. D. Webb (2017). Wild bootstrap inference for wildly different cluster sizes. *Journal of Applied Econometrics 32*(2), 233–254.

Martin, S. W., R. K. Roberts, S. L. Larkin, J. A. Larson, K. W. Paxton, B. C. English, M. C. Marra, J. M. Reeves, et al. (2008). A binary logit estimation of factors affecting adoption of gps guidance systems by cotton producers. *Journal of Agricultural and Applied Economics 40*(1), 345–355.

Nelson, R. R. and E. S. Phelps (1966). Investment in humans, technological diffusion, and economic growth. *American Economic Review 56*(1/2), 69–75.

Oczkowski, E. and H. Doucouliagos (2015). Wine prices and quality ratings: A meta-regression analysis. *American Journal of Agricultural Economics 97*(1), 103–121.

Ogundari, K. and O. D. Bolarinwa (2018). Impact of agricultural innovation adoption: a meta-analysis. *Australian Journal of Agricultural and Resource Economics 62*(2), 217–236.

Pearson, K. (1933). On a method of determining whether a sample of size n supposed to have been drawn from a parent population having a known probability integral has probably been drawn at random. *Biometrika 25*(3-4), 379–410.

Rogers, E. M. (1962). Diffusion of innovations. New York: The Free Press of Glencoe.

Rogers, E. M. (1995). Diffusion of innovations. New York: Free Press.

Ruzzante, S., R. Labarta, and A. Bilton (2021). Adoption of agricultural technology in the developing world: a meta-analysis of the empirical literature. *World Development 146*, 105599.

Sayer, J. and K. G. Cassman (2013). Agricultural innovation to protect the environment. *Proceedings of the National Academy of Sciences 110*(21), 8345–8348.

Simpson, R. J. S. and K. Pearson (1904). Report on certain enteric fever inoculation statistics. *The British Medical Journal 2*(2288), 1243–1246.

Stanley, T. D. (2001). Wheat from chaff: Meta-analysis as quantitative literature review. *Journal of Economic Perspectives 15*(3), 131–150.

Stanley, T. D. (2005). Beyond publication bias. *Journal of Economic Surveys 19*(3), 309–345.

Stanley, T. D. (2008). Meta-regression methods for detecting and estimating empirical effects in the presence of publication selection. *Oxford Bulletin of Economics and Statistics 70*(1), 103–127.

Stanley, T. D. and H. Doucouliagos (2014). Meta-regression approximations to reduce publication selection bias. *Research Synthesis Methods 5*(1), 60–78.

Stanley, T. D. and H. Doucouliagos (2015). Neither fixed nor random: weighted least squares meta-analysis. *Statistics in Medicine 34*(13), 2116–2127.

Stanley, T. D. and H. Doucouliagos (2017). Neither fixed nor random: weighted least squares meta-regression. *Research Synthesis Methods 8*(1), 19–42.

Stanley, T. D., H. Doucouliagos, M. Giles, J. H. Heckemeyer, R. J. Johnston, P. Laroche, J. P. Nelson, M. Paldam, J. Poot, G. Pugh, et al. (2013). Meta-analysis of economics research reporting guidelines. *Journal of Economic Surveys 27*(2), 390–394.

Stanley, T. D. and S. B. Jarrell (2005). Meta-regression analysis: a quantitative method of literature surveys. *Journal of Economic Surveys 19*(3), 299–308.

Sunding, D. and D. Zilberman (2001). The agricultural innovation process: research and technology adoption in a changing agricultural sector. *Handbook of Agricultural Economics 1*, 207–261.

Takahashi, K., R. Muraoka, and K. Otsuka (2020). Technology adoption, impact, and extension in developing countries' agriculture: A review of the recent literature. *Agricultural Economics 51*(1), 31–45.

Appendix

A Description of Meta-Data

Table A.1: List of Academic Outlets Included in the Meta-Analysis

Outlet	Abbreviation
AgBioForum	ABF
Agrekon	AGK
Agricultural and Resource Economics Review	ARER
Agricultural Economics	AE
Agricultural Systems	AS
Agriculture and Human Values	AHV
Agroforestry Systems	AS
American Journal of Agricultural Economics	AJAE
American Journal of Rural Development	AJRD
Canadian Journal of Agricultural Economics	CJAE
Development Southern Africa	DSA
Economic Development and Cultural Change	EDCC
Economics of Innovation and New Technology	EINT
Environmental and Resource Economics	ERE
European Review of Agricultural Economics	ERAE
Food Policy	FP
Indian Journal of Agricultural Economics	IJAE
International Food and Agribusiness Management Review	IFAMR
Journal of Agribusiness	JAgB
Journal of Agricultural and Applied Economics	JAAE
Journal of Agricultural and Resource Economics	JARE
Journal of Agricultural Economics	JAE
Journal of Development Economics	JDE
Journal of Development Studies	JDS
Journal of Sustainable Agriculture	JSA
Land Economics	LE
Nutrient Cycling in Agroecosystems	NCA
Precision Agriculture	PA
Quarterly Journal of International Agriculture	QJIA
Review of Agricultural Economics	RAE
Review of Development Economics	RDE
Southern Journal of Agricultural Economics	SJAE
Technological Forecasting & Social Change	TFSC
The Australian Journal of Agricultural and Resource Economics	AJARE
World Development	WD

We have also searched the following outlets but we didn't find any study published on technology adoption using a Probit, Tobit or Logit model: Agribusiness, American Journal of Alternative Agriculture, American Journal of Sociology, Australian Journal of Agricultural and Resource Economics, Australian Journal of Experimental Agriculture, International Journal of Agricultural Resources, Governance and Ecology, Journal of Food, Agriculture and Environment, Renewable Agriculture and Food Systems, Journal of Food Distribution Research, Review of Marketing and Agricultural Economics, Journal of Rural Development.

Table A.2: List of Variables, Units of Measurement and Number of Observations

Variable	Obs	Units of Measurement
Farmer's Age	216	in years
	11	dummies for different age ranges
Farmer's Education	104	in years of schooling
	115	more than 6 different dummies categories
Household size	109	No of household members
Farmer's Gender	122	dummy to indicate male
Membership in Groups	81	dummy to indicate membership to various groups
Access to Extension	84	dummy to indicate access to extension services
	13	distance to extension offices
	25	Frequency of extension visits
Access to Credit	87	dummy to indicate access to credit
Off-farm Income	83	dummy to indicate access to off-farm income
	27	share or the value of the off-farm income
Farm Size	185	in Ha, Acres, Mu, etc
Herd Size	104	in TLU or No of animals
	12	dummy to indicate livestock activities
Distance to the Market	112	in km
Land tenancy	50	dummies indicating status of land tenure
	40	% of owned land to total land
	16	owned land in Ha, acres etc
Experience	44	in years of farming
Value of Assets	33	value of agricultural assets in monetary terms
	25	value of non-farm assets in total or per member
	8	in asset index
Family Labor	29	No of adults in the hh or family labor force
	16	different definitions, e.g., in adult/male equivalent
Family farm income	25	Percentage or value in monetary terms
	5	dummies indicating different income levels
Agricultural Education	21	dummy indicating specialized education
Irrigation	21	dummy indicating irrigated land
	18	ratio of irrigated land to total land
Access to safety nets	22	dummies indicating government or crop insurance
Adult males	21	No of male adults
	5	Share of male members
Dependent members	20	No of children
	13	some kind of ratio, e.g., dependency ratio
Social Network	16	dummy indicating relatives in leadership positions
	15	No of traders the farmers know
	13	No of relatives in the community
	7	dummy indicating participation in community meetings
Adult females	17	No of female adults
Access to Information	13	dummy indicating access to information or not
	14	dummies on the owneship of TV, radio, smartphone
	13	dummies on the major sources of information
	6	dummy indicating exposure to mass media
Marital status	11	dummy indicating marriage
Machine Ownership	10	dummy on the ownership of mechanical equipment
Hired Labor	10	dummy indicating the use of hired labor
	8	wage expenditure rates e.g., per Ha
	6	No of employees
Sales	10	% of sales from farming operations
Household Expenditures	9	monthly or annual household expenditure per capita
Milking System	9	% pastured not rotated
	5	dummy indicating the use of parlor
Vehicle owneship	7	dummies on the ownership of car, bicycle, truck etc
Use of computers	6	dummy indicating the use or years of using PCs
Access to Seed	5	dummy indicating the access to seed or not

Table A.3: Number of Papers and Observations per Outlet for each Variable Included in the Meta-Regression Analysis

Outlet	No of Papers	No of Observations: Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8	Y9	Y10	Y11
ABF	9	12	3	1	1	2	2	1	5	4	3	
AGK	2	2	1	1	2			1	1	1	1	2
ARER	3	6	1	1				1	10		10	
AE	20	37	17	16	18	14	11	18	4	36	12	28
AS	10	6	4	5	6	3	1	6	3	14	5	12
AHV	1	2	2	2	2					2		2
AFS	2	1		1	1	1	1	1	1	1		1
AJAE	9	7	4	3	1	2	2	3	2	7	2	
CJAE	1		1			1	1	1				
DSA	1	2	2		2	2				2		2
EDCC	2	1						2	1	2		
ERAE	2	3		1	4	1	1			1	3	3
FP	13	34	21	25	29	10	24	12	15	32	6	27
IJAE	5	7	1	6	1	2	2			5	1	1
JAAE	6	19	3	1		1	2	1	12	9	12	
JARE	3	4	2				1			3		
JAE	9	9	5	7	10	8	5	5	8	8	10	
JDE	1		1	1				1		1		
JDS	3	4	2	1	4	1	1		1	4		1
JSA	1	1	1	1		1	1	1	1	1	1	
QJIA	3	4	2	2		2	3	3	1	4	2	1
RDE	3	5	1	1	2	4	1	5	3	5	4	5
AJARE	6	9	3	3	3	1	1	2		4		
WD	7	10	6	6	9	5	2	6	2	15	8	3
Total	122	185	83	85	95	61	62	70	70	161	80	88

Note: **Y1:** farmer's age, **Y2:** farmer's education, **Y3:** household size, **Y4:** farmer's gender, **Y5:** membership in groups, unions or associations, **Y6:** access to extension services, **Y7:** access to credit, **Y8:** access to off-farm income, **Y9:** farm's size, **Y10:** herd size, and **Y11:** distance from the market.

Table A.4: Number of Papers and Observations per Year of Publication for each Variable Included in the Meta-Regression Analysis

Publication	No of	No of Observations:										
Year	Papers	Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8	Y9	Y10	Y11
1985	1		1					1		1	1	
1990	1	1					1			1		
1994	1										1	
1997	1	2			2					2	2	
1998	1											1
2000	2	4							2	4		
2001	2		1	1				1		3		
2002	2			1		1	1				1	1
2003	4	3	1		1		1	3		3		1
2004	2	2							1			
2005	3	5	3		2	2			2	3	1	2
2006	6	5	2		1		1	1		9		8
2007	6	5	2	5	2	1	3	3		4		1
2008	7	11	4	2	1	3	2	1	1	5	1	
2009	5	8				2	1	3	1	4	1	3
2010	7	13	6	11	1	4	5	5	3	12	6	1
2011	6	4	5	4	7	3	1	2	1	9	4	2
2012	10	21	8	4	5	4	5	7	14	11	13	9
2013	4	5	2	3	3	1		2	2	2	3	1
2014	7	22	11	10	11	8	7	2	8	23	1	20
2015	4	2		1			1	1	11	3	10	
2016	5	13	9	8	12	8	8	9	1	10	11	12
2017	5	6	2	3	6	3		5	1	5	5	3
2018	10	23	9	15	14	5	9	12	8	17	9	7
2019	11	18	13	13	17	7	13	6	4	17	7	13
2020	8	12	4	4	6	5	3	6	6	13	3	3
2021	1				4	4			4			
Total	122	185	83	85	95	61	62	70	70	161	80	88

Note: **Y1:** farmer's age, **Y2:** farmer's education, **Y3:** household size, **Y4:** farmer's gender, **Y5:** membership in groups, unions or associations, **Y6:** access to extension services, **Y7:** access to credit, **Y8:** access to off-farm income, **Y9:** farm's size, **Y10:** herd size, and **Y11:** distance from the market.

Table A.5: Number of Papers and Observations per Country for each Variable Included in the Meta-Regression Analysis

Country	No of Papers	No of Observations: Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8	Y9	Y10	Y11
Argentina	1	1	1					1				
Australia	1									1		
Bangladesh	2	1	1			1	1			1		
Benin	1	1						1				
Bosnia	1	2			2					2		
Burkina Faso	1	3			3	3		3		3	3	
Cambodia	1	1	1		1			1	1	1		
Cameroon	2	2			1	1	1	1		1		1
Chile	1	1	1	1		1		1		1		
China	4	5	4	5	2	3	2	4	1	5	1	
Congo	3	5	1	1	3	2		1	1	1	4	4
Ethiopia	11	25	12	22	21	2	19	12	7	24	13	18
Ghana	2	11	1		1					11		10
Greece	3	2	2							1		1
Guinea	1									7		7
Honduras	2	2	2	1	1	1		1	1	2	1	1
India	9	13	3	6		8	3	7	4	12	4	7
Ireland	1	1							1	1		
Kenya	9	22	19	20	22	17	16	11	10	20	11	17
Madagascar	1	1			1							
Malawi	7	10	4	2	7	2	1	3	1	9	1	6
Mexico	1	4	2	4			2			4		
Mozambique	1		1			1	1	1				
Nepal	3	2	2	1	1	1	1	1	1	3	1	1
Netherlands	1	1		1								
Nigeria	5	4	3	4	5	8	5	4	4	3	3	2
Pakistan	2	2	2	1	1	2	2	1	1	2		
Philippines	6	2	7	5	2	1	3	3		6		2
Portugal, Italy	1									1		
Tanzania	3	4	1	1	4	1	1	1	1	3	2	2
Timor Leste	1	1	1					1	1	1	1	1
Tunisia	1							2		2		
Uganda	5	3	3	4	5	4	1	3	3	5	2	4
USA	21	46	3				2		28	16	27	
Vietnam	2			1	6	1	1			6	4	
Zambia	4	6	6	4	5	1		5	3	5	2	3
Zimbabwe	1	1		1	1			1	1	1		1
Total	122	185	83	85	95	61	62	70	70	161	80	88

Note: **Y1:** farmer's age, **Y2:** farmer's education, **Y3:** household size, **Y4:** farmer's gender, **Y5:** membership in groups, unions or associations, **Y6:** access to extension services, **Y7:** access to credit, **Y8:** access to off-farm income, **Y9:** farm's size, **Y10:** herd size, and **Y11:** distance from the market.

B Estimation of Marginal Effects

B.1 Binary Probit and Logit models

When the response variable assumes two values, 1 for adoption and 0 for non adoption, the average partial effect (APE) of the k-th covariate, if this covariate is continuous, is given by:

$$\text{APE}_k = g\left(\bar{\mathbf{x}}'\hat{\beta}\right)\hat{\beta}_k, \tag{B.5}$$

where $g(z)$ is the derivative of the link function, $\Phi(z) = \int_{-\infty}^{z} \frac{e^{-\frac{x^2}{2}}}{\sqrt{2\pi}}\,\mathrm{d}x$ for the Probit and $\Lambda(z) = \frac{e^z}{1+e^z}$ for the Logit model, respectively. Therefore:

$$\text{APE}_k = \frac{\partial\,\text{Prob}\,(y=1|\bar{\mathbf{x}})}{\partial x_k} = \begin{cases} \frac{e^{-\frac{(\bar{\mathbf{x}}'\hat{\boldsymbol{\beta}})^2}{2}}}{\sqrt{2\pi}}\hat{\beta}_k & \text{for Probit} \\ \frac{e^{\bar{\mathbf{x}}'\hat{\boldsymbol{\beta}}}}{\left(1+e^{\bar{\mathbf{x}}'\hat{\boldsymbol{\beta}}}\right)^2}\hat{\beta}_k & \text{for Logit} \end{cases} \tag{B.6}$$

If the k-th covariate is binary, the APE is calculated as the discrete difference in the probability of adoption when the binary covariate assumes the values 1 and 0 (Bartus, 2005):[25]

$$\text{APE}_k = \text{Prob}\,(y=1|\mathbf{x}_{k1}) - \text{Prob}\,(y=1|\mathbf{x}_{k0}) = \begin{cases} \Phi\left(\bar{\mathbf{x}}_{k1}'\hat{\boldsymbol{\beta}}\right) - \Phi\left(\bar{\mathbf{x}}_{k0}'\hat{\boldsymbol{\beta}}\right) & \text{for Probit} \\ \Lambda\left(\bar{\mathbf{x}}_{k1}'\hat{\boldsymbol{\beta}}\right) - \Lambda\left(\bar{\mathbf{x}}_{k0}'\hat{\boldsymbol{\beta}}\right) & \text{for Logit} \end{cases} \tag{B.7}$$

where $\bar{\mathbf{x}}_{k0}$ as a vector equal to $\bar{\mathbf{x}}$ (vector containing the sample means of the independent variables) but with 0 in the place of the k-th independent variable and $\bar{\mathbf{x}}_{k1}$ as a vector equal to $\bar{\mathbf{x}}$ but with 1 in the place of the k-th independent variable.

B.2 Type I Tobit model

Articles that model the degree or extend of adoption, typically employ Type I Tobit models:

$$\begin{aligned} y_i^* &= \mathbf{x}_i'\boldsymbol{\beta} + \varepsilon_i, \qquad \varepsilon_i \sim \text{N}\left(0,\sigma^2\right) \\ y_i &= \begin{cases} 0 & \text{if} \quad y_i^* \leq 0 \\ y_i^* & \text{if} \quad y_i^* > 0 \end{cases} \end{aligned} \tag{B.8}$$

The observed variable, y, is the degree or extend of adoption, which is censored from below at 0. After stacking observations, the equation in the latent variable, y^*, can be written as:

$$\mathbf{y}^* = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \tag{B.9}$$

[25] Bartus, T. Estimation of marginal effects using margeff. *The Stata Journal*, 2005, 5(3): 309-329.

The probability of non adoption is equal to the probability of lower truncation:

$$\text{Prob}\left(y_i = 0|\mathbf{x}_i\right) = \text{Prob}\left(y_i^* \leq 0|\mathbf{x}_i\right) = \text{Prob}\left(\varepsilon_i \leq -\mathbf{x}_i'\boldsymbol{\beta}|\mathbf{x}_i\right) = \Phi\left(\frac{-\mathbf{x}_i'\boldsymbol{\beta}}{\sigma}\right)$$

Because $\text{Prob}\left(y > 0|\bar{\mathbf{x}}\right) = 1 - \text{Prob}\left(y = 0|\bar{\mathbf{x}}\right) = \Phi\left(\frac{\mathbf{x}_i'\boldsymbol{\beta}}{\sigma}\right)$, the APE of the k-th covariate on the probability of adoption (to any extend) is calculated as:

$$\text{APE}_k = \frac{\partial\,\text{Prob}\left(y = 1|\bar{\mathbf{x}}\right)}{\partial x_k} = \begin{cases} \frac{\hat{\beta}_k}{\hat{\sigma}}\phi\left(\frac{\bar{\mathbf{x}}'\hat{\boldsymbol{\beta}}}{\hat{\sigma}}\right) & \text{if} \quad x_k \text{ is continuous} \\ \Phi\left(\frac{\bar{\mathbf{x}}_{k1}'\hat{\boldsymbol{\beta}}}{\hat{\sigma}}\right) - \Phi\left(\frac{\bar{\mathbf{x}}_{k0}'\hat{\boldsymbol{\beta}}}{\hat{\sigma}}\right) & \text{if} \quad x_k \text{ is binary} \end{cases}$$

B.3 Multivariate Probit model

The multivariate Probit model is used to model the probability of adoption of non exclusive techniques. This is a series of binary Probit models, for which the error terms may be correlated. Given that the vector of error terms follows a multivariate normal distribution, the error term in each equation of the system follows, marginally with respect to the remaining error terms, a univariate normal distribution. Therefore, the APE for the k-th independent variable for the m-th innovation is similar to the one obtained for the binary Probit model:

$$\text{APE}_{mk} = \frac{\partial\,\text{Prob}\left(y_m = 1|\bar{\mathbf{x}}\right)}{\partial x_{mk}} = \begin{cases} \phi\left(\bar{\mathbf{x}}_m'\hat{\boldsymbol{\beta}}_m\right)\hat{\beta}_{mk} & \text{if} \quad x_{mk} \text{ is continuous} \\ \Phi\left(\bar{\mathbf{x}}_{mk1}'\hat{\boldsymbol{\beta}}_m\right) - \Phi\left(\bar{\mathbf{x}}_{mk0}'\hat{\boldsymbol{\beta}}_m\right) & \text{if} \quad x_{mk} \text{ is binary} \end{cases}$$

where y_m is the m-th binary dependent variable and x_{mk} is the k-th independent variable in equation m. $\bar{\mathbf{x}}_m$ and $\hat{\boldsymbol{\beta}}_m$ are defined similarly.

C Estimation of Standard Errors Using the Delta method

Consider a consistent and asymptotically normal estimator, $\hat{\boldsymbol{\beta}}$, of a parameter vector, $\boldsymbol{\beta}$ and let $\boldsymbol{\Sigma}$ be the variance matrix of $\hat{\boldsymbol{\beta}}$. Also, let $h\left(\hat{\boldsymbol{\beta}}\right)$ be a real-valued function of $\hat{\boldsymbol{\beta}}$. Then, the variance of $h\left(\hat{\boldsymbol{\beta}}\right)$ is given by:

$$\text{Var}\left(h\left(\hat{\boldsymbol{\beta}}\right)\right) = \nabla h \cdot \boldsymbol{\Sigma} \cdot \nabla h'$$

In practice, we do not know $\boldsymbol{\Sigma}$ and we replace it by its estimate. So, to calculate the variance of a possibly non-linear function of the parameter estimates (APEs in our case), we derive the gradient, ∇h, and evaluate it at $\hat{\boldsymbol{\beta}}$ – call this $\widehat{\nabla h}$ – and then evaluate $\widehat{\nabla h} \cdot \widehat{V}(\hat{\boldsymbol{\beta}}) \cdot \widehat{\nabla h}'$, where $\widehat{V}(\hat{\boldsymbol{\beta}})$ is an estimate of $\boldsymbol{\Sigma}$.

If we stack the $\widehat{\nabla h}$s one under the other in a matrix $G(\hat{\boldsymbol{\beta}})$, we can use the Delta method to derive the formulas of the standard errors of the APEs with respect to all independent variables in one simple expression. The covariance matrix of the APEs is:

$$G(\hat{\boldsymbol{\beta}})\widehat{V}(\hat{\boldsymbol{\beta}})G(\hat{\boldsymbol{\beta}})' \tag{B.1}$$

Since we do not have $\widehat{V}(\hat{\boldsymbol{\beta}})$, we use the standard errors of the parameter estimates to approximate it by $\operatorname{diag}\left(\widehat{V}(\hat{\beta}_1),\ldots,\widehat{V}(\hat{\beta}_K)\right)$. $G(\hat{\boldsymbol{\beta}})$ is the Jacobian matrix of the derivatives of the APEs:

$$G(\hat{\boldsymbol{\beta}}) = \begin{bmatrix} \frac{\partial g_1}{\partial \beta_1} & \frac{\partial g_1}{\partial \beta_2} & \cdots & \frac{\partial g_1}{\partial \beta_K} \\ \frac{\partial g_2}{\partial \beta_1} & \frac{\partial g_2}{\partial \beta_2} & \cdots & \frac{\partial g_2}{\partial \beta_K} \\ \vdots & \cdots & \ddots & \vdots \\ \frac{\partial g_K}{\partial \beta_1} & \frac{\partial g_K}{\partial \beta_2} & \cdots & \frac{\partial g_K}{\partial \beta_K} \end{bmatrix} \tag{B.2}$$

with elements $G(\hat{\boldsymbol{\beta}})_{ij} = \frac{\partial \mathrm{APE}_i}{\partial \beta_j}\Big|_{\beta_j=\hat{\beta}_j}$. The standard errors of the APEs are given by the square roots of the diagonal elements of $G(\hat{\boldsymbol{\beta}})\widehat{V}(\hat{\boldsymbol{\beta}})G(\hat{\boldsymbol{\beta}})'$. Below we derive the formulas for the elements of $G(\hat{\boldsymbol{\beta}})$ for the different models.

C.1 Probit and Logit models

- For the case of continuous covariates:

$$\text{Probit: } G(\hat{\boldsymbol{\beta}})_{ij} = \begin{cases} \phi(\bar{\mathbf{x}}'\hat{\boldsymbol{\beta}})\left(-\bar{\mathbf{x}}'\hat{\boldsymbol{\beta}}\bar{x}_i\hat{\beta}_i + 1\right) & \text{if } i = j \\ \\ \phi(\bar{\mathbf{x}}'\hat{\boldsymbol{\beta}})\left(-\bar{\mathbf{x}}'\hat{\boldsymbol{\beta}}\bar{x}_j\hat{\beta}_i\right) & \text{if } i \neq j \end{cases} \tag{B.3}$$

$$\text{Logit: } G(\hat{\boldsymbol{\beta}})_{ij} = \begin{cases} \Lambda(\bar{\mathbf{x}}'\hat{\boldsymbol{\beta}})\left(1-\Lambda(\bar{\mathbf{x}}'\hat{\boldsymbol{\beta}})\right)\left[\bar{x}_i\hat{\beta}_i\left(1-2\Lambda(\bar{\mathbf{x}}'\hat{\boldsymbol{\beta}})\right)+1\right] & \text{if } i = j \\ \\ \Lambda(\bar{\mathbf{x}}'\hat{\boldsymbol{\beta}})\left(1-\Lambda(\bar{\mathbf{x}}'\hat{\boldsymbol{\beta}})\right)\left[\bar{x}_j\hat{\beta}_i\left(1-2\Lambda(\bar{\mathbf{x}}'\hat{\boldsymbol{\beta}})\right)\right] & \text{if } i \neq j \end{cases} \tag{B.4}$$

- For the case of binary covariates:

$$\text{Probit: } G(\hat{\boldsymbol{\beta}})_{ij} = \begin{cases} \phi\left(\sum_{k\neq i}\bar{x}_k\hat{\beta}_k + \hat{\beta}_i\right) & \text{if } i = j \\ \\ \left[\phi\left(\sum_{k\neq i}\bar{x}_k\hat{\beta}_k + \hat{\beta}_i\right) - \phi\left(\sum_{k\neq i}\bar{x}_k\hat{\beta}_k\right)\right]\bar{x}_j & \text{if } i \neq j \end{cases} \tag{B.5}$$

$$\text{Logit: } G(\hat{\boldsymbol{\beta}})_{ij} = \begin{cases} \Lambda\left(\sum_{k\neq i}\bar{x}_k\hat{\beta}_k + \hat{\beta}_i\right)\left[1-\Lambda\left(\sum_{k\neq i}\bar{x}_k\hat{\beta}_k + \hat{\beta}_i\right)\right] & \text{if } i=j \\ \\ \Lambda\left(\sum_{k\neq i}\bar{x}_k\hat{\beta}_k + \hat{\beta}_i\right)\left[1-\Lambda\left(\sum_{k\neq i}\bar{x}_k\hat{\beta}_k + \hat{\beta}_i\right)\right]\bar{x}_j \\ -\Lambda\left(\sum_{k\neq i}\bar{x}_k\hat{\beta}_k\right)\left[1-\Lambda\left(\sum_{k\neq i}\bar{x}_k\hat{\beta}_k\right)\right]\bar{x}_j & \text{if } i\neq j \end{cases} \tag{B.6}$$

The formulas for the multivariate Probit model are analogous to the ones for the binary Probit.

C.2 Type I Tobit model

For the case of continuous covariates:

$$G(\hat{\boldsymbol{\beta}})_{ij} = \begin{cases} \frac{1}{\hat{\sigma}}\phi(\frac{\bar{\mathbf{x}}'\hat{\boldsymbol{\beta}}}{\hat{\sigma}})\left(1-\frac{\bar{\mathbf{x}}'\hat{\boldsymbol{\beta}}}{\hat{\sigma}^2}\hat{\beta}_i\bar{x}_i\right) & \text{if } i=j \\ \\ -\frac{1}{\hat{\sigma}}\phi(\frac{\bar{\mathbf{x}}'\hat{\boldsymbol{\beta}}}{\hat{\sigma}})\frac{\bar{\mathbf{x}}'\hat{\boldsymbol{\beta}}}{\sigma^2}\hat{\beta}_i\bar{x}_j & \text{if } i\neq j \end{cases} \tag{B.7}$$

For the case of binary covariates:

$$G(\hat{\boldsymbol{\beta}})_{ij} = \begin{cases} \frac{1}{\hat{\sigma}}\phi\left(\frac{\sum_{k\neq i}\bar{x}_k\hat{\beta}_k+\hat{\beta}_i}{\hat{\sigma}}\right) & \text{if } i=j \\ \\ \frac{\bar{x}_j}{\hat{\sigma}}\left[\phi\left(\frac{\sum_{k\neq i}\bar{x}_k\hat{\beta}_k+\hat{\beta}_i}{\hat{\sigma}}\right)-\phi\left(\frac{\sum_{k\neq i}\bar{x}_k\hat{\beta}_k}{\hat{\sigma}}\right)\right] & \text{if } i\neq j \end{cases} \tag{B.8}$$

D Calculated Average Partial Effects

Table D.1: Calculated Average Partial Effect per Country

Country	Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8	Y9	Y10	Y11
Argentina	0.00000	0.02361					0.20140				
Australia									0.00003		
Bangladsh	-0.00300	-0.00298			0.03300	0.02500			-0.09700		
Benin	0.00330						-0.00438				
Bosnia	0.00550			-0.07750					0.00247		
Burkina Faso	0.00010			-0.02662	0.17435		-0.01569		0.05463	0.03318	
Cambodia	0.00100	0.00010		-0.00100			0.00400	0.01300	-0.03500		
Cameroon	-0.00406			0.10200	0.01000	0.14900	0.24200		0.04600		-0.03000
Chile	0.00170	0.00863	0.02419		0.07662		0.07550		0.02320		
China	0.00193	-0.00162	0.00986	0.01873	0.05139	0.25378	0.03214	0.04249	0.08233	0.03012	
Congo	0.00116	0.00400	-0.00100	-0.12067	0.22680		0.26000	0.04740	0.05000	0.01270	-0.00069
Ethiopia	-0.13684	-0.20705	0.20402	-0.67053	0.03400	0.26941	0.06483	-0.00345	0.21223	0.01299	-0.36331
Ghana	-0.00023	0.00288		-0.01544					-0.00811		0.00379
Greece	-0.05204	0.06604							-0.04000		-0.01685
Guinea									0.00408		0.03268
Honduras	-0.01000	0.00629	-0.00214	0.01369	0.00776		0.00000	-0.00500	-0.01235	-0.00140	-0.00300
India	-0.00133	0.00747	-0.00144		0.04739	0.00288	0.08080	-0.04247	0.02778	0.00200	-0.04498
Ireland	-0.00175							0.00000	0.00234		
Kenya	0.00224	0.00190	0.00234	0.00297	0.02554	0.02283	0.00400	0.02091	-0.01273	-0.00041	0.00005
Madagascar	-0.00300			-0.02500							
Malawi	-0.00650	0.01416	0.00835	-0.00307	-0.04936	0.08100	0.00227	0.02000	-0.01738	-0.00024	-0.00950
Mexico	-0.00022	0.00559	-0.00750			-0.00050			-0.00014		
Mozambique		0.00816			0.01473	0.00108	0.09722				
Nepal	0.00000	0.00014	0.00000	-0.00004	0.00016	0.23000	0.00025	0.00100	0.09027	0.03958	0.06400
Netherlands	-0.00095		0.02024								
Nigeria	0.00055	-0.00071	0.00023	0.00527	0.01589	0.13845	0.00800	0.07250	0.00338	0.00240	0.01790
Pakistan	-0.00367	0.01154	0.00074	0.11103	-0.03879	0.07395	0.03727	-0.08031	0.01211		
Philippines	-0.00166	0.00538	-0.01255	-0.00771	-0.00367	0.09973	0.02267		0.02359		-0.00051
Portugal&Italy									0.00155		
Tanzania	0.00135	0.00976	-0.00056	0.12028	0.01496	0.03289	-0.00874	-0.01660	-0.04406	0.00603	-0.00028
Timor Leste	-0.00067	-0.00394					-0.01860	-0.07820	0.03340	-0.01257	0.00524
Tunisia							0.06383		-0.00232		
Uganda	0.00238	0.01285	0.00500	-0.03250	0.10509	0.00000	-0.05013	-0.00790	0.03890	0.00255	-0.00374
USA	-0.00666	0.02580				0.01624		-0.01198	0.00006	0.01179	
Vietnam			0.01400	0.00902	0.18600	0.08600			0.01054	0.00666	
Zambia	-0.00447	0.01722	0.02750	-0.00866	-0.11126		-0.01283	-0.00033	0.02264	0.01264	0.03444
Zimbabwe	0.00167		-0.00439	0.07155			-0.01206	-0.00006	-0.00251		-0.00021
Mean	-0.02105	-0.02279	0.05508	-0.14736	0.04281	0.16849	0.03376	-0.00159	0.03230	0.00966	-0.07392

Note: **Y1:** farmer's age, **Y2:** farmer's education, **Y3:** household size, **Y4:** farmer's gender, **Y5:** membership in groups, unions or associations, **Y6:** access to extension services, **Y7:** access to credit, **Y8:** access to off-farm income, **Y9:** farm size, **Y10:** herd size and **Y11:** distance from the market.

Table D.2: Calculated Average Partial Effects per Year of Publication

Publication Year	Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8	Y9	Y10	Y11
1985	0.00000	0.00028					0.00025		-0.00095	0.03958	
1990	-0.00300					0.04248			0.00005		
1994										0.15814	
1997	0.00217			0.24056					-0.06546	0.00603	
1998											-0.01685
2000	-0.00290							-0.14119	0.00002		
2001		0.01634	-0.02907				-0.02997		0.00004		
2002			-0.00335		0.08669	0.10813				0.01263	0.03729
2003	-0.01877	0.02361		0.00000		0.23000	0.10969		0.08912		0.06400
2004	0.00044							-0.05700			
2005	0.00515	0.03454		-0.00955	-0.04936			-0.01564	0.00024	0.00366	-0.02148
2006	-0.02182	0.06604		-0.02500		-0.12262	0.00000		-0.00036		0.02840
2007	-0.01059	0.00529	0.00258	0.00685	0.00776	0.00288	0.20274		-0.00101		-0.00310
2008	0.00115	0.01135	0.03828	0.08000	0.12936	0.18878	0.13751	0.04249	-0.00394	0.03012	
2009	0.00165				0.03500	0.00000	0.03079	0.00000	0.00364	0.00000	-0.00126
2010	-0.00083	0.00537	0.00454	0.02580	-0.02258	0.03849	0.08984	-0.01475	0.00185	0.00581	-0.00300
2011	0.01075	0.00303	0.00082	0.00931	0.16266	0.18020	-0.00725	-0.14519	0.00688	0.00666	-0.00606
2012	-0.00138	0.00558	0.00468	0.00604	0.06589	0.06642	0.02294	-0.00523	0.00572	-0.00081	-0.00056
2013	-0.00061	0.00471	0.00454	0.01109	-0.00367		0.09414	-0.04669	0.04904	0.04555	-0.00029
2014	-0.00041	0.00062	0.00430	0.00093	0.02351	0.01477	0.01491	0.02384	-0.01949	0.00880	0.00153
2015	-0.01673		0.00016			0.00204	0.00000	0.00392	0.02729	0.00022	
2016	0.00158	0.01580	0.00056	-0.03600	-0.01217	0.01815	-0.00033	0.06100	0.06614	-0.00182	-0.00167
2017	0.00029	-0.00175	-0.00413	0.00350	0.13016		-0.00698	-0.00006	0.02685	0.02292	-0.00004
2018	-0.00836	0.00742	0.01286	-0.00519	0.00102	-0.01586	0.02401	-0.00115	0.01916	0.02388	0.01771
2019	-0.19369	-0.19356	0.33248	-0.83833	0.04981	0.39541	0.05963	0.03157	0.19581	0.00008	-0.50560
2020	-0.00227	-0.00297	0.00145	0.00240	0.09383	0.09567	-0.02750	-0.02150	0.04598	0.00267	-0.10267
2021				0.00650	0.01675			0.07250			
Mean	-0.02105	-0.02279	0.05508	-0.14736	0.04281	0.16849	0.03376	-0.00159	0.03230	0.00966	-0.07392

Note: **Y1:** farmer's age, **Y2:** farmer's education, **Y3:** household size, **Y4:** farmer's gender, **Y5:** membership in groups, unions or associations, **Y6:** access to extension services, **Y7:** access to credit, **Y8:** access to off-farm income, **Y9:** farm size, **Y10:** herd size, and **Y11:** distance from the market.

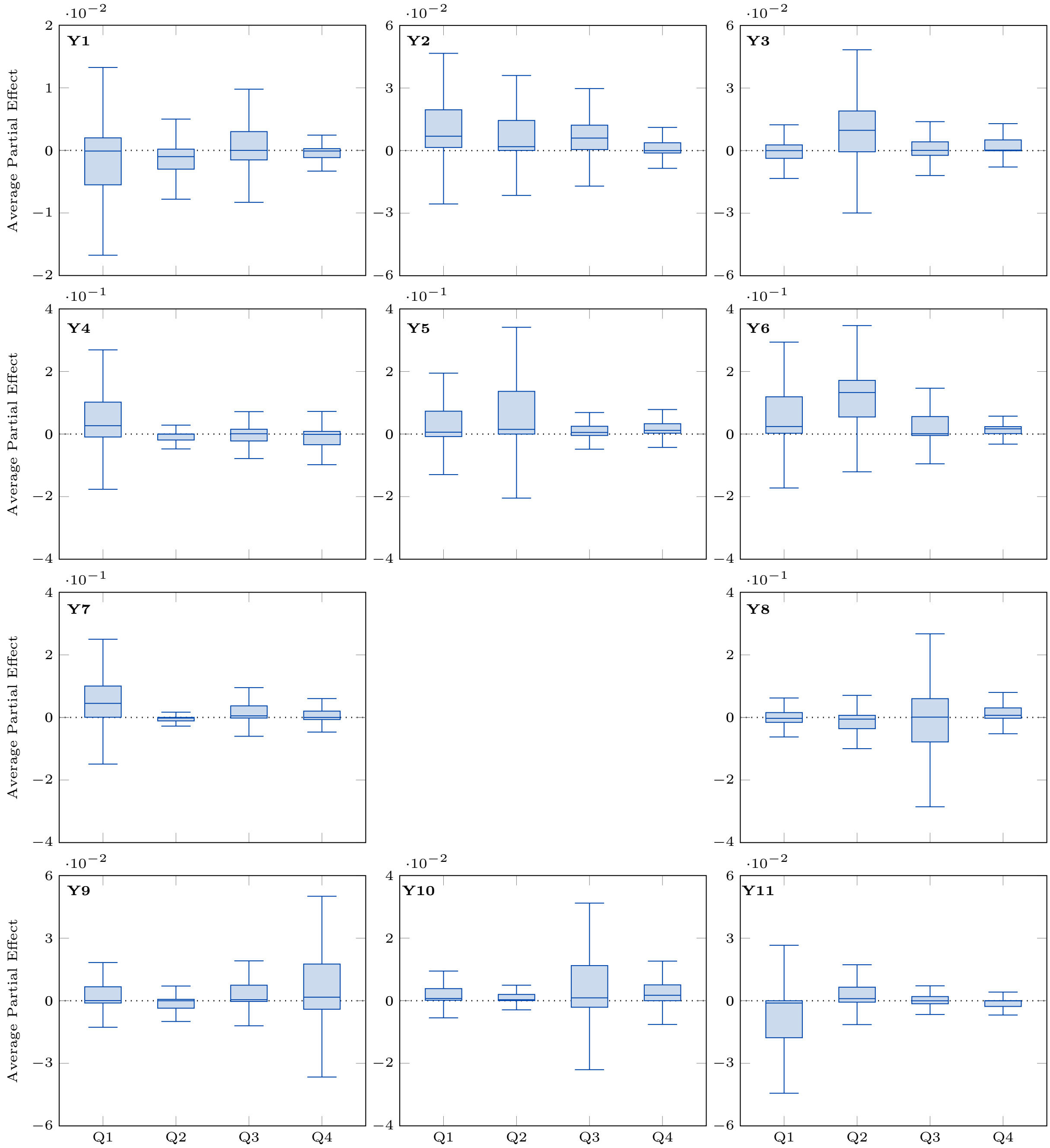


Figure D.1: **Calculated Average Partial Effects per Scientific Journal Ranking Quartiles**. **Y1:** farmer's age, **Y2:** farmer's education, **Y3:** household size, **Y4:** farmer's gender, **Y5:** membership in groups, unions or associations, **Y6:** access to extension services, **Y7:** access to credit, **Y8:** access to off-farm income, **Y9:** farm's size, **Y10:** herd size, and **Y11:** distance from the market.

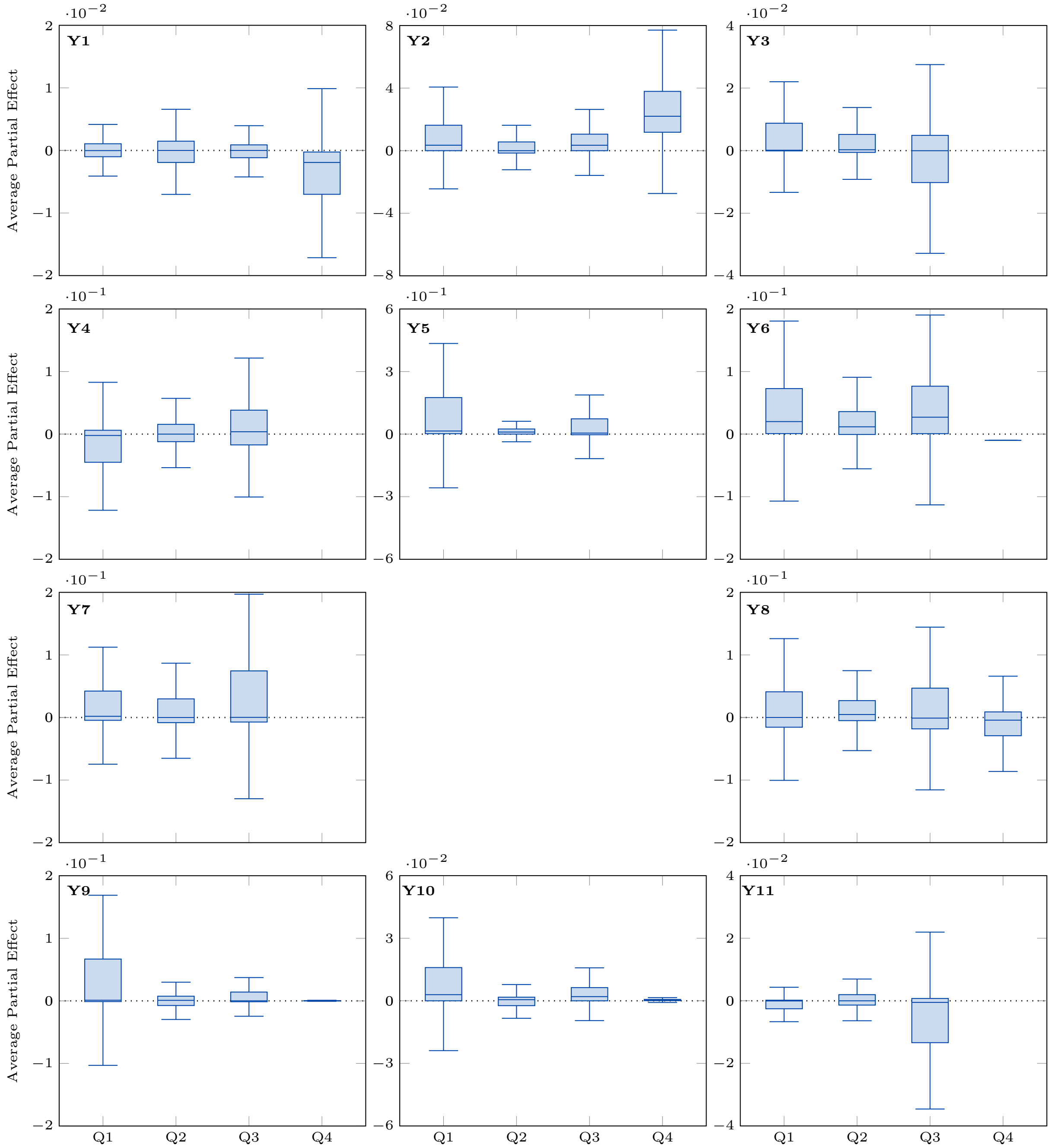


Figure D.2: **Calculated Average Partial Effects per GDP Quartiles**. **Y1:** farmer's age, **Y2:** farmer's education, **Y3:** household size, **Y4:** farmer's gender, **Y5:** membership in groups, unions or associations, **Y6:** access to extension services, **Y7:** access to credit, **Y8:** access to off-farm income, **Y9:** farm's size, **Y10:** herd size, and **Y11:** distance from the market.

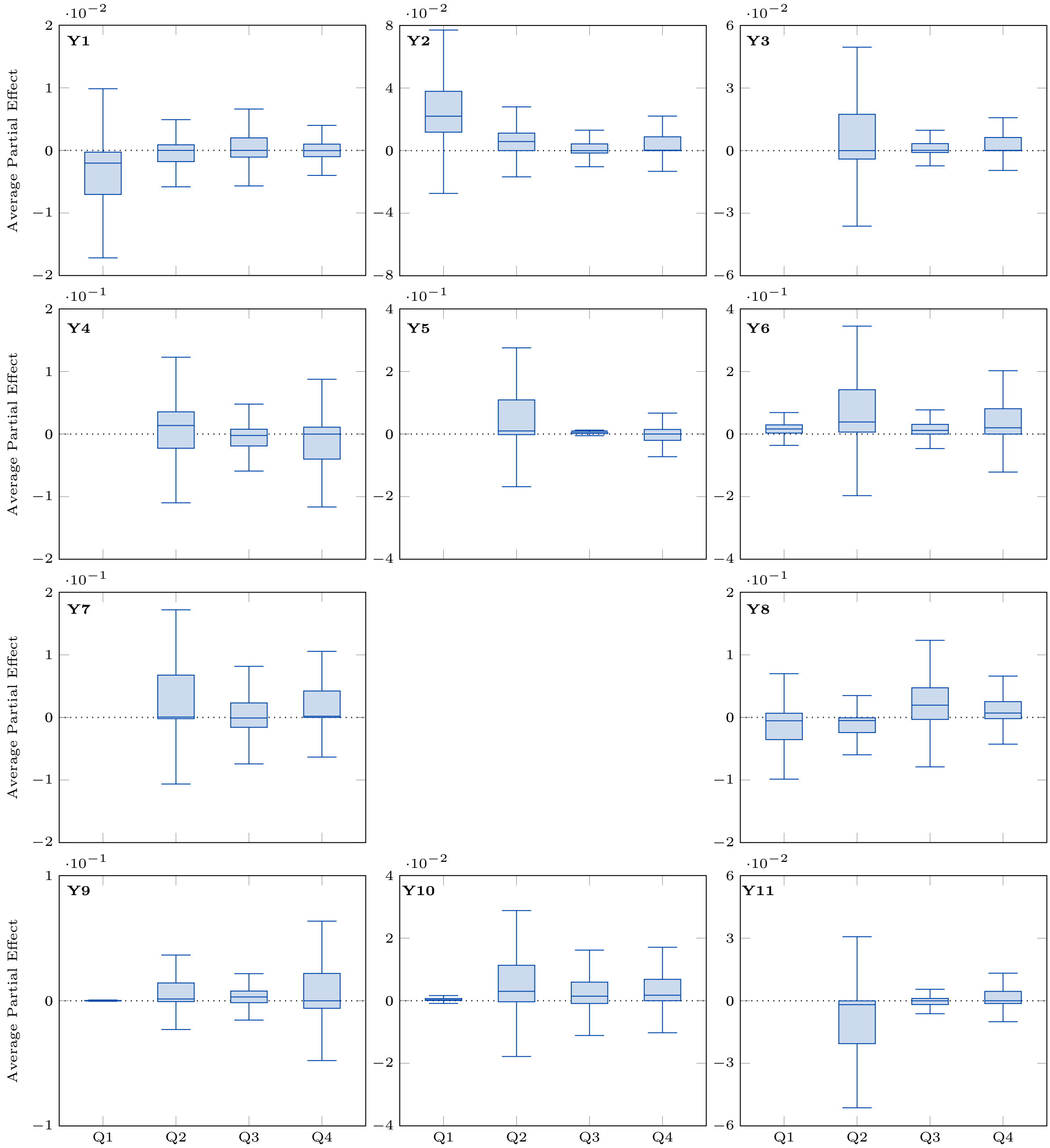


Figure D.3: **Calculated Average Partial Effects per Agriculture's Share on GDP Quartiles**. **Y1:** farmer's age, **Y2:** farmer's education, **Y3:** household size, **Y4:** farmer's gender, **Y5:** membership in groups, unions or associations, **Y6:** access to extension services, **Y7:** access to credit, **Y8:** access to off-farm income, **Y9:** farm's size, **Y10:** herd size, and **Y11:** distance from the market.

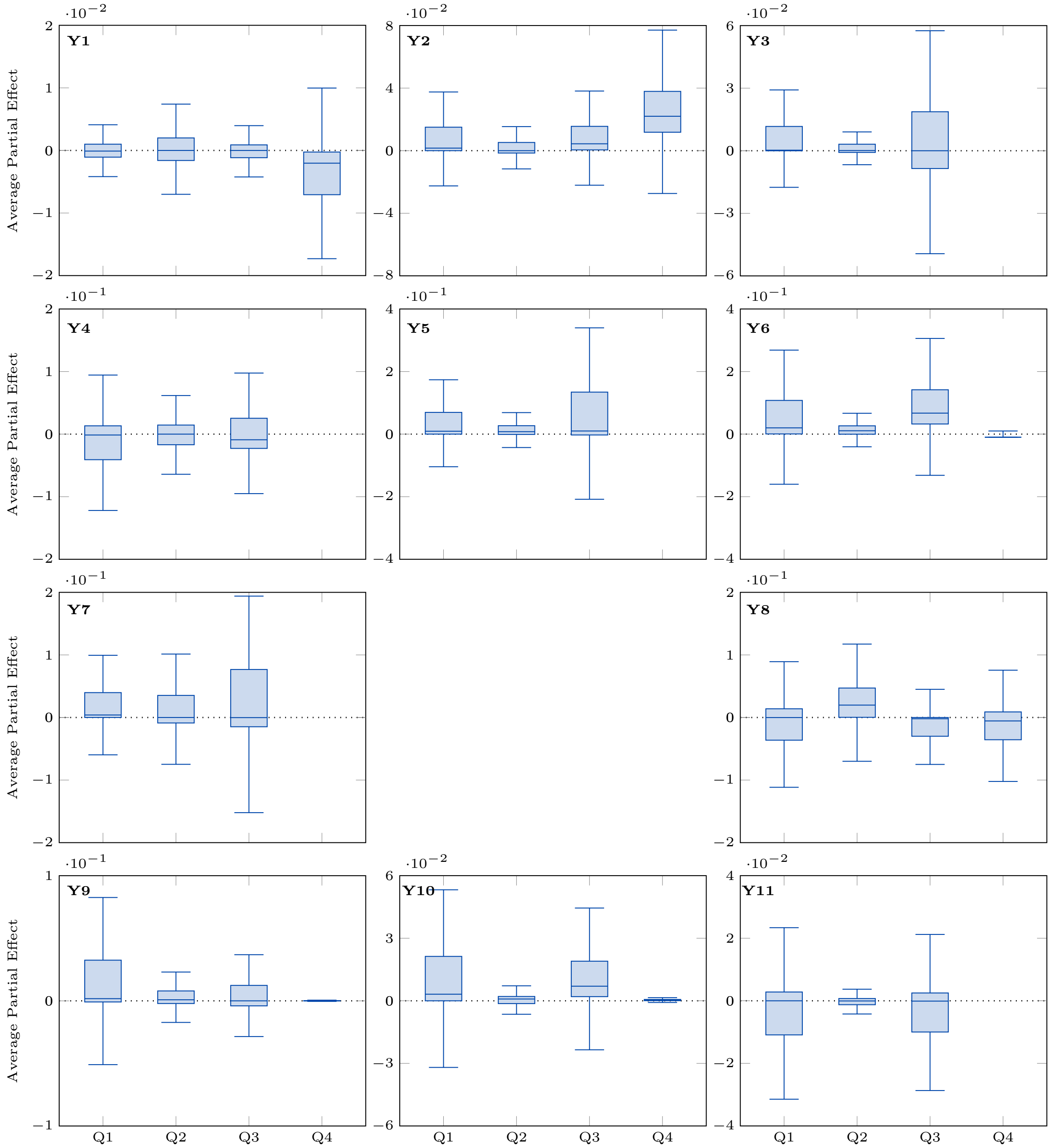


Figure D.4: **Calculated Average Partial Effects per Human Capital Quartiles**. **Y1:** farmer's age, **Y2:** farmer's education, **Y3:** household size, **Y4:** farmer's gender, **Y5:** membership in groups, unions or associations, **Y6:** access to extension services, **Y7:** access to credit, **Y8:** access to off-farm income, **Y9:** farm's size, **Y10:** herd size, and **Y11:** distance from the market.

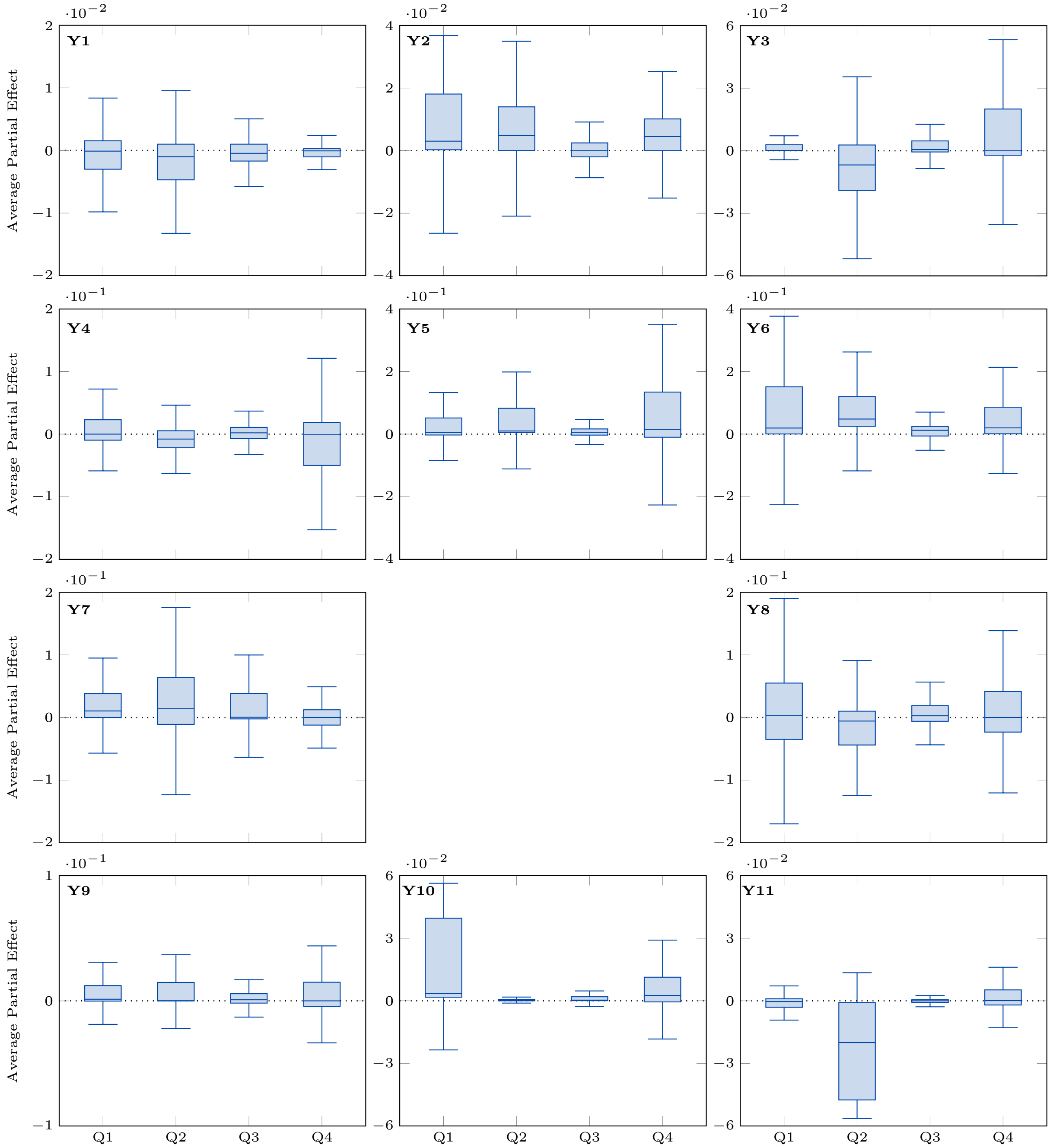


Figure D.5: **Calculated Average Partial Effects per FDI Quartiles**. **Y1:** farmer's age, **Y2:** farmer's education, **Y3:** household size, **Y4:** farmer's gender, **Y5:** membership in groups, unions or associations, **Y6:** access to extension services, **Y7:** access to credit, **Y8:** access to off-farm income, **Y9:** farm's size, **Y10:** herd size, and **Y11:** distance from the market.

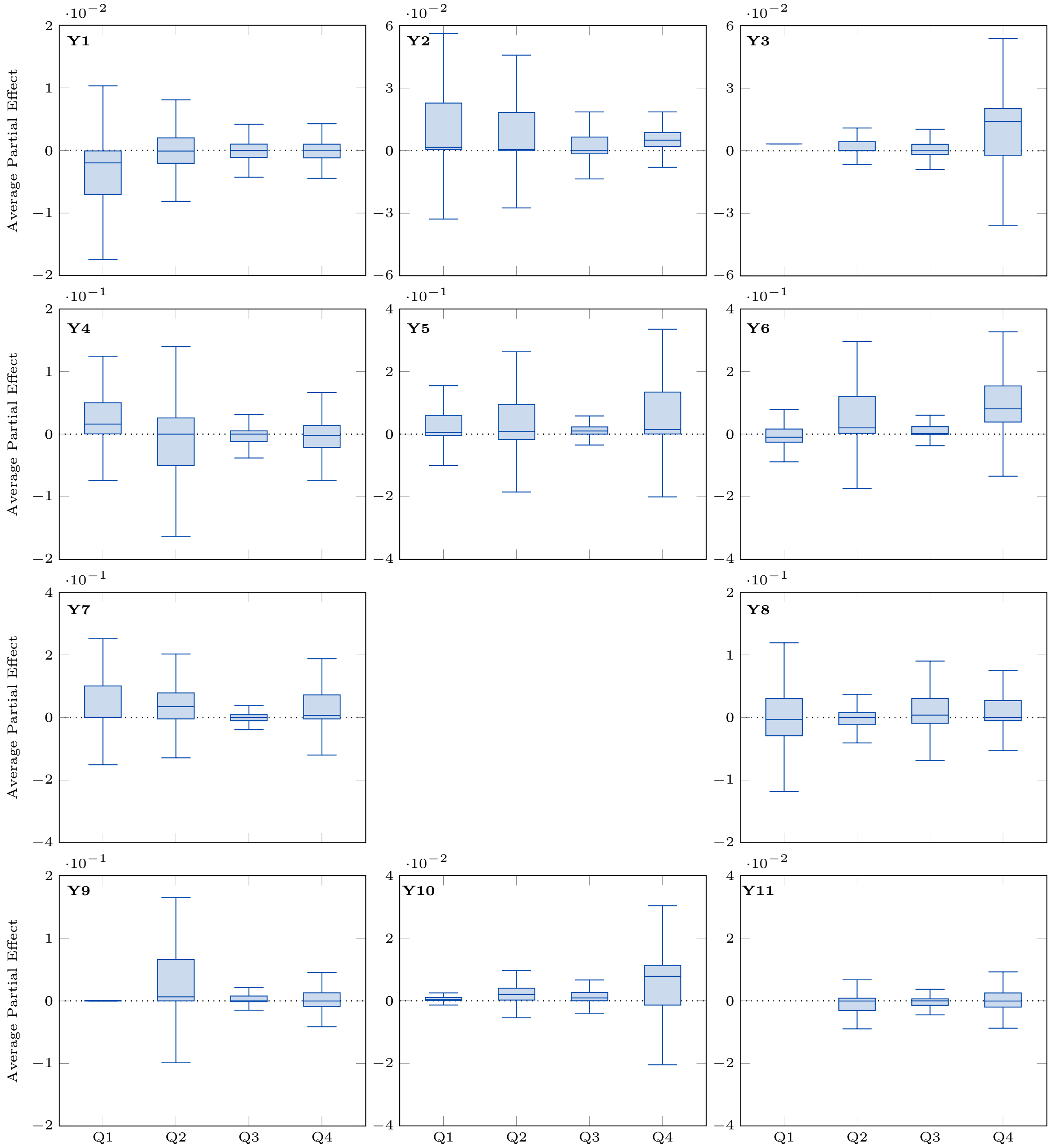


Figure D.6: **Calculated Average Partial Effects per Trade Openess Quartiles**. **Y1:** farmer's age, **Y2:** farmer's education, **Y3:** household size, **Y4:** farmer's gender, **Y5:** membership in groups, unions or associations, **Y6:** access to extension services, **Y7:** access to credit, **Y8:** access to off-farm income, **Y9:** farm's size, **Y10:** herd size, and **Y11:** distance from the market.

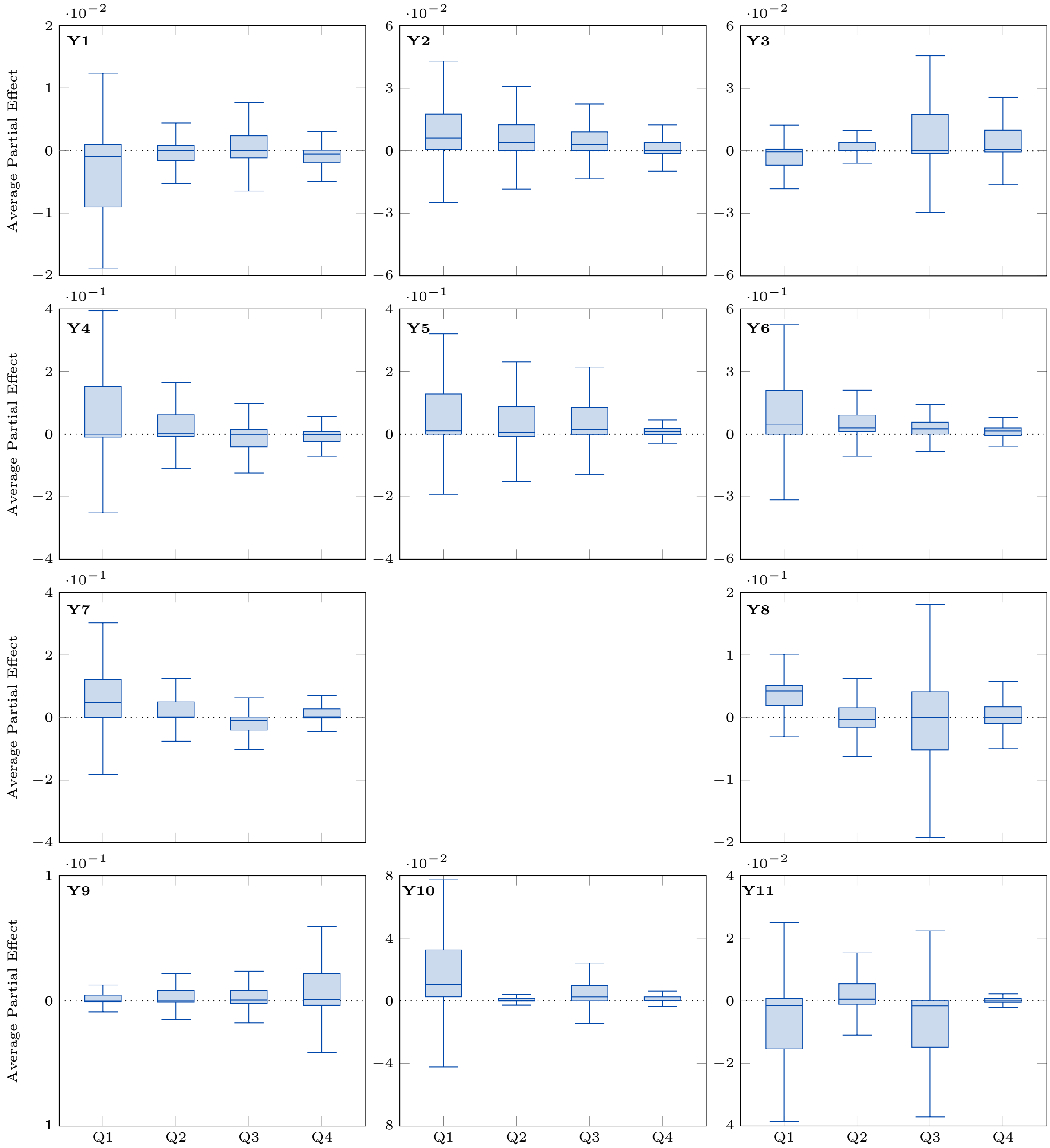


Figure D.7: **Calculated Average Partial Effects per Sample Size Quartiles**. **Y1:** farmer's age, **Y2:** farmer's education, **Y3:** household size, **Y4:** farmer's gender, **Y5:** membership in groups, unions or associations, **Y6:** access to extension services, **Y7:** access to credit, **Y8:** access to off-farm income, **Y9:** farm's size, **Y10:** herd size, and **Y11:** distance from the market.

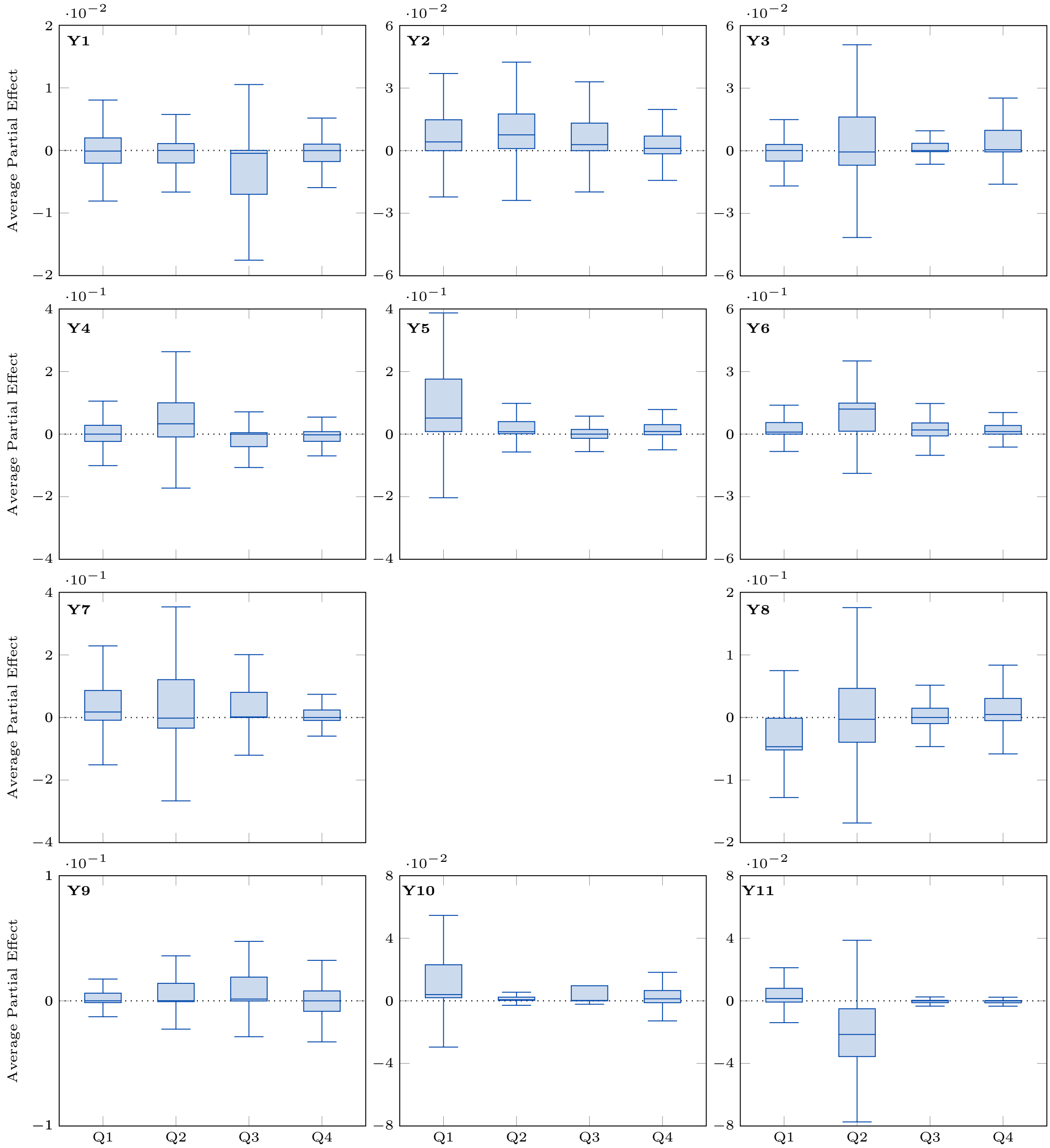


Figure D.8: **Calculated Average Partial Effects per No of Variables Quartiles.** **Y1:** farmer's age, **Y2:** farmer's education, **Y3:** household size, **Y4:** farmer's gender, **Y5:** membership in groups, unions or associations, **Y6:** access to extension services, **Y7:** access to credit, **Y8:** access to off-farm income, **Y9:** farm's size, **Y10:** herd size, and **Y11:** distance from the market.

E Moderator Variables: Description and Data Sources

Year of Survey refers to the year of data collection of the studies. If the survey was covering a period of two years, the starting year was considered. If the survey was covering a period of more than 2 years, the median year of the period was considered.

Sample Size includes the number of observations in the sample of the studies used in the estimation of the discrete choice model.

No of Variables refers to the number of explanatory variables used in the estimation of the discrete choice model in each study.

Probit Model is a dummy variable taking the value one for studies using Probit and Type I Tobit Models and zero for studies using Logit Model.

GDP per capita is measured at constant 2017 PPP international prices (in US$). Data were obtained from the *World Bank's* database on World Development Indicators. Data Download Date: March 25$^{\text{th}}$, 2022.

Share of agricultural sector in GDP refers to the percentage share of agricultural sector to GDP as observed at the year of the survey of the study. It was obtained from the *World Bank's* database on World Development Indicators. Data Download Date: March 26$^{\text{th}}$, 2022. If the dataset of the study was covering a period more than one year, than the annual average annual share of agricultural sector in GDP over the survey period was used. If more than one country was included in the dataset of the study, the average share of agricultural sector in GDP across countries was used.

Human Capital is proxied using Barro and Lee *Educational Attainment Data* defined as the average years of total schooling (http://www.barrolee.com). The dataset covers the period from 1950-2015. The 2021 September Update was used: Barro-Lee Estimates of Educational Attainment for the Population Aged 15-64 from 1950 to 2015. Data on educational attainment are available on 5-year intervals. Therfore, the nearest available year has been used. For instance, if the survey of the study was conducted in 2002, the observation on educational attainment for the year 2000 was used. If the year of survey was conducted in 2003, the observation for the year 2005 was used. For surveys after 2015, the observation on educational attainment for the year 2015 was used. If the survey was covering a period more than one year, then the average annual educational attainment over the survey period was used after considering first the nearest available year. For example, if the survey covered the period 2011-13, the average years of total schooling for 2010, 2010, and 2015 was considered. If more than one country was included in the survey, the average years of total schooling across countries was used. Barro and Lee *Educational Attainment Data* does not cover the following countries: *Nigeria*, *Ethiopia*, *Madagascar*, *Bosnia*, *Burkina Faso*, and *Timor Leste*. For these countries, we used compatible data on the mean years of schooling from *Unesco* (https://hdr.undp.org/en/indicators/103006).

Share of Foreign Direct Investments (FDI) in GDP refers to the net inflows (new investment inflows less disinvestment) in the reporting economy from foreign investors divided by GDP as observed at the year of the survey of the study. Data were obtained from the *World Bank's* database on World Development Indicators. Data Download Date: March 26$^{\text{th}}$, 2022. If the survey was covering a period of more than one year, then the average annual value over the survey period was used. If more than one country was included in the survey, the average value across countries was used.

Trade Openness refers to the sum of exports and imports of goods and services measured as a share of GDP. Data were obtained from the *World Bank's* database on World Development Indicators. Data Download Date: March 26$^{\text{th}}$, 2022. If the survey was covering a period more than one year, then the average annual value over the survey period was used. If more than one country was included in the survey, the average value across countries was used.

Type of farm technology. Papers in the sample were categorized according to the type of farm technology analyzed in the following groups:

- *AgTech1 - Improved seeds technologies* including GM, Bt, hybrid and improved seeds and modern varieties, and improved legume technologies.

- *AgTech2 - Soil conservation, plant protection and fertilization technologies* including soil fertility improvement, inorganic crops, soil conservation, pesticide and herbicides, soil bunds, nitrogen fertilizers, mineral fertilizers, reduced tillage, conservation tillage practices, mixed intercropping, and rotation practices.

- *AgTech3 - ICT, feeding, breeding, organic and water technologies* including computers in agriculture, precision farming, precision soil testing (PST) technology, internet use, precision soil sampling, climate-smart agriculture (CSA), GPS guidance systems, artificial insemination technology, feeding practices, pasture management, advanced breeding technologies, organic farming, integrated pest management, organic soil amendments (OSA), water conserving technologies and other irrigation technologies.

- *AgTech4 - other crop and livestock technologies* including *livestock* rBST (hormone enhancing milk production), planting of specialized fodder, integrated crop-livestock systems (ICLS), animal identification systems, individual animal recordkeeping, rotational grazing, improved garner-storage, medium-term practices, system of rice intensification (SRI), perennial crop technology, machinery use, animal traction, improved granary, metal silo technology, energy-savings installations, and improved production technologies such as: pruning, weeding, and roe planting.

Scimago Journal Rank Indicator is a measure of journal's impact, influence or prestige. It is calculated as the average number of weighted citations received in the selected year by the documents published in the journal in the last three years. Detailed information of the construction of the SJR indicator can be found in Guerrero-Bote, V.P. and F. Moya-Anegn. A further step forward in measuring journals's scientific prestige: The SJR2 indicator. *Journal of Informetrics*, 2012, 6: 674-688. For each study we used the corresponding indicator of the journal as observed at th year of publication. For the Journal of Agricultural and Applied Economics, the metrics are available only for the period 2016-2020. For earlier publications in this journal, the 2016 SJR score has been used.
US Co-author is a dummy vaiable taking the value if at least one of the authors of the paper is affiliated to a US institution at the year of publication.
Authors' H-index is measured as the average h-index of the authors of the study. The h-index of each author was obtained from Scopus.

References

Almeida, R. and A. M. Fernandes (2008). Openness and technological innovations in developing countries: evidence from firm-level surveys. *The Journal of Development Studies 44*(5), 701–727.

Balima, H. W., E. G. Kilama, and R. Tapsoba (2020). Inflation targeting: genuine effects or publication selection bias? *European Economic Review 128*, 103520.

Batz, F.-J., K. Peters, and W. Janssen (1999). The influence of technology characteristics on the rate and speed of adoption. *Agricultural Economics 21*(2), 121–130.

Cameron, A. C., J. B. Gelbach, and D. L. Miller (2008). Bootstrap-based improvements for inference with clustered errors. *The Review of Economics and Statistics 90*(3), 414–427.

Dinar, A. and D. Yaron (1992). Adoption and abandonment of irrigation technologies. *Agricultural Economics 6*(4), 315–332.

Egger, M., G. D. Smith, M. Schneider, and C. Minder (1997). Bias in meta-analysis detected by a simple, graphical test. *British Medical Journal 315*(7109), 629–634.

Evenson, R. E. and L. E. Westphal (1995). Technological change and technology strategy. *Handbook of Development Economics 3*, 2209–2299.

FAO (2020). Emissions due to agriculture: Global, regional and country trends 2000-2018. Technical report, FAOSTAT, Analytical Brief Series No 18 (Rome).

FAO et al. (2022). The state of food security and nutrition in the world 2022: Repurposing food and agricultural policies to make healthy diets more affordable. Technical report, FAO, Rome.

Feder, G., R. E. Just, and D. Zilberman (1985). Adoption of agricultural innovations in developing countries: A survey. *Economic Development and Cultural Change 33*(2), 255–298.

Feder, G. and D. L. Umali (1993). The adoption of agricultural innovations: a review. *Technological Forecasting and Social Change 43*(3-4), 215–239.

Glass, G. V. (1976). Primary, secondary, and meta-analysis of research. *Educational Researcher 5*(10), 3–8.

Glass, G. V. (1977). Integrating findings: the meta-analysis of research. *Review of Research in Education 5*(1), 351–379.

GNAF (2022). Global report on food crises: Joint analysis for better decisions. Technical report, Global Network Against Food (Rome).

Griliches, Z. (1957). Hybrid corn: An exploration in the economics of technological change. *Econometrica 25*(4), 501–522.

Havranek, T., Z. Irsova, and O. Zeynalova (2018). Tuition fees and university enrolment: a meta-regression analysis. *Oxford Bulletin of Economics and Statistics 80*(6), 1145–1184.

Huffman, W. E. (1977). Allocative efficiency: The role of human capital. *The Quarterly Journal of Economics 91*(1), 59–79.

Kassie, M., M. Jaleta, B. Shiferaw, F. Mmbando, and M. Mekuria (2013). Adoption of interrelated sustainable agricultural practices in smallholder systems: Evidence from rural tanzania. *Technological Forecasting and Social Change 80*(3), 525–540.

Kebebe, E. (2017). Household nutrition and income impacts of using dairy technologies in mixed crop–livestock production systems. *Australian Journal of Agricultural and Resource Economics 61*(4), 626–644.

Khanna, M. (2001). Sequential adoption of site-specific technologies and its implications for nitrogen productivity: A double selectivity model. *American Journal of Agricultural Economics 83*(1), 35–51.

Koundouri, P., C. Nauges, and V. Tzouvelekas (2006). Technology adoption under production uncertainty: theory and application to irrigation technology. *American Journal of Agricultural Economics 88*(3), 657–670.

Lin, J. Y. (1991). Education and innovation adoption in agriculture: Evidence from hybrid rice in china. *American Journal of Agricultural Economics 73*(3), 713–723.

Lipper, L., P. Thornton, B. M. Campbell, T. Baedeker, A. Braimoh, M. Bwalya, P. Caron, A. Cattaneo, D. Garrity, K. Henry, et al. (2014). Climate-smart agriculture for food security. *Nature Climate Change 4*(12), 1068–1072.

MacKinnon, J. G. and M. D. Webb (2017). Wild bootstrap inference for wildly different cluster sizes. *Journal of Applied Econometrics 32*(2), 233–254.

Martin, S. W., R. K. Roberts, S. L. Larkin, J. A. Larson, K. W. Paxton, B. C. English, M. C. Marra, J. M. Reeves, et al. (2008). A binary logit estimation of factors affecting adoption of gps guidance systems by cotton producers. *Journal of Agricultural and Applied Economics 40*(1), 345–355.

Nelson, R. R. and E. S. Phelps (1966). Investment in humans, technological diffusion, and economic growth. *American Economic Review 56*(1/2), 69–75.

Oczkowski, E. and H. Doucouliagos (2015). Wine prices and quality ratings: A meta-regression analysis. *American Journal of Agricultural Economics 97*(1), 103–121.

Ogundari, K. and O. D. Bolarinwa (2018). Impact of agricultural innovation adoption: a meta-analysis. *Australian Journal of Agricultural and Resource Economics 62*(2), 217–236.

Pearson, K. (1933). On a method of determining whether a sample of size n supposed to have been drawn from a parent population having a known probability integral has probably been drawn at random. *Biometrika 25*(3-4), 379–410.

Rogers, E. M. (1962). Diffusion of innovations. New York: The Free Press of Glencoe.

Rogers, E. M. (1995). Diffusion of innovations. New York: Free Press.

Ruzzante, S., R. Labarta, and A. Bilton (2021). Adoption of agricultural technology in the developing world: a meta-analysis of the empirical literature. *World Development 146*, 105599.

Sayer, J. and K. G. Cassman (2013). Agricultural innovation to protect the environment. *Proceedings of the National Academy of Sciences 110*(21), 8345–8348.

Simpson, R. J. S. and K. Pearson (1904). Report on certain enteric fever inoculation statistics. *The British Medical Journal 2*(2288), 1243–1246.

Stanley, T. D. (2001). Wheat from chaff: Meta-analysis as quantitative literature review. *Journal of Economic Perspectives 15*(3), 131–150.

Stanley, T. D. (2005). Beyond publication bias. *Journal of Economic Surveys 19*(3), 309–345.

Stanley, T. D. (2008). Meta-regression methods for detecting and estimating empirical effects in the presence of publication selection. *Oxford Bulletin of Economics and Statistics 70*(1), 103–127.

Stanley, T. D. and H. Doucouliagos (2014). Meta-regression approximations to reduce publication selection bias. *Research Synthesis Methods 5*(1), 60–78.

Stanley, T. D. and H. Doucouliagos (2015). Neither fixed nor random: weighted least squares meta-analysis. *Statistics in Medicine 34*(13), 2116–2127.

Stanley, T. D. and H. Doucouliagos (2017). Neither fixed nor random: weighted least squares meta-regression. *Research Synthesis Methods 8*(1), 19–42.

Stanley, T. D., H. Doucouliagos, M. Giles, J. H. Heckemeyer, R. J. Johnston, P. Laroche, J. P. Nelson, M. Paldam, J. Poot, G. Pugh, et al. (2013). Meta-analysis of economics research reporting guidelines. *Journal of Economic Surveys 27*(2), 390–394.

Stanley, T. D. and S. B. Jarrell (2005). Meta-regression analysis: a quantitative method of literature surveys. *Journal of Economic Surveys 19*(3), 299–308.

Sunding, D. and D. Zilberman (2001). The agricultural innovation process: research and technology adoption in a changing agricultural sector. *Handbook of Agricultural Economics 1*, 207–261.

Takahashi, K., R. Muraoka, and K. Otsuka (2020). Technology adoption, impact, and extension in developing countries' agriculture: A review of the recent literature. *Agricultural Economics 51*(1), 31–45.

F List of Papers Included in the Meta-Dataset

Abay, K.A., Berhane, G., Taffesse, A.S., Abay, K. and B. Koru. (2018). Estimating input complementarities with unobserved heterogeneity: Evidence from Ethiopia. *Journal of Agricultural Economics*, 69(2), 495-517.

Abdulai, A.N. (2016). Impact of conservation agriculture technology on household welfare in Zambia. *Agricultural Economics*, 47(6), 729-741.

Abebe, G.K., Bijman, J., Pascucci, S. and O. Omta. (2013). Adoption of improved potato varieties in Ethiopia: The role of agricultural knowledge and innovation system and smallholder farmers' quality assessment. *Agricultural Systems*, 122, 22-32.

Adegbola, P. and C. Gardebroek. (2007). The effect of information sources on technology adoption and modification decisions. *Agricultural Economics*, 37(1), 55-65.

Adesina, A.A. and J. Chianu. (2002). Determinants of farmers' adoption and adaptation of alley farming technology in Nigeria. *Agroforestry Systems*, 55(2), 99-112.

Akinola, A.A., Alene, A.D., Adeyemo, R., Sanogo, D., Olanrewaju, A.S., Nwoke, C. and G. Nziguheba. (2010). Determinants of adoption and intensity of use of balance nutrient management systems technologies in the northern Guinea savanna of Nigeria. *Quarterly Journal of International Agriculture*, 49(892-2016-65208), 25-45.

Alene, A. and V. Manyong. (2006). Endogenous technology adoption and household food security: the case of improved cowpea varieties in northern Nigeria. *Quarterly Journal of International Agriculture*, 45(3), 211-230.

Alexander, C.E. and T. Van Mellor. (2005). Determinants of corn rootworm resistant corn adoption in Indiana. *AgBioForum*, 8(4), 197-204.

Ali, A., Hussain, I., Rahut, D.B. and O. Erenstein. (2018). Laser-land leveling adoption and its impact on water use, crop yields and household income: Empirical evidence from the rice-wheat system of Pakistan Punjab. *Food Policy*, 77, 19-32.

Ali, A. and A. Abdulai. (2010). The adoption of genetically modified cotton and poverty reduction in Pakistan. *Journal of Agricultural Economics*, 61(1), 175-192.

Ali, D.A., Bowen, D. and K. Deininger. (2020). Personality traits, technology adoption, and technical efficiency: evidence from smallholder rice farms in Ghana. *Journal of Development Studies*, 56(7), 1330-1348.

Alwang, J., Gotor, E., Thiele, G., Hareau, G., Jaleta, M. and J. Chamberlin. (2019). Pathways from research on improved staple crop germplasm to poverty reduction for smallholder farmers. *Agricultural Systems*, 172, 16-27.

Amadu, F.O., McNamara, P.E. and D.C. Miller. (2020). Yield effects of climate-smart agriculture aid investment in southern Malawi. *Food Policy*, 92, 101869.

Aramyan, L.H., Lansink, A.G.J.M.O. and J.A.A.M. Verstegen. (2007). Factors underlying the investment decision in energy-saving systems in Dutch horticulture. *Agricultural Systems*, 94(2), 520-527.

Aryal, J.P., Farnworth, C.R., Khurana, R., Ray, S., Sapkota, T.B. and D.B. Rahut. (2020). Does women's participation in agricultural technology adoption decisions affect the adoption of climate-smart agriculture? Insights from Indo-Gangetic plains of India. *Review of Development Economics*, 24(3), 973-990.

Asfaw, S., Kassie, M., Simtowe, F., and L. Lipper. (2012). Poverty reduction effects of agricultural technology adoption: a micro-evidence from rural Tanzania. *Journal of Development Studies*, 48(9), 1288-1305.

Asfaw, S., Shiferaw, B., Simtowe, F. and L. Lipper. (2012). Impact of modern agricultural technologies on smallholder welfare: Evidence from Tanzania and Ethiopia. *Food Policy*, 37(3), 283?295.

Atanu, S., Love, H.A. and R. Schwart. (1994). Adoption of emerging technologies under output uncertainty. *American Journal of Agricultural Economics*, 76(4), 836-846.

Bairagi, S., Mishra, A.K. and A. Durand-Morat. (2020). Climate risk management strategies and food security: Evidence from Cambodian rice farmers. *Food Policy*, 95.

Banerjee, S. and S.W. Martin. (2009). A binary logit analysis of factors impacting adoption of genetically modified cotton. *AgBioForum*, 12(2), 218-225.

Bayan, B. and M.K. Dutta. (2018) What influences adoption and use intensity of artificial insemination technology among smallholder dairy farmers in Assam? A double hurdle approach. *Indian Journal of Agricultural Economics*, 73 (4).

Becerril, J. and A. Abdulai, A. (2010). The impact of improved maize varieties on poverty in Mexico: A propensity score-matching approach. *World development*, 38(7), 1024-1035.

Beltran, J.C., White, B., Burton, M., Doole, G.J., and D.J. Pannell. (2013). Determinants of herbicide use in rice production in the Philippines. *Agricultural Economics*, 44(1), 45?55.

Bezu, S., Kassie, G.T., Shiferaw, B. and J. Ricker-Gilbert. (2014). Impact of improved maize adoption on welfare of farm households in Malawi: A panel data analysis. *World Development*, 59, 120-131.

Canales, E., Bergtold, J.S. and J.R. Williams. (2018). Modeling the choice of tillage used for dryland corn, wheat and soybean production by farmers in Kansas. *Agricultural and Resource Economics Review*, 47(1), 90?117.

Cavatassi, R., Lipper, L. and U. Narloch. (2011). Modern variety adoption and risk management in drought prone areas: Insights from the sorghum farmers of eastern Ethiopia. *Agricultural Economics*, 42(3), 279-292.

Chirwa, E.W. (2005). Adoption of fertiliser and hybrid seeds by smallholder maize farmers in southern Malawi. *Development Southern Africa*, 22, 1-12.

Coulibaly, J.Y., Chiputwa, B., Nakelse, T. and G. Kundhlande. (2017). Adoption of agroforestry and the impact on household food security among farmers in Malawi. *Agricultural Systems*, 155, 52-69.

D'Emden, F.H., Llewellyn, R.S. and M.P. Burton. (2008). Factors influencing adoption of conservation tillage in Australian cropping regions. *Australian Journal of Agricultural and Resource Economics*, 52(2), 169-182.

Dalton, T.J., Lilja, N.K., Johnson, N. and R. Howeler. (2011). Farmer participatory research and soil conservation in Southeast Asian cassava systems. *World Development*, 39(12), 2176-2186.

DeGraft-Johnson, M., Suzuki, A., Sakurai, T. and K. Otsuka. (2014). On the transferability of the Asian rice green revolution to rainfed areas in sub-Saharan Africa: An assessment of technology intervention in Northern Ghana. *Agricultural Economics*, 45(5), 555-570.

Dimara, E. and D. Skuras. (1998). Adoption of new tobacco varieties in Greece: Impacts of empirical findings on policy design. *Agricultural Economics*, 19(3), 297-307.

Dinis, I., Ortolani, L., Bocci, R. and C. Brites. (2015). Organic agriculture values and practices in Portugal and Italy. *Agricultural Systems*, 136, 39-45.

Erenstein, O. (2006). Intensification or extensification? Factors affecting technology use in peri-urban lowlands along an agro-ecological gradient in West Africa. *Agricultural Systems*, 90(1-3), 132?158.

Fang, D. and T.J. Richards. (2018). New maize variety adoption in Mozambique: A spatial approach. *Canadian Journal of Agricultural Economics*, 66(3), 469-488.

Fisher, M. and V. Kandiwa. (2014). Can agricultural input subsidies reduce the gender gap in modern maize adoption? Evidence from Malawi. *Food Policy*, 45, 101-111.

Foltz, J.D. (2003). The economics of water-conserving technology adoption in Tunisia: An empirical estimation of farmer technology choice. *Economic Development and Cultural Change*, 51(2), 359-373.

Foltz, J.D. and H.H. Chang. (2002). The adoption and profitability of rbST on Connecticut dairy farms. *American Journal of Agricultural Economics*, 84(4), 1021-1032.

Gebremariam, G. and W. Tesfaye. (2018). The heterogeneous effect of shocks on agricultural innovations adoption: Microeconometric evidence from rural Ethiopia. *Food Policy*, 74, 154-161.

Gebremedhin, B., Jaleta, M. and D. Hoekstra. (2009). Smallholders, institutional services, and commercial transformation in Ethiopia. *Agricultural Economics*, 40(1), 773-787.

Genius, M., Pantzios, C.J. and V. Tzouvelekas. (2006). Information acquisition and adoption of organic farming practices. *Journal of Agricultural and Resource Economics*, 93-113.

Gillespie, J., Qushim, B., Nyaupane, N. and K. McMillin. (2015). Breeding technologies in US meat goat production: Who are the adopters and how does adoption impact productivity? *Agricultural and Resource Economics Review*, 44(3), 315-339.

Githiomi, C., Muriithi, B., Irungu, P., Mwungu, C.M., Diiro, G., Affognon, H. and S. Ekesi. (2019). Economic analysis of spillover effects of an integrated pest management (IPM) strategy for suppression of mango fruit fly in Kenya. *Food Policy*, 84, 121-132.

Gitonga, Z.M., De Groote, H., Kassie, M. and T. Tefera. (2013). Impact of metal silos on households' maize storage, storage losses and food security: An application of a propensity score matching. *Food Policy*, 43, 44-55.

Gockowski, J. and M. Ndoumbe. (2004). The adoption of intensive monocrop horticulture in southern Cameroon. *Agricultural Economics*, 30(3), 195-202.

He, X., Cao, H. and F. Li. (2008). Factors influencing the adoption of pasture crop rotation in the semiarid area of China's Loess Plateau. *Journal of Sustainable Agriculture*, 32(1), 161-180.

Jaleta, M., Kassie, M., Tesfaye, K., Teklewold, T., Jena, P.R., Marenya, P. and O. Erenstein. (2016). Resource saving and productivity enhancing impacts of crop management innovation packages in Ethiopia. *Agricultural Economics*, 47(5), 513-522.

Jara-Rojas, R., Bravo-Ureta, B.E. and J. Diaz. (2012). Adoption of water conservation practices: A socioeconomic analysis of small-scale farmers in Central Chile. *Agricultural Systems*, 110, 54-62.

Jarvis, A.M. (1990). Computer adoption decision-implications for research and extension: The case of Texas rice producers. *American Journal of Agricultural Economics*, 72(5), 1388-1394.

Kabunga, N.S., Dubois, T. and M. Qaim. (2012). Heterogeneous information exposure and technology adoption: The case of tissue culture bananas in Kenya. *Agricultural Economics*, 43(5), 473-486.

Kaliba, A.R., Featherstone, A.M. and D.W. Norman. (1997). A stall-feeding management for improved cattle in semiarid central Tanzania: Factors influencing adoption. *Agricultural Economics*, 17(2-3), 133-146.

Kassie, M., Shiferaw, B. and G. Muricho. (2011). Agricultural technology, crop income, and poverty alleviation in Uganda. *World Development*, 39(10), 1784-1795.

Kassie, M., Zikhali, P., Pender, J. and G. Köhlin. (2010). The economics of sustainable land management practices in the Ethiopian highlands. *Journal of Agricultural Economics*, 61(3), 605-627.

Keelan, C., Thorne, F.S., Flanagan, P., Newman, C. and E. Mullins. (2009). Predicted willingness of Irish farmers to adopt GM technology. *AgBioForum*, 12(3-4), 394-403.

Khanal, A. R. and J. Gillespie. (2013). Adoption and productivity of breeding technologies: Evidence from US dairy farms. *AgBioForum*, 16(1), 53-65.

Khanna, M. (2001). Sequential adoption of site-specific technologies and its implications for nitrogen productivity: A double selectivity model. *American Journal of Agricultural Economics*, 83(1), 35-51.

Khonje, M.G., Manda, J., Mkandawire, P., Tufa, A.H. and A.D. Alene. (2018). Adoption and welfare impacts of multiple agricultural technologies: Evidence from eastern Zambia. *Agricultural Economics*, 49(5), 599-609.

Kijima, Y., Otsuka, K. and D. Sserunkuuma. (2008). Assessing the impact of NERICA on income and poverty in central and western Uganda. *Agricultural Economics*, 38(3), 327-337.

Kim, S.A., Gillespie, J.M. and K.P. Paudel. (2008). Rotational grazing adoption in cattle production under a cost-share agreement: Does uncertainty have a role in conservation technology adoption? *Australian Journal of Agricultural and Resource Economics*, 52(3), 235?252.

Koundouri, P., Nauges, C. and V. Tzouvelekas. (2006). Technology adoption under production uncertainty: Theory and application to irrigation technology. *American Journal of Agricultural Economics*, 88(3), 657-670.

Kumar, A., Prasad, K., Kushwaha, R.R., Rajput, M.M. and B.S. Sachan. (2010). Determinants influencing the acceptance of resource conservation technology: Case of zero-tillage in rice-wheat farming systems in Uttar Pradesh, Bihar and Haryana States. *Indian Journal of Agricultural Economics*, 65, 902-917.

Lambert, D.M., Clark, C.D., Medwid, L.J., Hawkins, S.A. and H.A. McClellan. (2020). Best pasture management practice adoption and sediment abatement. *Journal of Agricultural and Applied Economics*, 52(2), 204-221.

Lambrecht, I., Vanlauwe, B., Merckx, R. M. Maertens. (2014). Understanding the process of agricultural technology adoption: Mineral fertilizer in eastern DR Congo. *World Development*, 59, 132-146.

Lambrecht, I., Vanlauwe, B. and M. Maertens. (2016). Agricultural extension in Eastern Democratic Republic of Congo: Does gender matter? *European Review of Agricultural Economics*, 43(5), 841-874.

Lampach, N., Nguyen-Van, P. and N. To-The. (2020). Robustness analysis of organic technology adoption: Evidence from Northern Vietnamese tea production. *European Review of Agricultural Economics*, 47(2), 529-557.

Laxmi, V. and V. Mishra. (2007). Factors affecting the adoption of resource conservation technology: Case of zero tillage in rice-wheat farming systems. *Indian Journal of Agricultural Economics*, 62(902-2016-67372).

Lee, S. and L. McCann. (2019). Adoption of cover crops by U.S. soybean producers. *Journal of Agricultural and Applied Economics*, 51(4), 527-544.

Liverpool Tasie, L.S.O. and C.M. Parkhi. (2021). Climate risk and technology adoption in the midstream of crop value chains: Evidence from Nigerian maize traders. *Journal of Agricultural Economics*, 72(1), 158-179.

Lunduka, R., Fisher, M. and S. Snapp. (2012). Could farmer interest in a diversity of seed attributes explain adoption plateaus for modern maize varieties in Malawi? *Food Policy*, 37(5), 504-510.

Ma, W., Abdulai, A. and R. Goetz. (2018). Agricultural cooperatives and investment in organic soil amendments and chemical fertilizer in China. *American Journal of Agricultural Economics*, 100(2), 502?520.

Makate, C., Wang, R., Makate, M. and N. Mango. (2017). Impact of drought tolerant maize adoption on maize productivity, sales and consumption in rural Zimbabwe. *Agrekon*, 56(1), 67-81.

Mal, P., Anik, A.R., Bauer, S. and P.M. Schmitz. (2012). Bt cotton adoption: A double-hurdle approach for north Indian farmers. *AgBioForum*, 15(3), 294-302.

Manda, J., Gardebroek, C., Kuntashula, E. and A.D. Alene. (2018). Impact of improved maize varieties on food security in Eastern Zambia: A doubly robust analysis. *Review of Development Economics*, 22(4), 1709-1728.

Manda, J., Khonje, M.G., Alene, A.D. and T. Gondwe. (2017). Welfare impacts of improved groundnut varieties in eastern Zambia: A heterogeneous treatment effects approach. *Agrekon*, 56(4), 313-329.

Mariano, M.J., Villano, R. and E. Fleming. (2012). Factors influencing farmers' adoption of modern rice technologies and good management practices in the Philippines. *Agricultural Systems*, 110, 41-53.

Martin, S.W., Roberts, R.K., Larkin, S.L., Larson, J.A., Paxton, K.W., English, B.C., and J.M. Reeves. (2008). A binary logit estimation of factors affecting adoption of GPS guidance systems by cotton producers. *Journal of Agricultural and Applied Economics*, 40(1), 345-355.

Martin, S.W., Roberts, R.K., Larson, J.A., Hogan Jr, R.J., Johnson, J.L. and K.W. Paxton. (2009). Adoption of conservation-tillage practices and herbicide-resistant seed in cotton production. *AgBioForum*, 12(3-4), 258-268.

Matuschke, I., Mishra, R.R. and M. Qaim. (2007). Adoption and impact of hybrid wheat in India. *World Development*, 35(8), 1422-1435.

Matuschke, I. and M. Qaim. (2009). The impact of social networks on hybrid seed adoption in India. *Agricultural Economics*, 40(5), 493-505.

Midingoyi, S.K.G., Kassie, M., Muriithi, B., Diiro, G. and S. Ekesi. (2019). Do farmers and the environment benefit from adopting integrated pest management practices? Evidence from Kenya. *Journal of Agricultural Economics*, 70(2), 452-470.

Mignouna, D.B., Manyong, V.M., Rusike, J., Mutabazi, K.D.S. and E.M. Senkondo. (2006). Determinants of adopting imazapyr-resistant maize technologies and its impact on household income in Western Kenya. *AgBioForum*, 14(3), 158-163.

Minten, B., Dereje, M., Engida, E. and T. Kuma. (2019). Coffee value chains on the move: Evidence in Ethiopia. *Food Policy*, 83, 370-383.

Moser, C.M. abd C.B. Barrett. (2006). The complex dynamics of smallholder technology adoption: The case of SRI in Madagascar. *Agricultural Economics*, 35(3), 373-388.

Moyo, S., Norton, G.W., Alwang, J., Rhinehart, I. and M. Deom. (2007). Peanut research and poverty reduction: Impacts of variety improvement to control peanut viruses in Uganda. *American Journal of Agricultural Economics*, 89(2), 448-460.

Mulimbi, W., Nalley, L., Dixon, B., Snell, H. and Q. Huang. (2019). Factors influencing adoption of conservation agriculture in the Democratic Republic of the Congo. *Journal of Agricultural and Applied Economics*, 51(4), 622-645.

Mutuc, M E.M., Rejesus, R.M., Pan, S. and J.M. Yorobe. (2012). Impact assessment of Bt corn adoption in the Philippines. *Journal of Agricultural and Applied Economics*, 44(1), 117-135.

Ndiritu, S.W., Kassie, M. and B. Shiferaw. (2014). Are there systematic gender differences in the adoption of sustainable agricultural intensification practices? Evidence from Kenya. *Food Policy*, 49(P1), 117-127.

Noltze, M., Schwarze, S. and M. Qaim. (2012). Understanding the adoption of system technologies in smallholder agriculture: The system of rice intensification (SRI) in Timor Leste. *Agricultural Systems*, 108, 64-73.

Paudel, G.P., Krishna, V.V. and A.J. McDonald. (2020). Apparent gains, hidden costs: Examining adoption drivers, yield, and profitability outcomes of rotavator tillage in wheat systems in Nepal. *Journal of Agricultural Economics*, 71(1), 199-218.

Pruitt, J.R., Gillespie, J.M., Nehring, R.F. and B. Qushim. (2012). Adoption of technology, management practices, and production systems by US beef cow-calf producers. *Journal of Agricultural and Applied Economics*, 44(2), 203-222.

Qaim, M. and A. De Janvry. (2003). Genetically modified crops, corporate pricing strategies, and farmers' adoption: The case of Bt cotton in Argentina. *American Journal of Agricultural Economics*, 85(4), 814-828.

Raghu, P.T., Erenstein, O., Böber, C. and V.V. Krishna. (2015). Adoption and outcomes of hybrid maize in the marginal areas of India. *Quarterly Journal of International Agriculture*, 54(892-2016-65242), 189-214.

Rahman, S. (2011). Resource use efficiency under self-selectivity: The case of Bangladeshi rice producers. *Australian Journal of Agricultural and Resource Economics*, 55(2), 273-290.

Ransom, J.K., Paudyal, K. and K. Adhikari. (2003). Adoption of improved maize varieties in the hills of Nepal. *Agricultural Economics*, 29(3), 299-305.

Rao, C.A., Rao, M.S., Naraiah, P., Malathi, B. and Y.V.R. Reddy. (2008). An economic analysis of adoption of integrated pest management in groundnut. *Indian Journal of Agricultural Economics*, 63(902-2016-67946).

Rejesus, R.M., Palis, F.G., Rodriguez, D.G.P., Lampayan, R.M. and B.A.M. Bouman. (2011). Impact of the alternate wetting and drying (AWD) water-saving irrigation technique: Evidence from rice producers in the Philippines. *Food Policy*, 36(2), 280-288.

Sanch-Maritan, M. and L. Vedrine. (2019). Forced displacement and technology adoption: An empirical analysis based on agricultural households in Bosnia and Herzegovina. *Journal of Development Studies*, 55(6), 1325-1343.

Sanglestsawai, S., Rodriguez, D.G.P., Rejesus, R.M. and J.M. Yorobe. (2017). Production risk, farmer welfare, and Bt Corn in the Philippines. *Agricultural and Resource Economics Review*, 46(3), 507-528.

Schoengold, K. and D.L. Sunding. (2014). The impact of water price uncertainty on the adoption of precision irrigation systems. *Agricultural Economics*, 45(6), 729-743.

Shakya, P.B. and J.C. Flinn. (1985). Adoption of modern varieties and fertilizer use on rice in the Eastern Tarai of Nepal. *Journal of Agricultural Economics*, 36(3), 409-419.

Shively, G.E. (2001). Poverty, consumption risk, and soil conservation. *Journal of Development Economics*, 65(2), 267-290.

Solis, D., Bravo-Ureta, B.E. and R.E. Quiroga. (2007). Soil conservation and technical efficiency among hillside farmers in Central America: A switching regression model. *Australian Journal of Agricultural and Resource Economics*, 51(4), 491-510.

Soule, M.J., Tegene, A. and K.D. Wiebe. (2000). Land tenure and the adoption of conservation practices. *American Journal of Agricultural Economics*, 82(4), 993-1005.

Takam-Fongang, G.M., Kamdem, C.B. and G.Q. Kane. (2019). Adoption and impact of improved maize varieties on maize yields: Evidence from central Cameroon. *Review of Development Economics*, 23(1), 172-188.

Tauer, L.W. (2005). The impact of recombinant bovine somatotropin on dairy farm profits: A switching regression analysis. *AgBioForum*, 8(1), 33-39.

Tauer, L.W. (2006). Impact of recombinant bovine somatotropin on dairy farm cost of production: Evidence from multiyear Data. *AgBioForum*, 9(2), 79-83.

Tefera, T. and M.W. Giorgis. (2010). Determinants of coffee husk manure adoption: A case study from southern Ethiopia. *Indian Journal of Agricultural Economics*, 65(902-2016-67363).

Thangata, P.H. and J.R.R. Alavalapati. (2003). Agroforestry adoption in southern Malawi: The case of mixed intercropping of Gliricidia sepium and maize. *Agricultural Systems*, 78(1), 57-71.

Theriault, V., Smale, M. and H. Haider. (2017). How does gender affect sustainable intensification of cereal production in the West African Sahel? Evidence from Burkina Faso. *World Development*, 92, 177-191.

Thuo, M., Bell, A.A., Bravo-Ureta, B.E., Lachaud, M.A., Okello, D.K., Okoko, E.N., ... and N. Puppala. (2014). Effects of social network factors on information acquisition and adoption of improved groundnut varieties: The case of Uganda and Kenya. *Agriculture and Human Values*, 31(3), 339-353.

Tshikala, S.K., Kostandini, G. and E.G. Fonsah. (2019). The impact of migration, remittances and public transfers on technology adoption: The case of cereal producers in rural Kenya. *Journal of Agricultural Economics*, 70(2), 316-331.

Wafula, L., Oduol, J., Oluoch-Kosura, W., Muriuki, J., Okello, J. and J. Mowo, J. (2016). Does strengthening technical capacity of smallholder farmers enhance adoption of conservation practices? The case of conservation agriculture with trees in Kenya. *Agroforestry Systems*, 90(6), 1045-1059.

Wainaina, P., Tongruksawattana, S. and M. Qaim. (2016). Tradeoffs and complementarities in the adoption of improved seeds, fertilizer, and natural resource management technologies in Kenya. *Agricultural Economics*, 47(3), 351-362.

Walton, J.C., Lambert, D.M., Roberts, R.K., Larson, J.A., English, B., Larkin, S.L., ... and J.M. Reeves. (2008). Adoption and abandonment of precision soil sampling in cotton production. *Journal of Agricultural and Resource Economics*, 428-448.

Wang, H.H., Young, D.L. and O.M. Camara. (2000). The role of environmental education in predicting adoption of wind erosion control practices. *Journal of Agricultural and Resource Economics*, 547-558.

Weir, S. and J. Knight. (2004). Externality effects of education: Dynamics of the adoption and diffusion of an innovation in rural Ethiopia. *Economic Development and Cultural Change*, 53(1), 93-113.

Wollni, M., Lee, D.R. and J.E. Thies. (2010). Conservation agriculture, organic marketing, and collective action in the Honduran hillsides. *Agricultural Economics*, 41(3-4), 373-384.

Wossen, T., Alene, A., Abdoulaye, T., Feleke, S., Rabbi, I.Y. and V. Manyong. (2019). Poverty reduction effects of agricultural technology adoption: The case of improved cassava varieties in Nigeria. *Journal of Agricultural Economics*, 70(2), 392-407.

Wossen, T., Berger, T. and S. Di Falco. (2015). Social capital, risk preference and adoption of improved farm land management practices in Ethiopia. *Agricultural Economics*, 46(1), 81-97.

Yigezu, Y.A., Alwang, J., Rahman, M.W., Mollah, M.B.R., El-Shater, T., Aw-Hassan, A. and A. Sarker. (2019). Is DNA fingerprinting the gold standard for estimation of adoption and impacts of improved lentil varieties? *Food Policy*, 83, 48-59.

Zheng, H., Ma, W. and G. Li. (2021). Adoption of organic soil amendments and its impact on farm performance: evidence from wheat farmers in China. *Australian Journal of Agricultural and Resource Economics*, 65(2), 367-390.

Zhou, X., Ma, W., Li, G. and H. Qiu. (2020). Farm machinery use and maize yields in China: An analysis accounting for selection bias and heterogeneity. *Australian Journal of Agricultural and Resource Economics*, 64(4), 1282-1307.

G List of Papers with Missing Data

Alem, Y., Bezabih, M., Kassie, M., and P. Zikhali (2010). Does fertilizer use respond to rainfall variability? Panel data evidence from Ethiopia. *Agricultural Economics*, 41(2), 165?175.

Areal, F.J., Riesgo, L., Gomez-Barbero, M., and E. Rodriguez-Cerezo (2012). Consequences of a coexistence policy on the adoption of GMHT crops in the European Union. *Food Policy*, 37(4), 401-411.

Bello, L.O., Baiyegunhi, L.J., and G. Danso-Abbeam (2021). Productivity impact of improved rice varieties adoption: case of smallholder rice farmers in Nigeria. *Economics of Innovation and New Technology*, 30(7), 750-766.

Croppenstedt, A., Demeke, M., and M.M. Meschi (2003). Technology adoption in the presence of constraints: the case of fertilizer demand in Ethiopia. *Review of Development Economics*, 7(1), 58-70.

D'souza, G., Cyphers, D., and T. Phipps (1993). Factors affecting the adoption of sustainable agricultural practices. *Agricultural and Resource Economics Review*, 22(2), 159-165.

Daberkow, S. G., and W.D. McBride (2003). Farm and operator characteristics affecting the awareness and adoption of precision agriculture technologies in the US. *Precision agriculture*, 4(2), 163-177.

Damania, R., Berg, C., Russ, J., Barra, A.F., Nash, J., and R. Ali (2017). Agricultural technology choice and transport. *American Journal of Agricultural Economics*, 99(1), 265?284.

Dercon, S., and L. Christiaensen (2011). Consumption risk, technology adoption and poverty traps: Evidence from Ethiopia. *Journal of Development Economics*, 96(2), 159-173.

Dinar, A., Campbell, M.B., and D. Zilberman (1992). Adoption of improved irrigation and drainage reduction technologies under limiting environmental conditions. *Environmental and Resource Economics*, 2(4), 373-398.

Feleke, S., and T. Zegeye (2006). Adoption of improved maize varieties in Southern Ethiopia: Factors and strategy options. *Food Policy*, 31(5), 442-457.

Fernandez-Cornejo, J., Beach, E. D., and W.Y. Huang (1994). The adoption of IPM techniques by vegetable growers in Florida, Michigan and Texas. *Journal of Agricultural and Applied Economics*, 26(1), 158-172.

Fernandez-Cornejo, J., and Wechsler, S. (2012). Revisiting the impact of Bt corn adoption by U.S. farmers. *Agricultural and Resource Economics Review*, 41(3), 377-390.

Houeninvo, G.H., Cilestin Quenum, C.V., and G.M.A. Nonvide (2020). Impact of improved maize variety adoption on smallholder farmers? welfare in Benin. *Economics of Innovation and New Technology*, 29(8), 831-846.

Kassie, M., Jaleta, M., Shiferaw, B., Mmbando, F., and M. Mekuria (2013). Adoption of interrelated sustainable agricultural practices in smallholder systems: Evidence from rural Tanzania. *Technological forecasting and social change*, 80(3), 525-540.

Katengeza, S.P., Holden, S.T., and R.W. Lunduka (2019). Adoption of drought tolerant maize varieties under rainfall stress in Malawi. *Journal of Agricultural Economics*, 70(1), 198-214.

Kaufmann, P., Zemeckis, R., Skulskis, V., Kairyte, E., and S. Stagl (2011). The diffusion of organic farming in Lithuania. *Journal of sustainable agriculture*, 35(5), 522-549.

Khonje, M., Manda, J., Alene, A.D., and M. Kassie (2015). Analysis of adoption and impacts of improved maize varieties in eastern Zambia. *World Development*, 66, 695-706.

Lewis, D.J., Barham, B.L., and B. Robinson (2011). Are there spatial spillovers in the adoption of clean technology? The case of organic dairy farming. *Land Economics*, 87(2), 250-267.

Li, J., Gomez, M.I., Rickard, B.J., and M. Skinner (2013). Factors influencing adoption of integrated pest management in Northeast greenhouse and nursery production. *Agricultural and Resource Economics Review*, 42(2), 310-324.

Lin, J. Y. (1991). Education and innovation adoption in agriculture: evidence from hybrid rice in China. *American Journal of Agricultural Economics*, 73(3), 713-723.

Llewellyn, R.S., Lindner, R.K., Pannell, D.J., and S.B. Powles (2007). Herbicide resistance and the adoption of integrated weed management by Western Australian grain growers. *Agricultural Economics*, 36(1), 123-130.

Magnan, N., Love, A.M., Mishili, F.J., and G. Sheremenko (2020). Husbands' and wives' risk preferences and improved maize adoption in Tanzania. *Agricultural Economics*, 51(5), 743-758.

Mayen, C.D., Balagtas, J.V., and C.E. Alexander (2010). Technology adoption and technical efficiency: Organic and conventional dairy farms in the United States. *American Journal of Agricultural Economics*, 92(1), 181-195.

McBride, W.D., Short, S., and H. El'Osta (2004). The adoption and impact of bovine somatotropin on US dairy farms. *Applied Economic Perspectives and Policy*, 26(4), 472-488.

Mishra, A.K., Williams, R.P., and J.D. Detre (2009). Internet access and Internet purchasing patterns of farm households. *Agricultural and Resource Economics Review*, 38(2), 240-257.

Moreno, G., and D.L. Sunding (2005). Joint estimation of technology adoption and land allocation with implications for the design of conservation policy. *American Journal of Agricultural Economics*, 87(4), 1009-1019.

Negatu, W., and A. Parikh (1999). The impact of perception and other factors on the adoption of agricultural technology in the Moret and Jiru Woreda (district) of Ethiopia . *Agricultural Economics*, 21(2), 205-216.

Nkala, P., Mango, N., and P. Zikhali (2011). Conservation agriculture and livelihoods of smallholder farmers in Central Mozambique. *Journal of Sustainable Agriculture*, 35(7), 757-779.

Ochieng, B.J., and J.E. Hobbs (2017). Factors affecting cattle producers' willingness to adopt an Escherichia coli O157: H7 vaccine: a probit analysis. *International Food and Agribusiness Management Review*, 20(3), 347-363.

Parra-Lopez, C., De-Haro-Giminez, T., and J. Calatrava-Requena (2007). Diffusion and adoption of organic farming in the southern Spanish olive groves. *Journal of Sustainable Agriculture*, 30(1), 105-151.

Pietola, K., and A.O. Lansink (2006). Energy-saving technology choices by Dutch glasshouse firms. *Journal of Agricultural Economics*, 57(1), 129-144.

Sarmiento, C., and W.W. Wilson (2005). Spatial modeling in technology adoption decisions: The case of shuttle train elevators. *American Journal of Agricultural Economics*, 87(4), 1034-1045.

Sauer, J., and D. Zilberman (2012). Sequential technology implementation, network externalities, and risk: The case of automatic milking systems. *Agricultural Economics*, 43(3), 233-252.

Schmitz, A., and A. Rimal (1999). Freeze risk and adoption of technology by orange producers. *Journal of Agribusiness*, 17(345-2016-15151), 93-103.

Shiferaw, B., Kassie, M., Jaleta, M., and C. Yirga (2014). Adoption of improved wheat varieties and impacts on household food security in Ethiopia. *Food Policy*, 44, 272-284.

Smale, M., Assima, A., Kergna, A., Theriault, V., and E. Weltzien (2018). Farm family effects of adopting improved and hybrid sorghum seed in the Sudan Savanna of West Africa. *Food Policy*, 74, 162-171.

Smale, M., Zambrano, P., Paz-Ybarnegaray, R., and W. Fernandez-Montano (2012). A Case of Resistance: Herbicide-tolerant Soybeans in Bolivia. *AgBioForum*, 15(2), 191-205.

Useche, P., Barham, B. L., and J.D. Foltz (2009). Integrating technology traits and producer heterogeneity: A mixed-multinomial model of genetically modified corn adoption. *American Journal of Agricultural Economics*, 91(2), 444-461.

Verkaart, S., Munyua, B.G., Mausch, K., and J.D. Michler (2017). Welfare impacts of improved chickpea adoption: A pathway for rural development in Ethiopia *Food Policy*, 66, 50-61.

Wainaina, P., Tongruksawattana, S., and M. Qaim (2018). Synergies between different types of agricultural technologies in the Kenyan small farm sector. *The Journal of Development Studies*, 54(11), 1974-1990.

Yorobe, J.M., Ali, J., Pede, V.O., Rejesus, R.M., Velarde, O.P., and H. Wang (2016). Yield and income effects of rice varieties with tolerance of multiple abiotic stresses: The case of green super rice (GSR) and flooding in the Philippines. *Agricultural Economics*, 47(3), 261-271.