Context and Technology Traits Explain Heterogeneity Across Adoption Studies of Agricultural Innovations: A Global Meta-Analysis

by Dario Schulz and Jan Börner

Context and technology traits explain heterogeneity across adoption studies of agricultural innovations: a global meta-analysis*

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Abstract

Sustainable intensification of agriculture is considered crucial to reconcile the increasing demand for food, feed and fibers with the long-term integrity of the ecosystems that are often degraded. Innovations such as variable rate application or mechanical (including autonomous) weeding are expected to remedy some of these problems, but there is substantial uncertainty regarding the context-specific drivers of their adoption. Therefore, this study synthesizes the results of past adoption studies for a wide range of innovations around the globe. Using multi-level random effects meta regression, we provide mean global estimates for 50 commonly used measures used as adoption determinants such as farm size, assistance, access to credit. Controlling for study characteristics, remaining heterogeneity in adoption determinants is partially explained by innovation traits and socioeconomic context variables from secondary data sources. Our results show that land, capital and knowhow are generally more important when an innovation uses the respective factor intensively, but this effect is reduced when the factor is abundant in the study context. Finally, we present a set of guidelines to increase the reach of future adoption studies.

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1 Introduction

Innovations in agricultural production are considered crucial solutions to pressing issues such as food security, affordable and healthy diets and more sustainable use of natural resources (Rockström et al. 2017; Herrero et al. 2020). This study conceptualizes innovations as technologies and practices that, when implemented, result in a different production factor composition or factor productivity. Positive impacts on productivity and food security have been linked to the adoption of agricultural innovations in developing countries (Ogundari and Bolarinwa 2018; Stewart, R. et al. 2015; Gollin, Hansen, and Wingender June 2018). Along with other innovations under the umbrella of digitalization and smart farming, robots performing autonomous interventions have been hypothesized to play an important role in what scholars called the next agricultural revolution (Lowenberg-DeBoer 2015; Barrett, H. and Rose 2020; Torero 2021). Given the heterogeneous impacts farming innovations had in the past (Pingali 2012), a better understanding of the underlying diffusion patterns is needed. But the adoption of agricultural innovations by individuals depends on a wide range of interacting factors, such as biophysical context, farm structure, decision maker characteristics, technology attributes and institutions. Consequently, the literature aiming to disentangle the determinants of agricultural innovation adoption is rich in both theoretical and empirical studies from all over the world (Feder, Just, and Zilberman 1985; Knowler and Bradshaw 2007; Foster and Rosenzweig 2010; Prokopy, L. S. et al. 2019). However, prior reviews have been unable to determine an unambiguous direction and magnitude of adoption determinants (Knowler and Bradshaw 2007), or do so with limited generalizability in terms of geography and types of innovation (Baumgart-Getz, Prokopy, L. S., and Floress, K. 2012; Prokopy, L. S. et al. 2019; Shang et al. 2021). One reason for this is that, despite the long tradition of cross-sectional adoption studies in the socioeconomic literature, there is no unified methodological approach regarding data collection, analysis and reporting of results. This has led to a large variety of sampling methods, conceptual frameworks that inform variable choices and empirical estimation methods, all of which have implications for the validity, generalizability and comparability of research findings. While previous reviews have emphasized the importance of certain independent variables, there has been little effort to use harmonized measurement protocols for better comparability.

This study exploits the heterogeneity of adoption determinants across a wide range of innovations to better understand how determinants differ under the presence of certain traits. Adoption of an innovation depends on the innovation characteristics (Rogers 2003), and important progress towards understanding the importance of innovation traits has been made both theoretically and empirically (Macours 2019; Kuehne et al. 2017). While farm, operator and context characteristics are commonly included in adoption studies, innovation traits or the perception of such are rare to find in the adoption literature, although there are noteworthy examples (Ghimire and Huang 2015; Shiferaw et al. 2015; Fisher and SNAPP 2014). In addition, few existing quantitative reviews have analyzed the relation between innovation traits and the factors that determine their adoption, likely because their focus on a subset of innovations did not provide sufficient variation in these traits. In addition to the role of innovation traits, this study exploits the variation across space to understand how production contexts influence innovation adoption drivers. Even though a number of primary studies reports results across countries (Barnes et al. 2019; Sheahan and Barrett, C. B. 2017; Dinis et al. 2015), most studies remain specific to the sample population that is socially and physically embedded in a small region, state or country. Studies with a large geographic coverage can control for unobserved regional effects, but studies covering just a small district do not have sufficient heterogeneity across space to allow for generalization of results.

The Induced Innovation Hypothesis (IIH) first proposed by Hicks (1932) represents a useful point of departure for an attempt to generalize from a large number of adoption studies. The IIH states that technology adoption occurs to make better use of the relatively more expensive production factors. Boserup (1965) described the theory for the context of agriculture and Hayami and Ruttan (1971) provided first empirical evidence for a relationship between factor abundance and technology biased productivity growth in the United States and Japan. Since then, a number of studies have analyzed the IIH in agriculture both empirically and theoretically (Turner and Ali 1996; Muyanga and Jayne 2014; Becker and Angulo 2019; Pardey et al. 2007). Jayne et al. (2019) and Goldman (1993) theorized the diffusion potential of agricultural innovations across two gradients of population density and economic dynamism, highlighting the subnational heterogeneity in factor endowments. This study contributes to the debate by analyzing the relationship between context-specific production factor endowments and the adoption determinants of those innovations that use this production factor intensively. Departing from the production factors land, labor, capital, and knowhow, a set of propositions was derived, namely: P1) The extent to which the farm size determines the adoption of land-intensive innovations is moderated by the relative land-abundancy in the study context; P2) The extent to which labor availability determines the adoption of labor-intensive innovations is moderated by the relative labor-abundancy in the study context; P3)

The extent to which capital availability determines the adoption of capital-intensive innovations is moderated by the relative capital-abundancy in the study context; and P4) The extent to which knowhow determines the adoption of knowhow-intensive innovations is moderated by the relative knowhow-abundancy in the study context.

This research has three objectives. First, to provide average magnitude estimates of farm-level innovation adoption determinants. Second, to evaluate the effect that selected innovation traits and the geographic context have on the adoption determinants. This is achieved by decomposing and explaining the variances of aggregated effect sizes using innovation factor intensity and geographic factor abundance. Third, to establish an evidence-driven minimum standard for future adoption studies with respect to the inclusion and definition of independent variables as well as reporting guidelines of research findings. This is done by taking stock of the empirical adoption literature in order to identify the most commonly used independent variables that are used to explain adoption. In the following section we describe the process of identifying and coding primary studies, before specifying the empirical framework and secondary data. In Section 3 the results of the meta analysis are presented. Section 4 discusses implications and limitations of our research findings, before Section 5 provides the guidelines for future studies along with concluding remarks.

2 Materials & Methods

2.1 Primary data collection

We closely followed the guidelines for meta-analysis in economics by Havránek et al. (2020). For this study, a database containing agricultural innovation adoption determinants from prior studies was created in five steps. First, we gathered and assessed eligibility of 1.423 adoption studies from the reference lists of prior reviews. Second, we followed Grames et al. (2019) and used text mining on the eligible studies to derive a data-driven systematic search string before retrieved a total of 27.043 peer-reviewed articles from three literature databases, namely Web of Knowledge, EBSCOhost and AgEcon. Third, with the support of automation tools to prioritize relevant abstracts and titles, we screened all unique records according to the eligibility criteria presented in Table 1. We sorted records by the number of eligible studies published in the respective journal, and by the number of relevant multi-word expressions in the abstract. Furthermore, we prioritized studies from countries with less than five eligible studies in an attempt to balance the geographic distribution.

Table 1: PICOS inclusion criteria

Item	Include	Exclusion criteria
Population	Crop farming firms and households	- Purely non-crop farmers, greenhouse operations, actors beyond farm gate (processors, consumers...) - Aggregated units (e.g. village or municipality)
Intervention	Agricultural production innovation	- Program- or group-participation (e.g. Certification/ labelling, Conservation schemes, Local groups/ cooperatives, market access, marketing strategies - Exclude irrigation
Comparison	Non-adopters	- Estimates are not based on a reference group of non-adopters
Outcome	Discrete farm level innovation adoption levels	- Continuous outcomes (e.g., intensity of adoption), disadoption, ex-ante indicators such as willingness to pay/accept or intention to adopt
Study design	Ex-post empirical multiple-regression analysis	- purely qualitative assessments, quantitative results without measure of uncertainty (e.g. standard error, confidence interval, p-value, t-/z-statistic or significance codes such as ***) - Exclude analysis such as ANOVA, naïve means comparison

Fourth, we extracted and coded the results of 475 randomly selected primary studies along with meta data into a detailed spreadsheet, following Stanley and Doucouliagos (2012) and strongly building upon the work done by Floress, K. M. et al. (2019). Similar to Oca Munguia and Llewellyn, R. (2020), we base our analysis on a representative subset of the innovation adoption literature. Apart from the estimated adoption coefficients and their precision estimates, sample characteristics such as sample size, mean and standard deviation of independent variables, distribution of adopters/non-adopters, information about empirical specifications (e.g., logit, probit), and dependent variable characteristics (e.g. scale and innovation description) were collected. Fifth, we categorized all innovations and adoption determinants and extended the work by Floress et al. (2019) by including detailed information on measurement units, for example whether farm size was measured as total farm size or area cultivated, measured in hectares, acres or a (non-)linear transformation of the same.

2.2 Effect sizes

The primary data for this study are estimated log odds ratios of adoption determinants, which can be used in meta-analysis without further standardization (Cooper, Hedges, and Valentine 2009; Stanley and Doucouliagos 2012). They were directly given as estimated beta coefficients by from studies employing logit models and were derived from probit model coefficients using a scaling factor (Wooldridge 2013). The comparison of coefficients from non-linear probability models such and logit and probit is not always appropriate because of a sample-specific scaling factor, and multiple (partial) standardization methods have been proposed (Allison 1999; Breen, Holm, and Karlson 2014; Breen, Karlson, and Holm 2018). However, after confirming a strong correlation between raw and partially standardized coefficients for a small subset where standardization was possible, we rely on the raw log odds ratios, since we are specifically interested in unobserved context characteristics, so the presence of a sample-dependent scaling factor is desired in our analysis (Buis 2017). As a measure of precision, this study used the variance of the log odds ratio, calculated from the standard errors, t-statistics, p-values or p-significance thresholds (typically coded as stars) depending on availability.

Meta-regression relies on the assumption that outcomes (effects) are measured in a homogeneous manner, so one cannot directly aggregate, say, the effect of an additional year of education with the effect of having obtained a high school degree or the (frequently used) natural logarithm of years of education. First, because the scales are different (continuous versus binary). Second, because the measurement units are different, and in this example not even a linear scalar of the other. Nevertheless, some scales, measures and units are commonly used and can be compared, when properly controlling for these differences (Stanley and Doucouliagos 2012). For example, whether the measurement unit of total farm size was hectares or acres should relate to the true effect size by a fixed scalar. Similarly, capital availability measured as "access" to formal credit versus the slightly more precise "use" of formal credit (both binary variables), can be expected to be highly correlated. On the other hand, this study refrains from combining effect sizes relating to different scales or measurement units that are not used by a sufficiently large amount of studies. Effects relating to continuous variables that have been recoded into discrete variables (for example: age below 25, 25, 50 years with respective dummy-variables), were not considered. Finally, by selecting only effects that relate to categorical adoption outcomes (binary or multivariate with a reference group of non-adopters), this study makes sure that the scale of the dependent variable in the primary studies is consistent. This implies excluding linear probability models, tobit specifications and second stage (i.e. Heckman or double hurdle) intensity of adoption models as well as parametric duration models of innovation adoption. Due to these thorough restrictions, the original number of observations is reduced by more than 70%. We only analyzed determinants with a minimum of twenty effect sizes from at least five different studies representing at least three different innovations. This approach of not analyzing rarely reported measures was taken to reduce the potential for false interpretations. An extended PRISMA diagram (Page et al. 2020) with the number of studies that were excluded at each stage of the screening process along with the filtering process of comparable effect sizes is presented in Figure 1.

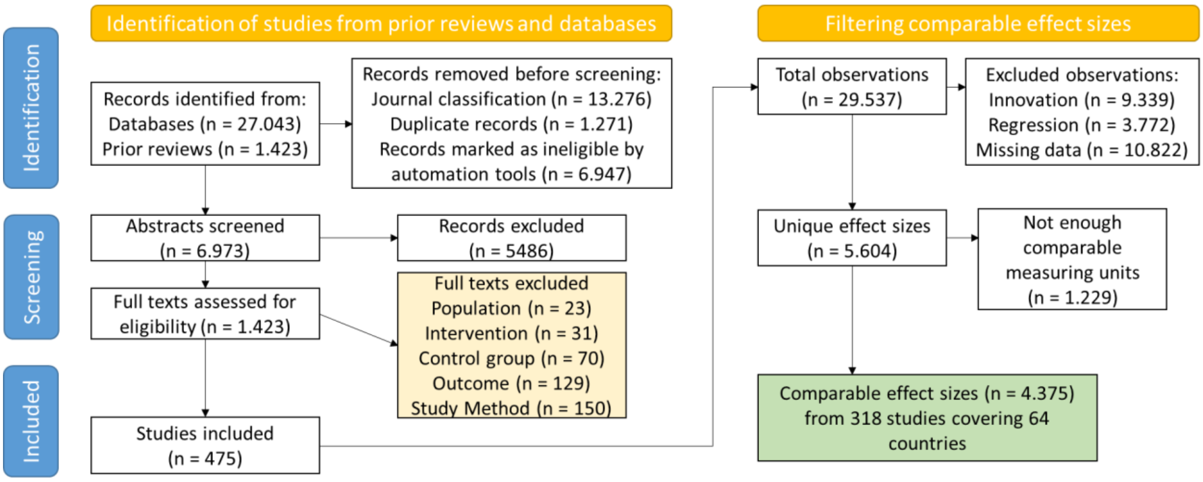

Figure 1: Extended PRISMA diagram of included studies and effect sizes

2.3 Empirical Framework

2.3.1 Aggregation of dependent effect sizes

When primary studies contribute several effects for the same outcome, as a result of multiple model specifications, such effect sizes can be expected to be strongly correlated and would bias the overall estimate towards studies that report many model specifications. To avoid this source of bias, this study aggregated within-study observations of the same effect for the same innovation category along with their variances into a composite effect size assuming a high correlation of 0.9 (Borenstein 2009; Hoyt and Del Re 2018). We used the log odds ratios as the outcome measure and fitted a multi-level random effects model to the data to account for different sources of heterogeneity (Borenstein et al. 2009). The random effects model assumes that there is a distribution of true effect sizes, from which each study may deviate not only by its sampling error, but also via a study-specific random effect. The resulting distribution of effects has a variance τ^2, which we estimated using the restricted maximum-likelihood estimator (Viechtbauer 2005). A second source of bias may occur, when studies provide multiple composite effect sizes relating to the adoption of several different innovations. Since the adopters are typically compared to the same (or at least strongly overlapping) group of non-adopters, the sampling errors within a study are no longer independent (Cheung 2015).

We used the robust variance estimation method (Hedges, Tipton, and Johnson 2010; Tanner-Smith, Tipton, and Polanin 2016), assuming a correlation of 0.3 between observations and of 0.9 for estimates from different model specifications relating to the same innovation within studies. The multi-level random effects model for multiple correlated observations within a study is given by Hedges, Tipton, and Johnson (2010)

$$y_{ij} = \beta_0 + u_j + e_{ij} \tag{1}$$

Where y_{ij} is the i[th] effect size (innovation) in study j (i=1…m, j=1…k), β_0 is the average population effect with a study-level random effect with variance τ^2 (between study variance) and e_{ij} are the known variances of the respective effect sizes. The inverse variance weights to aggregate correlated effect sizes are given by Hedges, Tipton, and Johnson (2010) as

$$w_{ij} = \frac{1}{g_j(v_j + \tau^2)} \tag{2}$$

Where v_j is the mean of the within-study variances for effect sizes in study j and g is the number of effect sizes in study j.

2.3.2 Induced Innovation: meta-regression framework

To test the propositions outlined in Section 1, interaction terms between the country- and time-specific factor endowments and innovation-specific factor intensities were used. Table 2 provides an overview of the dependent variables (adoption determinants), the factor intensities assigned as binary variables to each innovation and the factor abundancy proxies used in the analysis. For the binary trait-indicators, we developed a coding scheme with predefined criteria to assign factor intensities. Four reviewers independently assigned all innovation traits to all innovations based on the coding scheme, reaching a final inter-coder agreement of 96% (see SI for further details).

In the first step, mixed-effects models without intercept including fixed effects for the innovation traits were estimated to explain factor-related differences between innovations. To reduce unobserved variable bias arising from a given study context, random effects were estimated for each innovation within each study. The estimated model was

$$y_{ij} = \beta_0 T_{ij} + u_j + e_{ij} \tag{3}$$

Where T is a dummy variable taking the value of one if the factor of interest is intensively used and zero otherwise (see Table 2 for details), β is the estimated intercept for the innovations where factor T is intensively used (i.e. equal to one), u_j are study-level fixed effects and e_{ij} innovation-level random effects within each study.

In the second step, a set of moderators was included to explain between-study variation across countries. The variance term still contained study-level random effects, but the innovation-level random effects were omitted since these effects are expected to be explained by the moderators. The model can be written as

$$y_{ij} = \beta_0 + \beta_1 T_{ij} + \beta_2 X_{country} + \beta_3 X_{country} * T_{ij} + \beta_4 X_{control} + u_j + e_{ij} \qquad (4)$$

Where β_0 is an intercept, β_1 the estimated coefficient for the factor intensity dummy T, β_2 the coefficients for country-level moderator variables $X_{country}$ (factor abundances), $\beta_3$the coefficient of the interaction between factor abundance and factor intensity, β_4 the coefficients for additional control variables $X_{control}$, u_j and e_{ij} are study- and observation-level random effects.

2.3.3 Robustness checks and publication bias assessment

The aggregated effect was considered significant when its estimated 95% confidence interval did not include zero. To better interpret the magnitude, the aggregated log odds ratios were transformed to odds ratios. In the random effects model, true population effects may differ even in the absence of sampling error. We therefore tested within each outcome, whether the effect sizes belong to different populations by testing the significance of the Q statistic using a χ^2 distribution (Hedges and Olkin 1985). Following the approach of including the standard error of the effect size as a predictor by Habeck and Schultz (2015), we tested for the presence of publication bias using Egger's regression test with a significance threshold of p=0.10 (Egger, M. et al. 1997; Sterne and Egger, M. 2005). Results of all regressions after excluding influential observations are reported as robustness checks. Potentially influential observations were identified using Cook's distances; Studies with a Cook's distance larger than four standard deviations are considered to be influential. We tested whether results were sensitive to the choice of context-indicator by replacing the context moderators in an alternative model specification.

The analysis was conducted using the metafor package (Viechtbauer 2010) and clubSandwich package (Pustejovsky 2020) for R (R Core Team 2020). Further information including a full list of included studies, summary statistics, variable descriptions, robustness checks, and publication bias assessment is available as supplementary material upon request.

Table 2: Definition of dependent and independent variables

Dependent variables		**Independent variables**	
Adoption determinant	Scale & measuring units	Innovation factor intensity	Geographic factor abundance[a]
Land	Continuous variables: hectares or acres of total farm size or area under cultivation	Land intensity (i.e. 1 for contour farming, buffer strips, agroforestry, conservation practices, organic farming, 0 for all other)	Log of Land abundance (hectares of cropland equivalent per worker)
Labor	Continuous variables: number of women, men, adults or household members	Labor intensity (i.e. 1 for permanent cover, contour farming, buffer strips, agroforestry, conservation practices, fertilizer, non-chemical pest control, nutrient intensity optimization, organic farming, soil analysis, 0 for all other)	Labor abundance (workers per hectare of cropland equivalent)
Capital	Binary variables: access or use of formal credit	Capital intensity (i.e. 1 for buffer strips, agroforestry, fertilizer, non-chemical pest control, chemical pest control, soil analysis, mechanization, precision farming analysis support, precision farming interventions, improved seeds, GMOs, crop insurance, 0 for all other)	Log of Capital abundance (value of machinery and inputs per hectare of cropland equivalents)
Knowhow	Binary variables: access and use of extension services, consultants or agricultural trainings	Knowhow intensity (i.e. 1 for permanent cover, agroforestry, reduced tillage, conservation practices, non-chemical pest control, nutrient intensity optimization, chemical pest control, organic farming, soil analysis, analysis support for precision farming, contract farming, crop insurance, 0 for all other)	Human capital abundance (Government Expenditure On Education, Total (% Of GDP))

[a] Country-level indicators were obtained for the year of data collection of the primary study. Land-, labor- and capital-abundance was obtained from Fuglie (2012) and FAO (2020), while Government Expenditure On Education, Total (% Of GDP) stem from The World Bank (2020).

3 Results

The database query resulted in 27043 peer-reviewed articles. Due to the large number of studies, 13276 publications in journals from disciplines other than social and agricultural science were filtered out. In addition, 1423 studies were identified from other sources, primarily from prior reviews. After removing duplicates, 13920 studies were included for abstract screening. Based on abstract, 1495 were found eligible. Due to the large number of studies, a non-random subset of studies was selected for fulltext information retrieval. Journals were sorted by the frequency of studies and full-text information retrieval was conducted prioritizing journals with high numbers of relevant publications. Complementary, publications from countries with few included studies were purposefully prioritized. A total of 400 studies were excluded based on the full text.

This study synthesizes a total of 4607 estimates beta coefficients belonging to 21 different innovation adoption determinants. They originate from 304 unique publications, out of which 256 report results for a specific region, 46 on country level, and 2 across countries. Figure 2 illustrates the geographic distribution of studies. The size of the dots indicates the number of studies per country, while the color of the dots indicates the number of different innovations that have been studies in the country. The largest number of studies comes from the United States, which hints towards a potential language selection bias. Several Sub-Saharan countries, predominantly Ethiopia, also have substantial adoption literature. On the other hand, Latin America, Europe and Oceania are weakly represented in the dataset.

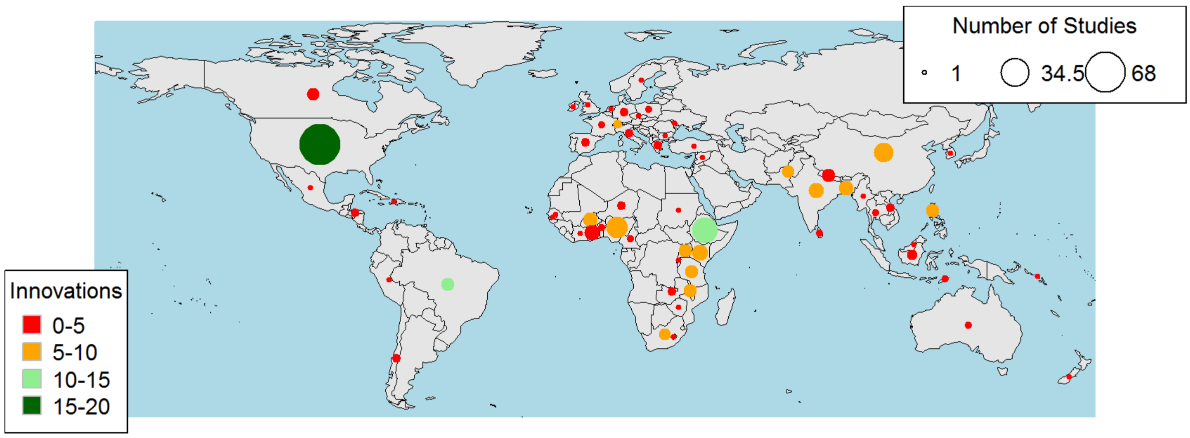

Figure 2: Geographic distribution of comparable studies and innovations

3.1 Effect size aggregation

Figure 3 and Figure 4 show the average odds ratios for comparable categories of binary and continuous adoption determinants respectively along with their 95% confidence intervals for each measuring unit. The columns on the right indicate the number of effect sizes used for the estimate (N), the number of studies from which these effects were extracted (S) and the p-value indicating whether the estimated intercept significantly differed from zero. Odds ratios can be interpreted as changes in the odds of adopting the innovation against the reference of one, all else being equal. For example, binary variables indicating that extension services were received have an average odds ratio of 1.672, which translates to an increase of 67.2% (95% CI: 37.0-103.9%) in the odds of adoption. Similarly, binary variables indicating access to and use of formal credit were grouped together in the FULL model specification, resulting in an average increase in the odds of adoption by 43.7% (95% CI: 15.4-78.9%).

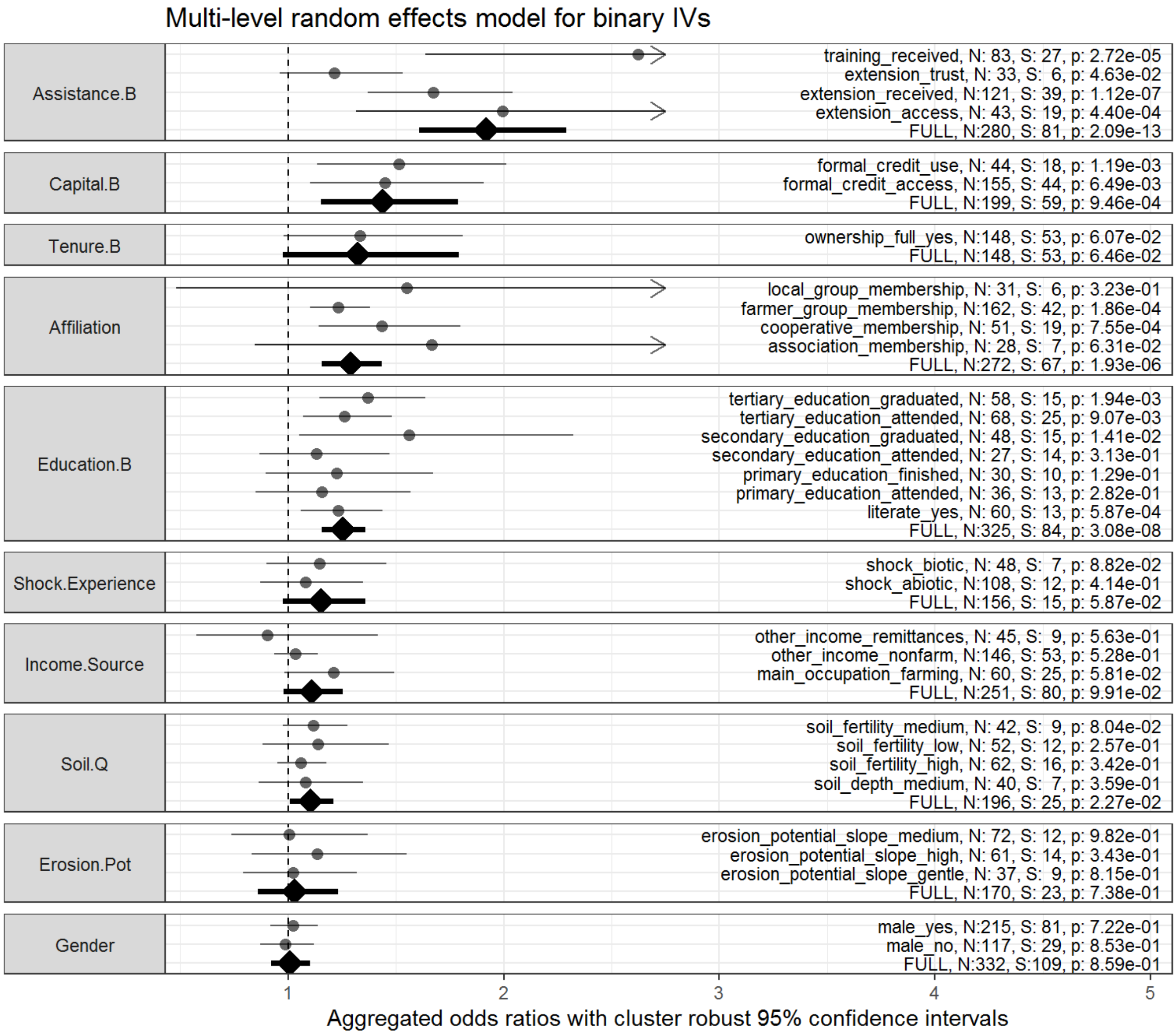

Figure 3: Mean odds ratios for binary adoption determinants by measuring unit

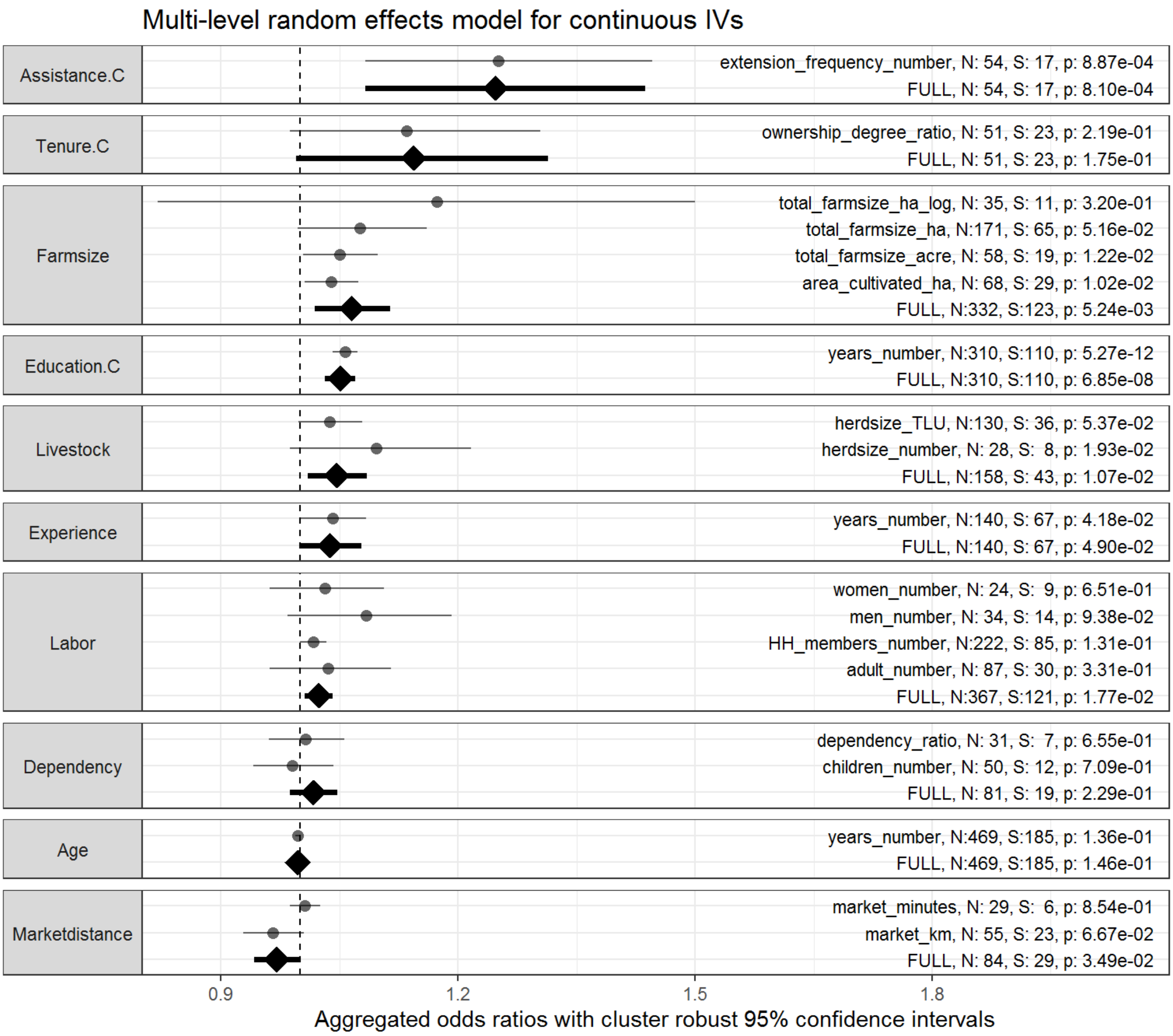

Figure 4: Mean odds ratios for continuous adoption determinants by measuring unit

The only adoption determinants that are consistently (i.e. for all measuring units) and significantly (i.e. p<0.1) differed from zero were Assistance.B, Capital.B, Tenure.B, Education.C, Assistance.C, Experience, Livestock, while farm size was rather inconsistent. Other commonly used determinants such as age and gender were not found to significantly differ from zero on average. Binary measures tended to have larger magnitudes than related continuous measures. For example, having graduated from a university increases the odds of adoption by 36.9% (95% CI: 14.7-63.5%), while one additional year of education has an effect of 5.1% (95% CI: 3.2-7.0%). At the same time, variables measured on a continuous scale have a much lower variance. Binary measures should be interpreted with great caution and not be used to draw conclusions about the relative magnitudes, since studies did not always clearly indicate reference categories. If tertiary school attainment is compared to secondary school attainment, one can expect a lower magnitude than when it is compared to another baseline category, for example, having received no primary education at all, which may be the case in developing countries. Notably, even within the relatively fine-grained outcome measures, all estimates still have significant residual heterogeneity ($p<0.01$) (reported in Table S5, supplementary material). The next subsection therefore presents the results of the meta-regression analysis in order to assess whether moderators can explain this heterogeneity.

3.2 Factor intensity intercepts

Figure 5 presents the results from the mixed effects factor intensity model without intercept term (Eq. 3). On the left, the factor intensity dummies are listed, while the grey boxes indicate the adoption determinants. The blue points with 95% confidence intervals indicate that the adoption determinant was larger when the associated factor was used intensively by the innovation.

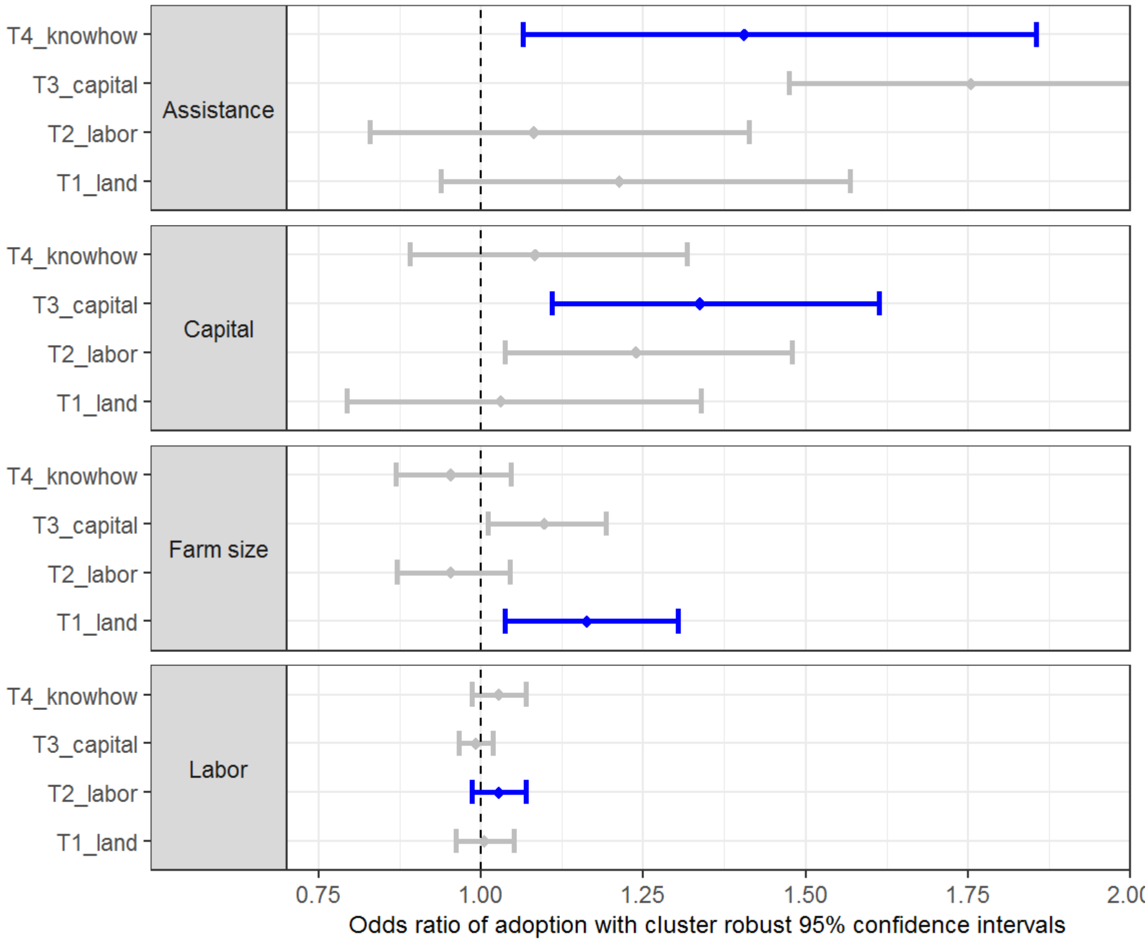

Figure 5: Factor intensity intercepts of selected adoption determinants

The positive and significant associations between the adoption determinant and the respective factor intensity of the innovation indicates that the variable has a higher influence on adoption when the factor is intensively used by the innovation. For example, a unit increase in farm size (as a proxy of land) increased the odds of adoption by 16.2% (95% CI: 3.7%-30.3%) when the innovation was land intensive, but when the technology was not land intensive its effect was not significantly different from zero. Similarly, access to formal credit increased the odds of adopting capital intensive innovations by 33.7% (95% CI: 10.8%-61.4%), while access to extension increased the odds on average by 40.5% (95% CI: 6.4%-85.6%). The determinants assistance and farm size were also higher when the innovation was capital intensive. This is not surprising, given that farm size and capital endowments typically correlate and extension services often provide access to credits and capital-intensive inputs. Lastly, we did not find indications that labor availability became a more important adoption determinant when the innovation was labor intensive.

3.3 Induced Innovation Hypothesis

The meta-regressions results presented in **Error! Reference source not found.** show the interaction effects between innovation specific factor intensity and country specific factor abundance for the four adoption determinants land, labor capital and knowhow. The corresponding innovation traits T1-T4 refer to a binary variable taking the value of one of the innovation uses the respective factor intensively (see Table 2 for details). All regressions were conducted by iteratively adding control variables; the reported result include the full set of controls.

We find consistently negative interaction terms for the four proxies of land, labor capital and knowhow, but these were only significant ($p<0.1$) for the binary adoption determinants (Credit and Assistance access). The results suggest that the extent to which a factor influences whether a farmer adopts an innovation increases when the innovation requires the respective factor intensively, and especially so when factor is relatively scarce in the geographic context. We do not find a significant interaction effect on labor, but considering that the between-study heterogeneity in true effects (σ_1^2) was estimated to be almost zero, it is unlikely that country-level moderators can explain this variation.

The results for the four outcomes shown in Table 3 remain stable for a different set of context variables and after the exclusion of potentially influential studies identified via cook's distance (see SI). The QE-test for residual heterogeneity remained highly significant after the inclusion of all moderators, indicating that the moderators included in this analysis can only explain a part of the variation in true effects.

Table 3: Interaction effects of factor intensity and factor abundance for Land, Labor, Capital and Knowhow

	Farmsize	Capital.B	Labor	Assistance.B
intercept	0.59 .	1.05 .	0.19 **	-0.25
	(0.15)	(0.62)	(0.09)	(0.57)
log_land_abundance	0.05	-0.21	0.01	0.04
	(0.08)	(0.33)	(0.03)	(0.41)
T1_land	0.14 *	0.13	-0.00	0.15
	(0.06)	(0.12)	(0.02)	(0.17)
log_cap_abundance	0.00	0.20	0.01	0.19 **
	(0.05)	(0.11)	(0.01)	(0.11)
gov_educ_spending_percent	0.01	-0.01	0.00	0.13
	(0.03)	(0.13)	(0.01)	(0.13)
labor_abundance	0.03	-0.14	0.02	0.08
	(0.06)	(0.33)	(0.03)	(0.22)
T2_labor	-0.13 *	0.05	0.00	-0.17
	(0.08)	(0.14)	(0.02)	(0.23)
T3_capital	-0.01	0.15	-0.04 .	0.16
	(0.06)	(0.19)	(0.03)	(0.20)
T4_knowhow	-0.11 **	0.03	0.03	0.18
	(0.06)	(0.14)	(0.02)	(0.13)
log_land_abundance:T1_land	-0.14 .			
	(0.09)			
log_cap_abundance:T3_capital		-0.18 *		
		(0.10)		
labor_abundance:T2_labor			-0.01	
			(0.02)	
gov_educ_spending_percent:T4_knowhow				-0.37 **
				(0.13)
Regression Type	Yes	Yes	Yes	Yes
Measurement Units	Yes	Yes	Yes	Yes
Model Specification	Yes	Yes	Yes	Yes
sigma2.1	0.04	0.47	0.00	0.06
sigma2.2	0.08	0.23	0.02	0.51
cochran.qe	9667.64	4559.04	4355.05	4680.54
p.value.cochran.qe	0	0	0	0
cochran.qm	27.98	22.62	22.93	31.55
p.value.cochran.qm	0.22	0.21	0.35	0.05
df.residual	281	171	318	194
logLik	-156.04	-188.76	91.85	-245.53
deviance	312.09	377.53	-183.71	491.06
AIC	364.09	419.53	-135.71	537.06
BIC	458.69	485.50	-45.42	612.22
AICc	369.62	425.73	-131.61	543.55
nobs	305	190	340	215

Note: Innovation traits (T1-T4) refer to binary variables indicating land intensive, labor intensive, capital intensive, and knowhow intensive, respectively (see Table 2 for details). A set of control dummies accounts for model specifications in primary studies: regression type (logit, probit), scale of dependent variable (binary and multivariate), whether the original model controlled for other independent variable categories or not, observation level (plot or farm), and spatial level (regional or national). Brackets contain cluster robust standard errors. The sigmas refer to estimated variation components between studies (σ_1^2) and within study (σ_2^2).

4 Discussion

We found large and significant positive average effects for binary adoption determinants related to assistance, credit access, group affiliation and education. In addition, we found smaller, but statistically significant positive average effects for continuously measured determinants related to years of formal education, livestock ownership and experience. Meanwhile, we find that evidence for age, gender, labor endowment, farm size, risk preferences, tenure status are mixed and do not statistically differ from zero for at least some measuring units. Instead, some but not all of these factors could be shown to matter under on a selected set of contextual conditions and related technology traits.

While we find no evidence for publication bias, the Q-statistic indicated significant heterogeneity in the true effects for all estimated average effects, which we attribute to differences in innovation, sample and study characteristics. This means that even though the average effect is significantly above zero, the distribution of true effects estimated by the random effects model may include effects smaller than zero. We partially decomposed this variation by including moderator variables, but many unobserved characteristics could not be accounted for due to missing data. The positive effects of capital and extension are in line with the findings by Baumgart-Getz, Prokopy, L. S., and Floress, K. (2012), who synthesized adoption determinants for best management practices in the United States. In contrast, we found a significant effect of education, mixed results for farm size, but cannot confirm their significant negative effect of age. This is not surprising, given the regional focus and subset of innovations studied. The findings highlight that agricultural extension plays an important role in the innovation adoption process, even though a lack of accountability and performance gaps have been highlighted in the literature on agricultural knowledge systems (Anderson, Feder, and Ganguly May 2006).

With respect to innovation characteristics as a source of heterogeneity, we found that the magnitude of the adoption determinants credit access, farm size and assistance increased when the innovation was capital-, land-, and knowhow intensive respectively. Similarly, Rubas (2004) found that education was more important for the adoption of information technologies as opposed to physical input innovations. Also Baumgart-Getz, Prokopy, L. S., and Floress, K. (2012) grouped innovations into thematic management groups, but did not report how this categorization explained adoption determinants. Going a step further and abstracting to innovation traits, Arslan et al. (2020) hypothesized that wealth-related variables should more often be significant and positive determinants for the adoption of innovations that require upfront investments, than for innovations that do not require capital. Using a vote-count analysis restricted to Africa, they find that credit access, wealth, land, and livestock assets are more often positively associated with inorganic fertilizer adoption, than what could be expected by chance. These results strengthen the notion that innovations can be characterized, distinguished, and their adoption determinants be related to certain traits, such as factor intensities. More importantly, our results point towards potential transferability of past research findings to future innovations, such as in the field of sensing and robotics, with known (or assumed) combination of such traits. Interacting innovation characteristics and the affinity of the innovator towards these characteristics has been proposed as a mediation mechanism in the ADOPT model by Kuehne et al. (2017; 2011). For the ex-ante diffusion assessment of new technologies, a trait-based uncertainty reduction of adoption determinants could provide important insights.

Regarding the interaction effect of factor intensity and factor abundance, we found indications that the propositions motivated by the induced innovation hypothesis may explain some of the variation in true effects across countries and innovations. Although the direction of estimates consistently pointed into the direction that we expected, our analysis may have been statistically underpowered to make more robust inference, especially for the decomposition of very small variations in true effects. The extent to which credit access and use determines adoption of capital intensive innovations was strongly moderated (reduced) by the capital abundance in the country. But this result must be interpreted with caution because the available observations are limited to non-OECD countries, which is not surprising given that capital markets can be expected to work well in OECD countries. However, our finding implies that a change in access to formal credit has a smaller effect on the adoption decision in capital abundant contexts (e.g. OECD countries), which is consistent with the propositions. The available data did not allow to test the effect on adoption determinants such as debt-asset-ratio, which was more commonly measured in capital abundant countries.

We find a statistically insignificant interaction effect for the factor labor. However, household size related variables are typically included in adoption studies as a proxy for farm labor usage in the presence of imperfect labor markets. Under functioning labor markets, the size of the household is not expected to have any influence on the farm labor usage, since labor supply and labor demand of the farm household are separable (Benjamin 1992). Instead of cheaper labor inducing a reduction on the role of farm labor to innovate, labor supply may actually be low due to imperfect markets, even though the country is labor abundant. Thus, the findings may point towards the discrepancy between labor abundancy and actual labor supply. Additionally, neither the country-level labor abundancy indicator nor the household level adoption determinants contained information on seasonal fluctuations in labor availability, potentially masking out some true effects. Again, the available data did not allow to test the hypothesis using other farm labor indicators such as number of employees, which is more common in labor scarce contexts.

Both farm size and assistance as drivers of land- and knowhow intensive innovations were moderated by the land and knowhow abundancy in the study context, respectively. Complementary analysis of the continuous knowhow indicators experience and years of schooling did not exhibit the same effect, although this may be due to the small variation in true effects for these indicators (results reported in SI).

The main policy lesson of our study is that the cost-efficiency of extension schemes could be improved by concentrating innovation diffusion efforts not only on the target group, but also consider the larger socioeconomic production context. Considering heterogeneous factor tradeoffs across different target groups, developers of new technologies may tailor them better to meet local needs. Finally, given the temporal dynamics of context factors, a structural understanding of the embeddedness of production systems can help to design policies with a longer time horizon.

This evidence synthesis of past research findings was mainly obstructed by the diversity of empirical strategies, (partially) unreported results and most of all by the lack of consistency in the measurement of commonly used adoption determinants. Overcoming comparability related issues by rigorously filtering out non-comparable observations and controlling for the exact measurement units lead to spatial imbalance of our dataset. Our categorization of innovations and consecutive assignment of factor intensities did not account for potential heterogeneity of factor intensities, especially when endogenously influenced by the geographic context. In addition, there may be a geographic publication bias with respect to the type of innovation (and thus factor intensities), which's adoption is studied. The same holds true for the measurement units. For example, Capital was commonly measured as access to credit in developing countries, but proxied by debt-asset ratio in industrial countries. Similarly, Farmsize was commonly measured in acres in the United States, but in hectares in most other places, so the related unit control dummy could potentially mask out geographic context effects.

5 Conclusion

This study quantitatively synthesized evidence on the direction, magnitude and variation of adoption determinants from 262 studies of diverse agricultural innovations across the world. Using a multi-level mixed effects meta model, we found that the variation in adoption determinants can be partially explained by innovation characteristics (factor intensities) and context characteristics (factor abundancies). Our findings show particularly the importance assistance and credit access play for the adoption of agricultural innovations knowhow- and capital-restricted contexts. A priority of decision makers should therefore be the design of policies and interventions that improve technical knowledge, skills, and capital access.

Future studies should explore, to what extent network meta-analysis may be suitable to accommodate the large variability in the way independent variable constructs were measured in primary studies. Finally, the abstraction from specific innovations to innovation traits demands closer attention both in meta-analysis and primary studies, because they facilitate transferability of research findings. Future evidence synthesis would benefit from mainstreaming a number of best practices in the design and documentation of primary adoption studies. Below we provide a non-exhaustive list of recommendations towards this goal:

1. All estimated effects should be reported in tabular format along with a measure of their sampling error independent of their significance.
2. Variables that were used in the regression, but omitted in the results table to save space should be clearly indicated.
3. Any (non-)linear transformation of variables should be clearly indicated.
4. The number of observations should be reported for each regression. Especially for data structures with multiple observations per individual (e.g. panel data, multiple plots), the unit of observation should be clearly indicated.
5. Summary statistics should be provided in tabular format and include at least the mean of all dependent and independent variables for the entire sample. In addition, the standard deviation should be reported for continuous variables. Additional summary statistics for different subgroups (e.g. adopters and non-adopters) are a desirable supplementary information.
6. Each study should provide a description of (a) the study area(s), (b) the innovation(s) considered, such as claimed advantages, historical adoption levels, and (c) the sample

characteristics in terms of market orientation (e.g. subsistence vs. commercial), product specialization (e.g. rice farmers, mixed livestock farmers etc.)

7. Continuous independent variables should be used as such and not be recoded into categorical, ordered or binary scales
8. If categorical independent variables are present, they should be recoded as binary variables and listed as such in the summary statistics
9. Where possible, independent variables should be measured in or converted to the International System of Units (i.e. hectares, tons, years).

Innovation in agricultural production remains one of the most important strategic pillars in the transformation towards sustainable food systems. Despite a large number of existing adoption studies worldwide, however, we still poorly understand why apparently beneficial agricultural technologies suffer from low or stagnating uptake. We systematically take stock of the existing mostly context-specific knowledge and find that agricultural knowledge and extension systems, especially in the developing world may deserve more attention than they currently receive. Our findings also suggest that established minimum standards for agricultural adoption studies are needed to extract further generalized lessons from this important subfield in agricultural economics.

Supplementary Information

Additional information including details on study selection, coding, summary statistics, description of variables, a full list of included studies, publication bias assessment, alternative model specifications and all robustness checks is provided in the supplementary material available from the author upon request.

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