1. INTRODUCTION

The effects and risks of climate change are increasingly apparent worldwide and can take many forms. They range from slow onset changes, like increasing temperature, drier weather patterns or sea-level rise, to sudden events, such as extreme weather events like tropical cyclones and floods. As they can severely impact the economic and social development of countries, adapting to climate change is of incalculable importance for societies. Financial instruments such as savings, credit or insurance can be considered drivers for adaptation measures as they enable financial planning and provide the required financial means for adaptation. Given the importance of credit in funding adaptation projects and programmes, this report addresses the question of whether access to credit leads to the adoption of climate change adaptation measures. Specifically, this report provides a meta-analysis of the evidence regarding the role of access to credit in determining the adoption of adaptation measures in the agricultural sector in low- and middle-income countries. It builds on the results of a recently published evidence gap map (EGM) that examines the evidence on the effectiveness of climate change adaptation interventions in low- and middle-income countries (Doswald et al., 2020).[2]

Different authors and stakeholders describe and use the concept of climate change adaptation in many ways. Different keywords and definitions regarding adaptation are used, such as “adjustment”, “practical steps”, “process”, and “outcome” (Doswald et al., 2020). As it is a multi-faceted process, we can categorize adaptation according to its many elements and dimensions, among which purposefulness and timing stand out as the primary, distinctive characteristics of the adaptive process. In this sense, autonomous adaptation is an action that takes place—invariably as a reactive response to climatic stimuli after initial impacts are manifest—as a matter of course, without the directed intervention of a public agency (IPCC, 2001). Adaptation, therefore, does not usually constitute a conscious response to climatic stimuli but is often triggered by ecological changes in natural systems and by market or welfare changes in human systems. Spontaneous adaptation is another term for autonomous adaptation.[3]

The success of autonomous adaptation to climate change critically depends on the availability of necessary resources, not only natural and economic resources, but also knowledge, institutional arrangements and technological progress. The types and extent of these resources, in turn, depend on the nature and predictability of environmental changes, as well as the range of feasible responses. Adaptation processes are complex in nature and highly dynamic. They often entail multiple interactions with and dependencies on existing local and temporal factors. For many years, the uncertainty introduced by the limited experience, complexity and scale of anthropogenic climate change has been the main explanation for research conducted on autonomous adaptation.[4] Autonomous adaptation modelling has relied on mechanistic assumptions (e.g. model-based projections on climate and economic consequences using scenarios) and has used historical data. Many social, economic, technological and environmental trends also critically shape the ability of societal systems to adapt to climate change both in the present and in the future. While factors such as increased demographic pressure and sustained economic growth will likely increase the potential volume of physical assets exposed to climate change, greater wealth and continuous technological progress are likely to extend the resources and capabilities necessary to adapt. This makes understanding the trajectories of autonomous adaptation complex.

[2] The evidence gap map report is accessible at the DEval website: *https://www.deval.org/en/discussion-papers.html*.

[3] Autonomous adaptation must be understood in contrast to planned adaptation, which is the result of a deliberative policy decision, based on the awareness that conditions have changed or are about to change and that action is required to return to, to maintain, or to achieve a desired state (Malik and Quin, 2010).

[4] See for instance Forsyth and Evans (2013), Mersha and van Laerhoven (2018) for applied research on autonomous adaptation.

In recent times, the empirical literature on climate change adaptation has shifted towards understanding the determinants of decisions to adopt strategies, make investments and use technological options that may help farmers and households to cope with the effects of climate change and to reduce associated risks. A range of factors has been examined using models to predict the probability of adopting adaptation strategies while controlling for different explanatory variables (e.g. societal, demographic, economic, geographic, climatic and technological). Among explanatory variables, access to financial instruments and credit have captured a large share of the literature's attention. There is a large and growing interest in the use of financial mechanisms in the rural environment, for example to encourage the adoption of climate-smart agricultural practices (CSA).[5] Some theoretical discussions have focused on credit instruments for financing short-term input purchases or supporting CSA, both as a direct pathway and as an indirect mechanism that generates economic incentives (Ruben at al., 2019). Additionally, financial instruments may also contribute to learning and behavioural change among value-chain participants, thus enabling them to invest in long-term solutions for more sustainable agriculture (Dercon and Christiaensen, 2011; Brick and Visser, 2015).

In this study, we perform a meta-analysis of publications that assess the determinants of adoption of adaptation measures by farmers in low- and middle-income countries and which include the role of credit in their analyses. The studies included in this meta-analysis are those previously reviewed in the recently published EGM on the effectiveness and impacts of climate change adaptation interventions (Doswald et al., 2020). More specifically, by inspecting the collected quantitative evidence in different multivariate regression models, we investigate the role of access to credit as one of the explanatory factors of the decision to adopt adaptation strategies in the agricultural sector, in low- and middle-income countries.

[5] CSA is defined by the Food and Agriculture Organization as agricultural practices that sustainably increase productivity and system resilience while reducing greenhouse gas emissions. See, for example, FAO (2018).

2. METHODOLOGY

2.1 Systematic Selection of the Literature

All the publications analysed in this study were identified in an EGM on the effectiveness of climate change adaptation interventions (Doswald et al., 2020). The EGM systematically compiled available quantitative evidence on the effectiveness of implemented actions of climate change adaptation in low- and middle-income countries between 2007 and 2018. Interventions and associated outcomes in these 464 studies were mapped according to a conceptual framework that covered different types of interventions, sectors and adaptation outcomes. Studies in the EGM included both autonomous and planned adaptation.

To populate this framework, we used a systematic map protocol that followed guidelines set out by the Collaboration for Environmental Evidence (CEE, 2018). Several databases (Web of Science, Scopus, 3ie database and CEE library) and grey literature from several organizational websites were searched using a search protocol. Searches were performed in English and identified all literature that had an English abstract. The search found a total of 13,121 papers. Once duplicates were removed, and after exclusion-based criteria were applied, 464 studies were retained for analysis. Included papers were given an identifier number, and all bibliographic information was recorded in a spreadsheet database. Each paper was analysed to identify all the interventions/outcomes tested in the studies. This generated a second database that included several fields relevant to the gap-map analysis.[6] The EGM was populated with the number of articles that were coded in each intervention/outcome cell. One single article may be coded into several cells in the EGM if they contain different interventions and/or outcomes. As a result, a total 1,042 individual pieces of evidence (contained in 464 papers) were mapped.

The meta-analysis in this study is based on the evidence collected for one particular set of studies corresponding to one cell of the EGM framework described. More precisely, the papers in this study are a selection fulfilling the following criteria:

- **Sector:** Forestry, fishing and agriculture.
- **Intervention:** Financial/market mechanisms (activities that include financial transactions or are market-driven).
- **Outcome:** Adoption studies, which include interventions likely to support the uptake of adaptation-related interventions.[7]

An initial number of 44 studies corresponding to these categories were identified for the meta-analysis. Further coding and additional systematic analyses of the evidence base were undertaken to determine the degree of comparability of interventions, outcomes and estimation methods. Additional inclusion and exclusion criteria were applied to select studies that particularly addressed the role of access to credit (independent variable or intervention) in adopting a particular set of adaptation strategies at the farm, plot or household level (dependent variable or outcome). Studies not addressing this specific question were excluded. Thus, for instance, those addressing other finance-related interventions (e.g. insurance, subsidies, entrepreneurial support, etc.) were not included in this selection.

Importantly, most evidence that examined the effectiveness of financial mechanisms to promote the adoption of adaptation strategies did not use experimental or quasi-experimental designs. This is an important caveat: the strength of evidence in this space showing attributable causal relationships was limited

[6] Categories included: (1) World Bank region; (2) country; (3) population sub-group; (4) sector; (5) intervention type; (6) intervention; (7) outcome; (8) outcome sub-group; (9) outcome indicator; (10) study design; and (11) methods. Fields 1, 3, 4, 5, 7, 8 and 10 were coded numerically to allow descriptive statistics, while fields 2, 6, 9 and 11 were coded descriptively.

[7] It should be noted that, whereas the EGM covers interventions corresponding to both autonomous and planned adaptation, this meta-analysis focuses on a particular section of the evidence, which addresses the role of access to credit as a stimulus for the autonomous adoption of other adaptation strategies by farmers in developing countries.

and at best, correlational. Most of the collected studies fall into a specific branch of research that examines the determinants of decisions to adapt by individual farmers/households, in which several characteristics are statistically tested by applying multivariate models. One of these determinants is whether households have access to credit in the period before the research survey. In some of the articles, access to credit was a specific intervention. In others, access to credit was a socioeconomic contextual variable that was included in the model and thus can be statistically associated with the probability of adapting to climate change.

As a result, a total number of 36 studies were retained for the meta-analysis, which in total contained 148 individual pieces of evidence (in this case, regression models). As explained above, this is because a single paper may contain different empirical formulations for the same overall research question, in the form of different regression models or different versions of the same dependent variable. The result of the final selection process is summarized in the table below.

Table 1 Number of included and excluded studies and the corresponding regressions

Intervention (Dependent Variable)	Number of Papers[8]	Number of Regression Models
Included (credit related)	**36**	**148**
Excluded (Non-credit related)	**9**	**21**
Access to crop insurance	2	7
Access to subsidy	3	10
Discounted price insurance	1	1
Entrepreneurial support	1	1
Undefined financial support	1	1
No financial intervention	1	1
Excluded (unrelated dependent variable)	**1**	**1**

Source: authors` own table.

2.2 Meta-Analysis Approach

Meta-analysis is a statistical approach that combines results from a series of studies addressing the same research question (Wampold et al., 2000). These methods can thoroughly test hypotheses that cannot be addressed clearly with a single or reduced set of studies, eliminating the uncertainty associated with qualitative reviews or to just counting the number of studies that support a particular hypothesis.

After consolidating the list of papers to be included in the study, each statistical regression contained in the selected articles was analysed and these were coded in a separate database. Each of the following elements was systematically categorized as a foundation for the meta-analysis:

[8] Total number of single papers adds up to 44, whereas the numbers here reported add up to 46, since two papers contained both excluded and included regressions.

Box 1 Variables extracted for each regression included in the meta-regression (36 studies; 148 regression models)

- Country of the study
- Population sub-group (households, farmers, land plots, etc.)
- Intervention (access to credit, formal loan, informal loan, etc.)
- Outcome group (single vs multiple adaptation strategies)
- Outcome category[9]
- Outcome indicator (indicator for the outcome)
- Study design (experimental, quasi-experimental, non-experimental)
- Method (model estimation method: logic, probit, multinomial logit, tobit, etc.)
- Number of observations
- Regression coefficient (associated with the "access to credit" variable)
- Standard error of the regression coefficients
- Significance level (90%, 95%, 99%)
- Marginal effect[10]
- Model fit parameter (R-squared, Adjusted R, etc.)
- Number of additional independent variables
- List of additional independent variables included in the study

Source: authors` own figure.

As noted above, most of the collected evidence corresponds to correlational empirical studies that do not present experimental or quasi-experimental designs, and therefore have methodological limitations to draw causal relationships. In these latter cases, meta-analysis techniques primarily consist of direct comparison of the marginal effects obtained individually in each of the analysed studies, which are commonly charted in a forest plot for comparative analysis.

In our study, we find that there is little calculation or reporting of marginal effects.[11] Therefore, no isolated causal effects associated with specific changes in the dependent variable (intervention) can be estimated in such an approach. Alternatively, a meta-analysis of correlational studies is possible by comparing and aggregating the regression parameters from different studies. This is a feasible and commonly used approach in research when several studies report on correlation or regression coefficients in the context of similar models.[12] However, most of the empirical literature collected in this study consists of binary statistical models that use different estimation methods, such as logit, probit, multinomial logistic regression etc. This complicates the use of aggregative or comparative techniques, which would require the aggregation of effect sizes (e.g. through forest plots) that decreases the confidence interval by increasing the sample size across included studies. In probit models, however, the rate of response is variable across different values of the independent variable. Combining results from different regression analyses in a meta-analysis often proves difficult. This is because differences in the applied estimation methods, in the units of measurement, or in the selection of covariates and encoding of the variables of interest, complicate a direct comparison of the

[9] Includes: Adapted crop varieties, Adoption of technology and assets, Agroforestry, Crop diversification/switching, Fertilizer management, Increased irrigation, Institutional/managerial adjustment, Labour adjustment, Land management, Livelihood diversification, Livestock management, Migration, Multiple measures, Planting/sowing times and techniques, Savings and borrowing, Soil and water conservation.

[10] Marginal effects were only reported by a fraction of papers (7 out of 36).

[11] Only four papers included quasi-experimental designs for testing the effect of access to credit on the adoption of adaptation strategies (mostly using an endogenous switching regression approach). However, due to the different scopes of the dependent variables and the limited number of cases, a comparative analysis of marginal effects was not feasible.

[12] Two methods are commonly used for meta-analysis of correlational studies: The Hedges-Olkin method, which is based on a conventional summary meta-analysis with a Fisher Z transformation of the correlation coefficient (Hedges and Olkin, 1985); and the Hunter-Schmidt method, which is effectively a weighted mean of the raw correlation coefficient (Hunter and Schmidt, 1990). An example of the application of such techniques in the medical sciences can be found in Diener et al. (2009).

regression coefficients. Some authors (e.g. Henningsen and Henningsen, 2018) have suggested approaches to overcome this difficulty, which in some cases require access to original data or parameters not reported in all of the studies. In light of these circumstances, we opted for the application of two alternative meta-analysis approaches available in the literature:

1. **Reporting the distribution of coefficients along with the sign and degree of statistical significance found in the empirical literature, regardless of the estimation method used.** This approach allows direct comparison across different studies, differentiating between those that found a significant positive correlation, from those that did not find significant results or even reported negative effects. A similar approach can be found, for instance, in Charmarbagwala et al. (2004). The following categories will be used to classify the sign and level of significance of different estimates (Table 2).

Table 2 Classification of significance levels

Significance Level	Symbol
Positive correlation (99% of confidence level)	++++
Positive correlation (95% of confidence level)	+++
Positive correlation (90% of confidence level)	++
Positive correlation (Non-significant)	(+)
Negative correlation (Non-significant)	(-)
Negative correlation (90% of confidence level)	--
Negative correlation (95% of confidence level)	---
Negative correlation (99% of confidence level)	----

Note: The two non-significant categories are in parentheses to signal that the sign can be a result of random, not statistically significant, variations. Source: authors` own table.

Certainly, this approach has its limitations and pitfalls, many of them due to the non-experimental nature of the reviewed studies. The lack of a counterfactual approach implies that causal effects cannot be rigorously measured from these designs and that the sign and significance level of the coefficients are dependent on other design elements, such as the selection of covariates. Direct comparisons between correlational signs are also problematic. This is because there is an extensive range of types and conceptualizations of dependent variables that capture a variety of adaptation strategies in highly diverse scenarios.

2. **Running a meta-regression analysis using an ordinal binary approach by applying a standardized scale to the sign and significance level of estimates.**[13] The meta-regression uses an indexed dependent variable reflecting, in our case, three different categories of studies: those that found a significant positive correlation, those that did not find a significant correlation, and those that found a significant negative correlation. The set of independent variables consists of regression model characteristics that could be systematically associated with the sign of the estimated effects. These could include the number of observations, the region where the study was performed, the number of independent variables used, the type of control variables included, the specific estimation method used, etc. Four different versions of the meta-regression model have been formulated for sensitivity purposes, combining logit and probit estimation methods, and different selections of covariates (Table 3).

[13] This approach is used, for example, in a meta-analysis on the relationship between uncertainty/investment (Koetse et al., 2009), or more relevantly to our case, in a meta-analysis on the distributional effects of climate change mitigation measures (Ohlendorf et al., 2018).

Table 3 Characteristics of the different formulations of meta-regression models

	Selected covariates included	All covariates included
Ordered probit	Model 1	Model 2
Ordered logit	Model 3	Model 4

Source: authors` own table.

The different determinants and controls introduced in the analysed studies have been classified into 29 separate categories. Only those potentially associated with the sign of the effect of access to credit on adopting adaptation measures were included in the meta-regression. The criteria to select the covariates in meta-regression models 1 and 3 are based on the a priori relationship between each of these covariates and the sign of the results found in the studies concerning access to credit. For each covariate, Table 4 shows the distribution of results in terms of the effect of access to credit. For example, out of the 148 regression models found in the 36 studies, 85 have been included as one of its covariates indicated whether the household/farm had access to extension services. From these 85 regression models, 14.1 per cent reported significant negative correlations with access to credit, and 27.1 per cent indicate significant positive results. Given this analysis, the top five covariates with the highest proportion of significant results on the credit variable, for both signs, were included in models 1 and 3 (see Table 4). For models 2 and 4, six additional covariates were added for sensitivity analysis. Covariates used in a limited number of studies or those used by a large majority have been disregarded. The explanation for this is as follows. First, we reduced the number of covariates in the meta-regression to avoid multi-collinearity problems. Second, our model contains variables that indicate whether the author has included that particular variable in her/his study or not, which does not capture effects of the actual variable in the study of the author (transport, access to market, access to information, etc.). In this respect, if almost all authors have systematically included a variable, then there will be minimal variance. This is equivalent to having a control group with five individuals, and a treated group with 95. Statistical inference is not very reliable in this scenario. Similarly, if specific variables are, for example, only included by 3 per cent of models, there is little use in including it in the model.

Table 4 Distribution of the regressions by type and sign of the coefficient of 'access to credit' as a determinant of the adoption of adaptation measures[14]

Covariates	Negative	Non-significant	Positive	N of regressions containing the covariate
Count of training/TA	27.3%	72.7%	0.0%	11
Count of ethnicity	66.7%	22.2%	11.1%	9
Irrigation**	16.7%	61.9%	21.4%	42
Access to transport*	28.3%	47.8%	23.9%	46
Distance to capital/markets	12.8%	62.8%	24.4%	78
Off-farm income	13.2%	60.4%	26.4%	53
Access to information/ICT controls	12.5%	60.9%	26.6%	64
Agricultural dependence*	19.2%	53.8%	26.9%	26

[14] See Section 3 for a detailed account of the different definitions of the "access to credit" variable used in different studies.

Covariates	Negative	Non-significant	Positive	N of regressions containing the covariate
Organization membership*	19.2%	53.8%	26.9%	52
Extension services	14.1%	58.8%	27.1%	85
Livestock*	23.7%	47.4%	28.9%	38
HH size/HH labour force/number of dependents	14.8%	55.7%	29.6%	115
Count of education level/human capital	14.5%	55.0%	30.5%	131
Government support	11.9%	57.1%	31.0%	42
Assets/physical capital controls	16.0%	52.0%	32.0%	75
Soil and terrain controls**	17.5%	50.0%	32.5%	40
Income	6.5%	60.9%	32.6%	46
Land/farm size	15.9%	51.4%	32.7%	107
CC perceptions/extreme events experience**	12.3%	54.3%	33.3%	81
Crop controls**	15.6%	50.0%	34.4%	32
Gender**	16.3%	49.0%	34.6%	104
Land tenure*	20.0%	45.3%	34.7%	75
Age**	12.8%	50.5%	36.7%	109
Geographical controls*	6.7%	56.7%	36.7%	60
Count of marital status	0.0%	60.0%	40.0%	5
Farming experience*	2.4%	56.1%	41.5%	41
Social capital controls*	0.0%	57.9%	42.1%	38
Rainfall*	7.5%	45.0%	47.5%	40
Other climate controls*	7.7%	38.5%	53.8%	26

Note: (*) Covariates selected for meta-regression models 1 and 3. (**). Covariates selected for regression models 2 and 4. Colour intensity scale indicates higher proportions. Please refer to Table 5 for the type of variables. Source: authors` own table.

We restricted the number of covariates included in the models because of the need to control the high risk of multi-collinearity in the context of multiple dichotomous variables. We applied a standard Variance Inflation Factor (VIF) test to both model formulations in the context of linear regression[15] to inspect for

[15] VIF test is not applicable in the context of logistic regressions, but multicollinearity can still be tested for a linear version of the model.

possible weaknesses. Models 1 and 3 yielded a VIF value of 7.9, whereas, for models 2 and 4, the value reached 10.3, just at the maximum recommended threshold (Hair et al., 1995). This means that the standard error in models 1 and 3 is less affected by multicollinearity than models 2 and 4.[16]

In estimating this model, it is necessary to consider the fact that multiple estimates come from a single study. An appropriate way to deal with this is to use Ohlendorf's (2018) approach and introduce weights per study in which each observation is weighted with the inverse of the total number of estimates that are drawn from the same study. This procedure prevents studies with a high number of regressions from having a disproportionally large influence on the estimation results.[17]

Table 5 provides an overview of the variables included in the meta-regression.

[16] Variance Inflation factor is the quotient of variance in a model with multiple terms divided by the variance of a model with one term alone. Intuitively, the VIF measures the severity of multicollinearity. It measures how much the variance or an estimated regression coefficient increases because of collinearity.

[17] For reasons of simplicity we follow a three-categories approach (non-significant, significant positive, and significant negative) in further analyses instead of the six levels of significance within positive or negative effects.

Table 5 Definition and descriptive statistics of variables included in the meta-regression

Variable	Definition	Mean	N	Max	Min	SD
Dependent Variable	0, if the regression finds a significantly negative effect of credit; 1 if the study does not find significant effects of credit; 2 if the study finds significantly positive effects of credit	1.20	148	2	0	0.65
Geographical						
Sub-Saharan Africa	1, if the study is performed in sub-Saharan Africa; 0 otherwise	0.76	148	1	0	0.43
South Asia	1, if the study is performed in South Asia; 0 otherwise	0.20	148	1	0	0.40
Study Design						
Plot	1, if the study defines land plots as the observation unit; 0 otherwise (households, or farmers)	0.09	148	1	0	0.29
Formal credit	1, if the study uses a formal concept of credit; 0 otherwise	0.12	148	1	0	0.33
Multi-adapt	1, if the study tests for multiple adaptation interventions; 0 otherwise	0.20	148	1	0	0.40
Prob-adapt	1, if the study uses a probabilistic (binary) approach for the dependent variable; 0 otherwise	0.83	148	1	0	0.38
N Observations	Number of observations included in the regression	2450.3	148	25119	58	5734.7
N Covariates	Number of additional covariates included in the regression design	18.08	148	38	4	7.64
Estimation Method						
Logit	1, if the study uses a logit model; 0 otherwise	0.16	148	1	0	0.36
Multinomial Logit	1, if the study uses a multinomial logit model; 0 otherwise	0.22	148	1	0	0.41
Multivariate Probit	1, if the study uses a multivariate probit model; 0 otherwise	0.16	148	1	0	0.36
Probit	1, if the study uses a probit model; 0 otherwise	0.20	148	1	0	0.40
Covariates						
Organization membership	1, if the study included membership to an organization as a covariate in the regression design; 0 otherwise	0.35	148	1	0	0.48
Livestock	1, if the study included ownership of livestock as a covariate in the regression design; 0 otherwise	0.26	148	1	0	0.44
Agricultural dependence	1, if the study included the degree of dependence on agriculture as a covariate in the regression design; 0 otherwise	0.18	148	1	0	0.38
Land tenure	1, if the study included land tenure as a covariate in the regression design; 0 otherwise	0.51	148	1	0	0.50

Variable	Definition	Mean	N	Max	Min	SD
Access to transport	1, if the study included access to transport as a covariate in the regression design; 0 otherwise	0.31	148	1	0	0.46
Rainfall	1, if the study included rainfall as a covariate in the regression design; 0 otherwise	0.27	148	1	0	0.45
Other climate controls	1, if the study included other climatic controls (temperature, etc.) as a covariate in the regression design; 0 otherwise	0.18	148	1	0	0.38
Geographical controls	1, if the study included geographical controls (regions, area) as a covariate in the regression design; 0 otherwise	0.41	148	1	0	0.49
Social capital controls	1, if the study included social capital variables (e.g. presence of relatives, etc.) as a covariate in the regression design; 0 otherwise	0.26	148	1	0	0.44
Farming experience	1, if the study included the level of farming experience as a covariate in the regression design; 0 otherwise	0.28	148	1	0	0.45
Gender	1, if the study included gender of household head as a covariate in the regression design; 0 otherwise	0.70	148	1	0	0.46
Age	1, if the study included the age of the household head as a covariate in the regression design; 0 otherwise	0.74	148	1	0	0.44
Irrigation	1, if the study included irrigation related variables as a covariate in the regression design; 0 otherwise	0.28	148	1	0	0.45
Crop controls	1, if the study included the type of crops as a covariate in the regression design; 0 otherwise	0.22	148	1	0	0.41
Soil and terrain controls	1, if the study included variables related to soil and terrain characteristics as a covariate in the regression design; 0 otherwise	0.27	148	1	0	0.45
CC perceptions / experience with extreme events	1, if the study included variables capturing perceptions on climate change manifestations or previous experience with extreme events as a covariate in the regression design; 0 otherwise	0.55	148	1	0	0.50

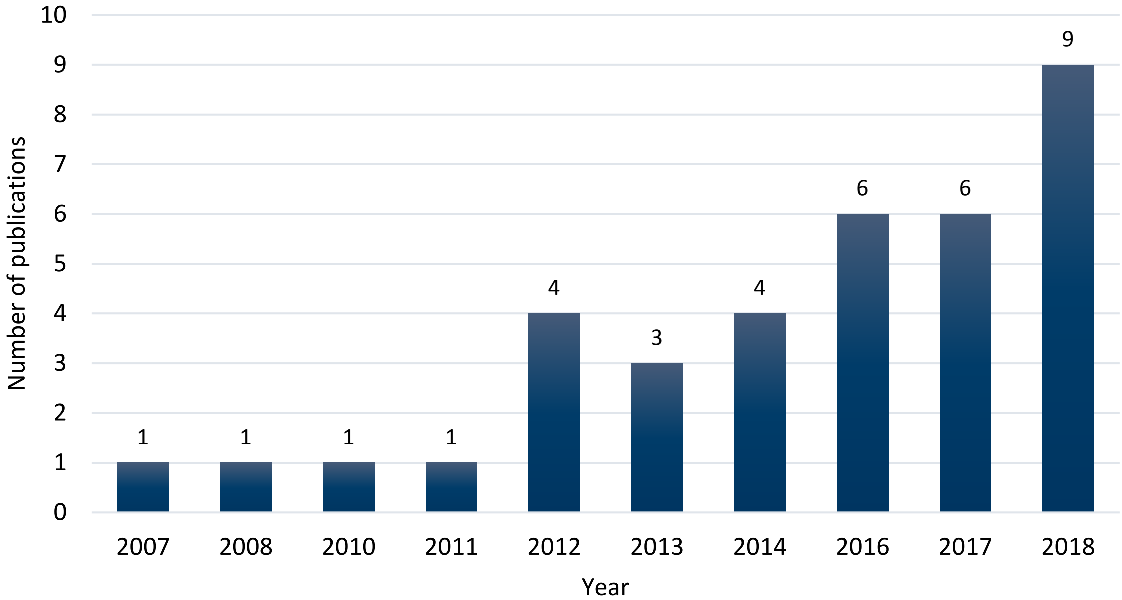
Note: (*) For the gender variable, we assume authors have used the conventional approach to coding the household head. Source: authors` own table.

We also assessed the evidence qualitatively by reviewing the comments and hypotheses made by the authors of the reviewed papers regarding their findings on the role of credit in the decision to adapt. Although few extensive theoretical discussions are included in the empirical analysis, some authors indicate possible explanations behind the identified correlations. We provide a summary of the arguments put forward by the authors regarding the interpretation of regression coefficients and the theory of change that could be behind the results.

3. CHARACTERISTICS OF THE INCLUDED STUDIES

A total number of 148 individual estimates (regression models), contained in 36 different studies, have been included in this meta-analysis. It is worth noting that the relevant literature has increased in frequency in recent years, particularly after 2012 (see Figure 1), when the number of publications grew dramatically. The largest number of publications per year was in 2018, the last year covered by the EGM and which is the source of evidence for this study.

Figure 1 Distribution of the selected literature by year of publication

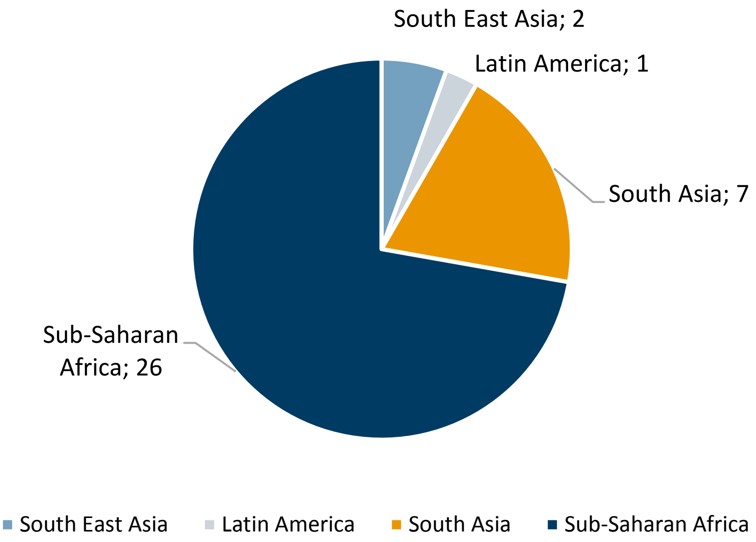


Note: for the years 2009 and 2015 no papers were analysed. Source: authors` own figure.

Geography: A vast majority of the studies has been collected through studies performed in sub-Saharan Africa, with a total number of 26 publications, which implies more than 70 per cent of the total. South Asia and South East Asia have seven and two publications respectively, whereas in Latin America only one relevant paper was identified.[18] No evidence has been collected for other regions such as Northern Africa or the Middle East (see Figure 2).

[18] The scarce evidence regarding empirical studies conducted in Latin America is inherited from the EGM search protocol, where only abstracts in English language where retrieved.

Figure 2 Distribution of the selected literature by region



Source: authors` own figure.

Definition: Access to credit is defined in different ways across the empirical literature (see Table 6). A majority of papers (20 out 36) included a broad definition of access to credit and used a dichotomous variable, usually "access to credit". The variable in most studies is usually drawn from a survey questionnaire, in which respondents state whether they have (had) access to credit, without specifying anything more. Only in a few cases do authors make explicit reference to farming or agricultural credit (De Matos et al., 2018; Tambo, 2013; Kumar and Sidana, 2018; Makate et al., 2017; Ng'ombe et al., 2017), whereas in the remaining studies, the type of credit is not further defined. Only in one case (e.g. Guloba, 2014), the survey question on access to credit was linked to a time horizon prior to the interview ("during the last one year").

A different formulation of the variable can be found in Fagariba et al. (2018) and Ndamani and Watanabe (2016), both in Ghana: they explicitly refer to "access to credit facilities". In this case, it is reasonable to think that access to credit is expressed in terms of the physical presence of brick and mortar institutions and organizations that can provide the services. Still, the definitions provided in both texts are insufficient to confirm this. One sub-group of papers made an explicit distinction between formal and informal credit.

Some authors (Berhanu and Beyene, 2014; Yesuf et al., 2008) focus solely on formal credit and do not include any variable related to informal loans/credits. Formal credit refers here to loans accessed through well-established credit providers, regardless of whether a public or private entity provided credit. Other authors include two dichotomous variables to estimate the effects of both formal and informal credit (Nkonya et al., 2011; Gorst et al., 2018; Mishra et al., 2018; Oyekale, 2014).[19]

Another sub-group of studies defines the credit variable differently: they identify credit-constrained households and differentiate them from the rest. For instance, in Mulwa et al. (2017) the credit constraint variable categorizes farmers into those who needed credit and did not receive it or received less than they needed (=1), and those who did not need credit (=0). Similar approaches have been adopted by Masud et al. (2017), Teklewold et al. (2017) and Yegbemey et al. (2014). Only three publications have specified access to credit as continuous variables. In two cases (Ngigi et al., 2012; Alam et al., 2016), authors define an indexed continuous variable that captures financial capital and institutional access through a composite of different

[19] Authors define formal credit as credit granted by banks, savings banks, and government loans. Informal institutions considered in the studies are: money lenders, pawnshops, and family or friends.

indicators, including access to credit. Only in one case (Iheke and Agodike, 2016) households were asked to report the actual amount received as a loan to construct a continuous variable for capturing access to credit.

Table 6 Distribution of evidence by the definition of "access to credit" provided in each paper (independent variable)

Independent Variable	Number of papers in which it is addressed	Number of regression models
Access to credit (binary variable i.e. 1 if yes there is; 0 if otherwise)	20	83
Access to credit facility (binary variable i.e. 1 if yes there is; 0 if otherwise)	2	2
Access to formal credit (binary variable i.e. 1 if yes there is; 0 if otherwise)	5	18
Access to informal credit (binary variable i.e. 1 if yes there is; 0 if otherwise)	4	12
Credit constrained household (binary variable i.e. 1 if yes constrained; 0 if otherwise)	4	14
Financial capital index (including access to informal credit - scaling not specified)	1	5
Institutional access index (including access to credit)[20]	1	5
Participation in financial support programme (including access to credit- (binary variable i.e. 1 if yes participated; 0 if otherwise)	1	8
Amount of credit obtained (continuous variable)	1	1

Source: authors` own table.

Measuring and identifying autonomous adaptation: Several authors adopt different approaches when defining the term autonomous: they examine the autonomous decision by households/farmers to adopt different adaptation strategies. As shown in Table 7, there are two types of studies according to the choice of dependent variable: those using a continuous measurement, and those using a probabilistic approach (binary variable). In six publications, authors have used a constant variable to capture the degree of adoption of multiple or single measures. In the case of individual measures, some examples of variables include crop and livestock diversification indexes (Kankwamba et al., 2018; Mekuria and Mekonnen, 2018), or the percentage of land dedicated to specific uses (Nguyen et al., 2017). For multiple interventions, authors use indexed variables to capture the intensity of adoption (Koshti and Mankar, 2016; Masud et al., 2017) or count the number of adaptation strategies adopted (Tambo, 2016). Most of the literature opted for a probabilistic approach by defining a dichotomous variable for capturing adaptation, in which the value one is taken if the subject has adopted at least one measure among a set of available strategies (an approach used in nine papers).

[20] The index was scaled into high and low. High refers to access to (at least) more than three institutional facilities and low otherwise (See Alam et al., 2016).

Table 7 Distribution of the evidence by type of outcome (autonomous adaptation measured adopted)

Dependent variables (adaptation measure to be adopted)	Number of regression models	Number of papers in which addressed
Continuous measurement	**25**	**6**
Single measure	**22**	**3**
Adapted crop varieties	2	1
Crop diversification/switching	4	1
Land use measures	12	1
Livelihood diversification	3	1
Livestock management	1	1
Multiple measures	**3**	**3**
Probability of Adaptation	**123**	**30**
Single measure	**97**	**21**
Adapted crop varieties	13	4
Adoption of technology and assets	12	1
Agroforestry	4	1
Crop diversification/switching	10	4
Fertilizer management	3	1
Increase irrigation	3	1
Institutional/managerial adjustment	2	1
Labour adjustment	2	1
Land-use measures	3	1
Livelihood diversification	4	2
Livestock management	14	2
Migration	2	1
Planting/sowing times and techniques	10	2
Savings and borrowing	4	1
Soil and water conservation	11	1
Multiple measures	**26**	**9**

Source: authors` own table.

Overall, the empirical evidence in the 36 papers has used a variety of estimation methods (Table 8). More than 70 per cent of all estimates used one of four methods, namely the multinomial logistic model (32 regressions), probit model (29 regressions), logit model (23 regressions) and the multivariate probit model (23 regressions). All of these are binary models used for cases with a probabilistic approach to adaptation. In cases that use non-dichotomous independent variables, estimation models such as ordinary least squares (OLS) or panel data regressions have been applied.

Table 8 Distribution of the evidence by estimation method

Method	Number of Regressions
Multinomial Logistic Regression	32
Probit Regression	29
Logit Regression	23
Multivariate Probit Regression	23
Seemingly Unrelated Fixed-Effects Regression	9
Tobit Models	7
Fixed-Effects Regression	6
OLS Regression	6
Other	13

Source: authors` own table.

4. RESULTS

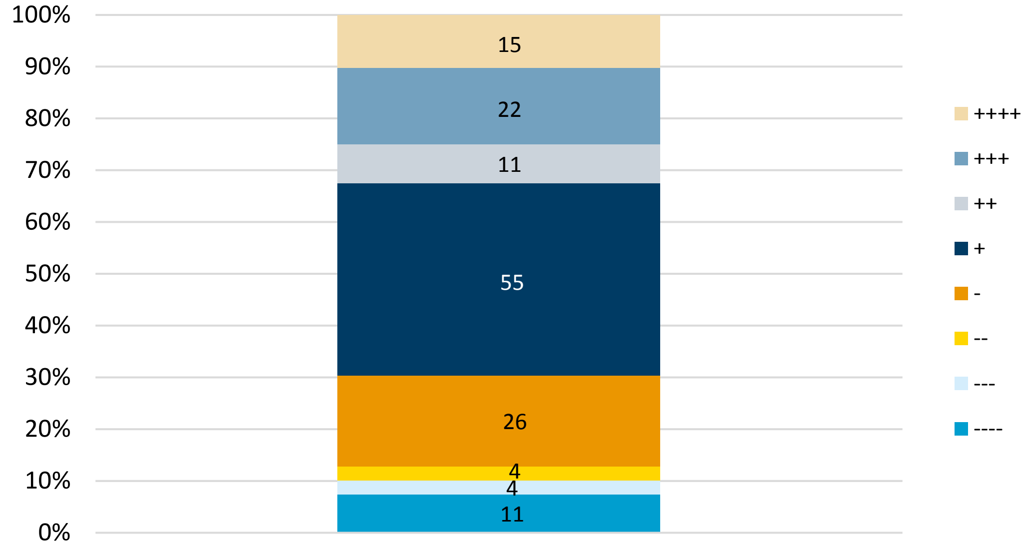
This section gives an overview of the results. It summarizes the sign and significance of the correlations found between access to credit as a determinant of the adoption of adaptation measures (Section 4.1). Given the high variance of results, the subsequent analysis discusses possible explanations. We present the qualitative commentary by the authors on the possible explanations behind their results (Section 4.2) and run a meta-regression in search of possible design features of the reviewed studies that could be systematically associated with the sign of their results (Section 4.3).

4.1 Distribution of the Evidence by Sign and Significance

A straightforward method to assess the degree of consensus within the empirical literature is to examine the distribution of results across papers in terms of the sign and significance of the estimates. We do this to understand the relationship between access to credit and the adoption of adaptation measures. As pointed out in the methods section, this has certain limitations, given the variance of study designs, variable definitions and the fact that non-experimental designs are subject to many possible biases, which we attempt to address in more depth in the following section.

The overall result is summarized in Figure 3, where all individual regressions have been included, regardless of the definition of "access to credit" and "autonomous adaptation." At first glance, it is evident that the role of access to credit as a determinant of autonomous adaptation is disputed, as highlighted by the large variety of results across the different studies. It is striking to observe that more than half the estimates (81 regression coefficients, or 54 per cent of the total evidence) did not find any significant correlation. Another 48 regressions (nearly a third of the evidence) found a significantly positive correlation, with 37 of them showing significance levels of 95 percent or higher. Surprisingly enough, a non-negligible share of the evidence (19 estimates collected in nine different papers, amounting to 12.8 per cent of the evidence) obtained negative correlational relationships between both variables.

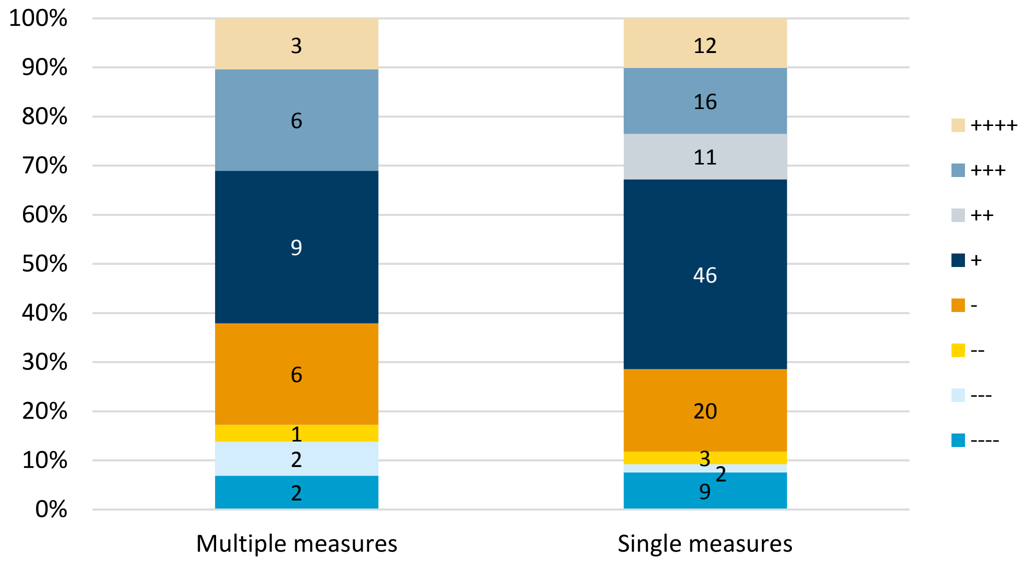
Figure 3 Sign and significance of correlation for access to credit as a determinant of the adoption of adaptation measures: distribution of evidence



Source: authors` own figure.

As noted earlier, it is reasonable to think that different design features in different studies, as well as the different specifications of the adaptation variable, might explain the variance in results. We have already seen that some authors tested the effect of credit on the adoption of a single adaptation measure, whereas others examined it for a set of multiple strategies. A priori, one may hypothesize that the relationship between access to credit and autonomous adaptation is stronger when more than one possible strategy is available to farmers. Figure 4 plots aggregated results for two cases – multiple versus single adaptation options – resulting in, contrary to intuition, very similar distributions according to sign and significance of the estimates. It is worth noting, however, that the number of estimates for the case of multiple adaptation measures is significantly lower than single ones.

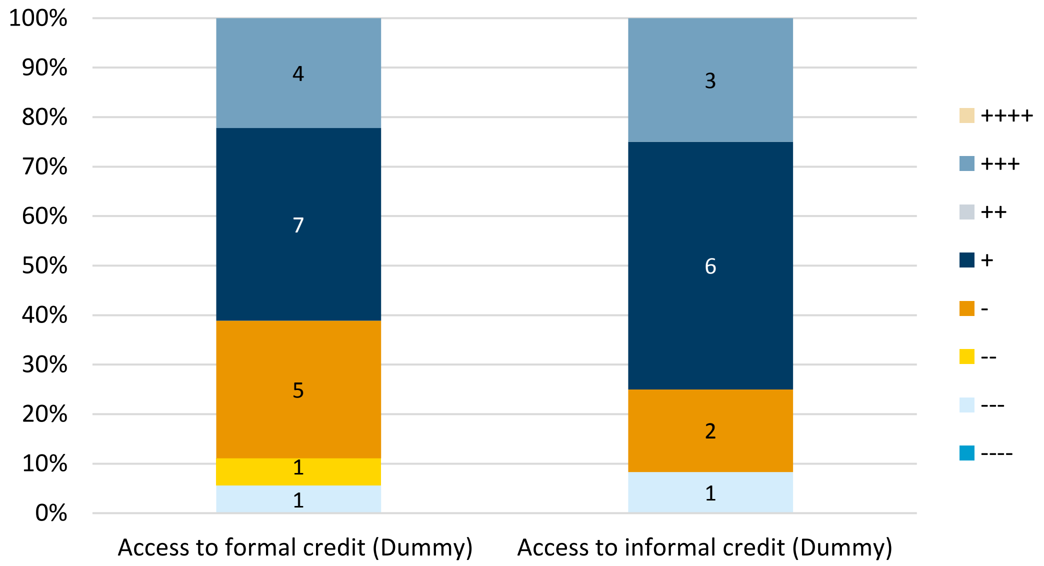
Figure 4 Sign and significance of correlation for access to credit as a determinant of the adoption of adaptation measures: distribution of evidence (multiple vs single adaptation measures)



Source: authors` own figure.

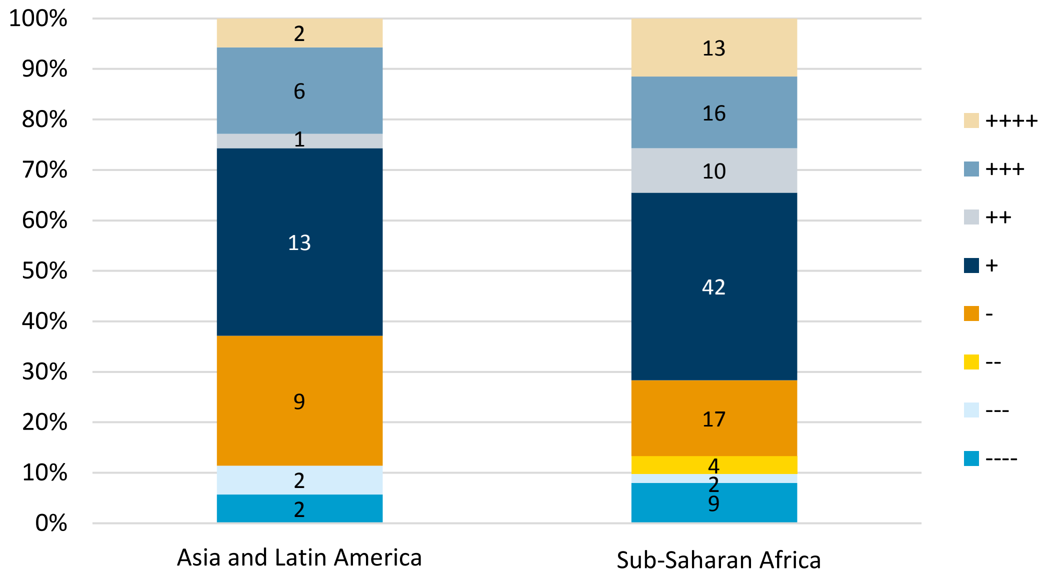
Another interesting question is whether the role of credit as a determinant of adopting adaptation strategies is more conclusive when it is granted through formal rather than informal modalities. Despite the limited number of papers specifically addressing this question, a comparison of results between estimates of the role of formal and informal modalities of credit is worth inspecting. As shown in Figure 5, no relevant differences in the distribution can be observed. In both cases, formal and informal credit, a majority of studies found non-significant effects on the adoption of autonomous adaptation measures. The proportion of the literature that found positive effects is also similar in both cases, and greater than the one obtaining a negative correlation. It is worth considering, however, that only five papers have addressed this question separately, providing 18 estimates for formal credit and 12 for informal credit. Section 4.3 further tests this aspect through a meta-regression approach.

Figure 5 Sign and significance of correlation for access to credit as a determinant of the adoption of adaptation measures: distribution of evidence (formal vs informal access to credit)



Source: authors` own figure.

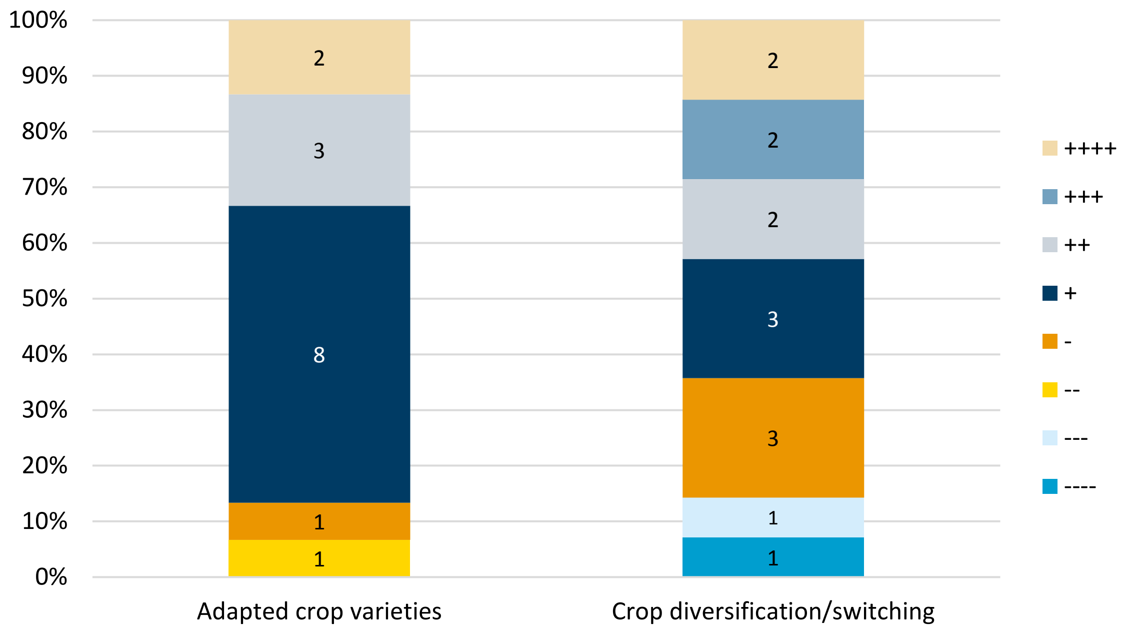
Figure 6 Sign and significance of correlation for access to credit as a determinant of the adoption of adaptation measures: distribution of evidence (Sub-Saharan Africa vs Asia and Latin America)



Source: authors` own figure.

Finally, there is the question of whether access to credit might be associated to a greater degree with the adoption of certain types of adaptation strategies compared to others. It has already been observed that no significant differences exist between studies where multiple adaptation strategies were measured, and those that include single strategies as their outcome variable. For the case of single strategies, only two adaptation options, namely the adoption of modified crop varieties and crop diversification strategies, have sufficient estimates in the literature. Fifteen estimates in 12 different publications examine the strategy of modified seeds/crops, and 14 estimates from eight studies for crop diversification and switching strategies. Figure 7 shows a similar distribution to the overall results for both cases. Still, the literature seems to have found slightly more supportive evidence of the role of credit in promoting the adoption of crop diversification (42.8 per cent of the evidence reported a positive significant correlation, albeit with a small number of cases) than adapted/modified crops (33.3 per cent). However, these results should be taken cautiously in the light of the limited number of papers addressing these particular cases and the diverse methodological approaches used.

Figure 7 Sign and significance of correlation for access to credit as a determinant of the adoption of adaptation measures: distribution of evidence (specific adaptation strategies)



Source: authors` own figure.

In sum, we see that the empirical literature on the role of access to credit in promoting autonomous adaptation to climate change shows diverse results, with a majority of them reporting non-significant regression coefficients. Although the proportion of the evidence showing significantly positive effects is higher than those finding negative results, we need to be cautious when thinking of possible policy implications. When inspecting the results by geographical area, type of credit (formal or informal) or the set of adaptation strategies considered, the distribution of results is significantly different (Figures 5 to 7).

4.2 Qualitative Assessment

The variance of empirical results on access to credit as a determinant of the adoption of adaptation measures can be further inspected through the commentary and hypotheses contemplated in the literature. It is worth noting, however, that in many cases the authors of included studies restrict their discussion to only highlighting the sign and significance of the correlation analysis, without discussing possible interpretations or providing survey-based evidence on possible causes. Here we will focus on those studies where authors have added insights in addition to presenting their quantitative evidence.

Some authors were surprised by the inconclusive results (for example, see Mango et al., 2018). Those who found negative effects discuss some explanatory factors. In one of the most elaborated hypotheses, Priya et al. (2013) explain that the studied community (the Chepangs in Nepal) use credit to fulfil their subsistence needs rather than for productive investments. According to the authors, (access to) credit can be negatively correlated with conventional coping strategies (such as migration of a household member, in this context) as households only access it when they are constrained to adopt any other alternative coping measures. The Chepangs often lacked fixed assets needed as collateral to obtain a loan from formal lending institutions. Some other authors provide survey-based evidence on factors that discourage farmers from applying for loans, such as excessive bureaucracy, lack of knowledge concerning the granting process, or even uncertainty over financing systems (De Matos et al., 2018). In similar terms, Fagariba et al. (2018) point out that difficulties in accessing credit coupled with high interest rates make credit facilities unattractive, compelling most farmers to rely on their meagre income to purchase farm inputs. Part of the research community seems to be already aware of the possibility of obtaining negative effects (e.g. Mishra et al., 2018; Ng'ombe et al., 2017). A particular case is found in Gorst et al. (2018), whose results show that formal credit is positively related to the propensity to adapt, whereas informal credit is negatively related. According to the authors, this would provide evidence that credit channels affect the costs and benefits of investing in new technologies because informal loans are typically granted to support consumption over short durations. Informal loans tend to support consumption-smoothing activities rather than productive investments on-farm.

Studies that support ex ante hypotheses discuss some theoretical foundations of the role of credit in adaptation policy. For instance, Ojo and Baiyegunhi (2018) highlight that, in the absence of credit, farmers may find it difficult to adopt any adaptation strategy, even when provided with climate information, as they might not be able to purchase the required inputs. Lack of credit as a vulnerability factor that, in general, hinders access to rural services, is highlighted by Nkonya et al. (2011). Yegbemey et al. (2014) stresses the importance of farmers' investment capacity in their adaptation process, noting that producers with access to credit can quickly develop adaptation strategies. However, the profitability of the activity remains essential to ensure reimbursement. In a slightly different discussion, Nhemachena and Hassan (2007) highlight the role of transaction costs in the adaptation process. According to the authors, more extensive financial resources enable farmers to change their management practices in response to changing climate and being able to use all available information on changing conditions (e.g. buying new crops). Other alternative views stress the importance of credit in reducing the odds of utilizing savings as opposed to lowering consumption during drought (Guloba, 2014), or the possibility of facing higher crop price risks through a more robust financial situation and higher levels of investment (Takeshima and Yamauchi, 2010).

4.3 Meta-Regression

In the light of the high disparity of results found in the literature and the different study design features used by the authors, we inspect if specific methodological options may be systematically associated with the results. A meta-regression approach allows testing whether different study specifications may be related to the sign of the estimates on the role of credit (see Table 9).

Here we present the results of four different formulations of an ordered logit/probit regression. The regression uses an indexed dependent variable to capture the sign of the correlation coefficient of the "access to credit as a determinant of the adoption of adaptation measures" variable (0 = significantly negative, 1 = non-significant, 2 = significantly positive), as well as a set of model design elements such as estimation methods, choice of covariates, formulation of measurements etc., as the independent variables.

Table 9 Results of the meta-regression models

	Role of access to credit as a determinant of the adoption of adaptation measures (ordinal). (0 = significantly negative, 1 = non significant, 2 = significantly positive)			
	Ordinal Probit (selected covariates)	Ordinal Probit (all covariates)	Ordinal Logit (selected covariates)	Ordinal Logit (all covariates)
Variables	Model 1	Model 2	Model 3	Model 4
Geographical				
Sub-Saharan Africa	0.245 (0.8196)	0.385 (1.014)	0.322 (1.412)	0.522 (1.801)
South Asia	-0.136 (0.9721)	0.176 (1.209)	-0.412 (1.647)	0.176 (0.223)
Study Design				
Plot	3.751** (1.7619)	5.649*** (1.515)	6.271** (3.365)	9.200*** (2.794)
Formal credit	0.586 (0.6796)	0.475 (0.689)	0.843 (1.538)	0.643 (1.646)
Multiadapt	-0.679 (0.4736)	-0.296 (0.450)	-1.254 (1.048)	-0.635 (0.875)
ProbAdapt	0.427 (0.6460)	0.508 (0.606)	0.746 (1.108)	0.889 (1.010)
N Observations[st]	0.082 (0.233)	-0.289 (0.310)	-0.240 (0.427)	-0.623 (0.578)
N Covariates	-0.086** (0.0409)	-0.071 (0.048)	-0.144** (0.076)	-0.108 (0.088)
Estimation Method				
Logit	-1.137 (0.7421)	-0.569 (0.849)	-2.063 (1.303)	-1.059 (1.513)
Multinomial Logit	-2.370** (1.0866)	-3.335*** (1.101)	-4.008*** (1.898)	-5.557*** (2.081)
Multivariate Probit	-1.234* (0.6703)	-1.713** (0.721)	-2.057 (1.280)	-2.996** (1.287)
Probit	-0.316 (0.5920)	-0.527 (0.663)	-0.529 (1.073)	-0.851 (1.255)
Included covariates				
Organization membership	-0.451 (0.3940)	-0.865* (0.465)	-0.751 (0.755)	-1.416 (0.887)
Livestock	-0.530 (0.4838)	-1.264** (1.589)	-0.919 (0.884)	-1.935** (1.344)
Agricultural dependence	1.011 (0.9779)	1.005 (1.074)	1.532 (1.865)	1.718 (2.378)
Land tenure	0.800* (0.4553)	1.089** (0.526)	1.391 (0.941)	1.830* (1.201)
Access to transport	-1.378***	-1.525***	-2.420***	-2.657***

	Role of access to credit as a determinant of the adoption of adaptation measures (ordinal). (0 = significantly negative, 1 = non significant, 2 = significantly positive)			
	Ordinal Probit (selected covariates)	Ordinal Probit (all covariates)	Ordinal Logit (selected covariates)	Ordinal Logit (all covariates)
	(0.4966)	(0.490)	(0.964)	(0.878)
Rainfall	-0.618 (0.5439)	-0.557 (0.521)	-1.003 (0.970)	-0.911 (0.993)
Other climate controls	0.837 (0.6232)	0.595 (0.678)	1.332 (1.212)	0.935 (1.447)
Geographical controls	0.319 (0.2664)	0.666 (0.421)	0.567 (0.509)	1.161 (0.778)
Social capital controls	1.491*** (0.4677)	1.346** (0.551)	2.532*** (0.892)	2.371** (1.009)
Farming experience	1.197*** (0.3454)	1.465*** (0.431)	2.044*** (0.691)	2.666** (1.055)
Crop controls		-0.944** (0.430)		-1.736** (0.837)
Soil and terrain controls		-0.652 (0.430)		-1.050 (1.286)
Irrigation		-0.300 (0.709)		-0.806 (1.682)
CC perceptions		0.602 (0.450)		0.907 (1.033)
Gender		1.059** (0.441)		1.775** (0.837)
Age		1.129** (0.487)		1.799* (0.929)
	N =148 Pseudo-R^2= 0.2098	N =148 Pseudo-R^2= 0.2927	N =148 Pseudo-R^2= 0.2091	N =148 Pseudo-R^2= 0.2922
* Significant at 90% confidence level ** Significant at 95% confidence level *** Significant at 99% confidence level				

Note: st = standardized variable. Source: authors` own table.

4.3.1 Geographical Differences

In accordance with the descriptive analysis in previous sections, the meta-regression seems to support the idea that no regional differences have been found regarding access to credit as a determinant of the adoption of adaptation measures. In all four models, the corresponding coefficients were non-significant for the two regional variables introduced (Sub-Saharan Africa and South Asia). In the case of South Asia, they even showed some disparities in their sign among different model formulations.

4.3.2 Design Features

The meta-regression models also tested whether different design features of the reviewed studies could be systematically associated with the results, including:[21]

- the choice of observation unit (land plots vs household/farms)
- whether credit was formal or informal
- the use of multiple or single adaptation strategies as the dependent variable
- the use of a probabilistic approach or continuous measurement of the dependent variable
- the number of observations
- the number of control variables and other determinants introduced in the original regression models

Among these, only two elements related to the effect of access to credit. The first one refers to the use of land plots as the observation unit. These plot studies have identified a significant positive relationship (in all four models) with 'access to credit' being a determinant for the adoption of adaptation measures. Plot studies also show the largest coefficients of any variable. A characteristic of these studies is their much larger average number of observations; although this aspect is also included in the meta-regression, here it iscontrolled for. A reasonable explanation of why plot studies often show that 'access to credit' led to changes in adaptation practices could be that they often offer a more fine-grained assessment of practices on the farm, including those to reduce risk (such as rotation, intercropping, land husbandry techniques).

The second design feature systematically associated with the results is the number of covariates. Specifically, the larger the number of additional determinants and control variables in the studies, the less access to credit influenced the adoption of adaptation measures. However, the result was significant in models 1 and 3 only, not when further control variables (such as age and gender) were added in models 2 and 4 (which improve the 'explanatory' power of the model from 0.21 to 0.29).

Whether the studies use a probabilistic approach or a multi-strategy definition of adaptation as their dependent variable, it seems there is no correlation with the sign of the effect of 'access to credit'. In principle, this challenges the intuitive hypothesis (i.e. a priori it would be reasonable to expect more significant effects when defining a broader concept of adaptation). Lastly, in Section 4.1 (see Figure 5), it was found that no apparent differences could be observed in the sign and significance between studies that separately tested the effects of formal and informal types of credit. The meta-regression confirms this observation in a multivariate framework, as no significant relationship was found in any of the four model formulations.

4.3.3 Estimation Method

Regarding the possible influence of the estimation method, the meta-regression tested the four most common approaches used by the literature to analyse the possible systematic effects on the results. The associated coefficients show that studies using multivariate probit and multinomial logit models are significantly associated with a negative role of 'access to credit' as a determinant of the adoption of adaptation strategies. This implies, first, that once both binary and multinomial logit and probit models are controlled for, alternative statistical approaches tend to find somewhat positive effects of access to credit. These approaches are very diverse, ranging from quasi-experimental designs, such as endogenous switching regressions, to OLS. Secondly, it should be noted that both multivariate probit and multinomial logit are generalized specifications of binary regression models in which the dependent variable is nominal and for which there are more than two categories. This means that when the dependent variable is more differentiated in multivariate and multinomial models, these differentiated research designs highlight negative tendencies in terms of access to credit as a determinant of the adoption of adaptation measures (which are not apparent in binary models). In other words, when 'access to credit' is broken down into

[21] Two further design features which we would have liked to have included are: (i) the timing when credit was given; (ii) whether there was a lag between credit and study. The scope of the present paper did not allow the authors to include these two aspects.

different steps, the influence on autonomous adaptation appears negative. This warrants further investigation.

4.3.4 Choice of Covariates (Additional Determinants)

Finally, the last question to be addressed by the meta-regression analysis is whether including certain additional determinants in the original studies influence the sign and significance of access to credit on the adoption of adaptation measures.

When analysing the influence of some of these particular covariates, we see that studies including the variables ‘land tenure’, ‘social capital controls’ and the level of ‘farming experience’ as additional covariates show a significant and positive influence of ‘access to credit’ as a determinant of adopting adaptation measures (see Table 9). This is observed in almost all of the model formulations for all three variables. Also, two variables that are only present in models 2 and 4 – ‘gender’ and ‘age’ – also show a significant positive sign. One way to interpret these findings is that, once we control these important household characteristics, the influence of access to credit as a determinant of adopting on-farm adaptation strategies is easier to observe.

However, when regressions include ‘access to transport’ as a covariate, the studies show that the relationship of ‘access to credit’ with adopting adaptation measures tends to be negative (also confirmed in all four models). Such coefficients are difficult to understand. One interpretation of this finding is that households with easier access to transport corridors adapt in different ways and that the data do not accurately capture these decisions (as household members might not be present, and remittance flows might be hard to measure).

Further variables also show that, when included in the regression models, the relationship of ‘access to credit’ with adopting adaptation practices tends to be negative. Partial evidence can be observed regarding the variable ‘livestock’. The inclusion of this variable in a regression model is associated with a significant negative effect of access to credit on adopting adaptation practices in models 2 and 4. The same can be seen for ‘organization membership’ and ‘crop controls’. The reasons for the negative effect, when these variables are included, are difficult to determine and should be the focus of further investigation.

In general terms, the additional set of covariates in models 2 and 4 increases the Pseudo R-squared from 0.21 to 0.29. The inclusion of the additional set of covariates has an ambivalent effect on significance levels with some coefficients increasing the significance level considerably (‘Livestock’, ‘Land tenure’, ‘Plot’ and ‘Multivariate Probit’) while others become insignificant (‘N Covariates’, ‘Social capital controls’).

Meta-regression models do not directly test the influence that those variables can have on the decision to adapt, nor the role of the access to credit. Such models rather test whether the inclusion of those variables in the original models influences the role of ‘access to credit’ on adopting adaptation practices. One interesting extension of these findings could be the identification of interaction effects between independent variables, something that has not been performed in the reviewed empirical literature.

This analysis, rather than providing directly applicable policy implications, aims to understand whether the diverse results in terms of the role of access to credit as a determinant of the adoption of adaptation measures, could be the consequence of different methodological choices by the authors. Our evidence partially confirms this in connection with the selection of some covariates, as well as in some of the previously noted design features. Nonetheless, it is also evident that not all the variability in the credit effects can be attributable to diverse methodological choices. Indeed, our meta-regression models managed to explain just around 30 per cent of the variance in the best case (see Pseudo-R2 statistics in Table 9.

5. CONCLUSION

In light of the results presented above, it is evident that the empirical literature on the determinants of adoption of climate change adaptation measures is far from being unanimous when it comes to assigning a role to access to credit. First, by computing the sign and significance of the correlation across studies, we have seen that a majority of regression models (54.7 per cent) reported non-significant estimates for credit-related variables in connection to the adoption of adaptation measures. However, nearly a third (32.4 per cent) of the evidence supported a positive significant relationship (with a remaining 12.8 per cent showing significant negative effects).

Just a small proportion of the literature has ventured to provide possible explanations for such results, particularly in cases where non-significant, and even where negative effects were obtained. Some explanations point to the propensity of vulnerable farmers to use credit for subsistence- or consumption-related expenses, rather than on investments. Other authors have indicated some of the shortcomings and barriers for taking up loans in highly-vulnerable communities (bureaucratic burdens, unavailable facilities, etc.). Although plausible, this still begs the question of how credit could lead to adopting fewer adaptation practices. One possible explanation is that the financial burden of this type of loans on borrowers is so high that they will not incur any other (perceived) risk of trying out new “adaptive” practices. Farmers with credit may thus stick to what they know works most of the time instead of trying out, for instance, new seeds or irrigation techniques.

Apart from the different explanations and interpretations provided by the authors of the empirical studies, some possible methodological issues could be related to the sign and significance of the results. Certain methodological aspects, such as the estimation method and the number of covariates, correlated with the sign and significance of the credit variable. The meta-regression results also indicate that the inclusion of certain covariates in their regression models is related to significant effects of access to credit as a determinant of the adoption of adaptation measures, hinting at some possible interaction effects. Methodological divergences, however, would explain only partially the variability of results.

An element commonly observed in a significant proportion of the studies is the broad definition of ‘access to credit’, which in many cases remains undefined in the reviewed articles. This could also be one of the elements explaining the ambiguous and inconclusive results of this meta-analysis. More precisely, it is reasonable to think that targeted credit products aimed at specific agricultural needs might lead to different results when compared to loans that are not linked to any particular purpose. However, the collected evidence does not allow identifying those cases and their relationship with the adoption of adaptive measures.

Therefore, future academic research should formulate “access to credit” in a more detailed way that provides more nuanced definitions and scenarios on providing credit. Also, the use of experimental and quasi-experimental designs (almost absent from the evidence collected in the EGM that served as a basis for this meta-analysis), should be encouraged to obtain more isolated and causal effects of credit-related interventions.

From a policy perspective, the results should be taken cautiously before pointing out any implications for future lending policies and programmes. The lack of significant correlations supporting the role of credit in these types of empirical studies possibly indicates that access to credit without proper targeting and understanding of preference structures may be insufficient in promoting access to credit as a determinant in the adoption of adaptation measures. Hence, financial products specifically aiming at adaptation purposes and delivered under comprehensive programmes that include, among others, consumption and transport needs, as well as training, should be taken as a guiding principle for future action.

6. LIMITATIONS

Systematic reviews and meta-analyses are regarded as the epitome of high-quality evidence. This is especially relevant for policy makers, who need synthesized evidence at an aggregated level on what works and what does not. In this study, we applied meta-analysis in the field of international development cooperation on climate change adaptation, in order to provide high-level evidence. In our field, experience shows that there are a number of issues to take into account. Therefore, we summarize the limitations when conducting a systematic review or meta-analysis on intervention studies and evaluations in international development cooperation, and in our case based on a previously conducted evidence gap map.

First, it is essential to carefully review the study designs of the papers to be included in the meta-analysis, as this determines the depth of possible analyses. The research question of the meta-analysis depends on the appropriate study designs to be included. If the objective is to evaluate the effect size of an intervention, mostly quasi- and experimental study designs should be included. These types of studies typically report (comparable) effect sizes and treatment effects. This meta-analysis was not able to aggregate effect sizes rigorously, given that most of the available studies were non-experimental correlational studies, e.g. reporting results from multivariate regressions. Correlational studies were included in the EGM given the limited rigorous evidence base on the effectiveness and impacts of climate change adaptation interventions in low- and middle income countries. Possible research questions in meta-analyses heavily depend on the methodological designs of included studies.

Second, the studies to be included need to be carefully reviewed for their differing definitions and measurements of the intervention and outcome. The papers included in this meta-analysis defined access to credit heterogeneously, limiting the comparability of the studies. Intervention and outcomes were also measured and reported differently in various units, further complicating the analysis. This is a common problem in meta-analysis. Meta-analyses on the one hand require a minimum number of studies to perform an econometrically sound analysis and on the other hand require studies that define comparable units and (dependent) variables. Ideally, meta-analyses include only studies that are sufficiently homogeneous in their definitions and measurements of the intervention and outcome, in order to be comparable.

Third, meta-analyses require substantial time and technical expertise. A careful review of potential intervention/outcome cells in an EGM is required in order to decide whether available evidence is suitable and adequate for meta-analysis. Meta-analyses require knowledge about the subject and study designs, demand advanced statistical techniques, knowledge of various possible biases, and in-depth expertise of the selected intervention/outcome to be able to interpret and contextualize the findings. The more rigorous the included studies are (i.e. typically experiments or quasi-experiments) the better they are suited for meta-analyses. The less rigorous the study designs of included studies are, the less methodological options are available for meta-analysis.

Fourth, despite the need for more evidence-based policy-making, this meta-analysis primarily provides conclusions for the scientific and evaluation communities for future research. This is because the included correlational studies do not enable the computation of effect size estimates.

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