CREDIT USE AND THE ADOPTION OF CLIMATE SMART AGRICULTURAL PRACTICES AMONG SMALLHOLDER FARMERS

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CONTENT

LIST OF ABBREVIATION

BL	= Baseline
CO	= Colombia
CCAFS	= Research Program on Climate Change Agriculture and Food Security
CSA	= Climate Smart Agriculture
CSAP	= Climate Smart Agricultural Practices
CSV	= Climate Smart Village
GH	= Ghana
UG	= Uganda
GU	= Guatemala
HD	= Honduras
NI	= Nicaragua
EL	= Endline

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1. Climate Smart Agriculture, Finance and Development

A major share of the world's food production as well as livelihoods depends on small-scale agriculture (IFAD, 2011). In numbers, 90% of the farms worldwide cover less than 2 hectares and are cultivated by 1.5 billion of the world's poor (Rapsomanikis, 2015). Following the United Nations Sustainable Development Agenda, strategies for making these small farms more productive and sustainable are consequently essential to eradicate hunger and malnutrition, end poverty and tackle climate change within the next decade (Palmer, 2016)

Climate change has already reduced the growth in global crop production in the past century, with a large share of its adverse effect on agricultural productivity yet to come (IPCC, 2014). Next to the temperature rise, changes in the frequency and intensity of precipitation and extreme weather phenomena, as well as on increase of the CO_2 level available for photosynthesis will be the main drivers of change (Nastis et al., 2012). While moderate regions locally profit from the shifting climate conditions, yield losses and increased volatility have been and will continue to be especially severe in tropical and subtropical areas (IPCC, 2014; Lobell et al., 2009). Climate change perpetuates the low productivity and high risk of harvest failure of smallholder-farms, reinforcing the urgent need to significantly transform and adopt agricultural production systems in these regions (FAO, 2013).

Climate-Smart Agriculture (CSA) aims to simultaneously increase agricultural productivity and resilience in the face of climate change, while reducing greenhouse gas emissions from agricultural systems (Lipper et al. 2014). The concept of CSA is embodied in a variety of agricultural practices. It includes typical technologies like climate stress tolerant seed, irrigation and fertilizer, which are classic examples in technology adoption studies (Simtowe and Zeller, 2006; Abate et al., 2016) as well as practices like intercropping, conservation agriculture, manuring and water harvesting, elsewhere discussed under terms like sustainable practices or conservation agriculture (Bryan et al., 2013; Ntshangase et al., 2018). Evidence shows that the adoption of locally adapted CSA portfolios can lead to an increase of productivity between 7 to 18% (IPCC, 2014, Challinor et al., 2014). Additionally, CSA options typically reduce the production risk by increasing the resilience of the agricultural system (Lipper et al., 2014). As Teklewold et al. (2013) show for Ethiopia and Arslan et al. (2014) for Zambia adoption rates of CSAPs among smallholders often remain low, despite the potential of CSAPs to increase productivity and resilience (Branca et al., 2011).

Given the assumption that a specific practice or technology is profitable for farmers in a certain context in the long run, credit market failures are a frequently cited reason for low adoption rates (Makate et al., 2019; Ogada et al., 2014). Credit temporarily transfers purchasing power to the borrower in the form of cash or physical means (Nwaru, 2004; Petrick, 2005), and therewith facilitates the use of agricultural inputs and investments in technologies (Helms, 2006). However, credit markets in rural areas of developing countries are typically mal functioning, meaning that a large share of smallholder farmers do not have access to formal credit from financial institutions. For resource poor farmers this restricts their ability to invest in new technologies below the optimal level (Arslan et al., 2017; Sharma & Buchenrieder, 2002) and consequently hampers the efficiency and productivity of their farming operations (Boniphace et al., 2015).

Multiple studies investigated the determinants of adoption of CSA practices, not specifically focussing on the role of credit, but often including it as one of many determinants (i.e. Teklewold et al., 2017). They find mainly positive overall effects, but also different effects for different practices and even negative overall effects (see literature review Chapter 2). Since none of these studies specifically focusses on credit, they mostly speculate why the impact of credit access differs between practices, even in the same context. It is not far to seek, that the economic nature of the investment, meaning the timing and magnitude of different input needs and returns determines the role of credit in adoption. This is in line with Senyolo et al. (2018) who show, that farmer perceptions of the technology-specific attributes are a major factor determining adoption and use intensities. They stress that to explore the drivers and barriers for adoption of different CSAPs it is necessary to gather knowledge on the characteristics of the practices and technologies. While cost-benefit analyses are a rich source of information on the economic nature of CSA practices (Sain et al., 2017), few studies combine the analysis of the characteristics of multiple CSA practices and the adoption by farmers in a systematic way.

To fill this research gap, we present empirical results on the role of credit for practices with different economic properties. We group climate smart practices according to their repayment period and capital intensity and regress the adoption of these practices on credit use as well as other known determinants of technology adoption. We use two data rounds from the Climate Smart Village (CSV) Project operated by the Research Program for Climate Change, Agriculture and Food Security (CCAFS). The study is the first one to make use of the second round of data collection within the CSV project by combining them with the baseline data to a panel dataset. The CSA practices investigated in the study include management practices like crop rotation, intercropping, reduced tillage and mulching, alternative nutrient management like retention of crop residue, organic fertilizer or "integrated nutrient management", improved varieties, homegardens for growing vegetables, agroforestry and water harvesting techniques with planting pits, bunds, ridges and tanks as well as terracing irrigation, water pumps and grain dryers.

We find that the adoption of capital-intensive practices is positively but insignificantly correlated with credit use. The adoption of practices with a long payback period is positively and significantly correlated with credit use. For actors trying to foster CSAPs in different environments, the results indicate that especially if they want to increase the adoption of practices with a long payback period, increasing the availability of credit simultaneously can be beneficial. The other way around in a credit constraint environment, the payback period should be considered as a factor when selecting suitable practices. With these findings we contribute to the CCAFS objective to identify constraints and enablers of CSAP adoption and assess the benefits, synergies and trade-offs of technologies from the perspective of individual farmers.

The rest of the thesis is structured as following. Section 2 summarized the theory and evidence on the role of credit for CSAP adoption among smallholders and present a framework for distinguishing the practices in terms of their economic nature. Section 3 presents the methodological approach. In section 4 we present the descriptive and empirical results and section 5 closes the thesis with a discussion and conclusion.

2. The Role of Credit for CSAP Adoption

We define credit rationing in a brought sense in line with Guirkinger & Boucher (2008), including quantity, risk and transaction cost rationing. Quantity rationed farmers cannot get a loan due to distance to the lending institution or because they do not fulfil lending requirements like ownership of collateral or credit records (Abay et al., 2018; Beaman et al., 2014). Farmers who restrict their credit uptake for making a rentable investment voluntary because of high transaction costs or perceived risk are also considered credit constraint (Guirkinger & Boucher, 2008). So, all farmers who would and could borrow under the given conditions in order to do a rentable investment are not credit rationed, and hence have access to credit. We keep in mind, that among these farmers there are potentially also some who have enough liquid financial means and therefore do not need to enter the credit market (Teklewold et al., 2017; Simtowe and Zeller, 2006).

In the following section we present empirical evidence (2.1) and the theoretical background on the role of credit for the adoption of CSAPs (2.2). Afterwards we move on to the argumentation why the magnitude of the initial investment and the length of the repayment period determine the role of credit access on the adoption of different technologies (2.3).

2.1 Evidence on Credit and CSAP Adoption

CSAPs include different technologies and practices which are increasing the resilience and productivity of farming systems under the given natural conditions. Included are classical agricultural technologies like improved seeds or irrigation systems, as well as agricultural practices like reduced tillage, crop rotation, water harvesting or agroforestry (Aggarwal et al., 2018).

For classical agricultural technologies like improved seed and artificial fertilizer, most empirical studies suggest a positive influence of credit availability on their adoption (Simtowe & Zeller, 2006; Abate et al., 2016; Porgo et al., 2018, Moser & Barrett's, 2006). Komicha & Öhlmer (2006) find that farmers with credit access have a 12% higher technical efficiency than credit constraint households. Other studies find no positive effect of credit access on technological efficiency (Pinheiro, 1992; Chaovanapoonphol et al., 2005). The most robust results in the role of credit on investment in agriculture and other outcomes like productivity, income and consumption were presented by Banerjee, Karlan & Zinman (2015), based on six randomized controlled trials. While for downstream outcomes like consumption the impact is ambiguous, all six studies gave positive and partly significant results for the impact on business assets, investment, revenue and expenses. The authors draw the conclusion that expanded access to credit increases business activity, which does however not necessarily transform into poverty reduction.

Literature on the adoption of multiple CSAPs reveals, that next to characteristics of the farmer and local circumstances, the effect of credit on adoption depends on the nature of the practice or technology. Holden & Shiferaw (2004) test the effect of access to input credit for seed and fertilizer on adoption of sustainable soil and water management strategies in Ethiopia. They find that increased access to input credit for fertilizer reduces farmer investments in traditional soil and water conservation. This finding hints at a certain substitutability between the two and a trade of in input allocation. Teklewold et al. (2017) get a significant coefficient of credit access for the adoption of either inorganic fertilizer or agricultural water management practice alone but not for modern seed or for a combination of practices. Wood et al. (2014) find that disaggregated by practice there is a positive effect of a membership in credit groups on adoption of improved varieties and land management practices, while there was no significant effect for agricultural timing and increased fertilizer. They conclude that access to credit is associated with the sorts of changes that require the highest investments. Similarly, Bryan et al. (2013) show that many households have made small adjustments like changing planting patterns in response to climate change, while few households are able to make more costly investments in agroforestry or irrigation, despite the desire to do so. These ambivalent results on the role of credit for different practices and combinations of practices within the same context suggests that the role of credit depends not only on the regional circumstances and the characteristics of the farmers, but obviously also on differences in the quantity and timing liquid financial means that need to be invested (Barrett et al., 2002).

2.2 Theory on the Adoption of Different CSAPs under Credit Rationing

When all markets are functioning, agricultural households will first maximize the production function of their farm business and then, conditional on the income, maximize the utility of consumption (Upadhyay, 2003; Taylor & Adelman, 2003). To maximize the profit of the farming operation, neoclassical investment theory predicts that farmers invest into new practices and technologies until the net present value of the next best investment is 0. An investment is expected to generate a stream of future cash flows C(t) and the investment represents an outlay at time 0, which can be expressed as a negative cash flow $-C_0$.

$$(1) \quad NPV = -C_0 + \int_0^{\infty} C(t)e^{(g-r)t}\,dt$$

Distinguishing between different possible investment, the farmer chooses the innovations with the highest returns until the net present value is 0 (Shiferaw et al., 2009). This implies that investments in CSAPs will take place if adoption increases discounted net benefits (Di Falco et al., 2011). Thereby the costs include the price of implementation and credit (Doss, 2006) and the benefits include increased net income from agricultural production as well as reduced production risk under climate variability (Kato et al., 2011).

Agricultural production implies that there is a certain time period between the occurrence of cost and return, typically at least the growing cycle of a crop. So, the amount $-C_0$ needs to be mobilized over this time period, either with the farmers own savings and assets or through borrowing money. In the case of credit rationing, desirable investments are inhibited, because most farmers possibility to mobilize the liquid means to invest are restricted, even if in the investment would increase the income of the farm in the long term. Empirical evidence confirms, that despite the willingness to invest, poor smallholders often have limited capacity to mobilize labour, land and cash for investment, even for effective and profitable natural resource management practices (Barrett et al., 2002).

Since basically all practices and technologies do need investment to a certain degree (Doss, 2006; McCarthy et al., 2011), we assume therefore **H1: The use of credit is positively correlated with the adoption of Climate Smart Agricultural Practices.**

2.3 The Role of the Economic Properties of the Innovation

The timing and the magnitude of the occurrence of different input needs or costs in form of labour, cash, knowledge, risk or opportunities and economic, ecological and social benefits (Sin et al., 2012) differs substantially between different CSA technologies and practices. While seeds and fertilizer for example require smaller outlays at the start of the growing season, physical installations like machinery or irrigation systems require large cash expenditures on installation (Doss, 2006). Muriithi et al. (2018) classify practices as low external input (use of organic manure, legume intercropping and rotations, and soil and water conservation) and input intensification strategies (use of inorganic fertilizer). McCarthy et al. (2011), D'Souza & Mishra (2018), Chhetri et al. (2017) find that costs of implementation and especially high up-front investment costs put the adoption of certain practices beyond the reach of households with limited cash and labour availability.

The magnitude of the initial costs $-C_0$ as well as the timing of the positive cash flow are two factors determining how much of a barrier to adoption a mal functioning credit market is.

2.3.1 The Role of Capital Intensity

The capital intensity (CI) of a practice is the magnitude of the initial investment $-C_0$ needed to implement the practice. For liquidity constraint farmers the possibility to mobilize enough resources to invest in a practice is lower, the higher its capital intensity.

If farmers do not have access to credit, their only possibility to invest is to save enough money. In the context of rural farms in developing countries however, incomes are low, the possibilities for saving are likely to be limited and returns to savings are low. Therefore, especially large non-divisible investments are difficult to finance without credit (Fafchamps & Pender, 1997).

Additional to the simple inability to invest, household models assume that the malfunctioning of at least one market leads to non-separability of production a consumption in the agricultural household. This typically increases the variety of foods produced with the cost of productivity and leads to a low shadow price of household labour. Consequently, labour intensive practices are given preference before capital intensive ones, even if under perfect conditions the capital-intensive practice would be the more profitable investment (Eswaran & Kotwal 1986).

We assume therefore **H2: The use of credit shows a higher correlation with capital-intensive practices than with non-capital-intensive ones**

2.3.2 The Role of the Payback Period

The time period a farmer needs to bridge before the returns balance out the investment is another important determinant of adoption in a credit constraint environment. Some CSAPs technologies and practices, like improved varieties or intercropping, are associated with immediate benefits after the first cropping season, while many benefits arise only in the long term (Senyolo et al., 2018; Dunnett et al., 2018). Most CSAPs increase productivity indirectly through the strengthening of ecosystem services like soil fertility. The yield response therefore appears with a considerable time lag (Sain et al., 2017). In some cases, yields can even decline in the short run (Mafongoya et al., 2016). A measure for this time period it takes until the investment starts having a positive return is the payback period used in cost-benefit analysis (Sain et al., 2017; Ng'ang'a et al., 2017; Lan et al. 2018). For example, many agroforestry systems have negative net present values in the first years after adoption and positive cash flows only occur after 5 and 15 years (Cacho et al., 2003).

Long payback periods go along with high intertemporal opportunity costs (Barrett et al., 2002) and other losses associated with the waiting period, which smallholder farmers are often not able to absorb due to their lack of an economic buffer (Fischer et al. 2015). Under credit constraints farmers must rely on savings to finance the investment. In the time between the investment and the repayment, the invested financial means are bound, and they have less financial buffer to smooth out consumption and respond to income shocks. Since farmers tend to be risk averse and first secure consumption (Mendola, 2005), they will be more reluctant to invest in innovations with a long repayment period. This leads to **H3: The use of credit shows a higher correlation with practices with a long payback period**

2.4 OTHER FACTORS INFLUENCING ADOPTION AND CREDIT USE

The adoption of technologies and practices by small-scale farmers is determined by demographic, economic, ecological, cultural and political factors as well as by personality traits of the farmer. For an overview over the general determinants of technology adoption see Feder & Umali (1993), Sunding and Zilberman (2001) as well as Doss (2003).

We discuss two demographic and two economic factors, because they are directly intertwined with both credit and technology adoption. The demographic factors are gender and household size. Gender, because it is a crucial factor in the dataset and specific factor of focus for CCAFS. The household size, because it is directly correlated with the household demand for produce as well as the household endowment with labour which are both crucial for the theory presented in the study. The economic factors are the availability of savings, other payed income and insurance as well as the number of landholdings and other assets owned. Additionally, we look at character traits and knowledge about the effect of adoption which are factors difficult to observe for the researcher.

2.4.1 DEMOGRAPHIC FACTORS

Gender plays a role because of the selection of lenders by gender and the physical and social differences between man and women. Even though many microfinance institutions specifically target women, they are said to be in disadvantage concerning access to credit, because of social structures in rural areas (Makate et al. 2019). Addison & Ohene-Yankyera (2018) show childcare and limited access to land inhibit adoption of improved rice variety and fertilizer by females. Especially labour-intensive technologies are less likely to be adopted because of the interference with their reproductive role (Addison & Ohene-Yankyera 2018). Therefore, credit uptake and adoption are expected to be negatively correlated with the female, especially for management intensive technologies.

The **Household Size** correlates with the household labour endowment and the household consumption. More household labour increases the possibilities to adopt labour intensive practices. On the other hand, the household size determines the amount of production and income that is necessary to ensure food security for every household member. Therefore, a high number of young children and elderly can increase the need to produce, the credit demand and reduce the ability to mobilize resources for investment. Monfared (2011) found a positive relationship between technology adoption and amount of family labour available. Employing wage labour is beyond the reach of a majority if smallholders with little surplus income. Therefore, specific investments that are labour intensive depend directly on the amount of agricultural labour available within the household. This is especially the case with investments that require a large amount of labour in the moment of installation like agroforestry, stone buns, grassed waterways and retaining walls for gully control are highly labour intensive (Yila & Thapa, 2008). Therefore, agricultural household labour is expected to be especially relevant for short term, management intensive practices. The role of household labour depends on the ability to hire labour (Ngwira et al. 2014).

2.4.2 ECONOMIC CHARACTERISTICS OF THE FARM AND HOUSEHOLD

Economic and biophysical characteristics of the farm determine the access to credit, the rentability of investments and the role of credit for the adoption of different kinds on investments.

Savings and Income are expected to be substitutes to credit in determining adoption while **insurance** is a complement. As shown by Simtowe & Zeller (2006), adoption needs liquid financial means and credit is only necessary if there is not enough liquidity within the household. Makate et al. (2019) show that all other income sources are expected to increase adoption, if credit constraints are present. Additionally, all income sources except for insurance are expected to reduce credit demand, but potentially increase access from formal sources. Insurance is expected to increase credit use and have a positive effect on adoption.

Thirtle et al. (2003) find nonfarm income positive and significant in explaining adoption of genetically modified cotton in South Africa. They attribute this finding to both, the farmers' access to cash and to the fact that households with non-farm income are less risk averse (Doss 2006). While off-farm income increases the cash availability and therefore the adoption possibilities, it also decreases the available family labour and therefore gives an incentive for mechanization (Savadogo et al., 1994). Gedikoglu et al. (2011) show that off farm employment increases manure injection, which is capital intensive, while it has no effect on record keeping.

Insurance availability increases risk taking and therefore encourages credit use as well as adoption (Abdulai et al. 2018). The same is valid for remittance (Xing, 2018) and migration (Ng'ang'a et al. 2016). Karlan et al. (2014) investigate the impact of access to credit and access to index-insurance on agricultural investment in a factorial designed randomized controlled trial in Ghana. They find a strong response of agricultural investment to the rainfall insurance grant, but a relatively small effect in the cash grants alone. This leads to the conclusion, that uninsured risk is a binding constraint on farmers investment. They conclude that when farmers are insured against their primary catastrophic risk, they are able to find resources to increase expenditure, therefore liquidity constraints are not as binding as commonly thought. According to Bryan et al. (2013) these larger investments were more frequently done by farmers with greater access to resources.

Landholdings and other assets facilitate access to cash and increase the rentability of new investments. Twine et al. (2019) demonstrate, that farm production characteristics and factor endowments are determinants of credit use. Like the additional income, wealth in the form of assets is expected to increase adoption as well as credit access (Doss, 2006). They can be sold and therefore function as a source of cash or can be used as collateral, which increases the access to credit from formal banks (Muriithi et al., 2018).

Ngwira et al. (2014) and Makate et al. (2019) find the amount of own land to be crucial for adoption of technologies. Farm size is expected to be positively correlated with adoption in general since larger farms have better access to financial means and farmers with a larger land area can more easily devote a part of their land to trying a new technology. For capital intensive technologies the connection is expected to be strong, because they usually involve a fixed investment. Such investments are more profitable on a larger scale. For labour intensive technologies the connection is expected to be different. Because of imperfect labour markets, the shadow price of family labour is supposed to be low for small farms that do not yet use their whole capacity (Mwangi & Kariuki, 2015). Therefore, they are expected to be more likely to adopt labour intensive technologies. Simtowe & Zeller (2006) show that landholding size has opposite effects on adoption in the two regimes of credit constraint and unconstrained households. Generally, adopters have larger land holdings than non-adopters, but conditional on adoption households with high off-farm income will allocate smaller portions of land to hybrid production. This can be explained by the fact that small farms farm land more intensively to meet subsistence needs.

2.4.3 “Soft” Factors

Two factors that seem to crucially increase both adoption of technologies and credit use are an entrepreneurial spirit and risk seeking behaviour. These very complex personal traits influencing adoption that are hard to measure. Therefore, they are typically unobserved and therefore a source for selection bias and endogeneity. In order to fully understand the adoption of sustainable practices, the researcher must understand an individual's objectives and learning process next to the biophysical, institutional and policy factors and the incentives and constraints discussed above (Barrett et al., 2002). These traits are also related to the role that a farmer takes in a technology diffusion process. Less risk averse more entrepreneurial farmers are expected to be among the early adopters, while the opposite is the case for ‘laggers’ (Rogers, 1995). How this study will handle these cofounding factors methodologically will be discussed in the following section. Finally, it is likely that farmers have heterogenous returns to borrowing as well as to adoption of practices. It is likely that farmers can estimate these returns to a certain degree. Therefore, farmers with higher returns are likely to self-select into credit uptake and adoption (Barrett et al., 2002).

Most of the economic and demographic variables discussed above are given in the data set. The unobservable factors cannot be directly controlled for. They are approximated by the adoptability index in the baseline period.

3. Data

We use two rounds of datasets obtained in a subsample of the CCAFS CSV network. The household monitoring survey from 2017/18, which we call endline survey (EL) and the household level baseline survey (BL), which was conducted before the start of the project. Both contain partly the same households and we combined them to a panel dataset. In the following chapter we give a short introduction to the CSV approach (Chapter 3.1) and an overview over the two survey rounds and their communalities and differences (Chapter 3.2) and the final panel dataset (3.3).

3.1 The Climate Smart Village Approach

The CSV approach is the conceptual framework of the agricultural research for development program on Climate Change, Agriculture and Food Security (CCAFS) implemented by the Consultative Group for International Agricultural Research (CGIAR). Within this framework, a network of selected villages in different regions of the global south act as a learning ground. The goal is to create science-based evidence on the efficacy of technological and institutional solutions for increasing productivity and resilience under climate change. Suitable options are evaluated with respect to local biophysical, social and political conditions. Furthermore, options for scaling up are explored through partnerships with local governments and other institutions. The program started in East and West Africa as well as South Asia in 2010/2011. Two additional target regions (Southeast Asia and Latin America) were added in late 2012. Clusters of villages, small landscapes or 10km grids with high poverty and vulnerability to climate change were selected. The regions were chosen with the aim of a high representativity of different socio-cultural, climatic and institutional context, as well as enough political stability and capacity for generating transferable results (Aggarwal et al., 2018). This brought range of represented political, social and climatic conditions increases the external validity of the analysis as opposed to the use of a single country dataset.

Different CSA solutions are evaluated together with local stakeholders like governments, research institutes, NGOs and farmer groups for each village. The stakeholders selected promising options with respect to productivity, resilience and mitigation into a portfolio of practices. The practices reach from weather forecast, over agronomic practices and technologies to institutional innovations like insurance. Each village has its own theory of change linked to the national priorities (Taneja et al., 2014). In Latin America, the shortlist of practices is presented to the farmers in field schools or workshops of "Participatory Integrated Climate Services for Agriculture" which then chose for themselves which practices they want to use on their farm. The implementation on farm is accompanied by the technical and economical advice of an agricultural professional. I assume, that all farm households covered by the surveys have the possibility to take part in theses workshops. Farmer chose themselves if they take part in the activities. The project also aims to foster institutional and finance capacities that enable the success of the CSAPs. Finance mechanisms have however not yet been implemented in the villages, all finance mechanisms present are originated from third institutions (Aggarwal et al., 2018). The CSV approach provides only limited funding, which makes the project a more realistic environment to study the impact of credit.

3.2 The Two Datasets

In 2018, the CSV Monitoring survey, which provides our endline data, was implemented across 8 CSV sites, 4 in Latin America (Colombia, Nicaragua, Honduras and Guatemala), 3 in South Asia (Nepal, India), 1 in East Africa (Uganda) and 1 in West Africa (Ghana). It covered a total of 1,391 households and 2,337 farmers and was generated through a mobile adoptive survey method.[1] The data available for this thesis is originated from Ghana, Colombia, Nicaragua, Guatemala, Honduras, Uganda, including 1882 observations from 1111 households. The 771 double observations were answered by a second household member of the opposite gender to get insights on the gender roles within the household. This led to a 51% quota of female respondents. 3 to 6 of the 26 CSA options were targeted per project region. Only the practices which were prioritized in the region were monitored, hence the monitored practices vary between the regions.

The first round of the CCAFS baseline household-level survey was implemented in late 2010/early 2011 in 12 countries across 15 core sites covering 108 villages and 2095 households over East Africa, West Africa and South Asia. The second round in in Latin America and Southeast Asia in 2014–15 covering 6 additional sites. It covers detailed cross-site household level data, which contains demographic and economic data as well as indicators of food security, assets, agricultural production diversity, agricultural sales diversity, adoption of farming practices and technologies, reception of weather information, emissions of greenhouse gases and gender roles. The adoption to climate change is measured through the question which 0f 59 potential changes a household has done in 10 years before the survey.

[1] The method allows fast data collection through a smartphone application. The mobile survey tool minimizes the number of questions asked covering 5 thematic modules (Climate shocks, Climate services, Livelihood security & financial services, Food security and Climate-smart options) and redirecting the interviewer to different questions depending on the answer to the previous question. This survey technique made it possible to gather almost uniform data over the 8 sites. At the same time, it brings along some methodological challenges since most variables are not available for all participants but only for some who gave a certain answer before.

During In each site the aim was to revisit the 140 households visited during the CCAFS BL study (20 households in each of the 7 districts), keeping the original household IDs. Additionally, all farmers involved in CSA implementation or evaluation activities and additional non-adopters were surveyed and registered with new ID numbers. The aim was to create a balance between the number of adopters in the second dataset (Bonilla-Findji et al., 2019). This implies that the sampling framework of the EL is not random and as opposed to the BL, where 140 households were selected randomly from 7 randomly selected villages within the CSV site.[2] Therefore, the BL is expected to be representative for the whole population in the respective CSV site, while for the monitoring survey this internal validity is not guaranteed.

3.3 The Panel Datasets

The goal of the second survey round was to resurvey all 840 households from the BL. However due to multiple reasons like migration or death the rate of attrition was quite high in some countries. Another frequent reason for attrition was the unwillingness to answer the second survey. 605 out of 840 household could be successfully identified as a panel dataset. Appendix 1 describes in detail how the two datasets were merged to a panel dataset. In Colombia one village dropped out and another one was taken in. In some other villages in Latin America the number of resurveyed households went down to 3. To check if the attrition is systematic, we compared the averages of a variety of variables between the full EL and BL datasets and the panel subsample (see Appendix 2). We found only minor differences between the values of different variables in the full BL dataset and the partial BL data in the panel dataset. Therefore, we find that the internal validity created though the randomization of the baseline dataset was maintained despite the attrition.

In the BL data more variables were observed, and some of the monitoring variables were not observed. The BL provides values of 59 potential adoption options over 10 years before the survey, while the EL tracks only the adoption of the prioritized practices tested by CCAFS in the previous implementation year. Some specific practices like homegardens were not covered by the baseline. Others were specified slightly different in the BL and EL. For example, water harvesting was specified as water harvesting with micro-catchments, ridges or bunds in the BL, while in the EL ridges, bunds and planting pits where asked for in Ghana. The Latin American countries asked for water harvesting in general, however referring to a more technical method involving tanks and water pumps. Like this many of the outcome variables are specified in a slightly different way in BL and EL. For this reason, the panel dataset does not allow us to analyse a fixed effect model, which would be the best option to control for unobserved heterogeneity like farmers risk aversion and entrepreneurial spirit. Connecting the two datasets still improves the analysis, since it allows to connect the outcomes of the project with the more complete information captured by the baseline, keep the advantage of the random sampling of the baseline and account for reverse causality as will be discussed afterwards.

[2] https://ccafs.cgiar.org/olopa-climate-smart-village-guatemala#.XW5hPntCTiW

4. METHODOLOGY

This methodology section describes the method of classifying the CSAP practices according to their payback period and their capital intensity (4.1) and evaluating and describing the with respect to the data at hand best possible empirical approach to answer the research questions (4.2).

4.1. CLASSIFICATION OF THE CSAPS

Based on the discussion above, the practices where grouped according to the capital intensity and the length of the repayment period based on three sources.

(1) A literature review of cost benefit analysis (i.e. Sain et al. 2017; Ng'ang'a et al., 2017) and other selected sources.
(2) Analysis of the responses of farmers in the CSV gender survey, which asks farmers for benefits and costs of the practices
(3) A survey which asks experts in the climate smart villages to evaluate the labour, capital and knowledge intensity of the practices they work with

For each of the sources I chose decision values for classifying the practice as capital or non-capital intensive and as long or short-term investment.

Table 1 Classification Methodology

Practice	Cost benefit analysis	Gender survey	Online questionnaire
Capital intensity	Initial- and Maintenance costs in the first year as compared to other practices in the cost benefit analysis; classification as below of above average	Gender survey: mentioned as the 1.,2. or 3rd most important cost/benefit of the practice +mentioned as a reason for interest/ non-interest/ reason for stopping the practice -> Capital Intensity score	5-point Likert scale 1-2 = low 4-5 = high Mentioned as most important obstacle=+2 Mentioned as second most important obstacle=+1 Not mentioned=-1
Payback period	1-2 years short 3-more years long		1-2 years short 3-more years long
Both	additional literature sources on the cost structure of specific practices		

One source of information are the cost benefit analyses conducted in the CSV regions (Lan et al., 2018; Sain et al., 2017; Mwongera et al., 2017; Ng'ang'a et al., 2017; Steenwerth et al., 2014 and Adesina et al., 2002). These studies evaluate the initial and maintenance cost as well as the labour demand for different CSV practices. The studies contain additional labour costs, additional capital costs and repayment periods for different practices and combinations of practices. As a first step, we extracted the information available in this literature for the classification.

A second source of information is the CCAFS gender survey (CCAFS, 2013) which investigates farmers reasons to adopt and dis-adopt practices. It was conducted in several CSV sites which partly overlap with the ones used in this study. Despite not all the sites are covered, the survey provides a cross country evaluation of the input needs of most of the practices. It is asking about the three most important advantages and disadvantages of a practice, as well as the reason for being interested or not interested among non-adopters. From these different answers we created an index of capital intensity depending on how many time costs are mentioned as a barrier, respectively cost savings are mentioned as a benefit. We are aiming at a rough, overall classification of the practices, and we assume that the same practice is based on similar input needs and mechanisms of benefit creation in every context.

Thirdly, a survey was implemented online, asking experts from the CSV sites to evaluate the capital, labour and knowledge intensity as well as the payback period for the practices fostered in their CSV site. Additionally, they were asked to rate which of these 4 factors was the most important barrier to adoption of the practice. Further information on the financial service situation in the villages was also collected. The response rates to the survey however were very low, with 8 people starting the survey and 4 people completing it, all the later from Latin America. For every value left or write of the median of the 5-point likers skala, the practice received a minus or plus.

None of the sources by itself could provide the full information needed for the classification. With the combination of the sources we could provide a decent triangulation of the classification approach.

4.2 Empirical approaches in earlier studies

There are three major challenges that guide the choice of methodological approaches in the literature on the interface between credit market participation and adoption of agricultural practices. (1) The binary or censored nature of dependent and independent variable; (2) the complementary nature of the adoption of different technologies and technology portfolios and (3) the simultaneity of the determination of credit use and adoption.

In the case of adoption studies, the dependent variables are mostly binary, which makes different forms of bivariate model like probit or logit the appropriate choice. Other frequently used outcomes are measures of intensity like the number of adopted practices (Teklewold et al., 2013; Muriithi et al., 2018) or the share of land under the practice (Ngwira et al., 2014). The CCAFS baseline (BL) study uses a similar measure of "innovativeness", counting the number of adoptive changes in the production system made in the last ten years (Kristjanson et al., 2012).

Dealing with multiple CSAPs, multinomial models are frequently applied. Makate (2019) and Teklewold et al. (2017) both use adoption of three different sustainable practices and their combinations as adoption categories and end up with 8 categories considering all possible combinations of the practice. Other authors applying multinomial models are Nhemachena and Hassan (2008); Gbetibouo (2009); Deressa et al. (2009) and Hisali et al., (2011). The advantage of a multinomial model as opposed to a simple adoption dummy is, that it allows to distinguish determinants for different practices and combinations of practices. However, this is restricted to a few practices at once, because every possible combination of practices needs to be included to fulfil the assumption of the independence from irrelevant alternatives (Hausmann & McFadden, 1973). For this reason, Bryan et al. (2013) opt for running separate regressions for each adoption, since it allows to look at a higher number of different practices.

An important factor not considered by logit, probit or multinomial models are the interdependencies of the adoption of different CSAPs (Muriithi et al., 2018; Ogada, Mwabu & Muchai, 2014). The decision to adopt one practice influences the decision to adopt other CSAPs (Aryal et al., 2018). Practices can be complements or substitutes, most studies however find complementary effects (Teklewold et al., 2017, Aryal et al., 2018). Barrett et al. (2002), show that for farmers who have already invested in valuable perennials it is relatively more attractive to invest in complementary adoption of soil and water conservation. A multivariate model is appropriate, since it accounts for these correlations as it simultaneously models the effect of a set of covariates on each of the different practices while allowing the error terms to be correlated (Greene, 2003). Examples of the adoption of multivariate models can be found in the publications of Kassie et al. (2012), Teklewold et al. (2013), Aryal et al. (2018). These studies are using the most appropriate approach to model the adoption of multiple practices for cross sectional datasets however they often fail to appropriately control for endogeneity, omitted variables and reverse causality in the connection between credit and adoption.

Borrowers get selected and self-select into the credit market and consequently borrows tend to differ from non-borrow in certain traits (Banerjee, Karlan & Zinman, 2015; Abay et al., 2018). Beaman et al's (2014) experimental evidence shows that this selection bias is mostly positive through both, self-selection and lender screening. So, people who are anyways better off or those who are able the generate higher returns from taking the loan are entering the credit market.

To eliminate some of the bias, most studies try to find a measure for access to credit, because a supply-side access variable is relatively more exogenous than credit use (Swaminathan, Du Bois & Findeis, 2010). Most of the reviewed studies use the direct elicitation approach. This means they directly ask respondents if they are credit constraint or quantify how much they do borrow and how much they would like to borrow and translate it into an access dummy variable (Simtowe and Zeller, 2006). Porgo et al. (2018) apply two methods of credit constraints which are complementing each other. A direct question to the farmer whether he could access credit if he wanted and an indirect method using the violations of the life cycle or permanent income hypothesis by credit constraints. Abate et al. (2016) compare people from villages with credit access who do use credit with people from villages without financial institutions, hence to ones who are exogenously excluded from the credit market. They first predict the use of credit with a regression and then the intensity of adoption. An external access variable restricts the omitted variable problem to the easier to measure supply side constraint factors.

Supply side factors are typically easier to observe for the researcher than the factors determining self-selection and therefore easy to control either through exogenous variation of treatment offers in RCTs or through instrumenting the credit access variable with external factors like the availability of credit in a certain area and the requirements for borrowers like collateral of gender. Knowing that a supply side constraint is the problem also makes concrete policy recommendations possible (Doss, 2006; Boucher et al., 2009).

The self-selection process is guided by variables that are harder to measure, such as managerial skills, motivation and risk aversion (Teklewold et al., 2017). These can best be controlled for applying panel fixed effect models, which is still rare in studies connecting credit access and adoption behaviour. Next to the general bias in the access of credit, the combination with the adoption of technology increases the risk of endogeneity, because the factors that affect the household's eligibility for credit may also affect the adoption decision (Simtowe and Zeller, 2006). As discussed in chapter 2.4.3 "soft" factors like entrepreneurial spirit, risk taking behaviour and knowledge on attainable returns, as well as on the social network are important factors determining adoption as well as credit uptake.

The second endogeneity problem is the reverse causality, respectively simultaneity between credit use and access and technology adoption. The relationship between technology adoption and credit is mutually dependent. This means that access to credit facilitates technology adoption which also leads to greater access to credit. "Thus, this leads to a two-way argument that could be simultaneous or could be causal in one direction or another" (Abdallah, 2016). For credit use the bias is even higher. The wish to adopt a practice that needs investment, will cause farmers to search more actively for possibilities to borrow (Banerjee, Karlan & Zinman, 2015). D'Souza & Mishra (2018) and Twine et al. (2019) give an empirical evidence for the reverse causality between adoption and credit access, arguing that technology adoption on the one hand motivates borrowers to actively seek for credit and on the other hand the adoption can increase the creditworthiness of borrowers in the eyes of lenders, depending on how it influences production level and risk.

As shown earlier, the ideal analysis of observational data includes a multivariate model for binary and censored data and controls for all factors influencing adoption, while varying the credit access exogenously either through controlled treatment or through instrumental variables. However, all these factors are hard to consider in one model with respect to the data at hand. Therefore, we perform a logit regression with a lagged credit variable to exclude the possibility of reverse causality.

4.3 The Main Empirical Model

Despite the advantages of multivariate models for controlling for interaction between the practices it is not possible to apply such a model to the data at hand, since the samples per country are quite small and, in each country, different practices are implemented and monitored. As discussed above a panel model with fixed effects can also not be applied due to the differences in the survey round. All three hypothesis are tested using a logit model, regressing the use of agricultural credit in the baseline period as well as demographic and economic control variables.

The model is specified as following:

$$Y_{EL} = X_{BL} + C_{BL} + e$$

Y_{EL} is the adoption variable from the EL survey, X_{BL} is the credit variable from the BL and C_{BL} is a vector of the control variables.

Among several options of credit variables in the BL and EL we use agricultural credit in the 12 months before the baseline as the main credit variable X_{BL}. The BL and EL survey offer multiple credit variables. The one question which is constant over both survey rounds is "Did you receive credit for agricultural practices in the last 12 months?". The BL additionally offers a variable on the general use of credit, differentiated by formal and informal sources for the last 12 months as well as respective for any time before the baseline.[3] The EL does not contain this question, but gives more detailed information about the purpose and origin of the agricultural credit used. We choose the use of agricultural credit in the 12 months before the BL as the independent variable to make sure that the credit taken up is taken up for investment into agriculture. We use the value from the BL to exclude the possibility of reverse causality. The credit variable is hence a dummy which takes the value 0 if a household did not use

[3] According to Doss (2006) the measure "did the farmer ever use credit would be the better proxy for access, since there is a high variability in credit use from year to year. In the analysis of Beaman et al. (2014) only about 65% of borrowers in the first year of their observation took out another loan in the next year. However, the respective question was removed from the BL questionnaire in the later surveys in Latin American countries and therefore the measure is only available for half of the countries.

agricultural credit and 1 if the household did use agricultural credit in the 12 months before the BL survey. Other authors like Salasya et al. (1998) equalize the access and the use of credit in their analysis. According Bryan et al (2013) credit use can serve as an imperfect proxy for credit access. The two variables are positively correlated, and usage is an easy to observe measure (Beck et al., 2009). However, there is a high variability in credit use (Doss, 2006) and as discussed above non-use can have different reasons than the lack of access. Therefore, we conduct robustness checks of the results with different credit variables.

The outcome variable $\mathbf{Y_{EL}}$ represents a different outcome for each of the three hypotheses. All outcome variables were taken from the EL survey.[4]

Appendix 3 shows the exact definition of the adoption variables in the EL and BL survey. To test H1, "The use of credit is positively correlated with the adoption of CSAPs" we create a dummy which separates the study population in people who adopted at least one if the practices promoted by the CSV project and people who did not adopt any practice. Additionally, we regressed a count variable, adding up the number of adopted practices in an ordered logit model to see the differences in the effect on adoption and the effect on the intensity of adoption.

To investigate the hypothesis 2, we distinguish between adopters of at least one practice with a high capital intensity and adopters of at least one practice with a high capital intensity. We then compare the coefficients of both models using a seemingly unrelated regression estimation and a Wald test. This procedure is suggested by Mize et al., (2019) to compare coefficients across two logistic models with the same data and different outcome variables. It is based on the seemingly unrelated estimation developed by Weesie et al. (1999). Through the simultaneous computation of the two models the cross-model covariance is measures, which is like a multivariate model as suggested in the model specification above. Therefore, this specification also functions as a first robustness test for model misspecification.

To test hypothesis 3, we distinguish between the adoption of at least one practice with a short payback period and the adoption of at least one practice with a long payback period using the same method to compare the coefficients. The approach of making a summary index of each category instead of regressing each of the practices reduces the number of tests and therewith the danger of over rejecting the null hypothesis due to multiple inference (Casey et al., 2012; Anderson, 2008; Kling, Liebman and Katz, 2007).

The vector of control variables $\mathbf{C_{BL}}$ contains the gender of the household head, the number of household members, the highest education of any household member, an asset index, measuring the number of transport-, production-, information-, energy- and luxury assets, advice received on how to handle climate events, off farm work income and membership in a farmer group. We specified an additional model, including the adoption index from the baseline. We assume that this adaptiveness can approximate the hard to measure character traits like risk taking and entrepreneurial spirit which lead to a higher likelihood of adoption. However, it is also potentially endogenous to other control variables of the BL.

[4] After evaluating the differences in the practices, the BL and EL ask for, as well as summarizing the means of certain values in the data set, we concluded that using a fixed effect model is not possible, because the outcome variables are to different. Two other factors make the inclusion of the baseline outcome variable as a dependent variable difficult. Firstly, the questions in the baseline data sets about the adoption variables are generally based on a change in a certain time period before the survey. There is hardly any information about the static state of adoption. Additionally, for some variables adoption before the baseline does not mean that there is no change possible between the BL and the EL. If someone would have adopted a new variety before the baseline and another variety between the BL and the EL he would occur with 0 change in a difference model.

Generally, all control variables were taken from the BL. This choice was made since the BL contains almost no missing values, more homogenous measures over the study sites and more detailed information about the household. Based on the assumption that household characteristics are rather stable and economic factors are prone to reverse causality when taken from the EL, this specification seems the most cautious (i.e. Fernandez-Cornejo et al., 2005). Reverse causality arises when the adoption of a practice increases profitability and therefore leads to an increased asset index or the choice to mainly focus on activities on the farm instead of off-farm income. The model hence shows, which BL characteristics determine the choice of farmers to adopt one or more of the practices prioritized by CCAFS in the study region. To account for the reverse causality between credit use and adoption, the use of agricultural credit is also taken from the BL. After the estimation we ran several stability and robustness checks to ensure the validity of the results.

5. RESULTS

Section 5.1 divides the practices in the monitoring survey in four different categories, according to the method presented in Chapter 4.1. Section 5.2 presents descriptive results, and section 5.3 presents the empirical results which answer the three research questions.

5.1 ECONOMIC CLASSIFICATION OF THE PRACTICES

The classification into non-capital-intensive practices and capital-intensive practices as well as short and long payback period as well as resulted into the following categories.

Table 2 Classification of Practices

	Not Capital Intensive	**Capital Intensive**
Short Payback Period (<2 Years)	*Group1NS:* Crop rotation Intercropping Water harvesting with planting pits, bunds, ridges	*Group2CS:* Varieties INM Home gardens Terracing
Lond Payback Period (>2 Years)	*Group3NL:* Mulching Reduced tillage Retention/incorporation of crop residue Organic fertilizer	*Group4CS:* Agroforestry Water harvesting with Tanks Irrigation Water pumps Grain Dryer

The practices from different countries, which were initially summarized as the same practice, remained the same after the investigation of the cost-benefit analysis with exception of the water harvesting techniques. It was found that in Latin America water harvesting for the home gardens is implemented in form of a water harvesting device on the roofs, which is then stored in large tanks.[5] This is a lumpy investment as opposed to the labour-intensive ridges and bunds in Ghana. Therefore, these two were analysed separately and ended up in different categories.

[5] https://blog.ciat.cgiar.org/climate-smart-village-what-it-is-and-isnt/

5.2 Descriptive Statistics

Firstly, we describe the use of different kinds of credit in the six study sites (Chapter 5.5.1). Afterwards we present the adoption rates of the monitored practices in the six countries (Chapter 5.1.3).

5.2.1 Differences in Credit Use and Source by Country and Adoption Status

Table 3 shows the use of agricultural credit and formal and informal credit in the study sites in both observed periods. The rates of credit use in BL and EL differ substantially between the CSV sites. The BL values show that in the beginning of the CSV project credit use and access where the highest in Colombia with 49% followed by Uganda with 44% of the farmers using credit in the last 12 months before the baseline. The lowest rates of credit use persist in Honduras and Guatemala with 14% and 21%.

In average over the whole population, 31% of farmers used credit in the year before the baseline and 18% used credit for agricultural purposes. While in Colombia, Honduras and Guatemala most of the borrowers also invested in agriculture, in Ghana, Uganda and Nicaragua, the rates of credit use for agricultural purposes are only half of the general rate of credit use. This shows that a significant share of credit uptake to the study population, especially in these countries, has different purposes than the investment in agriculture.

Generally, in the Latin American countries, formal providers were the main source of credit, while in Africa informal credit is the predominant source. In Honduras, where both sources are used equally with 8%. Colombia has the highest rate of formal credit use with 47% and the lowest rate of informal credit use with 5%. Generally, in Latin American Countries the use of informal credit is 10% or lower. In the two African sites, the informal credit rate ranges around 30%. This show either a difference in borrowing culture between the two regions or a better availability of formal credit sources in Latin America. The rates of membership in credit groups shows the opposite patterns. 30% of farmers are members in credit groups in Africa, while in the Latin American countries the rate is way lower.

The comparison of adopters and non-adopters shows that there is a significant positive correlation between the credit access in the BL and the use of informal credit in the BL and adoption. It is striking, that the countries with higher adoption rates are also the countries with higher rates of credit use. The t test results are likely driven by the differences in adoption rates between the countries. Again, this shows that the analysis must be done including regional fixed effects before drawing conclusions.

Table 3 Baseline Credit Use

CREDIT	Ghana	Uganda	Colombia	Guatemala	Honduras	Nicaragua	**Average**
BL Agricultural Credit Use	14%	19%	40%	14%	15%	13%	18%
EL Agricultural Credit Use	18%	27%	40%	26%	24%	25%	26%
BL Credit Use	37%	44%	49%	21%	14%	26%	31%
BL Formal Credit	10%	20%	47%	14%	8%	17%	18%
BL Informal Credit	31%	29%	5%	7%	8%	10%	16%
Credit group membership	34%	21%	4%	9%	1%	12%	15%

The EL survey provides more information about the source of credit as well as the agricultural investment which is made with that credit. Table 4 presents the origin and use of credit in the

6 CSV sites. Again, the observed patterns differ between the two continents. In Latin America banks are the main source of credit, followed by cooperatives, while in Africa the mayor share of credit comes from community savings groups and banks hardly play a role.

The main purpose for the uptake of agricultural credit is in both countries is the purchase of management or production inputs. For Latin America more than three quarters of respondents mentioned this as the main reason, while in Africa also the payment of labour time plays a substantial role.

Table 4 Credit Sources and Purpose Endline

	Ghana	Uganda	Colombia	Guatemala	Honduras	Nicaragua	**Average**
Source							
EL Bank	9%	5%	**91%**	**31%**	9%	**40%**	36%
EL Community Savings Group	**70%**	**79%**	0%	0%	0%	8%	22%
EL Credit Cooperative	13%	11%	6%	24%	**64%**	**44%**	26%
EL Family, Friends	9%	5%	3%	**41%**	14%	8%	14%
EL Private Lender	0%	0%	0%	3%	14%	0%	3%
Purpose							
Purchase Input	24%	42%	79%	67%	95%	12%	60%
To Change Crop /Livestock	24%	11%	6%	7%	0%	0%	8%
Infrastructure Investment	12%	5%	12%	7%	0%	3%	9%
To Pay Labour Time	40%	42%	3%	4%	5%	1%	15%
Other	0%	0%	0%	15%	0%	9%	9%

5.2.2 Adoption Rates

Table 5 reports the adoption rates of the 18 practices captured by the EL survey in the six study sites as well as the share of adopters in the survey population. With adopters we mean people who adopted at least one of the practices promoted by the climate smart village in the EL survey. This adoption rate ranges between 98% in Ghana and 18% in Honduras. Generally, the countries in which the CSV project started earlier, namely Ghana, Uganda and Nicaragua have higher adoption rates. The obvious reason is, that the practices have been fostered for a longer time in the region. Additionally, there might be some differences in the interpretation what is measured as an adopted practice. In the countries with the lower averages lower numbers of practices were monitored. In Ghana 12 practices were monitored, including things like crop rotation, which is unlikely a completely new thing to most of the farmers. In Latin America the adopted practices were more specifically defined and therefore answers probably cover mainly the practices which were indeed newly adopted within the CSV project. A look at the average number of adopted practices tells the same story. In Ghana the surveyed farmers adopted in average 5.4 practices, followed by Uganda and Nicaragua with around 2 practices in average. In Colombia, Guatemala and Honduras the average number of adopted practices is below 1.

The adoption index in the BL, based on the question about 50 potential changes in the 10 years, gives a measure of adoptability of the farmers in the regions. It is less dependent on the state of implementation of the CSV project than the EL adoption count and therefore a more comparable measure of adaptiveness of those farmers. It is specifically high in Ghana and Nicaragua, the countries which also have the highest adoption rates in the EL survey. Parallel to the EL, Honduras has the lowest average BL adoption index. This can be interpreted in two ways, either there is a difference in measurements between the countries which is consistent over the two survey rounds or cultural differences lead to different adoption behaviour.

Table 5 Adoption rates in BL and EL

	Ghana	Uganda	Colombia	Guatemala	Honduras	Nicaragua	**Average overall**
Number of observations	132	85	85	112	92	99	**605**
BL Adoption Index	3.86	2.87	3.15	2.81	2.49	3.9	**3.23**
EL Adoption Rate	98%	79%	35%	64%	15%	90%	**66%**
EL Average Number of Practices	5.37	2.07	0.49	0.93	0.18	1.9	**2.05**

Appendix 4 shows the adoption rates of different practices. The practice with the highest adoption over all CSV cites are improved varieties, followed by home garden diversification in all countries except for Uganda and agroforestry, organic fertilizer and water harvesting, which are adopted in three countries. Comparing the adoption rates between the BL and EL in different practices shows, that farmers who adopted this practice before the BL could again be measured as adopters within the CSV project. With the practices that had a one on one measure in the BL, like it is the case with intercropping, rotation, mulching, tillage, terracing and irrigation the adoption rate increases slightly in the monitoring round.

The practices with a random deviation between the BL and the EL are the ones where the practice description was similar but not identical between the BL and the EL. Some BL values were approximated by similar measures in the BL, because the exact practice was not particularly asked for. Integrated nutrient management i.e. was approximated with the use of inorganic fertilizer and homegardens by growing vegetables. Manure and compost were measured as 91% adopted in the BL and 71% adopted in the monitoring survey. A potential reason is, that the question in the EL is targeted at a more specific method or composting not the general use of either manure or compost. Comparing the adoption rates of varieties, in average 71% of farmers adopted a new variety in the 10 years before the BL, while in the 12 months before the EL, between 1% and 62% adopted new varieties, depending on the countries. These differences occur, because in Colombia the question was if the farmer adopted drought resistant, biofortified beans and in Ghana the question was about improved varieties in general.

5.3. Empirical Results

In table 6 we show the logit and ordered logit model results for adoption in general as well as the different outcome groups. The model includes the use of agricultural credit in the year of the baseline as the main predictor of interest, as well as the main control variables derived from theory and former studies.

5.3.1 Adoption in General

Column 1 and Column 6 shows the regressions which test hypothesis 1. The odd ratio of the logit model is 1.29, interpreted in a causal way, this means that the use of credit increases the odds of adopting at least one practice by 1.29. However, this value in not significant. The odd ratio of credit in the ordered logit model explaining the number of adopted practices has a value of 1.39 and is with a p-value of 0.12 not far from being significant. Since both values are not significant, we cannot reject the null hypothesis that the correlation of credit use in the baseline and the adoption of the CSA practices fostered within the CSVs is 0. In other words, hypothesis 1 could not be proven with the given dataset and model specification. These results might indicate that credit use is indeed not correlated with the adoption of at least one of the practices, because some of them do not require a large amount if initial investment and farmers can manage to save of gather small amounts of liquid means. Having different practice for choice which are partly supplementary might cover up for the positive correlation of credit with some of the practices.

Looking at the odd ratios of the control variables, a female households head reduces the odds of adopting at least of practice. Also, education seems to play a role for adoption with a positive correlation as expected. A strong predictor seems to be the number of memberships in farmer groups. This variable was constructed excluding credit groups. We see it as a proxy for the farmers access to information, support from peers, inputs and field examples of the benefits of practices. In general farmers who are more open to new things might also be more likely to be part of a farmers group. The country fixed effects are all significant at the lowest threshold. As already expected from the mean comparisons the country effects are the strongest predictors, representing different states of adoption of the CSV project, cultural, institutional and economic differences as well as the different ways of implementing the survey.

5.3.2 Adoption of Practices with Different Economic Nature

Column 2-5 and 7-10 show the results for the two alternative ways of classifying the practices, capital intensity and payback period, with two categories each. We divide the same outcome dummies consequently in two different ways. First into capital-intensive and non-capital-intensive practices and then into practices with a short and practices with a long payback period.

We find no significant correlation of credit with the adoption of at least one capital intensive practice. The odd ratio of the logit model however is larger than 1. In the ordered logit count model (Column 8) the odd ration of credit is 1.42. It suggests a positive correlation between credit and the adoption of capital-intensive practices, which is however, with a p-value of 0.12 not significant. Also, for the non-capital-intensive practices, the odd ratios are above 1, indicating a positive correlation with a higher p-value. The odd rations of the practices with higher capital intensity is higher than the one with low capital intensity.

For the repayment period the coefficient of credit is positive and almost significant for the dummy outcome and positive and significant for the number of practices with a long repayment period. Both credit odd ratios are larger in magnitude than the ones of the short repayment group. In line with the theory presented above, this can be interpreted as following. The adoption of practices with a short repayment period does not require credit, because the farmer picks the most rentable one and has lower risk due to fast repayment. He is likely to manage to mobilize the liquid financial mean through his own income or family sources even without the use of credit. Investments in practices with a long repayment period have the strongest correlation to the use of agricultural credit and the only significant effect for the first practice and for the number of practices adopted. Apparently, the intertemporal risk of investing own liquid means, without the insurance effect of not repaying the loan in a case of failure of the investment is a significant barrier to adoption. Another explanation for these results is, that credit rationed farmers need to bridge a large period with less liquid means without being able to take out credit in the meantime to smooth out consumption.

Table 6 Benchmark Model with Odd Ratios of Logit on Adoption Dummies and Ordered Logit on Adoption Count

VARIABLES	(1) Adoption Dummy	(2) Non-Capital Intensive Dummy	(3) Capital Intensive Dummy	(4) Short Payback Dummy	(5) Long Payback Dummy	(6) Adoption Count	(7) Non-Capital Intensive	(8) Capital Intensive	(9) Short Payback	(10) Long Payback
BL Agricultural credit	1.29	1.12	1.24	1.14	1.59	1.39	1.31	1.42	1.18	1.66**
	(0.42)	(0.77)	(0.43)	(0.67)	(0.11)	(0.12)	(0.32)	(0.12)	(0.48)	(0.03)
BL female HH head	0.48**	0.50*	0.65	0.57*	0.69	0.56**	0.69	0.61*	0.58**	0.73
BL Highest education in HH	1.39	1.18	1.50**	1.59**	1.11	1.34**	0.98	1.46***	1.42**	1.06
BL Asset index	0.91	0.94	0.94	0.94	1.03	1.00	1.04	0.99	1.02	1.04
BL Number if HH members	0.98	1.09	1.02	0.94	1.12**	1.02	1.11	1.01	0.95	1.14***
BL Owned land (ha)	1.02	1.01	1.02	1.00	1.03	1.01	1.01	1.01	1.01	1.01*
BL Climate advice	0.97	1.21	0.76	0.66*	0.77	0.70**	0.90	0.67**	0.65**	0.77
BL Off-farm work income	1.10	0.79	1.23	0.91	0.82	0.88	0.82	0.87	0.83	0.87
BL number of memberships in farmer groups[1]	1.33*	1.05	1.53***	1.40***	1.14	1.30***	1.22***	1.30***	1.32***	1.23***
Site fixed effects										
Uganda	0.25***	0.11***	1.00	4.85***	0.07***	0.07***	0.00***	0.54**	0.01***	0.05***
Colombia	0.04***	0.05***	0.09***	0.20***	0.09***	0.00***	0.00***	0.06***	0.00***	0.07***
Guatemala	0.21***	-	0.54	2.84***	0.04***	0.01***	0.00	0.34***	0.00***	0.02***
Honduras	0.02***	-	0.07***	0.34**	0.00***	0.00***	0.00	0.04***	0.00***	0.00***
Nicaragua	-	-	0.42***	-	1.04	0.06***	0.00***	0.29***	0.00***	0.78
Constant	12.51***	3.19*	1.55	0.67	2					
Observations	473	269	604	473	604	604	216	604	315	604
Pseudo R2	0.292	0.239	0.227	0.232	0.388	0.244	0.476	0.208	0.281	0.120

*** p<0.01, ** p<0.05, * p<0.5

To test further is the effect of the credit is coming from capital intensity or from the payback period, we also regressed the four categories singularly on the model. The results in Appendix 6 show, that the strongly significant factor are indeed practices which are capital intensive AND have a long payback period, namely agroforestry, water harvesting with tanks irrigation, water pumps and the grain dryer.

To test hypothesis 2 and 3 formally, we need to compare the coefficients of the capital regressions with the coefficients of the non-capital regression. As mentioned above we do this in accordance with Mize et al., (2019), using seemingly unrelated estimation and a Wald test. Another advantage is, that this estimation is additionally the first robustness check for model misspecification (For SUEST estimation results see Appendix 7, Robustness Check 1). Table 7 shows the estimates of the coefficient comparison, which are jointly insignificant. The two comparisons with the lowest Prob > chi2 are the comparisons of the long and the short payback periods and the comparison of Group4 (capital intensive and long payback period) and Group1 (non-capital intensive and short payback period). Still both are not significant, hence we cannot proof that that credit has a stronger effect on the adoption of practices with a long payback period that on the adoption of practices with a short payback period. The same is valid for the capital intensity.

Table 7 Coefficient Comparison

	Logit Dummy Regressions		Ordered Logit Count Regressions	
Difference Capital and Non-Capital Dummy	$chi^2(1)$ =	0.07	$chi^2(1)$ =	0.09
	Prob > chi2 =	0.79	Prob > chi2 =	0.76
Difference Long and Short Payback Period	$chi^2(1)$ =	0.89	$chi^2(1)$ =	1.81
	Prob > chi2 =	0.34	Prob > chi2 =	0.18
Difference Group4CL and Group1NS	$chi^2(1)$ =	1.17	$chi^2(1)$ =	1.84
	Prob > chi2 =	0.28	Prob > chi2 =	0.17
Difference Group4CL and Group2CS	$chi^2(1)$ =	0.68	$chi^2(1)$ =	0.62
	Prob > chi2 =	0.41	Prob > chi2 =	0.43
Difference Group4CL and Group3NL	$chi^2(1)$ =	0.05	$chi^2(1)$ =	0.00
	Prob > chi2 =	0.82	Prob > chi2 =	0.97
Difference Group4CS and Group1NS	$chi^2(1)$ =	0.45	$chi^2(1)$ =	0.76
	Prob > chi2 =	0.50	Prob > chi2 =	0.38

Note: The results were obtained by from Wald tests following three separate seemingly unrelated estimations with the SUEST post estimation command. Model 1 is the joint estimation of the adoption of Capital and Non-Capital-intensive Practices; Model 2 is the joint estimation of the short and long payback period.

5.3.3 Robustness Tests

As discussed above, the method applied includes some risk of endogeneity due to reverse causality and omitted variables. Since we do have two observations in time but no random assignment and no possibility to control for household level fixed effects, we conducted several robustness and stability tests partly inspired by Beck et al. (2017). The robustness test results can be found in Appendix 7.

The first test (Robustness test 1) shows the results of the seemingly unrelated estimation coefficients in comparison with the coefficients of the logit model. This model was fit to test for model misspecification.

The second test (Robustness Test 2) is the alternative specialization of the outcome variables. Since the endline survey contained responses from two household members which were in many cases incomplete or contradicting. For the main specification, we inserted the value of the other household member in case of a missing value. For the rest we chose randomly one of the responses. The alternative specialization is that when the household members disagree the positive response will be taken over for the whole household. With this specification the adoption rates of certain practices in Ghana and Nicaragua which had only few non adoption responses before reach 100%. Therefore, they are removed from Group1NS because of collinearity and there are only 85 observations and one practice from Uganda left for this group. For this group consequently the estimates for the impact of credit change but stay un-significant. For the rest of the regression groups the add ratio of the credit variable stays stable.

Robustness test 3 involves the conclusion of several additional control variables. We control for the adoption index as suggested by the baseline because it gives a relatively nuanced measure of people's likelihood to change their farming system. With this variable we hoped to capture some of the unobserved personality traits that lead to a higher likelihood to adopt. However, for this same reason including it is a potential source of endogeneity, because it can be related to the same omitted variables as the adoption variables. Additionally, we deconstruct the asset index, which is highly insignificant throughout the model. Instead we include the different categories of assets, namely production means, means of transport, information devices and energy generators as well as the bank account as the only luxury good, since it is a direct prerequisite of savings and some forms of credit taking. We insert the potential to hire labour, which enables farms to make decisions about practices more independently from their own labour force. Additionally, we include the diversification index, the commercialization index and the presence of big animals, which are often s sign of at least some wealth and can be collateral and insurance at the same time. The findings show that the inclusion of the variables does not change the significance level of direction of the effect of credit on any of the adoption outcomes.

As a next step (Robustness Test 4) we assess how sensitive the estimate is to the credit variables we chose. When replacing the credit variable from did you use agricultural credit in the last 12 month before the baseline to did you ever use credit (in the case of Ghana, Uganda and Nicaragua) and did you use any credit in the 12 month before the baseline the estimates change the magnitude of the odd ratios slightly but not the fact that the ones for the long payback period and especially for the capital intensive long payback group are the only ones which are significant and positive.

Robustness test 5 uses the stability test suggested by Bellows and Miguel (2009). We start with a model which contains only the credit variable and then add stepwise the control variables.

We considered instrumental variables like connection to the electricity grid which is an external factor and correlates with credit use negatively. The theory is, that it is connected to remoteness and therefore to access to formal credits. Another potential instrument can be found in the locations of different finance institutions in the CSVs as found in Wattel & Asseldonk (2018) through a construction of a distance to the household using GPS data.

6. DISCUSSION AND CONCLUSION

To summarize, we from theoretical considerations on the connection between the adoption of different practices and their economic nature. We set up the theory that the capital intensity and the repayment period of the technology or practice are crucial factors determining if credit use is relevant for the adoption of a CSAP. To test this assumption, we classify the 18 practices fostered in 6 CSV sites in Latin America and Africa based on capital intensity and payback period. Then we regressed credit use in the baseline period as well as a control vector on the different outcome groups. For each outcome group we run a logit model with an adoption dummy and an ordered logit model with the number of adopted practices. We compare the coefficients across the models with the post-estimation command SUEST and a Wald test.

We find no significant coefficients of credit in most of the groups, except for the category of the long payback period. For this group of practices, the association of credit with adoption is positive and significant. Further differentiation of the practices showed that these results are mainly driven by the group of outcomes, which are capital intensive and have a long repayment period. Namely the practices are agroforestry, water harvesting with tanks, irrigation, water pumps and the grain dryer.

Except for the agroforestry these are all lumpy indivisible investments which purey require capital and save labour once they are bought. It is striking that all these lumpy capital-intensive practices have relatively low adoption rates in the study regions, even though they were selected as climate smart "no regret solutions". Also, only 0 – 12 % of the farmers gave infrastructure investments as a purpose of using credit, while for the majority buying input was the goal. This finding supports the theory that there are many risks and costs going along with allocating liquid financial means into a long-term investment, especially without having the possibility to take credit to smooth out consumption in case of an income shock.

Knowing this, fostering the offer of loans which are tailored to long term investment needs (Beaman et al., 2014) and take into account the farmers fear of being in debt or loosing assets (Abay et al, 2018) can be good options to optimize the conditions for scaling up CSAPs. The amount, the procedure of granting the loans, as well as the schedule of granting and repayment are very important factors hindering or facilitating the accessibility and usefulness of loans for farmers (Simon, 2013; Nweze, 1991). Optimally the amounts and payback rates should target towards the cost and return structure of the farm investment.

In general, the findings suggest that the theory on CSV adoption should distinguish between practices with different economic nature when thinking about how to shape the institutional environment the facilitate the adoption of these CSAPs. The regular way of classifying CSAPs, which is also applied by the CSV project, is mainly based on the function of the practice in managing the biophysical conditions (water management, soil management, genetic resources etc.) (FAO, 2013; Aggarwal et al., 2018). When thinking about an institutional environment which can facilitate the adoption of practices, defining the economic nature of these practices in terms of their needs for different inputs is useful. Within the same functional group (water management, soil management ect.) different practices are likely to be partly substitutable. Considering the input needs allows either prioritizing the practices which do not only fit the biophysical and social context but also in the institutional offer. The integration of CSAP adoption studies, cost benefit analysis and theory on different types of investments offers much potential to enrich theory on the one hand and help advancing the adoption of CSA practices on the other hand. Therefore, this connection should be explored further.

Next to the role of credit, the study stresses the importance of gender, education and especially the high significance of the membership in farmers groups as determinants for the adoption of all types of CSAPs. Targeting women specifically or fostering education and rich landscape of village institutions which facilitates the exchange of information, knowledge and labour are other promising strategies to improve the conditions for adoption.

Another main result is, that the country effects are the strongest predictors for adoption of all groups and subgroups. This can mainly be attributed to the longer implementation period in the African countries, cultural differences, different approaches and theories of change in the different projects, as well as to the heterogenous way in which the monitoring survey was implemented in the different countries.

This leads to the first of the several limitations of the method and the data set. One challenge with the data is that the outcome variables differ between countries in the EL survey. While one country simply records improved varieties, another one specifies climate-resilient biofortified cassava, leading to extremely different adoption rates. Also, the number of practices recorded varied greatly and some countries had hardly any overlapping practices, which makes cross site comparisons, i.e. in a multivariate model, difficult. A fixed effect difference-in-difference model was also not possible, even though 605 households were surveyed twice. This is because not all the outcome variables were recorded in both surveys. Additionally, it would have been difficult to know a state of adoption in the baseline period. It asks about a potential change which happened in 10 years before the survey but for most practices not about current implementation. The limitations of the data led to the decision to implement separate logit models with the EL outcome and BL controls.

To interpret the results of the logit model as a causal relationship, the assumption that all relevant covariates are controlled for and exogeneous is required. However, this is most likely not the case since there are certain character traits which are hard to measure, and they most likely have an influence on adoption as well as credit uptake. These traits are for example openness for new things or an entrepreneurial spirit. Next to a panel model with fixed effects, a suitable instrument which exogenously influencing the credit variable would have been helpful to draw causal conclusions and test the endogeneity of the credit variable. However, we could not identify such an instrument.

Concerning the testing of hypothesis, we need to make clear that most of the conclusions are built on the magnitude of the odd ratios of the regression on the practices in with high capital demand and a long payback period. We can say that credit seems to have a significant effect in the adoption of variables from this group of practices. However, the actual Wald test for the size of the coefficients is not significant. So, we cannot say that the effect is larger than for practices with a short payback period. Therefore, any conclusions should be handled with caution,

Another critical factor is the specification of the credit access with the question for credit use. The “use variable” as an approximation of credit access includes also not liquidity-constraint farmers in the control group of the estimation, leads to a potential underestimation of the treatment effect of relaxing credit constraints, since liquidity un-constrained households are expected to experience no effect (Teklewold et al., 2017, Simtowe and Zeller, 2006). On the other hand, Beaman et al. (2014) discovered in a very rigorous assessment, that conditional on a wide range of observed characteristics those who borrow have substantially higher marginal returns to capital than those who do not borrow. Hence there are heterogeneous returns across farmers, and the lending process sorts farmers into higher and lower productivity farmers. Therefore, with normal matching on observable criteria, they would have overestimated the impact of credit (Beaman et al., 2014). There are therefore at least two factors confounding the effect in opposite direction which we could not measure.

Secondly the use variable is fluctuating a lot between the years. According to Beaman et al. (2014), only about 65% of borrowers in the first year of their observation took out another loan in the second year, confirming, that not taking a credit at one point in time does not mean that there is no access. The use variable makes it also hard to estimate the reasons for not borrowing among the really credit constraint farmers and therefore to give policy recommendation on how to reduce credit constraints.

To improve the concrete study at hand, more detailed insights in the cost and benefit structure by country of the practices would be helpful to construct a more sensitive outcome measure. Potentially the same practice can fall in different categories depending on the pre-existing infrastructure and the natural conditions in the region. Since the classification on this study was drawn from different sources and generalized overall countries this could be a potential reason for a confounded effect. In case there would have been significant effects to draw conclusions from, we should also control for the stability of the categories by taking single practices out. Some practices might be dominantly driving the results while others might have a small impact due to the different number of observations. Additionally, we would have to account for multiple hypothesis testing and endogeneity. Especially in the case of credit the ownership of large infrastructure like irrigation facilities or a Agroforestry system could very well be a determinant of credit access. We tried to account for this danger of reverse causality by using the baseline credit as a proxy, however this practice is also highly criticized (Bellemare et al., 2017). Concerning the setting of the project we do not know how much of the costs the farmer must bear. When costs are being take over it is possible that in a more realistic setting credit is even more important for adoption or adoption rates are way lower (Senyolo et al. 2018).

For further research, the classification should be applied for different input needs like labour and knowledge. Knowledge intensive practices will most likely depend on access to extension services and training, while labour intensive practice should be easier adopted with higher numbers of family workers of functioning labour markets or exchange systems. Another interesting step further would be to collect several biophysical, economic and social properties of each innovation and them cluster them to categories based on more evidence than used in this study before seeing which farmers are adopting which practice. Adopting a multivariate model, looking at the interaction effects between the practices would need larger sample sizes and a consistent measurement of the adoption of the same practices over all countries. Soon new EL data will become available from 3 CSV sites in Nepal, 2 sites in Bangladesh as well as Ethiopia, Vietnam, Senegal and Colombia which will be used to check the robustness of estimated results.

REFERENCES

Abay, K. A., Koru, B., Chamberlin, J., & Berhane, G. (2018). *Does weather risk explain low uptake of agricultural credit? Evidence from Ethiopia* (Vol. 128). Intl Food Policy Res Inst.

Abate, G. T., Rashid, S., Borzaga, C., & Getnet, K. (2016). Rural finance and agricultural technology adoption in Ethiopia: does the institutional design of lending organizations matter?. *World Development*, *84*, 235-253.

Abdallah, A. (2016), "Agricultural credit and technical efficiency in Ghana: is there a nexus?", Agricultural Finance Review, Vol. 76 No. 2, pp. 309-324.

Abdulai, A., Goetz, R., Ali, W., & Owusu, V. (2018). *Liquidity constraints, risk preferences and farmers' willingness to participate in crop insurance programs in Ghana* (No. 2172-2018-8189).

Adesina, A.A., Chianu, J., 2002. Determinants of farmers' adoption and adaptation of alley farming technology in Nigeria. Agrof. Syst. 55, 99e112.

Addison, M., & Ohene-Yankyera, K. (2018). Gender Effect on Adoption of Selected Improved Rice Technologies in Ghana.

Aggarwal, P. K., Jarvis, A., Campbell, B. M., Zougmoré, R., Khatri-Chhetri, A., Vermeulen, S., ... & Radeny, M. (2018). The climate-smart village approach: framework of an integrative strategy for scaling up adaptation options in agriculture. *Ecology and Society*, *23*(1: 14).

Anderson, M. L. (2008). Multiple inference and gender differences in the effects of early intervention: A reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects. *Journal of the American statistical Association*, *103*(484), 1481-1495.

Arslan, A., McCarthy, N., Lipper, L., Asfaw, S., & Cattaneo, A. (2014). Adoption and intensity of adoption of conservation farming practices in Zambia. *Agriculture, ecosystems & environment*, *187*, 72-86.

Arslan, A., Belotti, F., & Lipper, L. (2017). Smallholder productivity and weather shocks: Adoption and impact of widely promoted agricultural practices in Tanzania. *Food policy*, *69*, 68-81.

Banerjee, A., Karlan, D., & Zinman, J. (2015). Six randomized evaluations of microcredit: Introduction and further steps. American Economic Journal: Applied Economics, 7(1), 1-21

Barrett, C. B., Place, F., Aboud, A., & Brown, D. R. (2002). The challenge of stimulating adoption of improved natural resource management practices in African agriculture. *Natural resource management in African agriculture*, 1-21.

Beaman, L., Karlan, D., Thuysbaert, B., & Udry, C. (2014). *Self-Selection into Credit Markets: Evidence from Agriculture in Mali-Working Paper 377* (No. 377).

Beck, T., Demirgüç-Kunt, A., & Honohan, P. (2009). Access to financial services: Measurement, impact, and policies. *The World Bank Research Observer*, *24*(1), 119-145.

Beck, T., Pamuk, H., & Uras, B. R. (2017). Entrepreneurial saving practices and reinvestment: Theory and evidence. *Review of Development Economics*, *21*(4), 1205-1228.

Bellemare, M. F., Masaki, T., & Pepinsky, T. B. (2017). Lagged explanatory variables and the estimation of causal effect. *The Journal of Politics*, *79*(3), 949-963.

Bonilla-Findji, O., Bejarano, G., Eitzinger, A., & Andrieu, N. (2019). Status of CSA adoption and related impact on farming communities across 8 CSV implementing the CSV monitoring plan in 2018.

Boniphace, N. S., Fengying, N. & Chen, F. (2015). An analysis of smallholder farmers' socio-economic determinants for inputs use: A case of major rice producing regions in Tanzania. Russian Journal of Agricultural and Socio-Economic Sciences (RJOAS), 2 (38), 41–55.

Boucher, S. R., Guirkinger, C., & Trivelli, C. (2009). Direct elicitation of credit constraints: Conceptual and practical issues with an application to Peruvian agriculture. *Economic Development and Cultural Change*, *57*(4), 609-640.

Branca, G., McCarthy, N., Lipper, L., & Jolejole, M. C. (2011). Climate-smart agriculture: a synthesis of empirical evidence of food security and mitigation benefits from improved cropland management. *Mitigation of climate change in agriculture series*, *3*, 1-42.

Bryan, E., Ringler, C., Okoba, B., Roncoli, C., Silvestri, S., & Herrero, M. (2013). Adapting agriculture to climate change in Kenya: Household strategies and determinants. *Journal of environmental management*, *114*, 26-35.

Cacho, O. J., Marshall, G. R., & Milne, M. (2003). Smallholder agroforestry projects: potential for carbon sequestration and poverty alleviation.

Carter, J., 1995. Alley farming: have resource poor farmersbenefited?. Nat. Resource Perspectives 3, 1–4.

Casey, K., Glennerster, R., & Miguel, E. (2012). Reshaping institutions: Evidence on aid impacts using a preanalysis plan. The Quarterly Journal of Economics, 127(4), 1755-1812.

CCAFS, IFPRI, ILRI. 2013. Gender Household Survey. Harvard Dataverse, V4.

Challinor, A.J., Watson, J., Lobell, D., Howden, S.M., Smith, D.R., Chhetri, N., 2014. A metaanalysis of crop yield under climate change and adaption. Nat. Clim. Chang. 4, 287–291.

Chaovanapoonphol, Y., Battese, G. E. & Chang, H. (2005). The impact of rural financial services on the technical efficiency of rice farmers in the Upper North of Thailand. Contributed Paper at the Annual Conference of the Australian Agricultural and Resource Economics Society at Coffs Harbour, 9-11 February 2005.

Deressa, T.T., Hassan, R.M., Ringler, C., Alemu, T., Yesuf, M., 2009. Determinants of farmers' choice of adaptation methods to climate change in the Nile Basin of Ethiopia. Global Environmental Change 19, 248e255.

Di Falco, S., Veronesi, M., & Yesuf, M. (2011). Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. *American Journal of Agricultural Economics*, *93*(3), 829-846.

Doss, C. R. (2003). *Understanding farm level technology adoption: lessons learned from CIMMYT's micro surveys in Eastern Africa* (pp. iv-20). CIMMYT.

Dunnett, A., Shirsath, P. B., Aggarwal, P. K., Thornton, P., Joshi, P. K., Pal, B. D., ... & Ghosh, J. (2018). Multi-objective land use allocation modelling for prioritizing climate-smart agricultural interventions. *Ecological modelling*, *381*, 23-35.

D'Souza, A., & Mishra, A. K. (2018). Adoption and abandonment of partial conservation technologies in developing economies: The case of South Asia

Eswaran, M., & Kotwal, A. (1986). Access to capital and agrarian production organisation. The Economic Journal, 96(382), 482-498.

FAO. (2013). Climate-smart Agriculture Sourcebook. Rome, Italy: Food and Agriculture Organization of the United Nations.

Fafchamps, M., & Pender, J. (1997). Precautionary saving, credit constraints, and irreversible investment: Theory and evidence from semi-arid India. *Journal of Business & Economic Statistics*, *15*(2), 180-194.

Feder, G. (1982). Adoption of interrelated agricultural innovations: Complementarity and the impacts of risk, scale, and credit. *American Journal of Agricultural Economics*, *64*(1), 94-101.

Feder, G., & Umali, D. L. (1993). The adoption of agricultural innovations: a review. *Technological forecasting and social change*, *43*(3-4), 215-239.

Fernandez-Cornejo, J., Hendricks, C., & Mishra, A. (2005). Technology adoption and off-farm household income: the case of herbicide-tolerant soybeans. *Journal of Agricultural and Applied Economics*, *37*(3), 549-563.

Fischer, K., Van den Berg, J., & Mutengwa, C. (2015). Is Bt maize effective in improving South African smallholder agriculture?. *South African Journal of Science*, *111*(1-2), 01-02.

Förch, W., Kristjanson, P., Cramer, L., Barahona, C., & Thornton, P. K. (2014). Back to baselines: measuring change and sharing data. *Agriculture & Food Security*, *3*(1), 13.

Förch, W., Kristjanson, P. M., Thornton, P. K., Kiplimo, J., Sijmons, K., Mutie, I., ... & Bhatta, G. D. (2013). CCAFS Site Portfolio: Core Sites in the CCAFS Regions: East Africa, West Africa and South Asia.

Gbetibouo, G.A., 2009. Understanding Farmers' Perceptions and Adaptations to Climate Change and Variability: the Case of the Limpopo Basin, South Africa. *IFPRI Discussion Paper, 849.*

Gedikoglu, H., McCann, L., & Artz, G. (2011). Off-farm employment effects on adoption of nutrient management practices. *Agricultural and Resource Economics Review*, *40*(2), 293-306.

Greene, W.H. (2003), Econometric Analysis, Journal of the American Statistical Association, Education, P. (Ed.), Prentice Hall, Upper Saddle River, NJ.

Guirkinger, C., & Boucher, S. R. (2008). Credit constraints and productivity in Peruvian agriculture. *Agricultural Economics*, *39*(3), 295-308.

Hausman, J., & McFadden, D. (1984). Specification tests for the multinomial logit model. *Econometrica: Journal of the Econometric Society*, 1219-1240.

Helms, B. (2006). *Access for all: building inclusive financial systems*. The World Bank.

Hisali, E., Birungi, P., Buyinza, F., 2011. Adaptation to climate change in Uganda: evidence from micro level data. Global Environmental Change 21, 1245e1261.

Holden, S., & Shiferaw, B. (2004). Land degradation, drought and food security in a less-favoured area in the Ethiopian highlands: a bio-economic model with market imperfections. *Agricultural Economics*, *30*(1), 31-49.

International Fund for Agricultural Development (IFAD). 2011. Rural poverty report 2011: new realities, new challenges: new opportunities for tomorrow's generation. IFAD, Rome.

IPCC: Porter, J. R., Xie, L., Challinor, A. J., Cochrane, K., Howden, S. M., Iqbal, M. M., ... & Travasso, M. I. (2014). Food security and food production systems.

Karlan, D., Osei, R., Osei-Akoto, I., & Udry, C. (2014). Agricultural decisions after relaxing credit and risk constraints. *The Quarterly Journal of Economics*, *129*(2), 597-652.

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

Kato, E., Ringler, C., Yesuf, M., & Bryan, E. (2011). Soil and water conservation technologies: a buffer against production risk in the face of climate change? Insights from the Nile basin in Ethiopia. *Agricultural Economics*, *42*(5), 593-604.

Khatri-Chhetri, A., Aggarwal, P. K., Joshi, P. K., & Vyas, S. (2017). Farmers' prioritization of climate-smart agriculture (CSA) technologies. *Agricultural systems*, *151*, 184-191.

Kling, J. R., Liebman, J. B., & Katz, L. F. (2007). Experimental analysis of neighborhood effects. *Econometrica*, *75*(1), 83-119.

Komicha, H. H., & Öhlmer, B. (2006). Effect of credit constraint on production efficiency of farm households in southeastern Ethiopia. Ethiopian Journal of Economics, 15(1), 1-33.

Kristjanson, P., Neufeldt, H., Gassner, A., Mango, J., Kyazze, F. B., Desta, S., ... & Coe, R. (2012). Are food insecure smallholder households making changes in their farming practices? Evidence from East Africa

Lan, L., Sain, G., Czaplicki, S., Guerten, N., Shikuku, K. M., Grosjean, G., & Läderach, P. (2018). Farm-level and community aggregate economic impacts of adopting climate smart agricultural practices in three mega environments. *PloS one*, *13*(11), e0207700.

Lipper, L., Thornton, P., Campbell, B. M., Baedeker, T., Braimoh, A., Bwalya, M., ... & Hottle, R. (2014). Climate-smart agriculture for food security. *Nature climate change*, *4*(12), 1068.

Lobell, D.B., M.B. Burke, C. Tebaldi, M.D. Mastrandrea, W.P. Falcon, and R.L. Naylor. (2008). Prioritizing climate change adaptation needs for food security in 2030. Science, 319(5863): 607-610.

Mafongoya, P., Rusinamhodzi, L., Siziba, S., Thierfelder, C., Mvumi, B. M., Nhau, B., ... & Chivenge, P. (2016). Maize productivity and profitability in Conservation Agriculture systems across agro-ecological regions in Zimbabwe: A review of knowledge and practice. *Agriculture, Ecosystems & Environment*, *220*, 211-225.

Makate, C., Makate, M., Mango, N., & Siziba, S. (2019). Increasing resilience of smallholder farmers to climate change through multiple adoption of proven climate-smart agriculture innovations. Lessons from Southern Africa. *Journal of environmental management*, *231*, 858-868.

McCarthy, N., Lipper, L., & Branca, G. (2011). Climate-smart agriculture: smallholder adoption and implications for climate change adaptation and mitigation. *Mitigation of Climate Change in Agriculture Working Paper*, *3*, 1-37.

Mendola, M. (2005). Farm Households Production Theories: A Review of Institutional and Behavioural Responses. *University of Milan Italy Economics Working Paper*, (2005-01).

Mize, T. D., Doan, L., & Long, J. S. (2019). A general framework for comparing predictions and marginal effects across models. *Sociological Methodology*, *49*(1), 152-189.

Monfared, N. (2011). Adoption and consequences of technologies on rural women in south and north of Iran. African Journal of Agricultural Research, 6(14), 3382-3387. https://doi.org/10.5897/AJAR11.410

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

Muriithi, B. W., Menale, K., Diiro, G., & Muricho, G. (2018). Does gender matter in the adoption of push-pull pest management and other sustainable agricultural practices? Evidence from Western Kenya.

Mwangi, M., & Kariuki, S. (2015). Factors determining adoption of new agricultural technology by smallholder farmers in developing countries. *Journal of Economics and sustainable development*, 6(5).

Mwongera, C., Shikuku, K. M., Twyman, J., Läderach, P., Ampaire, E., Van Asten, P., ... & Winowiecki, L. A. (2017). Climate smart agriculture rapid appraisal (CSA-RA): A tool for prioritizing context-specific climate smart agriculture technologies. *Agricultural Systems*, *151*, 192-203.

Nastis, S. A., Michailidis, A., & Chatzitheodoridis, F. (2012). Climate change and agricultural productivity. *African Journal of Agricultural Research*, *7*(35), 4885-4893.

Ng'ang'a, S. K., Bulte, E. H., Giller, K. E., McIntire, J. M., & Rufino, M. C. (2016). Migration and self-protection against climate change: A case study of Samburu County, Kenya. *World Development*, *84*, 55-68.

Ng'ang'a, S. K., Notenbaert, A. M. O., Mwungu, C. M., Mwongera, C., & Girvetz, E. H. (2017). Cost and benefit analysis for climate-smart soil practices in Western Kenya.

Ngwira, A., Johnsen, F. H., Aune, J. B., Mekuria, M., & Thierfelder, C. (2014). Adoption and extent of conservation agriculture practices among smallholder farmers in Malawi. *Journal of Soil and Water Conservation*, *69*(2), 107-119.

Nhemachena, C., Hassan, R., 2008. Determinants of African farmers' strategies for adapting to climate change: multinomial choice analysis. *African Journal of Agricultural and Resource Economics 2 (1), 83e104.*

Ntshangase, N., Muroyiwa, B., & Sibanda, M. (2018). Farmers' perceptions and factors influencing the adoption of no-till conservation agriculture by small-scale farmers in Zashuke, KwaZulu-Natal Province. *Sustainability*, *10*(2), 555.

Nwaru, J. C. (2004). Rural credit markets and resource use in arable crop production in Imo State of Nigeria. Ph.D. Dissertation, Michael Okpara University of Agriculture, Umudike, Nigeria.

Nweze, N. J. (1991). The Role of Women's Traditional Savings and Credit Cooperatives in Small-Farm Development. In Small Farm Development in Oguta C. A. (Ed) Issues In Africa Rural Development, pp: 234–236.

Ogada, M. J., Mwabu, G., & Muchai, D. (2014). Farm technology adoption in Kenya: a simultaneous estimation of inorganic fertilizer and improved maize variety adoption decisions.

Palmer, N. (2016). Making climate finance work in agriculture. Worldbank, http://documents.worldbank.org/curated/en/986961467721999165/pdf/ACS19080-REVISED-OUO-9-Making-Climate-Finance-Work-in-Agriculture-Final-Version.pdf

Petrick, M. (2005). Empirical measurement of credit rationing in agriculture: A methodological survey. Agricultural Economics, 33(2), 191-203.

Phillip, D., Nkonya, E., Pender, J. & Oni, O. A. (2008). Constraints to increasing agricultural productivity in Nigeria. Nigeria Strategy Support Program. Brief No. 4.

Pinheiro, A. E. (1992). An Econometric Analysis of Farm-level Efficiency of Small Farms in the Dominican Republic. Master's thesis, University of Connecticut.

Poole, N. (2017). *Smallholder agriculture and market participation*. Practical Action Publishing.

Porgo, M., Kuwornu, J. K., Zahonogo, P., Jatoe, J. B. D., & Egyir, I. S. (2018). Credit constraints and cropland allocation decisions in rural Burkina Faso. *Land use policy*, *70*, 666-674.

Rajan, R., and L. Zingales (1998) Financial dependence and growth. American Economic Review 88, 559-87

Rapsomanikis, G. (2015). The economic lives of smallholder farmers: An analysis based on household data from nine countries. *Food and Agriculture Organization of the United Nations*, 1-39.

Rogers, E.M. (1995) Diffusion of Innovations (4th edn). New York: The Free University Press.

Sain, G., A.M. Loboguerrero, C. Corner-Dolloff, M. Lizarazo, A. Nowak, D. Martínez-Barón, N. Andrieu (2017). Costs and benefits of climate-smart agriculture: The case of the Dry Corridor in Guatemala, Agricultural Systems)151): 163-173.

Salasya, B. D., Mwangi, W. M., Verkuijl, H., Odendo, M. A., & Odenya, J. O. (1998). *An Assessment of the Adoption of seed and fertilizer Packages and the Role of Credit in smallholder Maize Production in Kakamega and Vihiga Districts, Kenya*. CIMMYT.

Savadogo, K., Reardon, T., & Pietola, K. (1994). Farm productivity in Burkina Faso: effects of animal traction and nonfarm income. *American Journal of Agricultural Economics*, *76*(3), 608-612.

Senyolo, M. P., Long, T. B., Blok, V., & Omta, O. (2018). How the characteristics of innovations impact their adoption: An exploration of climate-smart agricultural innovations in South Africa. *Journal of Cleaner Production*, *172*, 3825-3840.

Simon, M. (2013). Determinants of farmers decision to access credit: the case of Zimbabwe. *Russian Journal of Agricultural and Socio-Economic Sciences*, *17*(5).

Simtowe, F., & Zeller, M. (2006). The Impact of Access to Credit on the Adoption of hybrid maize in Malawi: An Empirical test of an Agricultural Household Model under credit market failure.

Sharma, M., & Buchenrieder, G. (2002). Impact of microfinance on food security and poverty alleviation: A review and synthesis of empirical evidence. *The Triangle of Microfinance: Financial Sustainability, Outreach, and Impact' M. Zeller and RL Meyer (edited) International Food Policy Research Institute (IFPRI) Publication*, 221-240.

Shiferaw, B. A., Okello, J., & Reddy, R. V. (2009). Adoption and adaptation of natural resource management innovations in smallholder agriculture: reflections on key lessons and best practices. *Environment, development and sustainability*, *11*(3), 601-619.

Steenwerth, K. L., Hodson, A. K., Bloom, A. J., Carter, M. R., Cattaneo, A., Chartres, C. J., ... & Jenkins, B. M. (2014). Climate-smart agriculture global research agenda: scientific basis for action. *Agriculture & Food Security*, *3*(1), 11.

Sunding, D., & Zilberman, D. (2001). The agricultural innovation process: research and technology adoption in a changing agricultural sector. *Handbooks in Economics*, *18*(1A), 207-262.

Swaminathan, H., Du Bois, R. S., & Findeis, J. L. (2010). Impact of access to credit on labor allocation patterns in Malawi.

Taneja, G., B. D. Pal, P. K. Joshi, P. K.Aggarwal, and N. K. Tyagi.2014. Farmers preferences for climate-smart agriculture: an assessment in the Indo-Gangetic Plain. IFPRI Discussion Paper1337. New Delhi, India

Taylor, J. E., & Adelman, I. (2003). Agricultural household models: genesis, evolution, and extensions. *Review of Economics of the Household*, *1*(1-2), 33-58.

Teklewold, H., Kassie, M., & Shiferaw, B. (2013). Adoption of multiple sustainable agricultural practices in rural Ethiopia. *Journal of Agricultural Economics*, *64*(3), 597-623.

Teklewold, H., Mekonnen, A., Kohlin, G., & Di Falco, S. (2017). Does Adoption Of Multiple Climate-Smart Practices Improve Farmers' Climate Resilience? Empirical Evidence From The Nile Basin Of Ethiopia. *Climate Change Economics*, *8*(01), 1750001.

Thirtle, C., Beyers, L., Ismael, Y., & Piesse, J. (2003). Can GM-technologies help the poor? The impact of Bt cotton in Makhathini Flats, KwaZulu-Natal. *World development*, *31*(4), 717-732.

Twine, E. E., Rao, E. J., Baltenweck, I., & Omore, A. O. (2019). Are Technology Adoption and Collective Action Important in Accessing Credit? Evidence from Milk Producers in Tanzania. *The European Journal of Development Research*, *31*(3), 388-412.

Upadhyay, B. M., Young, D. L., Wang, H. H., & Wandschneider, P. (2003). How do farmers who adopt multiple conservation practices differ from their neighbors?. *American Journal of Alternative Agriculture*, *18*(1), 27-36.

Wattel, C., & Asseldonk, M. V. (2018). Financial service supply with potential for supporting climate-smart agriculture.

Weesie, J. (1999). Seemingly unrelated estimation and the cluster-adjusted sandwich estimator, STATA Technical Bulletin, STB 52, 34 47. *T able A*, *1*.

Wood, S. A., Jina, A. S., Jain, M., Kristjanson, P., & DeFries, R. S. (2014). Smallholder farmer cropping decisions related to climate variability across multiple regions. *Global Environmental Change*, *25*, 163-172.

Xing, Z. (2018). Development Impacts of Remittances in Agricultural Households in Fiji. *Remittances Review*, *3*(1), 19-49.

Yila, O. M., & Thapa, G. B. (2008). Adoption of agricultural land management technologies by smallholder farmers in the Jos Plateau, Nigeria. *International journal of agricultural sustainability*, *6*(4), 277-288.

APPENDIX 1 PROCEDURE OF DATA MERGING

To generate one data set with the six countries, the data for Ghana and Uganda was extracted from the initial BL data collected in 2010 to 2012 and the data for Nicaragua from the "additional sites" BL data set. Another round of single BL data was conducted in Colombia, Guatemala and Honduras in 2014 until 2015, which were merged with the original data. They are all based on the same questionnaire. However, a few variables were omitted, and a few added the later datasets.

The Monitoring Data was received countrywide, partly in Spanish, partly in English. The relevant variables were coded into numbers, recoded from string to numeric and then received a label with the English answer option. Additionally, there are many variables that only contained data from a part of the survey population. This is due to the adoptive design of the survey which leads to different questions depending on previous answers. In these cases, where possible, two variables from different answer paths could be combined to generate one variable for the whole study population. Additionally, many questions offer multiple categorical answer options. These questions where recoded into dummy variables that cover the whole study population. One challenge here was, that in different countries the questions were handled as multiple or single choice. So, when a question is handled as single choice, one can't know if another option would have also been selected.

The incomplete double observations in the monitoring survey were dropped first. For the rest of the double observations, one was dropped at random. Afterwards the two data sets were merged based on the village, site and household information.

Appendix 2 Overview over Variables in Baseline and Endline Model

Country	Dataset	Observations	Adoption Count	Adoption Ratio (%)	Formal Credit takers (Nr)	Formal Credit Takers (%)	Informal Credit Takers (Nr)	Informal Credit Takers (%)	General credit takers (Nr)	General credit takers (%)	Gained access to credit (Nr)	Gained access to credit (%)	Stopped taking credit (Nr)	Stopped taking credit (%)	Agricultural credit takers (Nr)	Agricultural Credit takers (%)	Member in credit group %	Education at least secondary %	Farm Size	HH members	Family workers	Female respondents (%)	HH Heads	Female household heads	Asset Index	At least one climate events	Production diversity	Months per year/Days per month food insecurity
Ghana	BL T2002 full	140			12	4,3	58	20,7	66	23,6																		
	BL T2002 Panel	132			6	4,6	29	22,0	33	25,0																		
	BL T2012 full	140	15,0	31,3	26	9,3	86	30,7	102	40,0	52	18,6	6	2,1	38	13,7	33,6	38,6	8,5	6,2	4,1	18,6	69,3	11,4	2,3		8	4,9
	BL T2012 Panel	132	15,1	31,5	13	9,8	132	31,1	132	37,1	24	18,2	3	2,3	18	13,7	34,1	40,2	8,7	6,2	4,1	19,7	68,2	6,6	2,3		8	1,3
	EL T2017 full	357	4,5	44,8	8	2,3	54	15,7	124	34,7						17,7		8,4	7,1	9,0	3,9	47,1	53,8	8,7		64,1		4,5
	EL T2017 full 1/HH	194	4,6	45,9	8	4,1	30	15,5	73	37,6						19,1		6,7	7,0	8,7	3,9	44,3	61,3	10,3		63,9		4,5
	EL T2017 Panel	132	4,5	45,2	7	5,3	21	15,9	53	40,2						20,5		7,6	7,4	8,7	3,5	44,7	62,9	12,1		62,1		4,7
Uganda	BL T2002 full	140			30	10,7	62	22,1	88	31,4																		
	BL T2002 Panel	85			9	10,6	18	21,2	26	30,6																		
	BL T2012 full	140	9,9	20,6	46	16,4	88	31,4	122	47,9	44	15,7	2	0,7	44	15,7	16,4	46,4	2,2	5,3	3,6	50,0	54,3	25,0	2,0		6,9	2,9
	BL T2012 Panel	85	10,3	21,4	17	20,0	85	29,4	85	43,5	15	17,6	1	1,2	16	18,8	21,2	52,9	2,4	5,5	3,8	51,8	48,2	17,6	2,1		7,1	2,5
	EL T2017 full	457	2,1	34,5	11	5,1	39	18,2	100	21,9					48	22,4		34,1	8,4	5,0	2,7	50,1	60,0	13,3	17,6	78,7		3,2
	EL T2017 full 1/hh	344	2,1	35,2	8	4,0	37	18,7	92	26,7					44	22,2		34,3	8,7	5,0	2,6	43,6	70,2	16,6		77,5		3,1
	EL T2017 Panel	85	2,1	35,3	3	4,3	15	21,4	25	29,4					18	25,7		20,0	5,9	4,9	2,5	60,0	62,7	22,4		77,9		3,8

Country	Dataset	Observations	Adoption Count	Adoption Ratio	Formal Credit takers (Nr)	Formal Credit Takers (%)	Informal Credit Takers (Nr)	Informal Credit Takers (%)	General credit takers (Nr)	General credit takers (%)	Gained access to credit (Nr)	Gained access to credit (%)	Lost access (Nr)	Lost access (%)	Agricultural credit takers (Nr)	Agricultural Credit takers (%)	Member in credit group %	Education at least secondary %	Farm Size	HH members	Family workers	Female respondents (%)	HH Heads	Female household heads (%)	Asset Index	At least one climate events	Production diversity	Food insecurity
Colombia	BL T2012 full	140	10,8	22,5	112	40,0	10	3,6	118	43,6	0	0,0	0	0,0	90	32,1	4,3	60,7	2,9	3,7	2,8	25,0	83,6	12,9	3,3		5,0	0,6
	BL T2012 Panel	85	11,0	22,9	40	47,1	85	4,7	85	49,4	0	0,0	0	0,0	0,4	34,0	3,5	60,0	2,4	3,8	3,0	25,9	84,7	10,6	3,3		4,8	3,5
	EL T2017 full	263	0,9	13,1	95	36,3	7	2,7	119	45,2					102	38,9		21,3	1,8	3,7	2,3	49,8	61,5	8,0		42,4		0,2
	EL T2017 full 1/hh	142	0,9	13,1	55	39,0	4	2,8	67	47,2					59	41,8		20,4	1,9	3,6	2,5	47,2	63,7	9,2		40,4		0,3
	EL T2017 Panel	85	0,5	7,6	31	36,9	2	2,4	39	45,9					33	39,3		16,5	1,7	3,2	2,3	45,9	64,0	7,1		38,1		0,4
Homduras	BL T2012 full	140	8,7	18,0	24	8,6	20	7,1	42	15,7					38	13,6	0,7	13,6	2,1	5,1	4,1	36,4	75,7	20,7	2,1		4,4	0,7
	BL T2012 Panel	92	8,8	18,4	7	7,6	92	7,6	92	14,1					14	15,2	1,1	12,0	1,9	4,9	3,9	35,9	81,5	18,5	2,1		4,4	3,7
	EL T2017 full	262	0,3	7,0	44	16,9	23	8,8	95	36,3					67	25,7		3,8	1,9	5,0	2,3	51,1	56,1	10,7		59,8		0,7
	EL T2017 full 1/hh	138	0,3	6,9	22	16,1	13	9,5	49	35,5					35	25,5		5,1	2,0	4,5	2,2	51,4	58,0	12,3		61,3		0,7
	EL T2017 Panel	92	0,2	4,6	13	14,1	8	8,7	30	32,6					21	22,8		2,2	1,7	4,5	2,0	53,3	57,6	15,2		60,4		0,9
Guatemala	BL T2012 full	140	9,7	0,0	48	17,1	22	7,9	66	25,0					48	17,1	10,0	10,7	1,1	5,8	4,4	65,0	45,0		1,5		4,4	3,8
	BL T2012 Panel	112	9,6	20,0	16	14,3	112	7,1	112	20,5					16	14,3	8,9	12,5	1,2	5,9	4,5	67,0	41,1	12,5	1,5		4,5	2,0
	EL T2017 full	280	1,1	28,4	34	12,3	34	12,3	91	32,5					68	24,6		4,3	14,1	5,3	1,9	55,6	53,8	13,6		87,3		6,7
	EL T2017 full 1/hh	147	1,2	29,8	18	12,3	16	11,0	47	32,0					34	23,3		4,1	11,0	5,1	1,8	56,8	61,0	20,4		87,0		6,4
	EL T2017 Panel	112	0,9	23,0	16	14,4	11	9,9	37	33,0					27	24,3		4,5	11,4	5,0	1,7	53,2	64,0	17,9		87,4		6,8

Country	Dataset	Observations	Adoption Count	Adoption Ratio	Formal Credit takers (Nr)	Formal Credit Takers (%)	Informal Credit Takers (Nr)	Informal Credit Takers (%)	General credit takers (Nr)	General credit takers (%)	Gained access to credit (Nr)	Gained access to credit (%)	Lost access (Nr)	Lost access (%)	Agricultural credit takers (Nr)	Agricultural Credit takers (%)	Member in credit group %	Education at least secondary %	Farm Size	HH members	Family workers	Female respondents (%)	HH Heads	Female household heads (%)	Asset Index	At least one climate events	Production diversity	Food insecurity
Nicaragua	BL T2002 full	140			58	20,7	48	17,1	92	32,9																		
	BL T2002 Panel	99			22	22,2	20	20,2	36	36,4																		
	BL T2012 full	140	14,8	30,8	58	20,7	26	9,3	80	30,0	22	7,9	24	8,6	40	14,3	10,7	50,7	.	5,3	4,2	46,4	63,6	22,1	2,7		5,5	2,9
	BL T2012 Panel	99	14,4	30,0	17	17,2	99	10,1	99	26,3	5	5,1	11	11,1	13	13,1	12,1	51,5	.	5,3	4,3	48,5	63,6	20,2	2,7		5,4	2,3
	EL T2017 full	263	2,3	38,8	46	17,6	12	4,6	77	29,3					58	22,1		17,1	6,5	5,2	2,5	54,1	55,7	17,1		66,9		3,3
	EL T2017 full 1/hh	146	2,3	38,6	31	21,4	6	4,1	50	34,2					37	25,5		15,1	6,8	5,1	2,6	58,7	62,1	23,3		65,5		3,6
	EL T2017 Panel	99	2,1	34,2	21	21,2	2	2,0	34	34,3					23	23,2		14,1	6,9	5,2	2,6	59,4	60,6	21,2		61,6		4,0
Full	BL T2002 full	420			100	6,0	168	10,0	246	14,6																		
	BL T2002 Panel	605			37	6,1	67	11,1	95	15,7																		
	BL T2012 full	840	11,5	23,9	314	18,7	252	15,0	530	33,7	118	7,0	32	1,9	298	17,8	12,6	36,8	3,2	5,2	3,8	40,2	65,2	22,3	2,3	0,0	5,2	2,6
	BL T2012 Panel	605	11,8	24,5	110	18,2	605	15,7	605	31,4	44	7,3	15	2,5	111	18,4	14,7	37,2	3,5	5,4	4,0	41,0	64,0	12,6	2,3	0,0	5,2	2,4
	EL T2017 full	1882	2,0	29,3	238	14,7	169	10,4	606	32,2					404	25,0		16,4	6,9	5,7	2,7	51,0	56,7	11,9		66,9		3,2
	EL T2017 full 1/hh	1111	2,1	30,5	142	14,8	106	11,0	378	34,0					246	25,6		17,6	6,9	5,5	2,7	48,9	64,0	15,4	22,3	67,6		3,2
	EL T2017 Panel	605	1,9	26,4	91	15,5	59	10,0	218	36,0					149	25,3	10,2	10,2	6,3	5,7	2,5	52,2	61,9	15,9		65,0		3,7

Full baseline dataset: all 140 observations per country from the baseline survey
Full monitoring dataset: All observation from the monitoring round, inclusive the double observation per household
Full monitoring dataset 1/hh: all households observed by the monitoring survey are represented once, double observations are dropped
Panel data sets: all 605 observations which were observed twice and can be handled as a panel

APPENDIX 3 NUMBER AND SPECIFICATION OF THE OUTCOME VARIABLES

Practice	Country	N	**Adoption variable baseline:** When not differently specified, asks about whether a certain change was made in the last 10 year in at least one crop	**Adoption variable monitoring:** Was the CSA practice adopted on the farm in the last 12 months?
Adoption of at least one practice	All	605	1 if at least one if the practices which is monitored in the monitoring survey of this country is adopted	1 if at least one if the practices which is monitored in the monitoring survey of this country is adopted
PRA 1 Crop Rotation	Ghana	132	Introduced crop rotation	Crop rotation
PRA2 Varieties	All	605	Introduced new variety	Gh: improved variety, Ug: (1) pest and disease resistant, early maturing, high yielding Cassava, pest and disease resistant, biofortified sweet potato or beans; CO: drought resistant, biofortified beans, GU/HD: varieties of black beans; NI: more climate tolerant varieties
PRA3 Integrated Nutrient Management	Ghana	132	.	Integrated Nutrient Management
PRA4 Intercropping	Ghana, Uganda	217	Introduced Intercropping	GH: Intercropping; UG: improved intercropping (Maize - beans/cassava)
PRA6 Reduced tillage	Ghana	132	.	Reduced tillage
PRA7 Home gardens	Ghana, Colombia, Nicaragua, Guatemala, Nicaragua	520	*Vegetable production?*	GH: new cropping system & additional crops (Home gardens); CO: Climate adopted home gardens, GU/HD: Vegetable gardens with and without water harvesting, NI: Home garden diversification
PRA8 Organic Fertilizer	Ghana, Colombia, Nicaragua	316	Introduced/ stopped producing Manure/Compost; Manure/Compost - any produced on the farm	GH, CO: Organic Manure
PRA9 Tree planting	Ghana, Uganda, Nicaragua	316	Any tree planted in the last 12 months?	GH: tree planting; UG: Agroforestry /tree planting, NI: Perennial crops as shade for livestock

PRA10 Water harvesting	Ghana, Colombia, Gulatemala	329	"Introduced micro-catchments", "Introduced/built ridges or bunds"	GH: Water harvesting with earth bunds/ties ridges/planting pits; CO: water harvesting; GU: Home garden with water harvesting
PRA11 Retention/ Incorporation of crop residue or Mulching	Ghana, Colombia, Nicaragua	231	"Introduced Mulching"	Mulching, Retention/ incorporation of crop residue
PRA13 Terraces	Uganda	85	Introduced Terracing	Terraces
PRA14 Irrigation	Colombia, Guatemala, Honduras	113	Introduced Irrigation (also stopped irrigating, irrigation available on farm, improved irrigation)	Irrigation
PRA18 Protecting water sources on the farm	Nicaragua	99	.	Protection of water source

Appendix 4 Adoption Rates By Practice and Country

	Survey round and number of observations	Ghana	Uganda	Colombia	Guatemala	Honduras	Nicaragua	**Average overall**
Number of observations		132	85	85	112	92	99	**605**
BL Adoption Index		3.86	2.87	3.15	2.81	2.49	3.9	**3.23**
EL Adoption Rate		98%	79%	35%	64%	15%	90%	**66%**
EL Average Number of Practices adopted		5.37	2.07	0.49	0.93	0.18	1.9	**2.05**
PRACTICE 1 Introduced Rotation	BL	**71%**	33%	13%	0%	0%	0%	**71%**
	EL	**92%**						**92%**
PRACTICE 2 Introduced New Variety	BL	**94%**	**79%**	**78%**	**58%**	**47%**	**58%**	**71%**
	EL	**62%**	**71%**	**1%**	**9%**	**2%**	**28%**	**30%**
PRACTICE 3 Integrated Nutrient Management	BL	**63%**	11%	41%	79%	18%	79%	**63%**
	EL	**33%**						**33%**
PRACTICE 4 Intercropping	BL	**67%**	**31%**	2%	18%	4%	18%	**53%**
	EL	**73%**	**38%**					**58%**
PRACTICE 5 Introduced Mulching	BL	**9%**	20%	0%	0%	0%	0%	**9%**
	EL	**8%**						**8%**
PRACTICE 6 Reduced Tillage	EL	**35%**						**35%**
PRACTICE 7 Home gardens	BL							
	EL	**12%**		**12%**	**62%**	**13%**	**62%**	**25%**
PRACTICE 8 Organic Fertilizer	BL	**91%**	24%	**20%**	0%	0%	**50%**	
	BL	**91%**	20%	**36%**	19%	2%	**3%**	**71%**
	EL	**77%**		**23%**			**17%**	**44%**
PRACTICE 9 Agroforestry	BL	**52%**	**47%**	41%	58%	55%	**41%**	**50%**
	EL	**47%**	**28%**				**27%**	**36%**
PRACTICE 10 Introduced Water Harvesting	BL	**56%**	16%	**14%**	**2%**	2%	1%	**21%**
	EL	**91%**		**18%**	**11%**			**24%**
PRACTICE 11 Retention /incorporation of crop residue	EL			**1%**			**66%**	**12%**
PRACTICE 13 Terracing	BL	0%	**4%**	0%	10%	0%	1%	**2%**
	EL		**18%**					**18%**
PRACTICE 14 Introduced irrigation	BL	1%	2%	4%	**20%**	15%	0%	**7%**
	BL	0%	5%	0%	**4%**	1%	0%	**2%**
	EL				**12%**			**12%**
PRACTICE 18 Protection of water sources on the farm	EL						4%	**4%**

Appendix 5 Regressions by Practice

	Rotation	INM	Mulch	Terraces	Reduced Tillage	Irrigation	Protect-ion of Water Sources	Varieties	Intercrop ping	Home Gardens	Organic Fertilizer	Agro-forestry	Water-harvest	Crop residue/ mulch
Country	GH	GH	GH	UG	GH	GU	NI	Multiple	Multiple	Multiple	Multiple	Multiple	Multiple	Multiple
BL Credit Access	**0.13**	**0.39**	**1.68**	**-0.4**	**-0.11**	**0.77**	**-0.055**	**-0.076**	**-0.43**	**0.26**	**-0.19**	**-0.26**	**0.47**	**0.68***
	(0.75)	**(0.41)**	**(0.98)**	**(0.76)**	**(0.39)**	**(0.68)**	**(0.59)**	**(0.24)**	**(0.33)**	**(0.26)**	**(0.31)**	**(0.29)**	**(0.36)**	**(0.41)**
Household is female headed	0	0.44	1.05	-0.99	-1.04	0.67	-1.22	-1.11**	-0.72	-0.5	-0.46	-0.21	-0.46	-0.16
	(.)	(0.84)	(1.33)	(0.87)	(0.92)	(0.90)	(0.86)	(0.39)	(0.54)	(0.36)	(0.51)	(0.41)	(0.51)	(0.54)
Highest Educ. in HH	0.82	-0.11	-0.034	0.057	-0.28	-0.55	-0.38	0.57**	-0.023	0.45*	0.12	0.25	0.53*	-0.15
	(0.60)	(0.29)	(0.60)	(0.53)	(0.29)	(0.65)	(0.51)	(0.19)	(0.24)	(0.21)	(0.24)	(0.23)	(0.29)	(0.33)
Asset Index	0.14	0.1	0.28	-0.097	0.043	0.35	0.69**	-0.0074	0.11	-0.19	-0.023	0.11	0.031	-0.15
	(0.47)	(0.22)	(0.40)	(0.37)	(0.21)	(0.27)	(0.23)	(0.11)	(0.17)	(0.099)	(0.13)	(0.13)	(0.12)	(0.16)
Number of people in the HH	0.11	0.079	-0.44	0.22	-0.15	0.054	0.31*	-0.0037	-0.13	0.014	0.12	0.054	-0.061	0.094
	(0.30)	(0.16)	(0.30)	(0.18)	(0.15)	(0.12)	(0.15)	(0.063)	(0.11)	(0.054)	(0.087)	(0.083)	(0.068)	(0.11)
Received Climate Advice	1.11	-0.0096	-1.51	-0.19	-0.55	0.083	0.55	-0.33	-0.015	-0.21	0.16	0.14	-0.077	-0.0036
	(0.80)	(0.49)	(0.81)	(0.75)	(0.47)	(0.64)	(0.56)	(0.26)	(0.36)	(0.24)	(0.33)	(0.31)	(0.31)	(0.41)
Off farm work income	-1.35	-1.01*	-1.44	0.41	-0.25	1.35	-1.65*	0.4	-0.1	0.11	0.24	0.36	0.033	-0.64
	(1.19)	(0.48)	(1.01)	(0.77)	(0.47)	(1.68)	(0.66)	(0.28)	(0.38)	(0.31)	(0.35)	(0.33)	(0.45)	(0.49)
Member in farmers group	-0.36	0.38	-0.32	0.32	0.26	0.72	1.34*	-0.039	0.26	-0.025	0.65*	-0.048	0.47	-0.33
	(0.76)	(0.39)	(0.81)	(0.90)	(0.38)	(0.73)	(0.68)	(0.26)	(0.33)	(0.26)	(0.33)	(0.32)	(0.34)	(0.46)
Used practice before	-0.45	-0.48	1.71	0		3.49**		0.5	0.67*	0.72*	0.23	0.14	-0.25	
	(0.91)	(0.39)	(1.01)	(.)		(1.28)		(0.31)	(0.32)	(0.31)	(0.45)	(0.30)	(0.65)	
Uganda								0.41	-1.16**			0.85		

								(0.33)	(0.36)			(0.45)		
Colombia								-3.32***		0.56	-2.23***	-0.97**		3.74***
								(0.56)		(0.51)	(0.52)	(0.34)		(0.48)
Guatemala								-2.80***		3.57***			0.077	
								(0.51)		(0.49)			(0.47)	
Honduras								-3.84***		1.56**			0	
								(0.82)		(0.58)			(.)	
Nicaragua								-1.26***		1.66***	-2.53***		0	
								(0.33)		(0.43)	(0.53)		(.)	
Constant	1.23	-0.43	0.45	0.8	1.38	-5.48*	-3.22**	-0.78	1.23	-3.02***	-0.12	0.13	-1.19	-2.33*
	(2.20)	(1.18)	(1.99)	(1.33)	(1.14)	(2.34)	(1.25)		(0.85)	(0.63)	(0.79)	(0.70)	(0.84)	(0.98)
Observations	124	132	132	80	132	112	99	602	214	520	315	313	196	231
Pseudo R-squared	0.085	0.042	0.154	0.057	0.031	0.184	0.241	0.326	0.119	0.192	0.323	0.089	0.049	0.404

APPENDIX 6 LOGIT AND ORDERED LOGIT MODEL BY OUTCOME GROUPS

VARIABLES	(6) Group1NS Dummy	(7) Group2CS Dummy	(8) Group3NL Dummy	(9) Group4CL Dummy	(5) Group1NS	(6) Group2CS	(7) Group3NL	(8) Group4CL
BL Agricultural credit	0.86	1.28	1.83	1.66*	0.91	1.30	1.61	1.63*
	(0.80)	(0.35)	(0.15)	(0.05)	(0.82)	(0.26)	(0.13)	(0.06)
BL female HH head	0.50	0.59*	0.61	0.75	0.89	0.56**	0.74	0.76
BL Highest education in HH	0.77	1.61***	1.15	1.14	0.94	1.49***	0.98	1.13
BL Asset index	1.15	0.96	0.90	1.04	1.33*	0.98	0.97	1.05
BL Number if HH members	1.02	0.97	1.14	1.10*	0.89	0.96	1.17**	1.10*
BL Owned land (ha)	1.01	1.01	1.02	1.01	1.01	1.01	1.02*	1.01
BL Climate advice	0.88	0.67*	1.19	0.84	0.90	0.64**	0.83	0.84
BL Off-farm work income	1.21	1.07	0.92	1.09	0.91	0.80	0.81	1.09
BL number of memberships in farmer groups[1]	0.99	1.35***	1.20	1.14*	1.11	1.33***	1.30***	1.14*
Site fixed effects								
Uganda	0.01***	1.42	-	0.61	0.00	0.60*	0.00	0.61
Colombia	-	0.07***	0.08***	0.34***	0.00	0.04***	0.07***	0.34***
Guatemala	-	0.90	-	0.27***	0.00	0.46**	0.00	0.28***
Honduras	-	0.11***	-	0.03***	0.00	0.06***	0.00	0.03***
Nicaragua	-	0.32***	1.52	0.65	0.00	0.23***	1.07	0.65
	59.94***	1.41	1.39	0.25***				
Observations	216	604	315	604	604	604	604	604
Pseudo R2	0.476	0.208	0.281	0.120	0.698	0.154	0.459	0.113

*** p<0.01, ** p<0.05, * p<0.1

APPENDIX 7 ROBUSTNESS CHECKS

Robustness Test 1: Controlling for model misspecification by comparing seemingly unrelated estimation and independent logit coefficients

VARIABLES	(1) Short Payback Dummy	(2) Long Payback Dummy	(3) Short Payback Dummy	(4) Long Payback Dummy	(5) Non-Capital Dummy	(6) Capital Dummy	(7) Non-Capital Dummy	(8) Capital Dummy
	SUEST	SUEST	LOGIT	LOGIT	SUEST	SUEST	LOGIT	LOGIT
BL Agricultural credit	0.13	0.46*	0.13	0.46	0.11	0.22	0.11	0.22
	(0.67)	(0.10)	(0.67)	(0.11)	(0.76)	(0.41)	(0.77)	(0.43)
BL female HH head	-0.57*	-0.37	-0.57*	-0.37	-0.7*	-0.43	-0.70*	-0.43
	(0.096)	(0.28)	(0.07)	(0.29)	(0.1)	(0.16)	(0.10)	(0.14)
BL Highest education in HH	0.47**	0.11	0.47**	0.11	0.16	0.41**	0.16	0.41**
	(0.023)	(0.60)	(0.02)	(0.57)	(0.51)	(0.03)	(0.49)	(0.02)
BL Asset index	-0.06	0.03	-0.06	0.03	-0.06	-0.06	-0.06	-0.06
	(0.517)	(0.77)	(0.54)	(0.78)	(0.63)	(0.47)	(0.64)	(0.51)
BL Number if HH members	-0.06	0.11**	-0.06	0.11**	0.08	0.02	0.08	0.02
	(0.29)	(0.03)	(0.27)	(0.05)	(0.27)	(0.73)	(0.31)	(0.70)
BL Owned land (ha)	-0.002	0.03	-0.00	0.03	0.01	0.02	0.01	0.02
	(0.883)	(0.40)	(0.90)	(0.23)	(0.65)	(0.12)	(0.66)	(0.21)
BL Climate advice	-0.41*	-0.27	-0.41*	-0.27	0.19	-0.27	0.19	-0.27
	(0.081)	(0.29)	(0.08)	(0.28)	(0.55)	(0.19)	(0.55)	(0.19)
BL Off-farm work income	-0.1	-0.20	-0.10	-0.20	-0.24	0.21	-0.24	0.21
	(0.728)	(0.47)	(0.73)	(0.47)	(0.46)	(0.4)	(0.48)	(0.40)
BL number of memberships	0.33***	0.13	0.33***	0.13	0.05	0.42	0.05	0.42***
in farmer groups[1]	(0.003)	(0.14)	(0.00)	(0.16)	(0.57)	(0)	(0.61)	(0.00)

Robustness Test 2: Alternative Model Specification

VARIABLES	(1) Adoption Count	(2) Non-Capital Intensive	(3) Capital Intensive	(4) Short Payback	(5) Long Payback	(6) Group1NS Dummy	(7) Group2CS Dummy	(8) Group3NL Dummy	(9) Group4CL Dummy
BL Agricultural credit	1.29	1.20	0.93	1.09	1.46	0.52	1.30	1.33	1.66*
	(0.41)	(0.50)	(0.84)	(0.79)	(0.18)	(0.33)	(0.33)	(0.46)	(0.05)
BL female HH head	0.48**	0.54**	0.44*	0.51**	0.85	0.38	0.51**	0.66	0.75
BL Highest education in HH	1.39	1.42**	1.01	1.58**	0.97	1.21	1.51**	0.86	1.14
BL Asset index	0.91	0.97	1.02	0.94	1.03	1.26	0.96	0.95	1.04
BL Number if HH members	0.98	0.99	1.05	0.93	1.09	1.01	0.96	1.03	1.10*
BL Owned land (ha)	1.02	1.03	1.11*	0.99	1.11**	0.94	1.00	1.19**	1.01
BL Climate advice	0.97	0.88	1.30	0.91	0.78	0.94	0.84	1.24	0.84
BL Off-farm work income	1.10	1.28	0.79	1.15	0.80	0.98	1.28	0.89	1.09
BL number of memberships in farmer groups[1]	1.33*	1.43***	0.98	1.28**	1.09	0.95	1.26**	1.19	1.14*
Site fixed effects									
Uganda	0.25***	0.81	0.08***	4.03***	0.05***	-	1.14		0.61
Colombia	0.04***	0.06***	0.04***	0.16***	0.08***	-	0.05***	0.10***	0.34***
Guatemala	0.21***	0.61	-	3.48***	0.04***	-	1.04		0.27***
Honduras	0.02***	0.06***	-	0.31**	0.00***	-	0.09***		0.03***
Nicaragua	-	0.40***	-		1.24	-	0.31***	2.21	0.65
Constant	12.51***	2.47*	6.11***	0.73	4.92***	0.48	1.91	2.97	0.25***
Observations	473	604	269	473	604	85	604	315	604
Pseudo R2	0.292	0.255	0.257	0.248	0.418	0.0585	0.230	0.321	0.120

*** p<0.01, ** p<0.05, * p<0.1

Robustness Check 3a: Additional Control Vector Dummy

VARIABLES	(1) Adoption Count	(2) Non-Capital Intensive	(3) Capital Intensive	(4) Short Payback	(5) Long Payback	(6) Group1NS Dummy	(7) Group2CS Dummy	(8) Group3NL Dummy	(9) Group4CL Dummy
BL Agricultural credit	1.20	1.15	1.20	1.02	1.54	0.96	1.14	1.59	1.69*
	(0.60)	(0.74)	(0.54)	(0.95)	(0.18)	(0.95)	(0.64)	(0.34)	(0.06)
BL female HH head	0.62	0.56	0.69	0.69	0.71	0.68	0.66	0.78	0.69
	(0.20)	(0.22)	(0.23)	(0.28)	(0.35)	(0.64)	(0.18)	(0.65)	(0.30)
BL Highest education in HH	1.46	1.25	1.51**	1.57**	1.17	0.54	1.59***	1.40	1.12
	(0.10)	(0.41)	(0.02)	(0.04)	(0.44)	(0.16)	(0.01)	(0.21)	(0.54)
BL Number if HH members	1.00	1.09	1.04	0.97	1.11*	1.11	0.98	1.13	1.09
	(0.99)	(0.35)	(0.48)	(0.59)	(0.08)	(0.51)	(0.73)	(0.22)	(0.14)
BL Owned land (ha)	1.02	1.00	1.02	0.99	1.03	1.01	1.01	1.02	1.01
	(0.62)	(0.86)	(0.20)	(0.68)	(0.35)	(0.89)	(0.47)	(0.40)	(0.25)
BL Climate advice	0.96	1.10	0.79	0.70	0.70	1.10	0.67*	0.97	0.84
	(0.87)	(0.78)	(0.28)	(0.14)	(0.17)	(0.88)	(0.06)	(0.94)	(0.46)
BL Off-farm work income	1.03	1.01	1.29	0.94	0.91	2.06	1.15	1.00	1.12
	(0.92)	(0.98)	(0.31)	(0.84)	(0.74)	(0.23)	(0.58)	(0.99)	(0.68)
BL number of memberships in farmer groups[1]	1.36*	1.02	1.52***	1.35***	1.15	0.91	1.31***	1.27	1.15*
	(0.08)	(0.84)	(0.00)	(0.01)	(0.17)	(0.59)	(0.01)	(0.24)	(0.07)
BL Adoption Index	0.92	0.94	1.10	1.02	1.05	1.07	1.12	1.02	1.04
	(0.62)	(0.68)	(0.45)	(0.92)	(0.71)	(0.77)	(0.33)	(0.93)	(0.72)
BL other income	0.40***	0.99	0.67*	0.55**	0.93	1.06	0.66*	0.64	1.19
	(0.00)	(0.97)	(0.07)	(0.02)	(0.75)	(0.91)	(0.05)	(0.18)	(0.42)
BL Bank account ownership	0.90	0.88	1.47	0.99	0.86	2.43	1.19	0.65	0.89
	(0.81)	(0.83)	(0.28)	(0.97)	(0.69)	(0.27)	(0.60)	(0.42)	(0.72)
BL Energy Asset Count	0.53	0.43*	0.50*	0.47*	0.56	0.61	0.56	0.37**	0.66
	(0.15)	(0.09)	(0.06)	(0.10)	(0.14)	(0.57)	(0.12)	(0.03)	(0.26)
BL Information Asset Count	0.74	0.58	0.68*	0.65*	0.77	0.30	0.72	0.67	0.83
	(0.24)	(0.12)	(0.08)	(0.07)	(0.32)	(0.18)	(0.13)	(0.25)	(0.46)

BL Transport Asset Count	1.09	1.20	1.33	1.69**	1.29	2.61	1.39	0.86	1.81**
	(0.74)	(0.58)	(0.20)	(0.03)	(0.33)	(0.18)	(0.15)	(0.69)	(0.02)
BL Production Asset Count	1.56	2.30*	1.09	0.92	1.56		1.01	2.38**	0.89
	(0.31)	(0.05)	(0.79)	(0.83)	(0.21)		(0.96)	(0.04)	(0.72)
BL Hired Labour	0.67	1.19	0.94	1.02	1.65*	1.00	1.16	2.04	1.33
	(0.16)	(0.66)	(0.78)	(0.93)	(0.08)	(0.99)	(0.54)	(0.12)	(0.29)
BL Farm Dependence	1.04	1.06	1.07	1.11	0.98	1.06	1.08	1.00	0.91
	(0.77)	(0.75)	(0.52)	(0.31)	(0.85)	(0.88)	(0.42)	(0.99)	(0.39)
BL Commercialization	1.13	0.94	1.10	1.07	0.99	1.01	1.06	0.93	0.97
	(0.24)	(0.59)	(0.23)	(0.48)	(0.90)	(0.96)	(0.43)	(0.49)	(0.71)
BL Diversification	1.19*	1.27**	1.05	1.15	1.16*	1.19	1.08	1.31**	1.08
	(0.07)	(0.03)	(0.53)	(0.12)	(0.08)	(0.42)	(0.30)	(0.02)	(0.32)
BL Ownership Big Animal	0.51*	0.50*	0.62	0.65	0.55*	0.36	0.69	0.37*	0.66
	(0.07)	(0.09)	(0.10)	(0.17)	(0.09)	(0.12)	(0.21)	(0.06)	(0.20)
Uganda	0.25*	0.10***	1.20	3.10**	0.09***	0.01***	1.93*		0.78
	(0.05)	(0.00)	(0.66)	(0.05)	(0.00)	(0.00)	(0.09)		(0.51)
Colombia	0.03***	0.04***	0.15***	0.19***	0.12***		0.13***	0.05***	0.59
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.37)
Guatemala	0.04**		0.55	3.27	0.01***		1.63		0.58
	(0.01)		(0.59)	(0.25)	(0.00)		(0.66)		(0.61)
Honduras	0.00***		0.08**	0.33	0.00***		0.18		0.08*
	(0.00)		(0.02)	(0.29)	(0.00)		(0.12)		(0.05)
Nicaragua	-	-	0.58		1.47		0.52	1.44	1.08
			(0.27)		(0.51)		(0.16)	(0.60)	(0.88)
Constant	9.43**	1.36	0.69	0.33	0.92	21.86*	0.39	0.47	0.15***
	(0.01)	(0.75)	(0.60)	(0.17)	(0.92)	(0.09)	(0.18)	(0.48)	(0.01)
Observations	469	265	600	469	600	199	600	311	600
Pseudo R2	0.331	0.297	0.248	0.261	0.413	0.513	0.227	0.359	0.140

p-value in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Robustness Check 3b: Additional Control Vector Dummy

VARIABLES	(1) EL Adoption Count	(2) Non-Capital	(3) Capital	(4) Short Payback	(5) Long Payback	(6) Group1NS Dummy	(7) Group2CS Dummy	(8) Group3NL Dummy	(9) Group4CL Dummy
BL Agricultural credit	1.38	1.25	1.39	1.08	1.54*	0.96	1.20	1.37	1.64*
	(0.16)	(0.43)	(0.16)	(0.76)	(0.09)	(0.91)	(0.45)	(0.34)	(0.07)
BL female HH head	0.64*	0.83	0.62*	0.63	0.76	0.92	0.61*	0.97	0.70
	(0.10)	(0.60)	(0.07)	(0.11)	(0.39)	(0.88)	(0.08)	(0.94)	(0.31)
BL Highest education in HH	1.35**	0.97	1.43**	1.34*	1.08	0.82	1.43**	1.05	1.10
	(0.03)	(0.85)	(0.02)	(0.06)	(0.62)	(0.41)	(0.02)	(0.80)	(0.58)
BL Number if HH members	1.03	1.10	1.02	0.96	1.13**	0.87	0.97	1.17**	1.09
	(0.50)	(0.17)	(0.70)	(0.37)	(0.02)	(0.23)	(0.54)	(0.04)	(0.13)
BL Owned land (ha)	1.01	1.01	1.01	1.00	1.01	1.01	1.00	1.01	1.01
	(0.26)	(0.36)	(0.26)	(0.82)	(0.12)	(0.64)	(0.58)	(0.16)	(0.25)
BL Climate advice	0.73*	0.85	0.69**	0.67**	0.74	0.92	0.65**	0.75	0.85
	(0.08)	(0.49)	(0.04)	(0.03)	(0.15)	(0.82)	(0.03)	(0.31)	(0.50)
BL Off-farm work income	0.95	0.95	0.92	0.89	0.96	0.96	0.86	0.92	1.12
	(0.79)	(0.83)	(0.71)	(0.62)	(0.86)	(0.92)	(0.52)	(0.77)	(0.67)
BL number of memberships	1.28***	1.21**	1.27***	1.27***	1.24***	1.11	1.28***	1.30***	1.15*
in farmer groups[1]	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.41)	(0.00)	(0.00)	(0.07)
BL Adoption Index	1.00	0.96	1.02	0.98	1.02	0.98	1.00	0.98	1.04
	(0.97)	(0.69)	(0.83)	(0.83)	(0.89)	(0.90)	(0.99)	(0.86)	(0.76)
BL other income	0.72*	0.83	0.83	0.73*	0.93	0.88	0.71*	0.71	1.19
	(0.06)	(0.39)	(0.31)	(0.09)	(0.71)	(0.68)	(0.07)	(0.18)	(0.42)
BL Bank account ownership	1.13	1.14	1.03	1.37	0.83	2.68**	1.10	0.69	0.89
	(0.65)	(0.68)	(0.90)	(0.24)	(0.54)	(0.03)	(0.72)	(0.38)	(0.74)
BL Energy Asset Count	0.61	0.73	0.56*	0.61	0.74	1.23	0.60	0.65	0.68
	(0.12)	(0.39)	(0.07)	(0.13)	(0.37)	(0.70)	(0.13)	(0.32)	(0.29)
BL Information Asset Count	0.66**	0.68	0.68**	0.61**	0.79	0.51	0.66**	0.76	0.84
	(0.03)	(0.17)	(0.05)	(0.02)	(0.30)	(0.18)	(0.05)	(0.36)	(0.47)

BL Transport Asset Count	1.60**	1.26	1.77***	1.82***	1.49*	1.69	1.67**	1.11	1.84**
	(0.01)	(0.37)	(0.00)	(0.00)	(0.07)	(0.33)	(0.01)	(0.73)	(0.01)
BL Production Asset Count	1.17	1.43	0.95	1.04	1.12	1.60	0.94	1.37	0.89
	(0.54)	(0.22)	(0.83)	(0.89)	(0.67)	(0.44)	(0.84)	(0.29)	(0.71)
BL Hired Labour	1.06	1.45	1.16	1.07	1.60**	1.09	1.14	1.86*	1.36
	(0.78)	(0.18)	(0.47)	(0.76)	(0.05)	(0.84)	(0.55)	(0.06)	(0.25)
BL Farm Dependence	1.11	1.19	1.02	1.11	0.99	1.08	1.08	1.10	0.90
	(0.22)	(0.16)	(0.77)	(0.25)	(0.89)	(0.72)	(0.37)	(0.46)	(0.34)
BL Commercialization	1.03	1.02	1.03	1.06	0.98	1.19*	1.04	0.97	0.97
	(0.59)	(0.83)	(0.60)	(0.34)	(0.72)	(0.07)	(0.58)	(0.69)	(0.72)
BL Diversification	1.15**	1.18**	1.12*	1.17**	1.15*	1.06	1.14*	1.16*	1.08
	(0.03)	(0.04)	(0.08)	(0.02)	(0.05)	(0.67)	(0.06)	(0.09)	(0.33)
BL Ownership Big Animal	0.53***	0.60*	0.58**	0.56**	0.66	0.45	0.65	0.77	0.67
	(0.01)	(0.10)	(0.03)	(0.03)	(0.14)	(0.13)	(0.10)	(0.48)	(0.22)
Uganda	0.07***	0.00***	0.65	0.01***	0.06***	0.00	0.70	0.00	0.80
	(0.00)	(0.00)	(0.17)	(0.00)	(0.00)	(0.98)	(0.27)	(0.99)	(0.56)
Colombia	0.01***	0.00***	0.11***	0.00***	0.10***	0.00	0.07***	0.07***	0.61
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.99)	(0.00)	(0.00)	(0.40)
Guatemala	0.01***	0.00	0.63	0.00***	0.03***	0.00	0.92	0.00	0.63
	(0.00)	(0.99)	(0.61)	(0.00)	(0.00)	(0.99)	(0.93)	(0.99)	(0.67)
Honduras	0.00***	0.00	0.07***	0.00***	0.00***	0.00	0.11**	0.00	0.09*
	(0.00)	(0.99)	(0.01)	(0.00)	(0.00)	(0.99)	(0.03)	(0.99)	(0.05)
Nicaragua	0.10***	0.01***	0.54	0.00***	1.32	0.00	0.44*	1.42	1.12
	(0.00)	(0.00)	(0.11)	(0.00)	(0.50)	(0.99)	(0.05)	(0.46)	(0.82)
/cut1	0.03***	0.00***	0.75	0.01***	0.86	0.00	0.93	1.70	6.91***
	(0.00)	(0.00)	(0.63)	(0.00)	(0.82)	(0.98)	(0.91)	(0.53)	(0.01)
/cut2	0.15***	0.07***	4.45**	0.05***	7.31***	0.02***	8.71***	20.50***	535.18***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
/cut3	0.51	0.72	24.97***	0.55	33.45***	0.41	142.09***	343.46***	
	(0.27)	(0.67)	(0.00)	(0.36)	(0.00)	(0.47)	(0.00)	(0.00)	
/cut4	1.99	4.80**	197.11***	2.61	495.56***				
	(0.25)	(0.04)	(0.00)	(0.13)	(0.00)				

/cut5	5.24***	23.40***		10.84***					
	(0.01)	(0.00)		(0.00)					
/cut6	13.82***	207.23***		80.26***					
	(0.00)	(0.00)		(0.00)					
/cut7	47.95***								
	(0.00)								
/cut8	102.48***								
	(0.00)								
Observations	600	600	600	600	600	600	600	600	600
Pseudo R2	0.258	0.528	0.157	0.372	0.296	0.710	0.171	0.478	0.132

pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Robustness Test 4a: Alternative Credit Specification: Did you ever use credit? Adoption Dummy

VARIABLES	(1) EL Adoption	(2) Non-Capital Dummy	(3) Capital Dummy	(4) Short Payback Dummy	(5) Long Payback Dummy	(6) Group1NS Dummy	(7) Group2CS Dummy	(8) Group3NL Dummy	(9) Group4CL Dummy
BL Agricultural credit	1.00	0.82	1.21	1.35	1.75**	0.67	1.20	1.33	1.45*
	(0.99)	(0.52)	(0.36)	(0.23)	(0.02)	(0.42)	(0.37)	(0.36)	(0.09)
BL female HH head	0.48**	0.50*	0.65	0.56*	0.71	0.52	0.59*	0.63	0.76
	(0.03)	(0.10)	(0.14)	(0.07)	(0.31)	(0.37)	(0.07)	(0.32)	(0.42)
BL Highest education in HH	1.41	1.20	1.49**	1.57**	1.10	0.79	1.61***	1.15	1.12
	(0.11)	(0.44)	(0.02)	(0.03)	(0.63)	(0.51)	(0.00)	(0.56)	(0.49)
BL Asset index	0.92	0.95	0.94	0.94	1.02	1.18	0.96	0.91	1.04
	(0.45)	(0.72)	(0.51)	(0.49)	(0.84)	(0.51)	(0.65)	(0.45)	(0.67)
BL Number if HH members	0.98	1.09	1.02	0.94	1.12**	1.04	0.97	1.15	1.10*
	(0.71)	(0.31)	(0.71)	(0.25)	(0.05)	(0.79)	(0.48)	(0.11)	(0.08)
BL Owned land (ha)	1.02	1.01	1.02	1.00	1.03	1.00	1.01	1.02	1.01
	(0.57)	(0.63)	(0.21)	(0.84)	(0.25)	(0.97)	(0.37)	(0.29)	(0.22)
BL Climate advice	1.00	1.26	0.77	0.66*	0.76	0.92	0.67*	1.25	0.85
	(0.99)	(0.46)	(0.20)	(0.08)	(0.26)	(0.87)	(0.06)	(0.50)	(0.47)
BL Off-farm work income	1.08	0.79	1.21	0.91	0.79	1.29	1.06	0.88	1.05
	(0.79)	(0.48)	(0.43)	(0.73)	(0.41)	(0.63)	(0.80)	(0.70)	(0.85)
BL number of memberships	1.33*	1.06	1.53***	1.39***	1.13	1.00	1.35***	1.20	1.13*
in farmer groups[1]	(0.06)	(0.55)	(0.00)	(0.00)	(0.21)	(0.98)	(0.00)	(0.25)	(0.09)
Site fixed effects									
Uganda	0.26***	0.11***	1.00	4.82***	0.07***	0.01***	1.42		0.62
	(0.01)	(0.00)	(0.99)	(0.00)	(0.00)	(0.00)	(0.29)		(0.14)
Colombia	0.04***	0.06***	0.09***	0.20***	0.09***		0.07***	0.10***	0.38**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.02)
Guatemala	0.20***		0.55	3.05***	0.04***		0.93		0.30***

	(0.00)		(0.13)	(0.01)	(0.00)		(0.85)		(0.00)
Honduras	0.02***		0.08***	0.36**	0.00***		0.11***		0.04***
	(0.00)		(0.00)	(0.03)	(0.00)		(0.00)		(0.00)
Nicaragua	-	-	0.42***		1.04		0.32***	1.52	0.66
			(0.01)		(0.92)		(0.00)	(0.29)	(0.17)
Constant	11.95***	3.16*	1.51	0.64	2.33	53.33***	1.37	1.24	0.23***
	(0.00)	(0.07)	(0.40)	(0.38)	(0.14)	(0.00)	(0.51)	(0.76)	(0.00)
Observations	473	269	605	473	605	217	605	316	605
Pseudo R2	0.291	0.240	0.228	0.234	0.392	0.480	0.209	0.278	0.118

p-value in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Robustness Test 4b: Alternative Credit specification: “Borrowed from formal source” and “Borrowed from informal source”, Adoption Dummy

VARIABLES	(1) EL Adoption	(2) Non-Capital Dummy	(3) Capital Dummy	(4) Short Payback Dummy	(5) Long Payback Dummy	(6) Group1NS Dummy	(7) Group2CS Dummy	(8) Group3NL Dummy	(9) Group4CL Dummy
BL formal borrowing	0.83	1.04	1.07	1.27	2.56***	0.99	1.05	2.47*	1.18
	(0.63)	(0.94)	(0.82)	(0.50)	(0.00)	(0.98)	(0.85)	(0.06)	(0.54)
BL informal borrowing	0.99	0.33***	1.23	1.31	0.81	0.30*	1.25	0.44**	1.57*
	(0.98)	(0.00)	(0.46)	(0.40)	(0.50)	(0.08)	(0.43)	(0.04)	(0.10)
BL female HH head	0.48**	0.51	0.66	0.57*	0.71	0.56	0.59*	0.65	0.76
	(0.03)	(0.11)	(0.14)	(0.07)	(0.32)	(0.42)	(0.07)	(0.35)	(0.42)
BL Highest education in HH	1.41	1.26	1.50**	1.59**	1.16	0.86	1.61***	1.20	1.12
	(0.11)	(0.34)	(0.02)	(0.02)	(0.43)	(0.67)	(0.00)	(0.44)	(0.49)
BL Asset index	0.93	1.02	0.94	0.93	1.03	1.29	0.96	0.93	1.03
	(0.48)	(0.88)	(0.51)	(0.46)	(0.74)	(0.35)	(0.65)	(0.61)	(0.73)
BL Number if HH members	0.98	1.10	1.02	0.94	1.13**	1.04	0.97	1.15	1.10*
	(0.71)	(0.25)	(0.71)	(0.26)	(0.03)	(0.77)	(0.48)	(0.10)	(0.09)
BL Owned land (ha)	1.02	1.02	1.02	1.00	1.04	1.00	1.01	1.03	1.01
	(0.58)	(0.50)	(0.22)	(0.79)	(0.20)	(0.95)	(0.40)	(0.24)	(0.28)
BL Climate advice	1.00	1.28	0.77	0.66*	0.77	0.87	0.67*	1.28	0.85
	(0.99)	(0.45)	(0.21)	(0.07)	(0.27)	(0.78)	(0.06)	(0.46)	(0.46)
BL Off-farm work income	1.09	0.71	1.23	0.89	0.69	1.19	1.08	0.73	1.08
	(0.76)	(0.32)	(0.41)	(0.70)	(0.20)	(0.75)	(0.76)	(0.39)	(0.76)
BL number of memberships	1.32*	1.10	1.52***	1.38***	1.16	0.98	1.34***	1.28	1.12
in farmer groups[1]	(0.07)	(0.32)	(0.00)	(0.00)	(0.14)	(0.91)	(0.00)	(0.12)	(0.11)
Site fixed effects									
Uganda	0.27**	0.11***	0.99	4.58***	0.07***	0.01***	1.40		0.60

	(0.01)	(0.00)	(0.97)	(0.00)	(0.00)	(0.00)	(0.32)		(0.11)
Colombia	0.04***	0.07***	0.09***	0.19***	0.13***		0.06***	0.15***	0.36**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.01)
Guatemala	0.20***		0.54	2.95***	0.04***		0.90		0.29***
	(0.00)		(0.12)	(0.01)	(0.00)		(0.78)		(0.00)
Honduras	0.02***		0.08***	0.35**	0.00***		0.11***		0.04***
	(0.00)		(0.00)	(0.03)	(0.00)		(0.00)		(0.00)
Nicaragua	-	-	0.42***		1.23		0.32***	1.86	0.66
			(0.01)		(0.61)		(0.00)	(0.12)	(0.18)
Constant	11.86***	2.70	1.55	0.68	2.09	44.51***	1.41	1.10	0.26***
	(0.00)	(0.13)	(0.37)	(0.45)	(0.20)	(0.00)	(0.47)	(0.90)	(0.01)
Observations	473	269	605	473	605	217	605	316	605
Pseudo R2	0.291	0.261	0.227	0.233	0.396	0.490	0.209	0.297	0.118

p-value in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Robustness Test 5: Stepwise inclusion of control variables (Only credit coefficients displayed)

Outcome variables	(1) Only Credit	(2) Add female head	(3) Add HH Education	(4) Add HH Size	(5) Add Asset Index	(6) Add owned land	(7) Add Climate Advice	(8) Add Off farm work income	(9) Membership in farmers group
Adoption Dummy	1.36	1.31	1.22	1.23	1.28	1.28	1.27	1.28	1.29
	(0.29)	(0.35)	(0.50)	(0.49)	(0.41)	(0.42)	(0.44)	(0.42)	(0.42)
Adoption Count	1.54**	1.51**	1.43*	1.41*	1.39	1.40	1.44*	1.45*	1.39
	(0.04)	(0.05)	(0.09)	(0.10)	(0.12)	(0.12)	(0.09)	(0.09)	(0.12)
Capital Dummy	1.37	1.34	1.24	1.23	1.25	1.25	1.28	1.28	1.24
	(0.22)	(0.25)	(0.41)	(0.42)	(0.40)	(0.40)	(0.36)	(0.34)	(0.43)
Non-Capital Dummy	1.24	1.22	1.18	1.17	1.19	1.18	1.12	1.12	1.12
	(0.54)	(0.57)	(0.65)	(0.66)	(0.64)	(0.65)	(0.76)	(0.76)	(0.77)
Short Payback Dummy	1.24	1.22	1.11	1.11	1.15	1.16	1.20	1.20	1.14
	(0.46)	(0.49)	(0.72)	(0.71)	(0.63)	(0.62)	(0.54)	(0.54)	(0.67)
Long Payback Dummy	1.72*	1.70*	1.65*	1.60*	1.55	1.56	1.61*	1.60	1.59
	(0.05)	(0.06)	(0.08)	(0.10)	(0.13)	(0.12)	(0.10)	(0.11)	(0.11)
Group1NS Dummy	0.84	0.89	0.91	0.91	0.87	0.88	0.89	0.86	0.86
	(0.76)	(0.84)	(0.87)	(0.86)	(0.81)	(0.82)	(0.85)	(0.80)	(0.80)
Group2CS Dummy	1.38	1.36	1.25	1.25	1.27	1.27	1.32	1.32	1.28
	(0.21)	(0.22)	(0.38)	(0.38)	(0.36)	(0.36)	(0.29)	(0.29)	(0.35)
Group3NL Dummy	2.11*	2.01*	1.96	1.91	1.97	1.96	1.86	1.84	1.83
	(0.07)	(0.09)	(0.10)	(0.11)	(0.10)	(0.10)	(0.14)	(0.15)	(0.15)
Group4CL Dummy	1.80**	1.78**	1.72**	1.70**	1.65*	1.65*	1.68**	1.68**	1.66*
	(0.02)	(0.02)	(0.03)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)