Spring 5-18-2018

Do Climate Shocks Affect Smallholder Farmers' Conservation Practices? Evidence from Peru

Heleene Tambet
htambet@gmail.com

Do Climate Shocks Affect Smallholder Farmers' Conservation Practices? Evidence from Peru

Key Words: *Climate Change, Smallholders, Adaptation, Conservation*

Heleene Tambet

e-mail: *htambet@usfca.edu*

Department of Economics
University of San Francisco
2130 Fulton St.
San Francisco, CA 94117

Thesis Submission for the Masters of Science Degree
in International and Development Economics

May 2018

Abstract: Peruvian agriculture is estimated to be subject to the greatest impacts of climate change in South America. Resulting shifts in rainfall patterns and extreme temperature realizations impose more frequent abnormal weather shocks on farmers and their production decisions. I study the impact of such shocks on agricultural practice choices of farmers growing two main staples, maize and potato; namely, I analyze adoption of practices reducing soil degradation, practices aimed towards water conservation, and application of inorganic fertilizer. I utilize unique cross-sectional data from Peru National Agricultural Survey over the years 2014 to 2016 in conjunction with long-term climate data, and construct georeferenced shocks posed by unusual rainfall levels as well as unusual variation by using a novel approach in the literature. I then apply fixed effects estimation to analyze how experienced shocks and, plausibly, changed perception regarding the riskiness of their environment affect farmers' choice of practices over an agricultural year following a shock(s). My analysis shows that soil practices' adoption is not sensitive to previous year's shocks but increases after multiple years abnormal rainfall, while rate of fertilizer users goes up by 7 to 9 percentage points following a drought year. Use of water conservation measures decreases drastically after years of abnormally high rainfall or low variability of it. I find limited heterogeneities in responses.

1. Introduction

In 2006, the seminal Stern Review claimed Peru to be one of the most vulnerable countries to climate change in the world (Stern 2006). IPCC[1] Special Report on Emissions Scenarios later estimated that Peru is going to see the greatest change in temperature levels among South American countries, with an estimated increase of 0.7°C to 1.8°C by 2020 and 1°C to 4°C by 2050 (Nakicenovic et al. 2000). As rainfall levels and patterns are expected to go through major shifts, weather-related emergencies became six times more frequent over the period of 1997 to 2006, and Peru's glaciers have irretrievably lost over third of their surface area since 1970 (MINAM 2010; USAID 2018). At the same time, 8.9 million people out of country's population of 31 million are involved in agriculture, a sector extremely vulnerable to more prevalent extreme heat and increasing water shortages (CIA 2017).

Globally, hundreds of millions of the world's poorest people depend directly on smallholder farming economies. These systems are tied to climate change through a double link: on one hand, there is a need for farmers to adapt to changing conditions; on the other hand, agricultural practices play an important part in the mitigation process (World Bank et al. 2015; Cohn et al. 2017). These facts underline the need to understand how farmers perceive and adapt to climate change, in order to guide future adaptation strategies and policy responses to reduce the negative impacts of changing weather patterns (Lipper et al. 2015). Potential on-farm responses from smallholder households include diversifying income among multiple crops (Arslan et al. 2017), changing the portfolio of crops/varieties and livestock (Seo and Mendelsohn 2007; Salazar-Espinoza et al. 2015), modifying planting times (Deressa et al. 2008), adopting improved soil and water conservation practices (Kurukulasuriya et al. 2008; Arslan et al. 2014, 2017), and adjusting the quantity of inputs applied (Salazar-Espinoza et al. 2015).

In the context of Peru, the World Bank has identified Climate Smart Agriculture (CSA) concept as a high-potential coping mechanism for smallholder agriculture (World Bank et al. 2015). CSA is an approach that involves different elements embedded in local context; farming practices are considered CSA if they maintain or achieve increases in productivity as well as contribute towards at least one of the other objectives of CSA, adaptation to climate change and/or reduction in greenhouse gas emissions (FAO 2012; World Bank et al. 2015). While hundreds of technologies and approaches around the world fall under the heading of CSA, in the current study I am going to

[1] Intergovernmental Panel on Climate Change

look at the adoption of those measured by the Peru National Agricultural Survey as desirable conservation practices. Importantly, although there is a wide range of practices that have the potential to increase the adaptive capacity of farming systems as well as to reduce emissions or enhance carbon storage in agricultural soils and biomass, implementing them may be costly for smallholders themselves, especially in the short run (McCarthy et al. 2011).

Therefore, in what follows, the main question I am going to ask is whether farmers themselves change their production behavior after they have witnessed unusual weather realizations. I am going to use repeated cross-sections of nationally representative agricultural survey data in conjunction with climate data that spans over the last 30 years, and therefore allows me to identify spatially and temporarily comparable weather shocks with high precision. I can then measure how changes in aggregated use of conservation practices on the level of small geographically homogenous units differ over time for those who receive (a) weather shock(s) and for those who do not. The study focuses exclusively on smallholders growing two main staples – potato and maize – that both form the basis of Peruvian diet, are in big part grown in the Andes highlands exposed to volatile weather patterns, and are cultivated as subsistence crops.

My results show robust evidence that Peruvian smallholders' adoption rates of soil conservation measures do not change, on average, after a year of abnormal rainfall, whether in terms of levels or variation. On the other hand, it appears that multiple years of both, too high and too low rainfall levels incentivizes more farmers to engage in these soil practices: I find an average treatment effect of 0.06 standard deviation increase in the composite soil practice adoption index for every additional year of excessive rainfall or drought, over the past 3- or 5-year window, respectively. Importantly, I find that at the same time the rate of chemical fertilizer application goes up after a single rainfall shock year, leading to the discussion about long- and short-term benefits of these two types of farmer responses towards maintenance of soil nutrients. Finally, as opposed to soil conservation, water conservation practices are rather sensitive to past year's abnormal weather and not to multiple years of shocks.

The main policy implication of the study is to contribute to the understanding of the likely uptake of farm-level adaptations in response to climatic variability. It is important to be able to differentiate between adaptations that farmers undertake autonomously, i.e. as a regular part of on-going management, from those that are consciously and specifically planned under climate-related risks (Smit and Skinner 2002), while as of today, relatively little empirical work has been done to examine the climatic factors that incentivize farmers to adopt different practices (Arslan et al. 2017;

Lipper et al. 2018). Additionally, the majority of the relevant studies come exclusively from African countries (Hassan et al. 2008; Seo et al. 2009; Deressa et al. 2010; Kassie et al. 2013; Teklewood et al. 2013; Asfaw et al. 2014; Arslan et al. 2014), while quantitative analyses of South American farmers' responses to weather shocks are rare[2]. In terms of empirical strategy, the study has a threefold contribution to the existing literature. First, I use large, nationally representative plot-level survey data that despite its rich socio-economic information has, to my knowledge, not yet been used in any empirical studies. Secondly, rainfall data that provide my identifying variation have likely the highest possible spatial resolution that is currently available for the area. Lastly, differently from the majority of prior studies, I conduct summary indices instead of analyzing each practice as a separate outcome to avoid the multiple hypothesis testing bias.

The rest of the paper is organized as follows. Section 2 discusses the relevant economic theory, empirical evidence on adaptation and conservation practices up to date, and the context of agriculture and climate change in Peru. Section 3 describes the empirical strategy. Section 4 introduces the data sources and construction of weather variables. Section 5 covers the econometric analysis and results. Section 6 discusses the findings, inference and limitations of the study, while Section 7 concludes with final remarks and policy recommendations.

2. Literature Review

2.1. Economic Theory

My study is based on theories of adoption and adaptation; the common objective for both subfields is to model economic agents' decisions on whether or not to undertake a given course of action. The central idea to the long stretch of literature on adoption – now also used by the adaptation studies – is that households are assumed to maximize their utility subject to their constraints, and adopt a given technology/input if and only if the selection decision is expected to be beneficial (Zilberman et al. 2012).

Modeling the course of adoption of a new technology started with seminal papers from Griliches (1957) and Rogers (1962). The latter set the general conceptual framework where diffusion of a new technology is modelled using an S-shaped curve. Central to this initial stage of theory is the assumption that farmers are homogenous, and therefore new innovations diffuse as farmers imitate each other, while different exogenous sources of heterogeneity affect the timing and magnitude of

[2] Seo and Mendelsohn (2008) analysis of crop choice across seven South American countries is methodologically the closest study to mine in the region.

adoption (Zilberman et al. 2000). It is later stated that these approaches lack a clear microeconomic foundation, namely explicit modeling of behavior by individuals (Zhao 2012). Thus, the family of threshold models was designed to overcome these shortcomings and to account for population heterogeneities (David 1975; Feder et al. 1985). The threshold model moves from diffusion to adoption process, and assumes that individuals make adoption decisions using economic decision-making rules; two other central assumptions are the heterogeneity of potential adopters (in terms of location, farm size, farm quality, human capital), and existence of dynamic processes/forces that make technology more attractive over time (Zilberman et al. 2000). This is where the literature prevailingly adopts the static expected utility portfolio model – a framework of choice for most applied work in agricultural economics –, where the main goal of a decision maker is to maximize his/her profits and, through that, utility (Zhao et al. 2012).

In summary, the earlier theory on farm-level adoption suggests that at each moment decision-makers select technologies with the best-expected net benefits, and thus, when a new technology is available, decision-makers continuously evaluate whether or not to adopt; when the discounted expected benefits of adoption are greater than the cost, the technology is going to be adopted. What varies across production units is timing of adoption, and that reflects differences in size, human capital, land quality, etc. However, this approach does not allow for adopters to incorporate dynamic learning processes, which for in the following literature the static expected utility portfolio model was replaced with a continuous optimization problem (Zilberman et al. 2000). Subsequent studies such as Foster and Rosenzweig (1995), Bandiera and Rasul (2006), and Conley and Udry (2010) integrate social interactions between farmers as a central piece in explaining the spread of new technologies.

A wide branch of literature has focused on the impact that risk has on production decisions, where technology adoption is a channel feeding into eventual production function that also incorporates different levels of risk. Moschini and Hennessy (2001) show how the most important economic modelling tools, *optimization* and *equilibrium* have only limited use under uncertainty, and a valid model of decision making under risk requires accounting for the entire distribution of risky variables that the agents are exposed to. It then needs to take into account how this randomness affects the distribution of outcomes over alternative courses of action. Simply put, decision maker's problem is more difficult under uncertainty as opposed to under certainty. According to Bardhan and Udry (1999), theory of risk in agricultural economy has three broader steps, if analyzed from the household perspective. Firstly, determining whether Pareto-efficient allocation of risk within a community is possible; seminal papers by Townsend (1994) and Udry (1995) have established that full risk-pooling is rarely achieved. Secondly, if full risk-pooling is not possible, a substitution by intertemporal consumption/income smoothing is attempted through saving and credit markets. Finally, if a (risk-averse) household is not able to achieve an entirely smooth consumption path through *ex post* mechanisms, it has an incentive to reallocate resources in production decisions in order to secure a less variable income stream through *ex ante* coping mechanisms (Bardhan et al. 1999; Salazar-Espinosa et al. 2015). Such measures involve maintaining diversified portfolio of land, and adopting conservative production technologies such as intercropping or drought-resistant crops, which for such decisions run into the climate change adaptation literature. These theoretical models as well as contribution from Binswanger et al. (1993) show that poorer households (which are more likely to be subject to binding liquidity constraints) choose a more conservative portfolio of activities than richer households, explaining why such households opt into activities that reduce the variance of their incomes but that also have lower expected incomes than the activities chosen by wealthier households.

The core difference between the question I ask and the traditional (agricultural) technology adoption literature is that the latter almost exclusively considers *modern technology* adoption, i.e. something that makes farmer incur fixed costs, that involves learning and information asymmetries, and which therefore is described by uncertain productivity. Adopting conservation practices, on the other hand, could be first seen as a response to uncertainty *posed* by exogenous climate forces, so that we could expect farmer to adopt if he/she behaves in a way that minimizes encountered risks. On the other hand, adoption and adaptation can both be modeled by using similar tools, as both are discrete responses to (plausibly) exogenous changes (Zilberman et al. 2004; Asfaw et al. 2014).

Adaptation has been defined as the response of economic agents and societies to political and economic shocks (e.g. famine) or major environmental changes (e.g. climate change) (Zhao et al. 2012). In the context of weather, it consists of adjustments that economics agents make in order to cope with a change in the expected weather distribution (Burke et al. 2010; Dell et al. 2014; Hsiang 2016). Economic theory suggests that adaptive actions are efficient – and thus desirable – only if their benefits exceed their costs, and also that private adaptations are likely to be efficient because the benefits and cost accrue to the decision maker (Mendelsohn 2012). The debate on the impacts of climate on agriculture started off with two main approaches. The first is production function approach that specifies a relationship between climate and agricultural output, and uses this to simulate the impacts of changing weather outcomes (Dell et al. 2014). This approach, however, does not include any mechanism to count for farmers behavioral responses, and thus suffers from the "dumb farmer bias", where a variety of the adaptations that farmers make in response to changing economic and environmental conditions are not incorporated in the models (Mendelsohn et al. 1994; Maddison 2007; Dell et al. 2014). In response, Ricardian analysis that assumes that farmers would adopt *the best* technology available *given* the new weather, was adopted in a seminal paper by Mendelsohn et al. (1994). Studying adaptation has claimed to be central to the question of how much the estimated impact of weather variations can be used to determine long-run effects of climates changes (Dell et al. 2014; Hsiang 2016).

Yet up to today, a body of strongly founded microeconomic theory on adaptation behavior is still to be shaped (Zilberman et al. 2012; Asfaw et al. 2014). The central questions here are how do economic agents perceive weather realizations, and how do they adjust their expectations in response. Maddison (2007) notes that a farmer may perceive several hot summers but rationally attribute them to random variation in a stationary climate, while in another situation a farmer might adapt by changing his production decisions immediately. One possibility is that farmers engage in simple Bayesian updating of their prior beliefs according to the standard formula, which indicates a slow process (Udry et al. 2010); the other option – shown by a few empirical studies of input and crop choices – is that farmers place more weight on recent information than is efficient (Maddison 2007). In support of this view, Cohen et al. (2008) formulates that perceptions can be understood as being derived from a sequence of past events, and so we expect the evaluation of risks by individuals to be dependent on past experiences. Under this process of "adaptive expectation formation", risk posed by weather can be proxied by past realizations of weather-related shocks experienced by a household. According to this view, droughts, floods and other climate hazards occurring in the *recent* past are likely to shape farmers' perceptions regarding the current riskiness of their environment (Maddison 2007; Cohen et al. 2008).

Once the change is perceived, a discrete choice among major response alternatives becomes the heart of the farm household adaptation process (Asfaw et al. 2014). These types of decisions are in essence adoption decisions, as Feder et al. (1985) and others emphasize. The pace and extent of these decisions then depends on agents' adaptive capacity, in the literature defined as "the ability of a system to prepare for stresses and changes in advance, or adjust and respond to the effects caused by the stresses … so as to decrease vulnerability" (Asfaw et al. 2014). Adaptive capacity describes the capacity of agents in a system to manage and influence resilience, an important conceptual idea in the case of conservation practices – while there is no coherent, widely-used theory base for these kind of resilience-management decisions. So far, the adaptation literature often just assumes that adaptive capacity can be directly measured through agents' engagement in agricultural practices or technologies that increase yields, or more specifically, incomes (Di Falco et al. 2011).

2.2. Empirical Studies of Adaptation

While empirical studies of farming practices' adoption in context of climate change are still sparse, there is an emerging body of work from past several years. These studies build on the literature on formulation of expectations under risk, discussed above, and the fact that sustainable land management techniques are often seen as risk decreasing; due to this property, it could be expected that greater variability in rainfall and higher maximum temperatures increase the use of such practices (Asfaw et al. 2014). While the first round of economic assessments of climate change impacts did not adequately account for the role of human behavior to fully or partially offset the effects of environmental change (Zilberman et al. 2012, Dell et al. 2014), recent studies have showed that farmers do perceive the changing climate, and they also take actions to reduce the negative impacts of the environmental change (Asfaw et al. 2014). Thus, similar modeling approaches to the agricultural technology adoption literature have now also been employed in climate change studies (Zhao et al. 2012).

Apart from implicit impacts of climate change, a great number of studies – starting with Ervin and Ervin (1982) – has analyzed factors contributing to as well as constraining the adoption of conservation measures in agriculture (Knowler et al. 2007; McCarthy et al. 2011). Until recently, the studies were exclusively cross-sectional *ex post* adoption studies that often suffer from endogeneity arising from omitted variable bias, and concerns regarding small sample sizes (Knowler et al. 2007; Schlenker et al. 2014). Probit and logit models are the most commonly used models in these analyses of practice adoption as the authors aim to model adoption decision as a binary (multivariate) choice that is an outcome of various (potentially endogenous) factors (Asfaw et al. 2014).

To name a few, Nhemachena et al. (2007) employed a multivariate probit model to analyze factors influencing the choice of climate change adaptation options in Southern Africa. Deressa et al. (2009) adopted the multinomial logit model to analyze factors that affect the choice of adaptation methods in the Nile basin of Ethiopia, while Deressa et al. (2013) used a two-step Heckman model where the first step is a farmer recognizing that change is happening and the second step is adapting. Kassie et al. (2013) and Teklewood et al. (2013) use the number of adopted conservation practices as a dependent variable, to then model adaptation in an ordered probit framework, where a certain number of practices is adopted through maximization of the latent variable – underlying utility function (Teklewood et al. 2013). Swinton (2000) and Posthumus et al. (2010) are studies specific to conservation practices in Peru, yet neither employs weather variation in their identification.

These cross-sectional studies suffer from the problematic identification of decision, including adaptation responses to changing climatic conditions (Dell et al. 2014). To avoid the most common issue of omitted variable bias, growing body of literature uses more advanced identification methods, namely panel data, high-resolution weather data, or those two in conjunction (Aufhammer et al. 2014). The idea there is that while average climate could be correlated with other time-invariant factors that we as analysts potentially cannot observe, short-run variation in climate (weather variation within a given area) is plausibly random (Schlenker et al. 2009; Dell et al. 2014). This fact helps to then identify the effects of changes in climate variables on economic outcomes.

Arslan et al. (2013) provides evidence for a positive correlation between rainfall variability and the selection of sustainable land management type practices. Kassie et al. (2008) analyze the impact of production risk arising from weather shocks on the adoption of conservation agriculture as well as use of inorganic fertilizer. They find that risk deters adoption of fertilizer, but has no effect on the conservation agriculture adoption decision. Seo et al. (2008) and Kurukulasuriya et al. (2008), using data of South American and African farmers respectively, show that crop choices are highly sensitive to changes in precipitation and temperature under different climate change scenarios. Di Falco and Veronesi (2013) find that crop adaptation is more effective when it is implemented along with a portfolio of sustainable land management practices rather than in isolation.

Specific to studies using panel data, various methodological approaches have been used in conjunction with weather data. Salazar-Espinoza et al. (2015) use pooled fractional probit to analyze shock responses among small-holders in Mozambique. They find that farmers shift land use away from non-staple crops one year after a weather shock, while two years later they tend to switch back to cash crops again. Asfaw et al. (2014) employ a multivariate probit with fixed effects to model farming practice selection decisions and their yield impact estimates in Malawi, finding that higher variation in rainfall and temperature predicts the choice of risk-reducing agricultural practices such as soil and water conservation practices; additionally, wealthier households as well as these with secure land rights are more likely to adopt both modern and sustainable land management practices. Closest to my study, Arslan et al. (2014) examine a set of potentially climate smart agricultural practices in Zambia by using socioeconomic panel data in conjunction with geo-referenced data on historical rainfall and temperature. They find that post-shocks, the use of modern inputs (seeds and fertilizers) is significantly reduced, whilehange in soil conservation practices and crop rotation does not turn out to be significant. Their productivity analysis shows that intercropping significantly reduces the probability of low yields when a household is under critical weather stress, proving its potential as an adaptation measure (Arslan et al. 2014).

2.3. Peruvian Agriculture and Climate Change

As indicated above, IPCC and the Stern Review have both identified Peru among the regions most vulnerable to adverse impact of changing weather patterns. UNDP Human Development Report states that 2°C increase in the maximum temperature and 20% increase in the variability of rainfall by 2020 would lower Peru's GDP 20% and 23.4% from a scenario without climate change, respectively (UNDP 2013). Peru is also among the Latin American countries with the most limited water resources (McCarthy 2015). Normally, glaciers store water in the rainy season and release it throughout the year, while in current glacial retreat conditions, flooding is often caused by too much water being released over the rainy season, and drought by not enough released during the dry season (USAID 2017). Currently, more than 80 percent of farmers practice rain fed subsistence agriculture in situation where changes in precipitation and melting glaciers are increasingly resulting in competition over water resources (USAID 2017).

Empirical evidence shows that Peruvian small-scale farmers have perceived climate change and that there is consensus about the more frequent extreme weather events as well as more unpredictability in weather patterns (Painter 2007). According to a 2013 Oxfam study, almost 50% of the households in Peru indicated that climate change has resulted in an expansion of the range of major pests (Oxfam Novib 2013), while the United Nations Food and Agriculture Organization reports that nine of the main crops in Peru – including potato and maize – suffer from significant yield losses under all six considered future climate change scenarios (FAO 2017). Results from Saldarriaga (2016) suggest that variability and not absolute levels of climate indicators have much greater effect on agricultural productivity in Peru, consistent with the rest of the economic literature on weather (Dell et al. 2014). He also shows the regionally distinct impacts, as weather variability affects agricultural activity in the Andes region and, to a large extent, in the Amazon region, while no statistically significant results are found for the Coast region (Saldarriaga 2016).

As suggested by the heterogeneity of natural conditions and crop compositions in Peru (World Bank 2015; Saldarriaga 2016 MINAGRI 2018;), I am going to focus on two main staple crops in my analysis: potato and maize. About one fourth of 3.5 million hectares that are used for agriculture are used for maize and potato cultivation (MINAGRI 2015), crops rank as second and third for their economic importance, comprising 0.2% and 0.3% of GDP, respectively (World Bank 2015), but most importantly, maize and potato are the most prevalent staple crops for Peruvians (UNDP 2013). 64% of farmers live in the Andean region and implement subsistence, rain fed methods to grow crops like potatoes and maize (USAID 2017). In context of climate change, according to IPCC scenarios potato and maize are both estimated to lose their climatic aptness across their current cultivation areas in Peru (IPCC 2000), and the cultivation areas of both crops are claimed to have high biophysical and social sensitivity due to both poverty levels and sensitivity to natural shocks (MINAM 2010; CIAT 2014). According to Oxfam's report, production risk for potato is especially high due to several recurrent factors, particularly drought, flooding, hail, and frost (Oxfam Novib 2013).

The rate of explicit agricultural adaptation in response to these climate observations appears to be low. Wheeler (2017) reports that 15% of farmers in their household survey reports having explicitly adopted adaptation behavior, while most households reports using one or more production practices that are considered to be climate adaptive by researchers (Wheeler 2017). According to the evidence on impact channels, greater emphasis must be placed on the use of irrigation technology, and prevention and elimination of pests arising from the effects of extreme temperatures (Saldarriaga 2016), while different stakeholders working with the Peruvian agriculture – FAO, the World Bank, CGIAR – have identified various sets of conservation measures that could potentially help small-holders to cope with the future weather pattern shifts.

An overarching theme is what the agricultural development discourse has defined as climate-smart agriculture (CSA), a context-specific approach "with many approaches potentially being CSA somewhere, but no single practice being CSA everywhere" (CGIAR 2017). Ideally, such practices would achieve at least two goals out of three: maintained productivity, enhanced resilience (adaptation), and mitigation, where "… productivity is the priority in developing countries dependent on agriculture for subsistence" (Rosenstrom et al. 2016). Most importantly, CSA technologies should address weather-related risks, and help to ameliorate the impacts of the latter both in short-term (i.e. current productivity) and in long-term (i.e. long run for variability in production under climate change) (Rosenstrom et al. 2016). Currently, an economic decision-making framework that could assist in identifying challenges for CSA application still needs to be developed (Lipper et al. 2017). CGIAR and the World Bank have conducted a situation-analysis of CSA in Peru, capturing the current status of CSA initiatives, vulnerabilities and threats given specific contexts, as well as the enabling environments at multiple levels (see Part C of Appendix) (World

Bank 2015). In the current study I am looking at approaches that multiple sources univocally identify as possessing adaptive potential.

The first outcome I analyze is a composite measure of four desirable soil conservation practices as they are identified and measured by Peru National Agricultural Survey. The first one, crop rotations, is meant to ensure differential nutrient uptake between crops, and to thus enhance soil fertility, reduce dependency on chemical fertilization, and lead to higher yields (McCarthy et al. 2011). The second, application of organic matter is a low-emission approach to increase soil's water holding capacity and chemical properties (Arslan et al. 2017); Altieri et al. (2015) quote occasions from Guatemala, Brazil and Honduras where organic fertilization led to 20–250% higher maize yields, and Scialabba et al. (2002) found that potato yields increased by over 250% in Bolivia. Thirdly, construction of terraces is a measure that reduces soil erosion after high magnitude rainfall and thus increases soil quality (Singh et al. 2017; Arslan et al. 2017); Altieri et al. (2015) has shown that restoration of Incan terraces has led to 50% increase in a range of upland crops. Finally, soil analysis is a practice not commonly included in compilations of climate smart practices but rather a local interest for the Peruvian stakeholders. However, as its adoption rate remains only around 2% over the years under study, and as we use covariation-based index to capture overall practices' uptake, we do not find it problematic to include it as one of four soil practices as suggested by INEI.

The second outcome under study is a composite measure of practices aimed to reduce water shortages. Just like soil conservation, there is four practices that form my composite index: determining plants' water needs prior to season, determining watering times, measuring irrigation, and maintenance of irrigation. The four are all simple ways to work towards a priority for Peruvian agriculture: to cope with upcoming water shortages (Singh et al. 2017). Proper water management can help capture more rainfall, use it more efficiently and make the maximum amount available to crops (McCarthy et al. 2011). The meta-analysis of climate-smart practices' benefits by McCarthy et al. (2011) estimates the average marginal yield increase from adoption of water management practices to be 92% in dry areas and 164% in humid areas.

The final outcome I analyze is the application of chemical fertilizer – an input that we expect to address rather short-term productivity-related concerns that farmers might have after shocks. The study most similar to mine, Arslan et al. (2017), finds that soil and water conservation practices are the main components of any combination of practices that result in improved yields in context of rainfall and temperature shocks; on the other hand, modern inputs – such as chemical fertilizer – are less resilient to shock but function better in combination with additional sustainable practices. As discussed in Arslan et al. (2017), while in the short run the productivity impact of chemical fertilizer is higher than that of organic fertilizer, in long perspective the latter appears to be more beneficial in terms of maintaining soil productivity and reducing soil erosion. While literature widely finds fertilizer use to increase yields, the majority of this evidence is valid under *average* climatic conditions, and the superiority of inorganic fertilizer under harsh climatic conditions – expected to get worse under climate change – needs more research (Arslan et al. 2017). Asfaw et al. (2015), for example, find that the productivity increasing effects of improved seeds disappear under very hot growing season temperatures, and that of inorganic fertilizers decrease significantly under false rainfall onsets in smallholder maize systems of Zambia.

3. Data

My analysis uses three types of data. The first source is three rounds of household surveys conducted by the Peru National Institute of Statistics and Informatics (INEI); the second and the third source are the Climate Hazards Group InfraRed Precipitation with Station (CHIRP) and the Center for Environmental Data Analysis (CEDA) for data on precipitation and temperature outcomes, respectively.

3.1. Socioeconomic Data

Peru National Agricultural Survey covers the years 2014, 2015 and 2016; each year's sample is 25,000 randomly drawn households, giving me a repeated cross-sectional dataset. The samples were chosen through a two-stage process using the 2012 Agricultural Census (IV CENAGRO 2012) as the sample frame, where the first step was randomly drawing 1,000 households from each department of the country. Thus, my socioeconomic data are nationally representative for Peru. After excluding the special strata included in the survey – medium and large sized agricultural operations with land size bigger than 50 hectares –, and households that do not grow potatoes or maize, the eventual numbers of households under study are 13,598 for 2014, 14,581 for 2015, and 15,200 for 2016[3]. The survey asked detailed questions on crops and livestock operations during last agricultural year, and the information was collected for each plot within a household, and each crop within a plot, which

[3] Despite the intentional equal sample size of 25,000 households for each cross section, the actual sample size increased slightly over years. Thus, I do not have to be concerned about potato/maize growers being proportionally more represented in 2015 or 2016.

TABLE I: SUMMARY STATISTICS

VARIABLES	2014	2015	2016	Total
Gender of household head (1 = male)	0.716	0.720	0.712	0.716
	(0.451)	(0.449)	(0.453)	(0.451)
Age of household head	51.67	52.30	52.59	52.20
	(15.67)	(15.27)	(15.10)	(15.34)
Primary school or less	0.788	0.790	0.776	0.784
	(0.409)	(0.408)	(0.417)	(0.411)
Indigenous	0.520	0.487	0.504	0.503
	(0.500)	(0.500)	(0.500)	(0.500)
Experience (years)	24.721	26.200	26.383	25.802
	(15.133)	(14.809)	(14.744)	(14.904)
Household size	3.909	3.820	3.812	3.845
	(2.120)	(2.076)	(2.049)	(2.081)
Distance to center (hours)	1.546	1.676	1.618	1.624
	(2.103)	(2.350)	(2.135)	(2.202)
Land size (hectares)	-	4.701	4.856	4.780
	(-)	(7.310)	(7.650)	(7.487)
Livestock ownership	0.825	0.858	0.870	0.852
	(0.380)	(0.349)	(0.337)	(0.356)
Technical irrigation	0.500	0.505	0.498	0.501
	(0.500)	(0.500)	(0.500)	(0.500)
Received extension	0.174	0.144	0.112	0.142
	(0.379)	(0.351)	(0.315)	(0.349)
Number of plots	2.772	3.528	3.921	3.429
	(2.976)	(3.393)	(3.498)	(3.339)
Number of crops per plot	2.058	2.359	2.542	2.329
	(1.687)	(1.995)	(2.196)	(1.990)
Cooperative membership	0.0574	0.0473	0.0499	0.0505
	(0.227)	(0.212)	(0.218)	(0.219)
Number of years	7.427	7.278	6.754	7.147
	(9.013)	(8.706)	(7.348)	(8.377)
Access to credit	0.121	0.111	0.118	0.116
	(0.326)	(0.314)	(0.322)	(0.321)
Saving account	0.060	0.191	0.227	0.163
	(0.238)	(0.393)	(0.419)	(0.369)
Land tenure (1 = own)	0.650	0.664	0.614	0.642
	(0.477)	(0.472)	(0.487)	(0.479)
Observations	13,598	14,579	15,200	43,377

Notes: Credit access refers to the percentage of households who requested credit and also received it during the preceding year. Receiving extension applies for the preceding three years. Number of crops is averaged over all plots that a household owns.

for I constructed the household level data from the plot and crop level data. The summary statistics for the socioeconomic data can be seen in Table I.

Each household in the survey is assigned into a spatial unit called *conglomerado*. These have higher spatial precision than the smallest administrative units (districts), and therefore less heterogeneity in terms of natural conditions that the households are exposed to. Across the nation, there is 1,454 *conglomerados* in total for the year of 2014, and 1,889 *conglomerados* for 2015 and 2016[4].

3.2. Climate Data

The second set of data is monthly rainfall totals from the InfraRed Precipitation with Station, a second generation dataset from the Climate Hazard Group. It is quasi-global rainfall data that goes back to 1981 and combines records from satellites and ground stations (Funk et al. 2015). The data have a resolution of 30" (around 1 km at the equator) and are extracted to cover the period of 1986-2016. After pre-processing the data for the right projection, we used ArcGIS 10.2.3 to extract values from interpolated surfaces for the longitude and latitude coordinates of all the *conglomerados* (spatial units in the household survey data), to capture the most precise possible local variability.

The third, temperature dataset comes from CEDA Web Services framework, a high resolution gridded observational climate record (CEDA 2018). The data points come, once again, for every *conglomerado,* and go back 30 years in time (1986-2016), with a temporal resolution of one month (i.e. featuring monthly means), and a spatial resolution of 5' (~10 km at the equator). While my temperature data have lower resolution than the precipitation data, the literature acknowledges that precipitation has much more spatial variation than temperature in general – especially in rugged areas like Peru –, which for it is more difficult to interpolate (Dell et al. 2014).

3.3. Construction of weather variables

In order to utilize weather shocks as treatment condition, I need to determine the definition of a shock and construct variables indicating whether a place received one. The most common approach in the economics literature is to define shocks as deviations from long-term normal, where the threshold level of deviation is open for interpretation (McKee et al. 1993; Auffhammer et al. 2013). For my calculations of climate variables, I am going to use a reference period of 1986-2016 that

---

[4] As the spatial units have perfect overlap for the last two years of the survey but not for the first one, I use Stata command Geonear to calculate the distances between the spatial units, and find the closest matches for each *conglomerado* among their counterparts in the 2014 sample; if two potential matches are available, I optimize the choice to achieve the minimal total distance between all the pairs. All the resulting pairs are within 10 kilometers from each other.

gives me a 30-year-window as done in previous literature (Dell et al. 2014); it is suggested that 30 years is long enough to not be insensitive to recent shocks, while not so long as to misrepresent the current local climatic conditions (Auffhammer et al. 2013; Salazar-Espinosa et al. 2015).

Climate data have complex structures due to spatial and temporal autocorrelation (Dell et al. 2014). To come around that, climate indices are time series that summarize the behavior of climate in a region, and that are thus used to characterize the factors impacting the global climate (Zhang et al. 2011). For rainfall, common approaches to model deviations from normal are Palmer Drought Index, Percentage of Normal Precipitation, and Standard Precipitation Index (SPI) (NOAA 2017). The latter is a drought index, first developed in McKee et al. (1993), that is now most commonly used and recommended by the World Meteorological Organization for dry spell monitoring (Zhang et al. 2011). SPI is expressed as a number of standard deviations that the observed precipitation deviates from the long-term – in my case, 30-year – mean, for normalized annual values (Salazar-Espinoza et al. 2015). Using this approach, for each location rainfall frequency needs to be transformed to another standard normal distribution, if appropriate for local rainfall patterns. Subsequently, there are different thresholds below which a shortfall in precipitation can be considered a negative rainfall shock (McKee et al. 1993); Zhang et al. (2011) suggest an interpretation where SPI above/below ±0.80 (standard deviations) indicates wet/dry weather outcomes, while SPI above/below ±1.60 indicates extremely wet/dry weather outcomes; I am initially going to restrict the analysis to a threshold of ±1.00 as a simply interpretable threshold that is widely used in previous literature (Dell et al. 2014; Salazar-Espinosa et al. 2015). For visual reference, level shock occurrences for the 2016 sample can be seen in Graph 3 in Appendix.

In addition to rainfall level shocks, I am interested in how abnormal variation of rainfall – a widely observed expression of climate change in Peru – affects farmers' behavior. For that purpose, I use a standardized version of a weather measure called Coefficient of Variation (CV), recently used in other studies of conservation agriculture as an absolute measure explaining adoption (Arslan et al. 2014; Asfaw et al. 2014; Arslan et al. 2017). Rainfall CV of any time period is calculated as the standard deviation divided by the mean of the respective period's rainfall, and it thus provides a comparable measure of variation for households that may have experienced very different rainfall levels (Asfaw et al. 2014). As an extension to this approach, I standardize each location's CV over years[5], obtaining a z-score of variation for each year under study. I can then define a shock as a CV

[5] Just like the SPI, coefficient of variation is calculated from monthly data; thus, the formula is standard deviation of monthly rainfall over mean of monthly rainfall for any given year.

z-score that is above/below ±1.00 standard deviations as in the case of SPI. This way, in addition to spatial comparability I now also have temporal comparability in my analysis of rainfall variation.

The main question I ask is how a shock experienced over past year affects farmers' input/practice choices over the current agricultural season, or – in other words – how do farmers update their expectations about the riskiness of the environment they work in. All rounds of the INEI survey are conducted over Southern hemisphere's winter months so that households report on their activities during the season that has just ended[6]. Therefore, I define "current year" as the 12 months leading up to the survey[7], and use these months to calculate annual weather variables for all the 30 years in the dataset. "Previous year's shock", the main treatment variable is thus a shock happening during the year prior to those 12 months, or prior to an agricultural year that the data is about (see also the decision-making timeline in Graph XX in Appendix).

Occurrences of defined climate shocks over the three year under study are summarized in Table II as proportions of *conglomerado*-s that experience respective abnormal rainfall years.

TABLE II: CLIMATE SHOCK OCCURRENCES BY LOCATION[8]

	Coast			Mountains			Forest		
VARIABLES	2014	2015	2016	2014	2015	2016	2014	2015	2016
High rainfall shock (t-1)	0.42	0.47	0.43	0.22	0.32	0.25	0.21	0.48	0.39
	(0.49)	(0.50)	(0.49)	(0.41)	(0.47)	(0.44)	(0.42)	(0.50)	(0.49)
Low rainfall shock (t-1)	0.013	0.024	0.035	0.145	0.059	0.099	0.071	0.007	0.064
	(0.11)	(0.15)	(0.18)	(0.35)	(0.24)	(0.30)	(0.26)	(0.08)	(0.24)
High variation shock (t-1)	0.17	0.16	0.27	0.01	0.04	0.13	0.01	0.18	0.26
	(0.37)	(0.37)	(0.45)	(0.07)	(0.26)	(0.33)	(0.05)	(0.39)	(0.44)
Low variation shock (t-1)	0.09	0.06	0.01	0.27	0.24	0.18	0.64	0.08	0.25
	(0.29)	(0.25)	(0.21)	(0.45)	(0.43)	(0.39)	(0.48)	(0.28)	(0.43)
# of conglomerados	259	334	334	874	1,174	1,174	301	381	381

Note: The figures indicate the proportion of *conglomerado*-s that experienced a respective shock (measured as 1/0 indicator variable) over the 12 months preceding the respective agricultural year (i.e., over period *t-1*), further split up by the three main natural regions of Peru.
Standard errors are in parentheses.

[6] Due to Peru's latitude of 4°S, maize and potatoes are both planted in October and less in November, and harvested after March (Ministerio de Agricultura y Riego 2017).

[7] The survey was conducted in two waves: from May 30 to July 1 in the Andes region, and from July 31 to August 31 in the Amazon and the Coast regions. Following these dates, I define previous 12 months as previous year's June up to current year's May for the Andes region, and previous year's August up to current year's July for the other two regions.

[8] Frequencies of occurrence are reported on the level of *conglomerados,* not individuals.

4. Empirical Strategy

Hsiang (2016) provides a term “time-series variation with stratification” as an econometric approach in the emerging climate-economy literature. Using the latter approach, my identification strategy builds on the fact that prior to shocks, different localities differ in terms of their agroecological conditions and resulting different levels of use of agricultural practices/inputs. To measure the behavioral response to these climate shocks, I then make an identifying assumption that the trend in outcomes in places that did not get the shock would have been the same as in the places that did get the shock, had they had the same recent weather realizations.

4.1. Hypotheses and Outcome Variables

Following the latter assumption, the primary hypothesis I am testing is whether recently experienced weather shocks incentivize farmers to use more conservational soil and water practices.
The outcomes of interest are a) soil conservation practices, b) water conservation practices, and c) use of chemical fertilizer. The first two are composite measures of what the INEI National Agricultural Survey calls “good agricultural practices” [*buenas practicas agriculturas*] and what the survey is aimed to measure[9]; the components of both are answers to four different questions, each indicating weather a farmer uses/does not use a given practice that is expected to reduce soil degradation or reduce water shortage, respectively[10]. Practice questions overlap partially with the practices included in the World Bank’s Peru-specific Climate Smart Agriculture concept[11].

Testing weather outcomes’ impact on each practice separately would suffer from the bias of multiple hypothesis testing, where I might see significant impact due to properties of probability distribution and not the actual causal mechanism in action (Anderson 2008). A potential solution is to compute indices that group the four soil and four water practice indicators together, are thus robust to over-testing and arguably allow for more powerful tests than individual-level inference (Anderson 2008; O’Brien 1984). As giving each practice an equal weight would not capture their overlapping functions as they occur to farmers, I rather utilize covariation between the practice

---

[9] The choice of these practices as outcomes under study derives directly from the fact that INEI’s own objective is to quantify the use of these practices; thus, while one could argue that it is not desirable to analyze adoption of identical methods/practices across so big and heterogeneous region, the motivation here is policy relevance, as identified by stakeholders in Peruvian agriculture.

[10] See the exact survey questions in Part III of Appendix, and corresponding summarized statistics for these variables in Part I, Table 1 and 2 of Appendix.

[11] See Part III of Appendix.

indicators to construct the composite indices[12] – a method also known as Anderson index – where outcomes highly correlated with each other receive less weight, while outcomes that are uncorrelated and thus represent new information are given more weight (Anderson 2008). As a result, two of my outcomes come in form of such indices. The third outcome analyzed, use of chemical fertilizer, is a binary indicator of use/no use rather than a level response.

4.2. Theoretical Model

As described in the literature review section, relying on the vast literature on choice of farming practices – including input use –, I treat the practice selection decision as an outcome of a constrained optimization problem by rational agents (Feder 1980; Feder et al. 1985). In the model of adoption, households are assumed to maximize their utility, subject to constraints, and adopt a given technology if and only if the technology is available and affordable, and if at the same time the selection decision is expected to be beneficial (Zhao et al. 2012). When forming expectations of the benefits of using an input, a household considers experienced climate shock among other deciding factors such farm characteristics (Zhao et al. 2012).

4.3. Fixed Effect Estimation

Using variation over time within a given spatial entity, I take a view of the climate model where level changes matter in proportion to an area's usual variation, not due to their absolute levels (Dell et al. 2014). The empirical approach then used is a cluster (*conglomerado*) and year fixed effects model. The fixed effects address the problem of unobserved heterogeneity, controlling for the time-invariant differences of the clusters – or *conglomerado*s –, and thus aim to identify impacts by eliminating the bias in estimates (Wooldridge 2010).

The key to fixed effects estimation is my identifying assumption that a weather shock is as good as randomly assigned conditional on observed characteristics and unobserved characteristics controlled for by fixed effects[13], i.e.:

$$E[\text{practice}_{pict} \mid X_{ic}, C_c, W_{ct-1}] = E[\text{practice}_{pict} \mid X_{ic}, C_c]$$

---

[12] To construct an index, first all the outcomes are transformed to take a standard normal distribution; for each observation's outcome in the domain of an index a weighted average is computed, where the weights are covariance matrices of the transformed outcomes in this domain. An efficient generalized least squares (GLS) estimator results. The preferred method to treat missing outcome values varies between studies; in my dataset, only 157 observations or 0.0021% of the total sample miss responses for the practice questions, and I decided to replace these with the mean of each respective outcome.

[13] Formally, $cov(u_{ict}, WS_{ct}) = 0$

where *practice*$_p$ indicates the three outcomes modeled, $p = 1,..,3$, c is a conglomerado index, $c = 1,...,1920$ and i an individual index; T_t is the time variable, $t = 2014, 2015, 2016$; and WS is the "weather shock" dummy variable that takes value 1 when *conglomerado i* has experienced an above/below average weather realization over preceding year *t-1*. C captures the fixed spatial (*conglomerado*) characteristics and T fixed year effects. Then, assuming that the causal effect of weather shocks is additive and constant, we can write the regression form to be estimated as giving a separate intercept for each spatial unit in the study:

$$\mathrm{E}[\mathrm{practice}_{\mathrm{pict}} \mid \mathrm{X}_{\mathrm{ic}}, \mathrm{C}_{\mathrm{c}}, \mathrm{W}_{\mathrm{c,t-1}}] = \beta_0 + \beta_1 \mathrm{WS}_{\mathrm{c,t-1}} + \beta_2 \mathrm{X}_{\mathrm{ic}} + \mathrm{T}_{\mathrm{t}} + \mathrm{C}_{\mathrm{c}} + \mathrm{u}_{\mathrm{ict}} \qquad (1)$$

Variable X_{it} represents a set of household control characteristics such as farm size[14], family size, livestock ownership, land tenure, distance to the center/market, cooperative membership, and access to financial services; u_{it} is the idiosyncratic error term. The fixed effects will then absorb fixed spatial characteristics – whether observed, such as topography or access to services, or unobserved – and time-specific effects across the spatial units, thus disentangling the shock from many possible sources of omitted variable bias[15] (Dell et al. 2014).

To address the expectations that households in a *conglomerado* a) are more similar to each other than households further away, and b) present autocorrelation over time, I cluster my errors at the level of *conglomerado* over years (Auffhammer et al. 2013). Cluster-robust standard errors then allow household outcomes to be correlated within a cluster as well as correct for the serial correlation of idiosyncratic errors that would otherwise violate the assumptions of fixed effects model. Clustering on year-*conglomerado* level would not work as errors within spatial units are expected to be serially correlated over time.

The second model I am interested in is the potential impact of frequent shocks. The logic here is that households can make adaptive efforts to reduce their risks in case adverse weather event

---

[14] Although all three rounds of surveys were designed to be identical, in reality the National Institute of Statistics and Informatics did not collect some sections of data for 2014. Therefore I do not have households' land (plot) areas for this year, and as a result no yield data either. I run a two-sample t-test with equal variances and find evidence that the mean area in 2016 is slightly higher than in the cross-section from the previous year, giving evidence that assuming equal land areas within *conglomerado*-s is not a reasonable assumption. Therefore, I predict sizes of landholdings for the 2014 cross-section using a set of household characteristics; among the models considered, quantile regression gives us the best fit with 92.5% correct prediction rate for 2015 and 2016 samples (see Graph 2 in Appendix).

[15] As the alternative option, random effects (RE) model assumes that the unobservable *conglomerado*-effects are random variables that are distributed independently of the regressors. To check this assumption here, Hausman test is run for the eventual models; H_0 is rejected in the case of every outcome and I can thus conclude that fixed effects should be used.

occurs, while the theory predicts that adaptive efforts are made only until their marginal cost is equal to the expected marginal benefits, assuming that the cost function is convex (Anttila-Hughes et al. 2015). Because such adaptation provides benefits only when an adverse events actually happens, locations that have more frequent events are expected to have greater returns to adaptation. Therefore, households located in areas with relatively frequent recent abnormal rainfall realizations will invest more in adaptation to reduce their marginal losses after a shock occurrence (Anttila-Hughes et al. 2015).

Thus, the model I am going to estimate considers the count of shocks over different time horizons as treatment conditions:

$$Y_{p1ict} = \beta_0 + \sum_{k=1}^{n} \beta_1 WS_{c,t-k} + \beta_2 X_{ic} + T_t + C_c + u_{ict} \tag{2}$$

where n $\in$ [3, 5, 10].

Finally, I am interested in heterogeneity in shock responses. It is clear from the literature that adaptation responses to shocks are often heterogeneous depending on households' characteristics (Fafchamps 1992; Rosenzweig et al. 1992). Following Dell et al. (2014), panel models can incorporate such heterogeneities simply by including the interaction term(s) between a variable that captures the differential of interest and the vector of climate variables. I am going to analyze such potential differences for one crucial determinant of both adaptation and adoption, size of land holdings; households with more land have shown to have higher capacity to mitigate production risks through their capital endowments (Feder et al. 1985; Zhao et al. 2012). The second characteristic that could result in heterogeneous adaptation and that I am going to look at is the age of a household head; we hypothesize that younger farmers could be more responsive to both, climatic changes as well as uptake of beneficial practices. For the empirical estimation, I construct variables indicating a household being a) below median landholding size, and b) below median age, to include their interaction terms with climate shock indicators in the main specification.

4.5. Robustness

To check the robustness of the models specified, one option is including "leads" – treatment indicators that turn on before actual treatment happens – to the model. The logic here is that weather shocks should not change outcomes before they appear, and if they do, we might suspect that there is another mechanism responsible for the results seen. The second Placebo-type test I implement is running the estimation with household-level variables that theoretically should not be affected by the shocks as outcome variables, as described in Section 5.

The properties of fixed effects do not allow me to eliminate the differences between the treatment and comparison groups that change over time. In the context of the study, the most problematic factor interfering with weather outcomes could be extension service. If areas that receive weather shocks also receive extended technical assistance, i.e. the service comes as an outcome of those shocks, we will not be able to separate out the effect of the weather and of the extension service by using the proposed model (Gertler 2016). I therefore test an alternative model where weather shocks as treatment are tested in conjunction with extension service as treatment (i.e. we can observe the occurrence of both, as well as change in outcomes, over the given time period).

5. Results

Descriptive statistics of the households are presented in Table I; based on observable characteristics, samples from three years are close to identical. Notably, the size of Peruvian rural families is decreasing, while farmers are getting older, as seen from the trends in household heads' age and experience as well as a high baseline mean value of 51 years of age. Interestingly, the biggest difference between the samples from three years is possession of a savings account: 6.1% of households has a savings account in the 2014 sample and 22.7% in the 2016 sample[16]. It is also important to note that the potato and maize farmers' subsample under study is less commercialized than the national average; while the whole survey sample has a median percentage of crops sold of 33.0%, the sub-sample has a median of 20.5%[17]. Baseline values of the outcome variables are reported in Tables 1 and 2 of Appendix, as well as visually in Graphs 3–5 of Appendix. Across the whole sample, depending on year 51% to 54% of the farmers use chemical fertilizer; four soil practices have different adoption rates where mixing soil with organic matter has the highest proportion of users with 53%, followed by crop rotations at the use rate of 48%. Use of four water practices ranges from 19% to 40% across the years. As the composite measures for both sets of practices are normalized around zero, base values do not enter further analysis and I estimate average treatment effects as decreases/increases by portions of standard deviations.

Climate shock occurrences are summarized in Table II. I observe that positive total rainfall shocks are much more common than negative shocks (droughts) over the years under study. The proportion of *conglomerado*-s that experience abnormally high rainfall conditions ranges between 21% to 48% over the years, while 1% to 14% experience a negative rainfall shock. The figures for rainfall

[16] The difference is statistically significant at 1% level.
[17] Mean values are 38.9% and 29.9%, respectively.

variation shocks have more heterogeneity between regions and years. Overall, each year 1% to 27% of *conglomerados* in the sample face a high variation shock (that is, rainfall variation that is more than one standard deviation above long-term average), and 1% to 64% a low variation shock.

The following analysis is conducted in five parts. First, I identify characteristics that correlate with adoption of practices under study. Secondly, I turn to the impacts of rainfall level shocks, and thirdly, add rainfall variation shocks to the analysis. Fourthly, I aim to determine whether including the occurrence of frequent shocks changes the results, and how does the latter's impact compare to that of past year's shocks in magnitude. Finally, I give attention to heterogeneous impacts; specifically, I look at whether abnormal weather triggers different responses from smaller farms, younger household heads, and – as a robustness check – whether the results are driven by specific regions.

5.1. Conservation Practices' Correlates

The analysis here first takes an approach prevailing in a large strand of conservation agriculture adoption studies – the majority of which are unidentified[18] – and looks at how various factors affect the probability that a farmer has adopted a conservation measure/practice. These initial results can be seen in three models in Table 3 of Appendix[19], with *conglomerado*-level fixed effects included for each, estimating how various household characteristics correlate with adoption of each outcome. The output largely aligns with previous literature on adoption of respective practices (Ervin et al. 1982; Feder et al. 1985; Bradshaw et al. 2007; Kassie et al. 2013). As expected, more education and years of experience correlate with higher likelihood of conservation practices' adoption, while indigenous indicator is associated with more adoption of soil practices but not water practices – which makes sense on the basis that the water practices under study could be considered more modern while soil practices are rather "ancestry methods". Bigger household size is positively correlated with every practice modeled, explained by labor-intensiveness of the latter, while ownership of land correlates with higher probability of using conservation practices – a highly expected outcome since tenure gives one an incentive to invest in their resources. Kassie et al. (2008), Teklewold et al. (2013) and Asfaw et al. (2014) all find that higher tenure security increases the likelihood that farmers adopt strategies that yield benefits in the long run, such as conservational

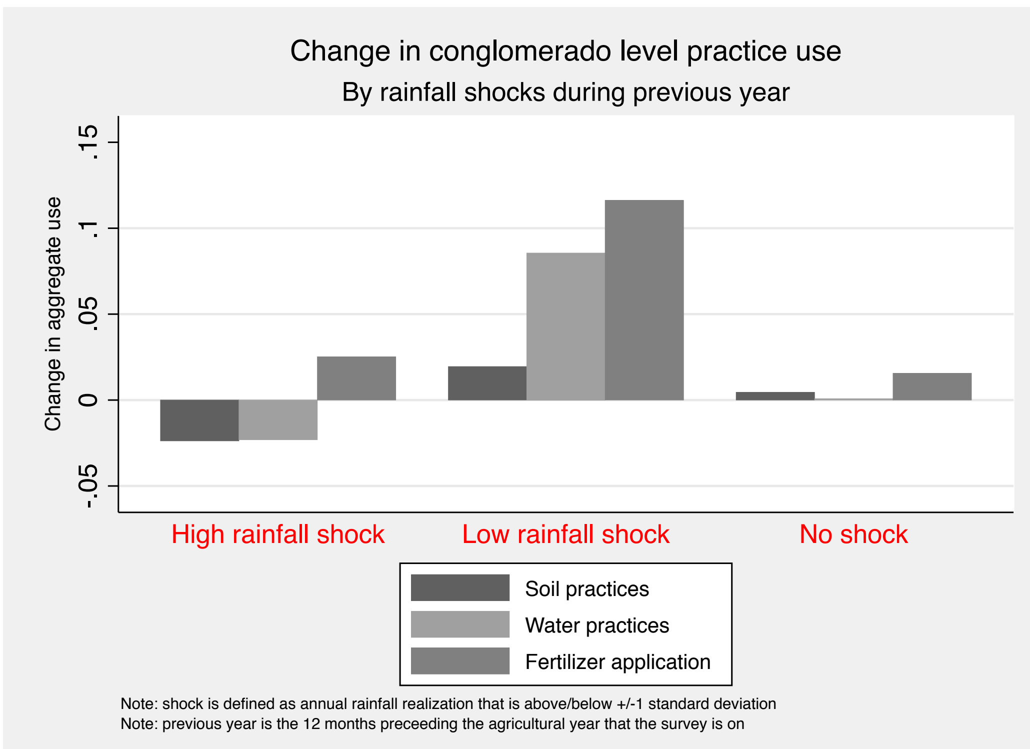
[18] See meta-analysis by Bradshaw and Knowler (2007).

[19] As the literature review discusses, many studies use logit/probit models for estimating factors correlated with adoption; here I find linear probability model sufficient as the probabilities modeled are not on the extreme ends of the [0,1] range, and most of all, true marginal effects are not of main interest at the first place.

practices, while farmers without tenure, in contrast, tend to use more inputs with short term benefits, like inorganic fertilizer and improved seeds.

Longer distance to center has no effect on conservation practices but correlates with less use of fertilizer, a result seen in the majority of previous literature (Bradshaw et al. 2007). Surprisingly, credit access as well as membership in a producer organization are both strong predictors of adoption of *all* the practices. Bigger land area is positively associated with all the practice and input variables, an established fact in the literature (Kassie et al. 2013), but we might expect this relationship to be parabolic; as exploration of correlating factors is not the first interest of this study, I am not going to estimate models with quadratic terms included.

GRAPH I: IMPACT OF PRECEDING YEAR'S RAINFALL SHOCKS ON PRACTICES



5.2. Level Shocks

Using weather realizations as treatment conditions, I first look at the effect of the plausibly exogenous climate shocks in isolation. To check the raw effects of abnormal rainfall, I categorize *conglomerado*-level differences in adoption rates by the shock that localities received over previous agricultural year. Graph I shows that although no controls or fixed effects are included, the adoption rate does not change in places without shocks, on average, while considerable changes are observed for places with shocks, on average.

Table III presents the results of the aggregate (*conglomerado-*) level adoption rate of fertilizer and standardized composite adoption rate of conservation practices regressed on the rainfall shocks of period *t-1* as modeled with fixed effects[20,21]. The results obtained do not change much after adding household level controls (columns 2, 4 and 6 of Table III). We see that a negative rainfall shock experienced by a *conglomerado* during the year preceding the current agricultural season causes the ratio of farmers using fertilizer go up by ~6.1 percentage points; the result is significance at 0.05. High rainfall shocks have no statistically significant impact, while the impact of current season's temperature is highly significant, lower temperatures being correlated with more fertilizer use.

For soil and water practices, raw differences on Graph I give a glimpse that abnormal rainfall during the preceding year do not affect the adoption rate of soil conservation practices as much as water conservation. Indeed, fixed effects regression confirms that a year of high rainfall results in less farmers applying water conservation practices during the following year; the reduction of 0.06 standard deviations is significant at 0.05 level. Time invariant household characteristics that are significant in the model with rainfall shocks are very similar to factors that were identified in the initial correlation analysis. The four factors that have a consistent, big correlation with outcome across three models are ownership of livestock, access to credit, extension services, and being a male.

5.3. Variability Shocks

Next, I add rainfall variation shocks to the previously estimated models, as well as interaction of the latter with rainfall level shocks. That is, that the treatments of interest here are highly variable rainfall combined with a shortage of it (drought conditions), and highly variable rainfall combined with an excess of it. The results are seen in Table IV and also illustrated in Graph II. It turns out that the drought shocks' great impact on fertilizer use remains robust and only grows bigger; the estimated treatment effect across the regions is 9 percentage points (column 5 and 6). At the same time, the use of this input – the only one that requires physical capital among the set analyzed – drops by 0.10

---

[20] The analysis took advantage of Stata package `reghdfe`, a robust algorithm coded in Mata that can efficiently absorb multiple levels of fixed effects.

[21] Although the data structure is repeated cross-sections and the individuals are only observed at one point in time, I do the analysis on the level of individual, as we expect the estimates to converge to *conglomerado*-level estimates. Analytical weights are added to each model to reflect the number of observations in clusters (*conglomerados*).

TABLE III: EFFECTS OF RAINFALL LEVEL SHOCKS

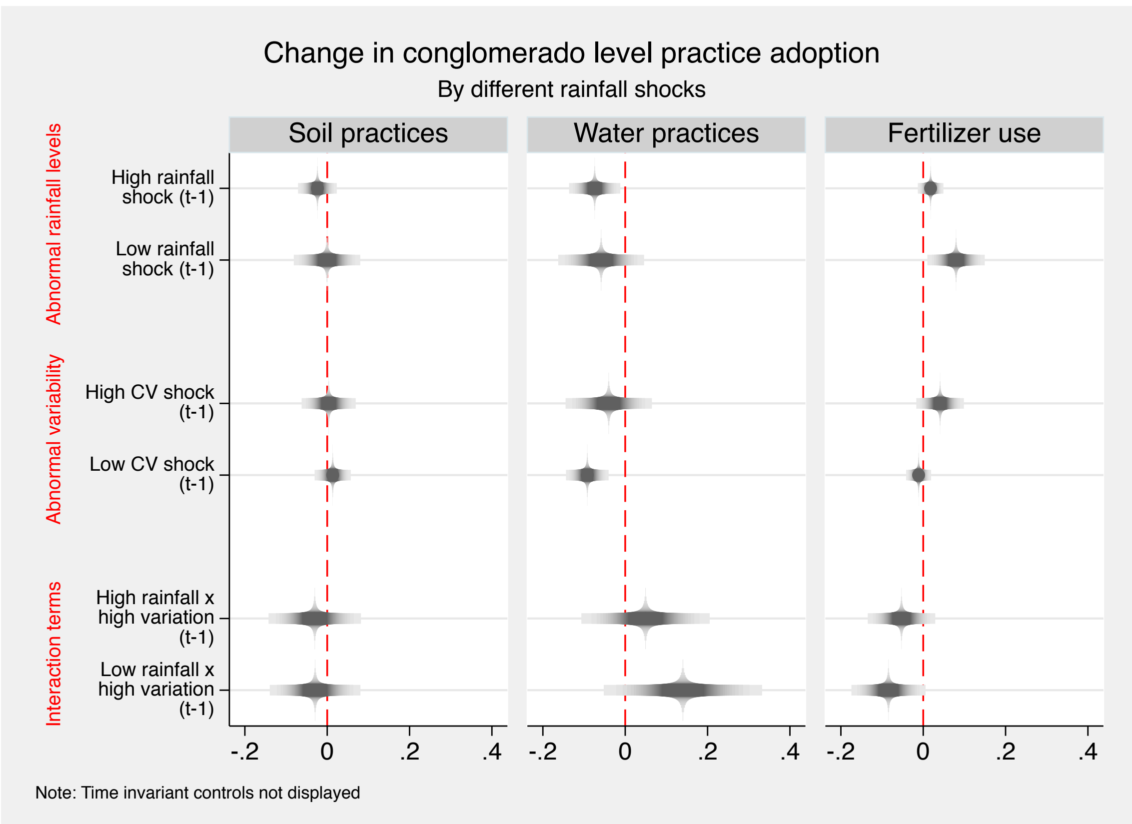
VARIABLES	(1) Soil index I	(2) Soil index II	(3) Water index I	(4) Water index II	(5) Fertilizer I	(6) Fertilizer II
High rainfall shock (t-1)	-0.0269	-0.0265	-0.0592**	-0.0566**	0.0164	0.0173
	(0.0182)	(0.0179)	(0.0230)	(0.0228)	(0.0119)	(0.0117)
Low rainfall shock (t-1)	0.0296	0.0295	-0.00101	-3.31e-05	0.0565**	0.0613**
	(0.0301)	(0.0302)	(0.0395)	(0.0392)	(0.0287)	(0.0285)
Rainfall z-score	-0.0118	-0.0106	0.00455	0.00558	-0.00967	-0.00806
	(0.0103)	(0.0101)	(0.0133)	(0.0133)	(0.00754)	(0.00738)
Grow season T°	-0.0450	-0.0369	-0.00385	0.00153	-0.104***	-0.1027***
	(0.0283)	(0.0281)	(0.0389)	(0.0388)	(0.0154)	(0.0151)
Male		0.0388***		0.0296***		0.0511***
		(0.00511)		(0.00604)		(0.00482)
Age		-0.000685**		-0.00111***		-0.00136***
		(0.000294)		(0.000312)		(0.000235)
Experience (years)		0.00102***		0.000721**		0.000252
		(0.000308)		(0.000330)		(0.000236)
Livestock		0.0520***		0.0505***		0.0298***
		(0.00814)		(0.00821)		(0.00620)
Indigenous		0.0200		0.00431		0.00434
		(0.0124)		(0.0165)		(0.00835)
Household size		0.00471***		0.00262*		0.00546***
		(0.00117)		(0.00136)		(0.00105)
Primary educ. or less		-0.0156**		-0.00486		-0.00609
		(0.00682)		(0.00713)		(0.00529)
Land tenure		0.0273***		0.00302		-0.00495
		(0.00757)		(0.00928)		(0.00610)
Technical irrigation		0.0441***		0.120***		0.102***
		(0.00859)		(0.0124)		(0.00862)
Coop. membership		0.0855***		-0.0126		0.0190*
		(0.0167)		(0.0141)		(0.0106)
Savings account		0.0170**		0.00607		0.00247
		(0.00820)		(0.00952)		(0.00642)
Credit access		0.0336***		0.0323***		0.0683***
		(0.00849)		(0.00894)		(0.00627)
Extension		0.119***		0.0409***		0.0772***
		(0.00967)		(0.00907)		(0.00655)
Distance (hours)		-0.000672		-0.00334		-0.0117***
		(0.00238)		(0.00295)		(0.00209)
Observations	42,996	42,728	42,996	42,728	43,004	42,728
R-squared	0.376	0.387	0.575	0.577	0.423	0.439
Number of clusters	2,016	2,016	2,016	2,016	2,016	2,016
Fixed effects	TxC	TxC	TxC	TxC	TxC	TxC

Note: growing season temperature is the mean temperature over December, January and February.
Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

standard deviations if the drought shock is combined with highly variable of rainfall, pointing to the risky decision of acquiring it under unknown conditions (see further discussion below).

The results in Table IV also confirm that Peruvian farmers on average do not seem to adjust their soil conservation practices following a bad year weather-wise; I see no effect of rainfall level shock, variation shocks, nor the combination the these (see columns 1 and 2). Next, inference regarding water practices is somewhat affected by the inclusion of variation shocks: the negative impact of a high rainfall shock is mitigated, as low variation during the previous year seems to be a

GRAPH II: RAINFALL LEVEL SHOCKS COMBINED WITH VARIATION SHOCKS



bigger driver of reduced water conservation – intuitively a very logical result. While I do not see any impact of low rainfall shocks on water practices' index, combined with a high variability shock – arguably the worst kind of combination for farmer – it has the greatest recorded impact so far, increasing the proportion of farmers who apply water conservation practices by 0.14 standard deviations (t = 1.84). The application of water conservation measures is thus very sensitive to past year's weather realizations, and farmers tend to adjust their production behavior especially in response to experienced abnormal variation in rain.

TABLE IV: VARIATION SHOCKS COMBINED WITH LEVEL SHOCKS OF PRECIPITATION

VARIABLES	(1) Soil index III	(2) Soil index IV	(3) Water index III	(4) Water index IV	(5) Fertilizer III	(6) Fertilizer IV
High rainfall shock (t-1)	-0.0253	-0.0238	-0.0701***	-0.0729***	0.0157	0.0184
	(0.0183)	(0.0185)	(0.0236)	(0.0238)	(0.0121)	(0.0122)
Low rainfall shock (t-1)	-0.00575	0.00351	-0.0301	-0.0569	0.0685***	0.0899***
	(0.0297)	(0.0310)	(0.0380)	(0.0401)	(0.0259)	(0.0278)
Rainfall z-score	-0.0104	-0.00959	-0.00105	-0.00489	-0.00910	-0.00643
	(0.0105)	(0.0106)	(0.0140)	(0.0143)	(0.00772)	(0.00776)
CV z-score	-0.00787	0.00874	0.000938	-0.0383	0.00843	0.0421*
	(0.0199)	(0.0255)	(0.0312)	(0.0407)	(0.0167)	(0.0227)
High CV shock (t-1)	0.00357	0.00396	0.0195	0.0177	-0.00250	-0.00121
	(0.00856)	(0.00864)	(0.0128)	(0.0129)	(0.00638)	(0.00641)
Low CV shock (t-1)	0.0114	0.0108	-0.0929***	-0.0911***	-0.00250	-0.0119
	(0.0170)	(0.0171)	(0.0199)	(0.0199)	(0.00638)	(0.0120)
Grow season T°	-0.0480*	-0.0463*	0.0219	0.0202	-0.0984***	-0.0961***
	(0.0279)	(0.0279)	(0.0389)	(0.0389)	(0.0152)	(0.0153)
High CV x high rainfall (t-1)		-0.0343		0.0484		-0.0514
		(0.0441)		(0.0606)		(0.0324)
High CV x low rainfall (t-1)		-0.0374		0.135**		-0.101***
		(0.0428)		(0.0734)		(0.0363)
Controls	YES	YES	YES	YES	YES	YES
Observations	42,713	42,713	42,713	42,713	42,713	42,713
R-squared	0.382	0.382	0.579	0.579	0.437	0.437

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Note: CV is calculated as annual standard deviation over annual mean precipitation. Subsequently both, rainfall level shock and rainfall variation shock are defined through standardization, where "high CV shock" is CV z-score that is >1 standard deviation of 30-year average CV, while the opposite applies for "low CV shock".

Support for the exogeneity of the weather shocks comes from the comparison between models with and without added controls (socioeconomic variables), as in every case the inclusion of confounding variables has only marginal effects of the sizes of shock impacts, while never affecting the significance or directionality.

5.4. Frequent occurrence of weather shocks

Next, I am interested how does counting for multiple years of experienced shock 1) alters the responses we have seen so far, 2) triggers different responses than experiencing bad weather realizations for just one year.

Two models were considered: consecutive shocks as a treatment condition, and a number of shocks over certain time frame as a treatment condition. I find the second option to be a more flexible measure and to capture more of the experience that a farmer is making a decision from; thus shock count is the chosen model[22]. I construct the number of experienced rainfall level shocks as well as high variation shocks – both defined as above – over past 3, 5 and 10 year horizons.

The results are reported in Table V, and in Table 4 and 5 of Appendix with additional model specifications considered. The most important result I can infer from the analysis considering multiple years of shocks is that the responses following past year's shock, presented above, are robust to adding previous years' weather outcomes. Practices concerning soil conservation are still insensitive to past year's abnormal weather, while the rate of water practices' users goes drastically down after a year of abnormally high rainfall or abnormally little variation in rain. Notably though, water practices do not seem to be sensitive to experiencing several years of shock (see columns 4–6 of Table V), while soil conservation tends to significantly increase after a locality receives multiple years of abnormally high or low rainfall (columns 1–3). Specifically, rate of soil practices use goes up by 0.06 standard deviations for every additional high rainfall shock received over previous 3 years, and by 0.07 standard deviations for every additional drought year experienced over previous 5 years. The result is robust to including the variability indicators or interactions of these with level shocks to the model (see additional specifications in Table 4 of Appendix).

We do not see major responses to multiple years of shock in regard to fertilizer; the results in columns 7–8 of Table V indicate that in long run (5 and 10 year horizon), people are less likely to use fertilizer if frequently experiencing more than 1 standard deviation of normal rain for a year. However,

---

[22] I also conduct the analysis with consecutive shocks as a treatment condition too, but it does not yield enough statistical power due to small number of households in the treatment group.

TABLE V: FIXED EFFECTS MODELS WITH FREQUENT WEATHER SHOCKS AS TREATMENT CONDITION

VARIABLES	(1) Soil index I	(2) Soil index II	(3) Soil index III	(4) Water index I	(5) Water index II	(6) Water index III	(7) Fertilizer I	(8) Fertilizer II	(9) Fertilizer III
High rainfall shock (t-1)	-0.0261	-0.0191	-0.0392**	-0.0691***	-0.0601**	-0.0772***	0.0253**	0.0250**	0.0250**
	(0.0187)	(0.0188)	(0.0186)	(0.0243)	(0.0244)	(0.0239)	(0.0122)	(0.0123)	(0.0123)
Low rainfall shock (t-1)	-0.0110	-0.0218	0.00835	-0.0270	-0.0223	-0.0223	0.0748***	0.0777***	0.0777***
	(0.0300)	(0.0303)	(0.0288)	(0.0382)	(0.0389)	(0.0380)	(0.0257)	(0.0260)	(0.0260)
High CV shock (t-1)	-0.0136	-0.0226	-0.0250	-0.00485	-0.00246	-0.00461	0.00779	0.00972	0.00972
	(0.0199)	(0.0202)	(0.0198)	(0.0313)	(0.0316)	(0.0310)	(0.0169)	(0.0171)	(0.0171)
Low CV shock (t-1)	0.0156	0.0205	0.0257	-0.0924***	-0.0894***	-0.0886***	-0.0125	-0.0112	-0.0112
	(0.0171)	(0.0172)	(0.0170)	(0.0201)	(0.0202)	(0.0203)	(0.0119)	(0.0119)	(0.0119)
Low RF shock count, 10 years	0.0125			0.0384*			-0.00284		
	(0.0138)			(0.0197)			(0.0111)		
High RF shock count, 10 years	0.00961			-0.0132			-0.0322**		
	(0.0178)			(0.0268)			(0.0135)		
Low RF shock count, 5 years		0.0639***			0.0211			-0.0196	
		(0.0214)			(0.0255)			(0.0148)	
High RF shock count, 5 years		-0.00993			-0.0364*			-0.0208*	
		(0.0139)			(0.0213)			(0.0107)	
Low RF shock count, 3 years			0.0289			0.00712			0.0254
			(0.0227)			(0.0324)			(0.0175)
High RF shock count, 3 years			0.0653***			0.0228			-0.00479
			(0.0146)			(0.0198)			(0.0101)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	42,825	42,825	42,825	41,674	41,674	41,674	41,674	41,674	41,674
R-squared	0.391	0.392	0.392	0.576	0.578	0.578	0.445	0.445	0.446

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

observe a change in responses to previous year's rainfall level shock after including the shock counts to analysis; namely, high amount of rainfall now has a positive and significant effect on following year's fertilizer use. This is in accordance with the literature that discusses high rainfall intensity leading to higher rates of soil erosion and leaching of agricultural chemicals, for which additional fertilizer application makes sense (Rosenzweig et al. 1995).

5.5. Heterogeneous treatment effects

I now turn to potential differences in responses between smaller and larger farms, between older and younger farmers, and finally, between the main natural regions. If present, I expect all three heterogeneities to have high policy relevance.

The first farm characteristic of interest is the land area used in production; as discussed in the literature review section, it has been established that bigger farms have higher adaptive capacity (Zhao et al. 2012) and also tend to adopt technologies before smaller farms (Foster et al. 1985; Rosenzweig et al. 1992). Since my survey data do not include land areas for year 2014 (see Section 4), I predict this variable using a set of household characteristics and samples from the other two years[23]. I then estimate treatment effects of interest for households below median[24] land area separately by interacting the small farm indicator with the treatment conditions. I find that, firstly, none of the water conservation responses is driven by small farms. Secondly, none of the soil conservation responses is driven by small farms either, neither for past year's analysis nor with added reoccurring shocks.

TABLE VI: RESPONSES TO SHOCKS BY SMALLER HOUSEHOLDS

VARIABLES	(1) Water Index
High rainfall shock (t-1)	-0.0616**
	(0.0277)
High rainfall shock (t-1) x small farm	-0.00481
	(0.0280)
Low rainfall shock (t-1)	-0.0480
	(0.0386)
Low rainfall shock (t-1) x small farm	0.0494

[23] Among the models considered, quantile regression gives us the best fit with 92.8% correct prediction rate.
[24] 1.28 hectares in 2014, 1.32 ha in 2015 and 1.45 ha in 2016. Importantly, according to national census, 85% of Peruvian farms have size below 10 ha – a fact confirmed by my data – so "above median" in this case does definitely not mean a big farm in absolute terms.

	(0.0382)
Low CV shock (t-1)	-0.126***
	(0.0226)
Low CV shock (t-1) x small farm	0.0814***
	(0.0304)
High CV shock (t-1)	0.0357
	(0.0288)
High CV shock (t-1) x small farm	-0.0811**
	(0.0352)
Observations	42,863
R-squared	0.581

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Use of water conservation is the only outcome that seems to respond differently to weather shocks depending on farm's size. I still see the main effects of decreased use of water practices after years of high rainfall and low variation, but it appears that small households are specifically responsive to rainfall variability. Both extra high and low variation trigger different responses from households who own less land than the sample median (see Table VI).

The second heterogeneity of interest is farmer's age. This interest is specific to local Peruvian context where farmers are increasingly becoming older, a fact that my own data highly supports. If some desirable practices are only adopted by younger farmers – as we might expect them to be more responsive to shocks – it would be a policy concern promotion of these practices. Simple correlation analysis with one cross-section shows that the likelihood of using all the practices analyzed decreases with farmer's age, and after including a quadratic age term I see a parabolic relationship present (see Table 3 of Appendix). I thus interact "young farmer dummy", here defined as being below the median age of 51, with different treatment conditions to check for heterogeneous responses of older and younger farmers. Across the nation, i.e. as an average treatment effect I see no effect of being a younger farmer in terms of increase/decrease in adoption rate of any practice after a weather shock (output available upon request). This is a surprising finding considering the correlations these characteristic have with overall adoption rates.

Considering the geographic scope of the study, it is clear that the impacts of weather shocks are not homogeneous across regions. While the results discussed so far are average treatment effects across the nation, I now turn to local-level effects that might differ depending on the natural (or social, for that matter) setting.

The three main natural regions of Peru are the coastal zone (Coast), the highlands of the Andes (Mountains), and the far west end of the Amazonian rainforest (Forest). Table 6 in Appendix reports the results of the analysis that breaks the shocks' impacts down by those three regions; from there, I can shed light on the validity of these regional trends by conducting the same analysis on scale that is one level coarser (i.e. the coarsest natural region indicator I have): sub-regions. This division breaks Coast and Mountain regions into three parts – North, Central and South – so I can compare whether the effects on sub-regional level follow the patterns identified on the regional level. In the latter case, we could claim the treatment effects to be representative of the three regions.

As Table 6 in Appendix shows, national level effects are often driven by individual regions. Specifically, Mountain region appears to be the most sensitive to weather shocks; the latter has also been reported to be subject to the most severe expression of climate change outcomes in the country so far (Painter 2007). The dramatic changes I see in both the number of fertilizer appliers and users of water conservation are all driven by the Mountain region and to a lesser extent by the Forest region. This, however, aligns perfectly with the population of interest of this study, as the majority of potato and maize growers (76% of the sample) as well as smallholder subsistence farms in general (65% nationally) are located in the Mountain region. Two more interesting aspects are, firstly, the observation that farmers in Forest region do increase their soil treatment after shocks, in contrary to what farmers in other regions do; and secondly, farmers in the coastal region seem to be much less responsive to weather shocks received. We might suspect that this has to do with relatively higher level of commercialization and closeness to markets that are distinctive to the Coast, but this aspect needs further exploration.

Finally, the sub-regional analysis mentioned above provides a good robustness check for this regional break-down by confirming similar regional trends on a coarser scale.

5.6. Robustness Checks

As discussed in the Section 4.4, the unbiasedness of my results could be threatened by the potential endogeneity of extension services. So far, I have included receiving technical assistance as a control variable and its positive effect of adoption of soil and water practices is robust to model specifications (see Table III and Table 3 in Appendix); on average, *conglomerado*-s that have received extension services have ~11 percentage points more fertilizer users, the use rate of soil practices is higher by 0.18 standard deviations and water practices by 0.06 standard deviations. However, there is yet no robust evidence to conclude that the assistance can be seen as independent from weather shocks. I could hypothesize that places that receive "bad" weather shocks are also targeted by agricultural extension service, which then in turn would also bias the estimated impacts of weather shocks.

In order to confirm robustness of the obtained standard errors, I re-analyze my models after collapsing the data to the level of clusters, i.e. to the *conglomerado*-level; the results are reported in Table 7 of Appendix. While I see few slight magnitude changes of up to 5%, no result loses their significance at any level, providing support for the robustness of the results seen.

As another way to check the validity of the causal mechanism under study, I conduct a Placebo-test and look at the impact of these same weather shocks on variables that have a low likelihood of changing from year-to-year, due to their capital-intensive nature or otherwise. One such variable is livestock ownership – we could hypothesize that even though farmers do adjust their livestock portfolio and the ratio of resources devoted to crop cultivation versus animal husbandry in response to climate change, they are not likely to systematically obtain/abandon animals in response to a single shock, as it is a transaction that requires capital. Indeed, the same models estimated with animal ownership as an outcome shows no impact of weather shocks at any significance level. Similarly, the second indicator I test here is educational attainment as, following a close logic, I do not expect the demographic composition of *conglomerado*-s to change after a single year of unusual weather realization, at least on the level of household heads (i.e. not considering schooling decisions regarding kids). Again, shocks have no statistically significant impact on education levels.

6. Discussion and Limitations

When placing my findings in the larger context, I first have to discuss the importance of the first part of the analysis determining the characteristics that correlate with different practices. While it does not identify any causal relationships and while similar unidentified analyses have been conducted already for decades, it is worth noting that – to my knowledge – there is no well-powered studies from Peru, and few from South America in general, so far.

Relying on two great meta-analysis compiled up to date[25] (Knowler et al. 2007; Knowler 2015), I can see that farmer characteristics that are associated with adoption of conservation practices largely align with what has been observed in other parts of the world. Knowler et al. (2007) conclude

[25] Excluding analyses that only consider developed countries.

that the few variables that are consistently and positively associated with adoption of conservation measures are, among others, experience, family size (labor availability), extension services, and membership in organizations, while factors with consistent negative relationship are distance to paved road and proportion irrigated. For soil conservation, I observe all these positive associations here; cooperative membership and receiving extension have especially large and statistically significant coefficients (see Table 3 in Appendix). Yet I cannot confirm the negative correlations reported by Knowler et al.: fixed effects estimation shows that distance to center only has a statistically significant relationship with fertilizer use but not conservation measures – an intuitive result that gives hope that conservation could also thrive in remoter areas as opposed to chemical inputs –, and using technical irrigation correlates highly with all the practices.

On the other hand, Knowler et al. show that variables with inconsistent contribution to adoption of conservational practices are age, education, farm size and tenure. I find a strong parabolic relationship between the first one, age, and adoption of any practice, a result of high policy relevance in context where higher age and smaller family size are important demographic trends for rural areas (Ministerio de Riego y Agricultura 2017), and an outcome that should thus be kept in mind for future promotional work regarding conservation practices. I also find that households who own their land are more likely to practice soil conservation; this finding is previously established in the adaptation literature (Arslan et al. 2014; Lawin et al. 2018), easy to explain with the incentives that owning land gives one, and has also a high policy relevance. Providing better incentives for sustainable management through improved land and water tenure systems have claimed to be one of the policy priorities for CSA-development (Caron et al. 2018). Thirdly, each conservation practice under study has higher adoption rate among educated as well as male household heads. The latter observation runs into a theme of high interest in the climate change research – gender-differentiated adaptations (CGIAR 2015). Nhemachena et al. (2007), for instance, argue that female-headed households are generally more likely to engage in climate change adaptation because of their greater involvement in related agricultural work, while Hassan et al. (2008) discuss female risk aversion as well as labor constraints, concluding that currently there is no consensus regarding the expected directionality of the relationship between gender and application of conservation measures.

Moving on to weather shocks, three robust average treatment effects among farmers across Peru are found. Firstly, water conservation practices appear to be highly responsive to past year's abnormal weather realization, but not to shocks over longer time periods. Specifically, use of water practices tends to drop after a year of a) high rainfall, or b) little variability of rainfall, while the biggest impact is seen after a simultaneous occurrence of high rainfall variation and drought during the same year – arguably the riskiest kind of conditions –, with an estimated average treatment effect of 0.14 standard deviation increase in the fraction of water conservation practitioners.

Secondly, while soil conservation does not seem to be sensitive to previous year's shock, farmers tend to alter their practices after experiencing multiple years of abnormal levels of rain. I find that proportion of soil practices' adopters see an increase similar in magnitude, around 0.06 standard deviations, for every extra drought year over past five years, and for every extra year of excessive rain over past three years. These findings fit somewhat into the (sparse) literature of adaptation studies that incorporate rainfall data. Asfaw et al. (2014) find that greater rainfall variability is positively associated with the choice of risk-reducing practices such as soil and water conservation, and Arsan et al. (2014) show that Zambian farmers mitigate the risk of rainfall variability by using minimum soil disturbance practices.

The third finding comes from the analysis of changes in fertilizer use, an element added to the study to see responses related to more immediate productivity related concerns that farmers might have. I show strong and statistically significant evidence that farmers respond to negative rainfall level shocks (that is, drought conditions) by taking up chemical fertilizer application over the agricultural year following a shock; I estimate an ATE of 6.1 to 8.9 percentage point increase in the proportion of fertilizer users. On the other hand, high rainfall combined with high variation induces the use rate to go down by close to 10 percentage points over the year following a shock. This finding aligns with what other studies have shown before: analyzing responses to previous year's rainfall shocks in Malawi and Mozambique, respectively, Asfaw et al. (2014) conclude that high variability reduces the use of inorganic fertilizer in Malawi, while Salazar-Espinosa et al. (2015) show that the probability of using fertilizer increases after rainfall level shocks, both positive and negative, as opposed to variability shocks.

The explanation for the latter and the ~7 percentage point increase found here is highly likely to be a decline in soil quality after a drought, that thus leads farmers to purchase inputs to recover productivity in soil (FAO 2005). The reduction in users after a variability shock, on the other hand, points to the behavioral response one might expect to see. As the act of purchasing fertilizer requires capital, experienced high variation makes risk averse producers hesitant to devote their resources towards this input despite its potential to enhance productivity. Previous studies analyzing yield impacts of various practices have found that timely access to fertilizer is one of the most robust determinants of both crop yields and yields' resilience to shocks (Arslan et al. 2015). Additionally, literature shows complementarities between conservational measures and "modern" practices such as chemical inputs and improved seeds: for example, inorganic fertilizer is found to provide significant yield benefits only when complemented with soil and water conservation practices or intercropping (Asfaw et al. 2014; Arslan et al. 2017). Putting this knowledge into the context of the current study, ideally we would like to see increase in fertilizer use being complemented with the other two types of conservational practices – which I unfortunately do not observe. From policy perspective, this means that the future promotion of farming practices should incorporate these complementarities as well as what we currently know about farmers simultaneous uptake of them.

The regional differences in both adoption of practices and shock responses is a crucial aspect of any climate-smart development in agriculture, in a diverse country like Peru especially. In their meta-analysis of climate-smart practices across developing countries, McCarthy et al. (2011) conclude that "[M]ost practices (agronomy, integrated nutrient management, tillage/residue management, agro forestry) show significant climate change mitigation potential in humid areas but smaller mitigation co-benefits in dry lands." As discussed in Section 3, the purpose of this study was never to determine which practices could be beneficial for smallholders facing new weather events, but rather to look at the adoption of a set of practices that Peruvian agencies have already defined as desirable in context of soil degradation and water shortages. Thus, by no means do I believe that when facing shocks, farmers across the nation adopt the same set of practices, and the regional breakdown (see Section 5 and Table 6 in Appendix) aimed to shed light to this aspect. The same analysis by McCarthy et al. (2011) also notes that "… only water management is found to be effective in delivering significant food security benefits and mitigation co-benefits [for smallholders] both in dry and humid areas". Interestingly, post-shock changes in water practices are the only ones that I find to show heterogeneity in terms of farms' land area.

Specifically, I aimed to detect heterogeneous responses in terms of household head's age and size of farm's landholdings. I cannot reject the hypothesis that weather shocks trigger homogeneous responses from farmers below and above median age, and households with less and more than median number of hectares. The latter comes with one exception: change in water conservation practices. It turns out that farmers with less land are more responsive to high variation in rainfall, and tend to increase water conservation after such shock (see Table VI). As higher rainfall variability is one of the main stressors imposed by climate change in Peru (USAID 2016), these heterogeneous responses to abnormal weather variation should be given more attention to – especially as I have not been able to locate any similar farm level analyses that include weather variability from South American countries.

Both adoption and adaptation studies have established that access to extension services is a crucial determinant for adoption of adaptive and conservational measures (Nhemachena et al. 2007; Deressa et al. 2009; Arslan et al. 2014). My analysis poses that received technical assistance has a positive and highly significant correlation with the three outcomes under study, while the estimated magnitude of the effect[26] is the greatest for soil conservation measures; such result makes sense considering the relative human capital intensiveness of the latter in comparison with the other two outcomes. However, correctly accounting for extension services currently remains one of the main pitfalls of the study as I have not yet determined its exogeneity in context of climate shocks.

My findings support the suggestions made by global policy experts regarding CSA (Caron et al. 2018): it is crucial to incorporate climate change effects into agricultural research and extension activities. That includes more integrated household-level and climatic data, research expansion to identify farming practices adapted to the specific climate and changes in it, and support to constantly updated training and extension programs (Caron et al. 2018). Specifically to the current article, in Peru there is no national-level household survey data that explicitly helps to understand weather related constraints and respective responses, while locality specific resilient practices are, to my knowledge, not identified and tested to sufficient extent. In general CSA and climate change context, the concern of farmers lacking capacity to utilize climate information has been raised by several policy experts (Caron et al. 2018).

In terms of extension, the agriculture revolution has in the past been based on major disruptive innovations, while the future transition will be more knowledge and information intensive (Caron et al. 2018). Thus, farmers' know-how needs to be integrated with disruptive technologies, and extension needs institutional arrangements that allow for information exchanges amongst stakeholders.

6.1. Limitations

Firstly, as mentioned above, disentangling extension services' impact from weather outcomes would give us relevant information on the full magnitude of the latter. Secondly, and most importantly, heterogeneous effects of shocks under study could potentially be addressed more carefully.

[26] Change as measured in standard deviations.

A second relevant concern is the fact that I have analyzed all the practices as lumped into one variable, which might not adequately count for the differences in these practices in terms of their characteristics such as labor needs and implementation time. However, one of the central ideas of this study was to take a different approach in practice modelling than the great majority of similar studies that have not taken into account multiple hypothesis testing and the impact it has on the results they observe. In addition, as the primary interest here is the *behavioral response* to shocks, or abnormal conditions, rather than the exact agronomic characteristics of practices and their uptake – which we might expect to be more place-specific if analyzed on individual basis –, a summary index fulfills this purpose better.

One more potential concern is people leaving agriculture – it would mean that the sample that I am looking at for 2016 differs from previous years by (potentially) other factors than demographic variables currently tell me. The mediating factor regarding this concern is the fact that my household survey data only span two years, winter of 2014 to winter of 2016. Due to the latter I do not expect there to be compositional demographic changes that would significantly alter the robustness of my analysis, as also confirmed by balance tests conducted on the three samples.

7. Conclusion

In the context of understanding the economic impact of climate change, adaptation ranks among the most important, yet the least understood (Di Falco et al. 2012; Zilberman et al. 2012). However, in order to design inclusive policies and programs that can help farmers adapt to new weather conditions, it is critical to understand what kind of adaptive choices people make when faced with shocks (CGIAR 2016). Motivated by the latter as well as the scarcity of adaptation studies from South America, the purpose of my research is to better understand farm-level adaptations to changing weather realizations in Peru, a country that is predicted to witness one of the greatest impacts of climate change over the decades to come.

Specifically, I have looked at the change in adoption rates of conservational measures towards soil and water, and use of a more short-sighted input, chemical fertilizer. I see that climate change-related effects are an important determinant of the practices that farmers growing staple crops, potato and maize, select, and that especially in the Andes highlands where the majority of subsistence farmers live. My main finding is that following a year of abnormal precipitation levels, the number of farmers who apply inorganic fertilizer goes up on average, after accounting for time-invariant, place-specific factors. At the same time, I do not see an increase in proportion of farmers who have adopted soil conservation measures, as indicated by an aggregate index over four practices. It appears, however, that more conservational practices are adopted after households have experienced multiple years of abnormal weather as opposed to a single shock over the preceding year. This points to a behavioral response: farmers who have experienced adverse conditions opt into a more short-sighed input, inorganic fertilizer, to address the reduction in soil quality, while it is not confirmed that this approach actually has yield benefits under extreme weather conditions.

The findings regarding water conservation practices – similarly measured with an index that captures the information contained in variation in adoption rates across four practices – show reduction in adoption rates after shock years. Namely, Peruvian farmers are less likely to engage in these practices after they have experienced abnormally high levels of rainfall, or abnormally little variation of it. Meanwhile, water conservation does not seem to be sensitive to multiple years of "bad" weather, as opposed to measures towards soil conservation.

While farm-level adaptation studies that incorporate climate data are increasing in numbers, they are yet hard to come by for South America, making it difficult to place my findings in a larger context-specific literature. This very same notion, however, points to the policy relevance of the work undertaken here. I have four specific suggestions to make.

First, in terms of policy prescriptions, I find that a behavioral response to years that decrease the nutrient levels in soil is to apply more fertilizer, while practices that are identified as potentially increasing soil's fertility in long term are not adopted. Yet previous studies have reported that inorganic fertilizer's yield benefits disappear under extreme weather shocks, unless combined with sustainable land management practices (Arslan et al. 2014, 2017). This points to a need for nudging farmers, and extending training and extension to areas that are likely to face such shocks over the coming years. Based on the analysis of factors that correlate with adoption of different practices, I can suggest that extension services should also have a differentiated approach in promotion with respect to gender, age, and tenure of farmers.

Secondly, I believe that there is a growing need for agricultural household surveys that incorporate climate change specific questions – for both, perceived risks as well as adaptive measures that farmers undertake – and that especially in panel format. Such surveys have been conducted in several African countries over the last decade, but to my knowledge, South America remains less studied. The current household survey data used give hints about potential threats that new weather patterns impose on farmers, but such information is not explicitly asked for from the households, while the climate projections for the coming decades indicate that there is definitely need for improved understanding of agricultural decisions on micro level.

Thirdly, in terms of future research I would like to point to the need for more experimental (behavioral) studies that incorporate a) farmer-specific incentives, such as land, water, and soil, and b) "new climate"-specific elements. In order to predict and incorporate choices that producers make under unusual and/or extreme conditions, we need a better understanding of their decision-making framework within the shocks–productivity–conservation nexus.

Lastly, a general framework for analyzing the interactions between humans' choices and weather *variability* is yet to be developed. Currently, there are no standard treatment conditions and mechanisms widely used in the literature, and therefore this study has also aimed to contribute to the climate-economy literature by a novel way of incorporating abnormal variation in weather outcomes: namely, by obtaining exogenous variation by standardizing the coefficient of variation in rainfall over a long time horizon for temporal comparability. This, as well as the practice indices that update the farm-level conservation and adaptation literature that largely does not account for multiple hypothesis testing are the big methodological contributions this paper has aimed to make. That in addition to the bottom-line message: climate change does matter in farm-level decision making, already today.

References

Altieri, M. A., Nicholls, C. I., Henao, A., and Lana, M. A. (2015). Agroecology and the design of climate change-resilient farming systems. Agronomy for sustainable development, 35(3), 869-890.

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): 1481–95.

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

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

Arslan, A., McCarthy, N., Lipper, L., Asfaw, S., Cattaneo, A., and Kokwe, M. (2015). Climate smart agriculture? Assessing the adaptation implications in Zambia. Journal of Agricultural Economics, 66(3), 753-780.

Asfaw, S., McCarthy, N., Lipper, L., Arslan, A., Cattaneo, A., and Kachulu, M. (2014). Climate variability, adaptation strategies and food security in Malawi. ESA Working Paper, 14-08.

Auffhammer, M., Hsiang, S. M., Schlenker, W., and Sobel, A. (2013). Using weather data and climate model output in economic analyses of climate change. Review of Environmental Economics and Policy, 7(2), 181-198.

Bardhan, P., and Udry, C. (1999). Development microeconomics. OUP Oxford.

Caron, P., Dev, M., Oluoch-Kosura, W., Phat, C. D., Lele, U., Sanchez, P., and Sibanda, L. M. (2018). Devising effective strategies and policies for CSA: insights from a panel of global policy experts. In Climate Smart Agriculture (pp. 599-620). Springer, Cham.

Central Intelligence Agency. (2017). The World Factbook 2017. Washington, DC: Central Intelligence Agency. Retrieved from https://www.cia.gov/library/publications/the-world-factbook/index.html.

Centro Internacional de Agricultura Tropical (CIAT). (2014). Evaluación de la vulnerabilidad al cambio climático de la agricultura en la región Andina de Perú. CIAT Políticas en Síntesis No. 14. CIAT, Cali, Colombia. 6 p.

Cohen, J., Etner, J., and Jeleva, M. (2008). Dynamic decision making when risk perception depends on past experience. Theory Decis., 64 (2–3), pp. 173-192.

Cohn, A.S., Newton, P., Gil, J.D., Kuhl, L., Samberg, L., Ricciardi, V., Manly, J.R. and Northrop, S. (2017). Smallholder agriculture and climate change. Annual Review of Environment and Resources, 42, 347-375.

Conley, T. G., and Udry, C. R. (2010). Learning about a new technology: Pineapple in Ghana. The American Economic Review, 100(1), 35-69.

Dell, M., Jones, B. F., and Olken, B. A. (2014). What Do We Learn from the Weather? The New Climate–Economy Literature. Journal of Economic Literature, vol. 52 (3), pp. 740–798.

Deressa, T. T., R.M. Hassan, C. Ringler, T. Alemu and M. Yesuf. (2009). Determinants of farmers' choice of adaptation methods to climate change in the Nile Basin of Ethiopia. Global Environmental Change 19:248-255.

Di Falco, S. and Veronesi, M. (2012). How African Agriculture Can Adapt to Climate Change? A Counterfactual Analysis from Ethiopia. Working Paper Series, Department of Economics, University of Verona No. 14.

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

Duncan, J. M. A., Dash, J., and Tompkins, E. L. (2017). Observing adaptive capacity in Indian rice production systems. AIMS Agriculture and Food, 2(2), 165-182.

Ervin, C. A., and Ervin, D. E. (1982). Factors affecting the use of soil conservation practices: hypotheses, evidence, and policy implications. Land economics, 58(3), 277-292.

Fafchamps, M. (1992). Cash crop production, food prices volatility, rural market integration in the third world. American Journal of Agricultural Economics, 74 (1), pp. 90-99.

FAO. (2005). Drought-Resistant Soils. Optimization of Soil Moisture for Sustainable Plant Production. FAO Land and Water Bulletin 11, Rome.

Feder, G. (1980). Farm Size, Risk Aversion, and the Adoption of New Technologies Under Uncertainty. Oxford Economics Papers 32(1980): 263-83.

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

Foster, A. D. and M. R. Rosenzweig (2010). Microeconomics of technology adoption. Annual Review of Economics 2.

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A. and Michaelsen, J. (2015). The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. Scientific data, 2, p.150066.

Gertler, P. J., Martinez, S., Premand, P., Rawlings, L. B., and Vermeersch, C. M. (2016). Impact evaluation in practice. World Bank Publications.

Harvey, C. A., Chacón, M., Donatti, C. I., Garen, E., Hannah, L., Andrade, A., and Clement, C. (2014). Climate-smart landscapes: opportunities and challenges for integrating adaptation and mitigation in tropical agriculture. Conservation Letters, 7(2), 77-90.

Hassan, R. and Nhemachena, C. (2008). Determinants of African farmers' strategies for adapting to climate change: multinomial choice analysis. African Journal of Agricultural and Resource Economics 2:83-104.

Howden, S.M., Soussana, J. F., Tubiello F. N., Chhetri N., Dunlop M., and Meinke H. (2007). Adapting agriculture to climate change.

Hsiang, S. (2016). Climate econometrics. Annual Review of Resource Economics, 8, 43-75.

IPCC (Grupo Intergubernamental de Expertos sobre el Cambio Climático). (2000). Informe Especial del IPCC sobre Escenarios de Emisiones: Resumen para responsables de políticas. Ginebra, Suiza. 21 p.

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

Kassie, M., Pender, J., Yesuf, M., Kohlin, G., Bluffstone, R., and Mulugeta, E. (2008). Estimating returns to soil conservation adoption in the northern Ethiopian highlands. Agricultural Economics, 38(2), 213-232.

Knowler, D. and Bradshaw, B. (2007). Farmers' adoption of conservation agriculture: A review and synthesis of recent research. Food Policy, 32(1): 25–48.

Kurukulasuriya, P. and Rosenthal, S. (2003). Climate change and agriculture: A review of impacts and adaptations. Climate Change Series, 91. Published jointly with the Agriculture and Rural Development Department.

Lawin, K. G., and Tamini, L. D. (2018). Land Tenure Differences and Adoption of Agri-Environmental Practices: Evidence from Benin. The Journal of Development Studies, 1-14.

Lipper, L., McCarthy, N., Zilberman, D., Asfaw, S., and Branca, G. (Eds.). (2018). Climate smart agriculture: building resilience to climate change (Vol. 52). Springer.

Lybbert T. J., Sumner T. A. (2012). Agricultural technologies for climate change in developing countries: policy options for innovation and technology diffusion. *Food Policy* 37:114–23.

Maddison, D. (2007). The perception of and adaptation to climate change in Africa (Vol. 4308). World Bank Publications.

McCarthy, N., Lipper, L., and 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.

McKee, T. B., N. J. Doesken, and J. Kleist. (1993). The relationship of drought frequency and duration of time scales. Eighth Conference on Applied Climatology, American Meteorological Society, Jan17-23, 1993, Anaheim CA, pp.179-186.

Mendelsohn R. (2000). Efficient adaptation to climate change. Climate Change 45:583–600.

Ministerio del Ambiente. (2010). El Perú y el Cambio Climático. Segunda Comunicación Nacional del Perú a la Convención Marco de las Naciones Unidas sobre Cambio Climático 2010. Ministerio del Ambiente. Lima, Peru. Retrieved from http://es.scribd.com/doc/45850105/Segunda-ComunicacionNacional-Del-Peru-a-La-CMNUCC-2010 on April 21, 2018.

Ministerio de Agricultura y Riego. (2017). Calendario de Siembras y Cosechas. Ministerio de Agricultura y Riego - SIEA - Dirección General de Seguimiento y Evaluación de Políticas. Retrieved from http://siea.minagri.gob.pe/calendario/ on January 31, 2018.

Moschini, G. C., and Hennessy, D. (1995). Uncertainty, Risk Aversion and Risk Management for Agricultural Producers. Economic Staff Paper Series. 315.

Nakicenovic, N., Alcamo, J., Grubler, A., Riahi, K., Roehrl, R. A., Rogner, H. H., and Victor, N. (2000). Special Report on Emissions Scenarios (SRES), A Special Report of Working Group III of the Intergovernmental Panel on Climate Change. Cambridge University Press.

Newson, R. B. (2010). Frequentist q-values for multiple-test procedures. Stata journal, 10(4), 568.

Oxfam Novib. (2013). Building on farmers' perceptions and traditional knowledge: Biodiversity management for climate change adaptation strategies. The Hague: Oxfam Novib, 8.

Painter, J. (2007). Deglaciation in the Andean Region. UN Human Development Report 2007/2008. United Nations.

Rogers, E. M. (1962). Diffusion of innovations. Simon and Schuster.

Rosenstock T. S., Lamanna C., Chesterman S., Bell P., Arslan A., Richards M., Rioux J., Akinleye A. O., Champalle C., Cheng Z., Corner-Dolloff C., Dohn J., English W., Eyrich A., Girvetz E. H., Kerr A., Lizarazo M., Madalinska A., McFatridge S., Morris K., Namoi N., Poultouchidou N., Ravina da Silva M., Rayess S., Ström H., Tully K. L., and Zhou W. (2016). The scientific basis of climate-smart agriculture: A systematic review protocol. CCAFS Working Paper no. 138. Copenhagen, Denmark: CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS).

Rosenzweig, M. R., and Binswanger, H. P. (1992). Wealth, weather risk, and the composition and profitability of agricultural investments (Vol. 1055). World Bank Publications.

Salazar-Espinoza, C., Jones, S. and Tarp, F. (2015). Weather shocks and cropland decisions in rural Mozambique. Food Policy, Volume 53, pp. 9-21.

Saldarriaga, V. (2016). Efectos de la variabilidad de la temperatura en la productividad y en los precios de los productos agrícolas: evidencia en Perú. Inter-American Development Bank.

Seo, N., Mendelsohn, R., Kurukulasuriya, P., Dinar, A., and Hassan, R. (2009). Differential adaptation strategies to climate change in African cropland by agro-ecological zones.

Seo, S. and Mendelsohn, R. (2008). An analysis of crop choice: adapting to climate change in South American farms. Ecological Economics 67 (1) (2008), pp. 109-116.

Singh, R., and Singh, G. S. (2017). Traditional agriculture: a climate-smart approach for sustainable food production. Energy, Ecology and Environment, 2(5), 296-316.

Smit, B., and Skinner, M. (2002). Adaptation options in agriculture to climate change: a typology. Mitigation and Adaptation Strategies for Global Change 7, 85–114.

Stern, N. (2006). Stern review report on the economics of climate change.

Thomas, D. S., Twyman, C., Osbahr, H., and Hewitson, B. (2007). Adaptation to climate change and variability: farmer responses to intra-seasonal precipitation trends in South Africa. Climatic change, 83(3), 301-322.

Trenberth. (2014). Global warming and changes in drought. Nature Climate Change 4, 17-22.

United Nations Development Programme (UNDP), Bureau for Crisis Prevention and Recovery (BCPR). (2013). Climate Risk Management for Agriculture in Peru: Focus on the Regions of Junín and Piura. New York, NY: UNDP BCPR. Retrieved from http://www.iisd.org/pdf/2013/crm_peru.pdf on January 17, 2018.

United Nations Food and Agriculture Organization (FAO). (2017). Recomendaciones de política pública para enfrentar el cambio climático y la vulnerabilidad de la seguridad alimentaria. Rome, Italy: United Nations Food and Agriculture Organization.

USAID. (2017). Climate Change Risk in Peru: Country Risk Profile. USAID.

World Bank; CIAT; CATIE. (2015). Climate-Smart Agriculture in Peru. CSA Country Profiles for Latin America Series. 2nd. ed. Washington D.C.: The World Bank Group.

Wooldridge, J.M. (2010). Econometric analysis of cross section and panel data. MIT press.

Zhang, X., Alexander, L., Hegerl, G.C., Jones, P., Tank, A.K., Peterson, T.C., Trewin, B. and Zwiers, F.W. (2011). Indices for monitoring changes in extremes based on daily temperature and precipitation data. Wiley Interdisciplinary Reviews: Climate Change, 2(6), pp.851-870.

Zilberman D., Liu X., Roland-Holst D., and Sundig D. (2004). The economics of climate change in agriculture. Mitig. Adapt. Strateg. Glob. Change 9(4):365–82.

Zilberman, D., Zhao, J., and Heiman, A. (2012). Adoption versus adaptation, with emphasis on climate change. Annual Review Resource Economics, 4(1), 27-53.

Appendix

Part A: Tables

		2014	2015	2016	Total
SOIL PRACTICES	Soil analysis	0.0286	0.0218	0.0177	0.0225
		(0.167)	(0.146)	(0.132)	(0.148)
	Mixing organic matter	0.530	0.504	0.555	0.530
		(0.499)	(0.500)	(0.497)	(0.499)
	Crop rotation	0.463	0.471	0.501	0.479
		(0.499)	(0.499)	(0.500)	(0.500)
	Terraces	0.0960	0.0821	0.0716	0.0829
		(0.295)	(0.274)	(0.258)	(0.276)
WATER PRACTICES	Determine crop water needs	0.243	0.147	0.182	0.192
		(0.475)	(0.354)	(0.386)	(0.415)
	Determine irrigation times	0.303	0.217	0.232	0.250
		(0.460)	(0.412)	(0.422)	(0.433)
	Irrigation measurement	0.0453	0.0518	0.0805	0.0597
		(0.208)	(0.222)	(0.272)	(0.237)
	Irrigation maintenance	0.386	0.383	0.430	0.400
		(0.487)	(0.486)	(0.495)	(0.490)
	Fertilizer	0.5145	0.5471	0.5524	0.5384
		(0.499)	(0.498)	(0.497)	(0.499)
	Pesticides/herbicides	0.466	0.482	0.508	0.486
		(0.499)	(0.500)	(0.500)	(0.500)
	Biological control	0.0140	0.00912	0.00597	0.00959
		(0.118)	(0.0951)	(0.0770)	(0.0974)
	Integrated pest management	0.0646	0.136	0.115	0.106
		(0.246)	(0.343)	(0.318)	(0.308)
	Observations	13,612	14,603	15,218	43,433

Table 1. Summary statistics of agricultural practice variables that are used to construct soil and water indices (responses correspond to the survey instrument in Part B of Appendix).

	2014	2015	2016	Total
Index of soil	0.0179	-0.0168	-0.0140	0.0004
practices	(0.627)	(0.576)	(0.548)	(0.583)
Index of water	0.0057	-0.0114	-0.0115	5.41e-06
practices	(0.774)	(0.743)	(0.724)	(0.746)
Fertilizer use	0.5145	0.5471	0.5524	0.5384
	(0.499)	(0.498)	(0.497)	(0.499)
Observations	13,612	14,603	15,218	43,433

Table 2. Outcome variables analyzed in the study. Composite measures for the use of soil/water conservation practices are calculated using Anderson index, or the covariation of the four components, as described in Section 3.

VARIABLES	(1) Soil index FE	(2) Water index FE	(3) Fertilizer LP/FE
Gender (1 = male)	0.0422***	0.0334***	0.0540***
	(0.00527)	(0.00619)	(0.00495)
Age	0.00428***	0.000852	0.00328***
	(0.000899)	(0.00103)	(0.000827)
Age^2	-4.69e-05***	-1.91e-05**	-4.34e-05***
	(8.20e-06)	(9.20e-06)	(7.41e-06)
Experience	0.00100***	0.000730**	0.000392
	(0.000315)	(0.000342)	(0.000239)
Livestock ownership	0.0568***	0.0548***	0.0428***
	(0.00845)	(0.00843)	(0.00633)
Indigenous	0.0238*	0.00335	0.000335
	(0.0129)	(0.0171)	(0.00863)
Household size	0.00459***	0.00286**	0.00534***
	(0.00122)	(0.00141)	(0.00109)
Primary education or less	-0.0225***	-0.00777	-0.0144***
	(0.00703)	(0.00730)	(0.00546)
Owns land	0.0255***	0.00581	-0.00530
	(0.00787)	(0.00965)	(0.00638)
Technical irrigation	0.0511***	0.122***	0.112***
	(0.00894)	(0.0127)	(0.00889)
Cooperative membership	0.130***	0.00191	0.0465***
	(0.0169)	(0.0140)	(0.0109)
Saving account	0.0164*	-0.00108	0.0185***
	(0.00868)	(0.0105)	(0.00683)
Credit access	0.0425***	0.0360***	0.0724***
	(0.00888)	(0.00922)	(0.00630)
Distance to market	-0.00139	-0.00337	-0.0128***
	(0.00894)	(0.0127)	(0.00889)
Constant	-0.0309*	0.0633***	0.603***
	(0.0173)	(0.0210)	(0.0151)
Observations	42,851	42,851	42,851
R-squared	0.380	0.573	0.431
Number of clusters	2,018	2,018	2,018

Standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$
Note: conglomerado-level fixed effects are absorbed.

Table 3. Estimated relationships between control variables and outcomes of interest, where fertilizer and single-cropping are 1/0 indicator variables, thus linear probability models are used.

VARIABLES	(1) Soil index IV	(2) Soil index V	(3) Soil index VI	(4) Soil index VII	(5) Soil index VIII	(6) Water index IV	(7) Water index V	(8) Water index VI	(9) Water index VII	(10) Water index VIII	(11) Fertilizer IV	(12) Fertilizer V	(13) Fertilizer VI	(14) Fertilizer VII	(15) Fertilizer VIII
High rainfall shock (t-1)	-0.0234	-0.0147	-0.0349*	-0.0392**	-0.0244	-0.072***	-0.0625**	-0.0771***	-0.0663***	-0.0664***	0.0304**	0.0315**	0.0269**	0.0220*	0.0204*
	(0.0191)	(0.0191)	(0.0190)	(0.0186)	(0.0181)	(0.0245)	(0.0245)	(0.0241)	(0.0236)	(0.0235)	(0.0123)	(0.0124)	(0.0122)	(0.0119)	(0.0120)
Low rainfall shock (t-1)	0.00796	0.00384	0.00580	0.00835	-0.00756	-0.0557	-0.0538	-0.0547	-0.0509	-0.0283	0.0913***	0.0916***	0.0795***	0.0599**	0.0735***
	(0.0311)	(0.0308)	(0.0314)	(0.0288)	(0.0297)	(0.0403)	(0.0406)	(0.0402)	(0.0371)	(0.0381)	(0.0277)	(0.0277)	(0.0278)	(0.0251)	(0.0254)
High CV shock (t-1)	0.0139	0.0108	0.0109		-0.0112	-0.0401	-0.0462	-0.0427			0.0425*	0.0428*	0.0423*		
	(0.0252)	(0.0252)	(0.0249)		(0.0236)	(0.0405)	(0.0404)	(0.0404)			(0.0232)	(0.0233)	(0.0233)		
Low CV shock (t-1)	0.0128	0.0189	0.0200		0.0146	-0.0811***	-0.0864***	-0.0859***			-0.0152	-0.0127	-0.0148		
	(0.0171)	(0.0172)	(0.0170)		(0.0170)	(0.0184)	(0.0200)	(0.0198)			(0.0118)	(0.0117)	(0.0118)		
High CV x high rainfall (t-1)	-0.0401	-0.0252	-0.0521			0.0596	0.0668	0.0370			-0.0440	-0.0365	-0.0299		
	(0.0433)	(0.0432)	(0.0426)			(0.0626)	(0.0616)	(0.0603)			(0.0329)	(0.0332)	(0.0333)		
High CV x low rainfall (t-1)	-0.0635	-0.133	-0.0815*			0.0951	0.107	0.127*			-0.108***	-0.0966**	-0.108***		
	(0.0475)	(0.1501)	(0.0450)			(0.0783)	(0.0788)	(0.0758)			(0.0366)	(0.0396)	(0.0385)		
Low rain shock count, 10 y.	0.0171					0.0342					0.00581				
	(0.0152)					(0.0208)					(0.0119)				
High rain shock count, 10 y.	0.00992					-0.0162					-0.0320**				
	(0.0186)					(0.0269)					(0.0137)				
Low rain shock count, 5 y.		0.0782***					0.00837					-0.00795			
		(0.0236)					(0.0265)					(0.0162)			
High rain shock count, 5 y.		-0.0124					-0.0326					-0.0202*			
		(0.0144)					(0.0208)					(0.0109)			
Low rain shock count, 3 y.			0.0334	0.0270				-0.00232	0.0254				0.0325*	0.0254	
			(0.0236)	(0.0225)				(0.0323)	(0.0172)				(0.0179)	(0.0172)	
High rain shock. count, 3 y.			0.0657***	0.0607***				0.0226	-0.00318				-0.00271	-0.00318	
			(0.0148)	(0.0145)				(0.0192)	(0.00994)				(0.0102)	(0.00994)	
High variation shock count, 5 y.					7.38e-05					0.0483*					-0.0236**
					(0.0137)					(0.0247)					(0.0104)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	41,674	41,674	41,674	42,825	42,825	41,674	41,674	41,674	41,674	41,674	41,674	41,674	41,674	41,674	41,674
R-squared	0.391	0.392	0.393	0.392	0.391	0.579	0.579	0.579	0.578	0.578	0.446	0.446	0.446	0.446	0.446

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Note: For each of the outcomes, IV model has 10 year level shocks' counts included, V model has 5 year level shocks' counts included, and VI model has 3 year level shocks' counts included. VII model checks the robustness and has only last year level shocks + 3 year count. Level VIII turns to frequent variation shocks by including the count over 5 years.

Table 4. Supplementary table for Table V in the main body of the paper. I check the robustness of results presented in Table V by adding previous year's level and variation shocks' interaction terms, as well as comparing the simplest model (denoted as model VII for each outcome) to the results found previously. Finally, impact of variation shocks' count is looked at (model VIII).

VARIABLES	(1) Soil practices 10 y.	(2) Soil practices. 5 y.	(3) Soil practices 3 y.	(4) Water practices 10 y.	(5) Water practices 5 y.	(6) Water practices 3 y.	(7) Fertilizer 10 y.	(8) Fertilizer 5 y.	(9) Fertilizer 3 y.
Low rain shock	0.0120			0.0412			0.00460		
count, 10 y.	(0.0133)			(0.0696)			(0.0105)		
High rain shock	-0.000930			-0.0201			-0.0191		
count, 10 y.	(0.0170)			(0.0262)			(0.0125)		
Low rain shock		0.0564***			0.0276			-0.00342	
count, 5 y.		(0.0201)			(0.0243)			(0.0134)	
High rain shock		-0.0166			-0.0487*			-0.00767	
count, 5 y.		(0.0132)			(0.0294)			(0.00957)	
Low rain shock			0.0299			0.00593			0.0244
count, 3 y.			(0.0214)			(0.0310)			(0.0156)
High rain shock.			0.0546***			0.0294			0.00154
count, 3 y.			(0.0141)			(0.0194)			(0.00930)
Rainfall z-score	-0.00527	-0.00758	-0.000910	0.00923	0.0126	0.0179	-0.0116	-0.00890	-0.00866
	(0.0104)	(0.0102)	(0.0101)	(0.0131)	(0.0126)	(0.0125)	(0.00715)	(0.00692)	(0.00697)
Grow season T	-0.0301	-0.0198	-0.0589**	0.0295	0.0366	-0.00847	-0.0843***	-0.0875***	-0.0882***
	(0.0287)	(0.0286)	(0.0293)	(0.0391)	(0.0400)	(0.0399)	(0.0159)	(0.0157)	(0.0159)
Observations	42,713	42,713	42,713	42,713	42,713	42,713	42,713	42,713	42,713
R-squared	0.389	0.390	0.391	0.578	0.578	0.578	0.467	0.467	0.467

Table 5. Supplementary table for Table V in the main body of the paper (cont.). All models with only shock counts for robustness check.

VARIABLES	(1) SOIL PRACTICES	(2) Coast	(3) Mountains	(4) Forest	(5) WATER PRACTICES	(6) Coast	(7) Mountains	(8) Forest	(9) FERTILIZER USE	(10) Coast	(11) Mountains	(12) Forest
High rainfall shock (t-1)	-0.0238	0.0484	-0.0454*	0.0932**	-0.0729***	0.0816	-0.0956***	0.00297	0.0184	0.0403*	0.0118	0.0328
	(0.0185)	(0.0544)	(0.0267)	(0.0361)	(0.0238)	(0.107)	(0.0273)	(0.0271)	(0.0122)	(0.0224)	(0.0141)	(0.0354)
Low rainfall shock (t-1)	0.00351	0.0275	-0.00435	-0.00690	-0.0569	0.197	-0.0964*	0.0391	0.0899***	0.0784	0.0844**	0.0715
	(0.0310)	(0.0933)	(0.0384)	(0.0567)	(0.0401)	(0.262)	(0.0514)	(0.0326)	(0.0278)	(0.0844)	(0.0328)	(0.0630)
Rainfall z-score	-0.00959	-0.00137	-0.000672	-0.00362	-0.00489	0.0626*	-0.0189	0.0635**	-0.00643	0.0122	0.00533	-0.0280*
	(0.0106)	(0.0232)	(0.0169)	(0.0165)	(0.0143)	(0.0355)	(0.0228)	(0.0249)	(0.00776)	(0.00898)	(0.0122)	(0.0158)
High CV shock (t-1)	0.00874	0.0636	0.0146	0.0372	-0.0383	-0.0193	-0.0886	0.0380	0.0421*	0.0730	0.0332	0.0352
	(0.0255)	(0.0883)	(0.0340)	(0.0433)	(0.0407)	(0.124)	(0.0584)	(0.0434)	(0.0227)	(0.0450)	(0.0293)	(0.0503)
Low CV shock (t-1)	0.0108	-0.0252	0.0290	0.0168	-0.0911***	-0.184	-0.0911***	0.0111	-0.0119	0.0217	-0.00435	-0.0123
	(0.0171)	(0.0666)	(0.0202)	(0.0244)	(0.0199)	(0.129)	(0.0245)	(0.0296)	(0.0120)	(0.0332)	(0.0140)	(0.0306)
CV z-score	0.00396	0.00503	0.0210**	-0.0212	0.0177	-0.00567	0.0273*	-0.0660***	-0.00121	0.00134	0.00230	0.00739
	(0.00864)	(0.0263)	(0.0103)	(0.0169)	(0.0129)	(0.0560)	(0.0153)	(0.0253)	(0.00641)	(0.0110)	(0.00779)	(0.0163)
High CV x high rainfall (t-1)	-0.0343	-0.126	-0.0542	0.00437	0.0484	0.118	-0.0647	-0.0580	-0.0514	-0.0966**	-0.0537	-0.0353
	(0.0441)	(0.0970)	(0.0875)	(0.0616)	(0.0606)	(0.142)	(0.112)	(0.0519)	(0.0324)	(0.0451)	(0.0670)	(0.0621)
High CV x low rainfall (t-1)	-0.0374	-0.127	-0.0601	0.272**	0.135**	-0.0971	0.206**	-0.296**	-0.101***	-0.262**	-0.0927**	-0.185***
	(0.0428)	(0.102)	(0.0510)	(0.123)	(0.0634)	(0.315)	(0.0872)	(0.122)	(0.0363)	(0.104)	(0.0419)	(0.0712)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
No. of conglomerados	1,889	334	1,174	381	1,889	334	1,174	381	1,889	334	1,174	381
Observations	42,713	4,401	32,768	5,535	42,713	4,401	32,768	5,535	42,713	4,401	32,768	5,535
R-squared	0.382	0.341	0.313	0.296	0.579	0.527	0.391	0.511	0.437	0.393	0.397	0.387

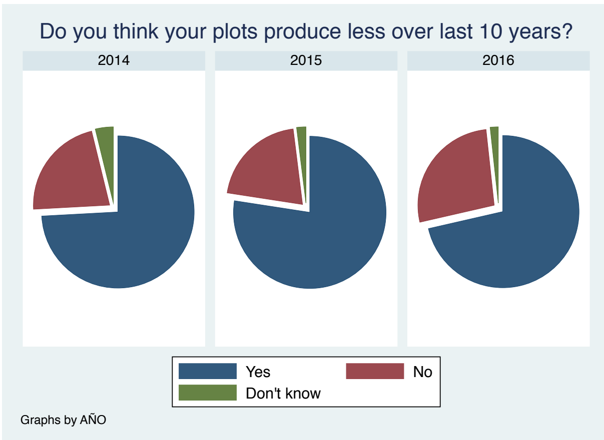
Table 6. Estimated average treatment effects across the nation broken down by the three main natural regions of Peru. Analysis on coarser scale, by the seven sub-regions is not shown here but it confirms the regional trends observed in the table above.

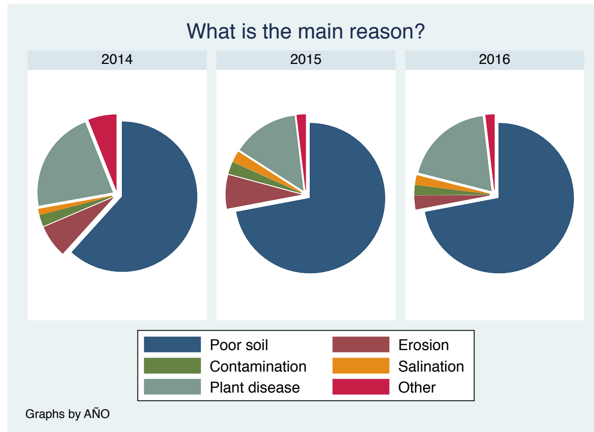
VARIABLES	(1) Fertilizer IND.	(2) Fertilizer CLUS.	(3) Soil index IND.	(4) Soil index CLUS.	(5) Index water IND.	(6) Index water CLUS.
High rainfall shock (t-1)	0.00943	0.00178	-0.00979	-0.00800	-0.0397*	-0.0266
	(0.0103)	(0.0101)	(0.0170)	(0.0165)	(0.0206)	(0.0202)
Low rainfall shock (t-1)	0.0897***	0.0926***	0.0239	0.0216	0.00218	-0.0104
	(0.0291)	(0.0287)	(0.0285)	(0.0282)	(0.0375)	(0.0374)
Rainfall z-score	-0.00751	-0.0101*	-0.0107	-0.00983	0.00154	0.00190
	(0.00603)	(0.00605)	(0.00843)	(0.00837)	(0.0112)	(0.0112)
CV z-score	0.0161	0.0130	0.00823	0.00394	0.0248	0.0134
	(0.0173)	(0.0171)	(0.0198)	(0.0190)	(0.0329)	(0.0314)
High CV shock (t-1)	-0.00545	-0.00558	0.0110	0.0120	-0.0802***	-0.0748***
	(0.0103)	(0.00989)	(0.0136)	(0.0136)	(0.0174)	(0.0173)
Low CV shock (t-1)	-0.000251	-0.00386	-0.00608	-0.00857	0.0205**	0.0197*
	(0.00510)	(0.00502)	(0.00687)	(0.00687)	(0.0103)	(0.0102)
High CV x high RF (t-1)	-0.0528**	-0.0510**	-0.0291	-0.0396	-0.0886*	-0.0870*
	(0.0227)	(0.0226)	(0.0346)	(0.0326)	(0.0496)	(0.0477)
High CV x low RF (t-1)	-0.0616	-0.0538	-0.0196	-0.0160	0.170**	0.161**
	(0.0447)	(0.0415)	(0.0477)	(0.0500)	(0.0821)	(0.0789)
Grow season temp.	-0.101***	-0.0757***	-0.0565**	-0.0587***	0.0109	0.00869
	(0.0135)	(0.0148)	(0.0219)	(0.0219)	(0.0305)	(0.0312)
LEVEL	Individual	Cluster	Individual	Cluster	Individual	Cluster
Controls	NO	NO	NO	NO	YES	YES
Observations	42,768	5,649	42,813	5,760	42,768	5,649
R-squared	0.407	0.785	0.360	0.785	0.574	0.769

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

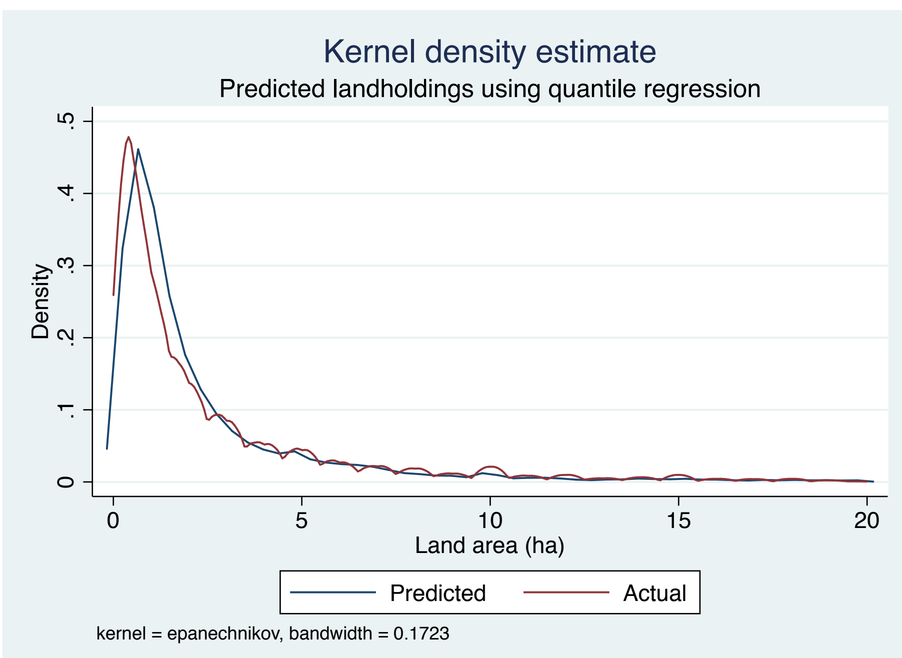
Table 7. Robustness check for the standard errors is conducted by collapsing the analysis to the level of clusters, or, *conglomerado*-level climate shock models.

Part II: Graphs

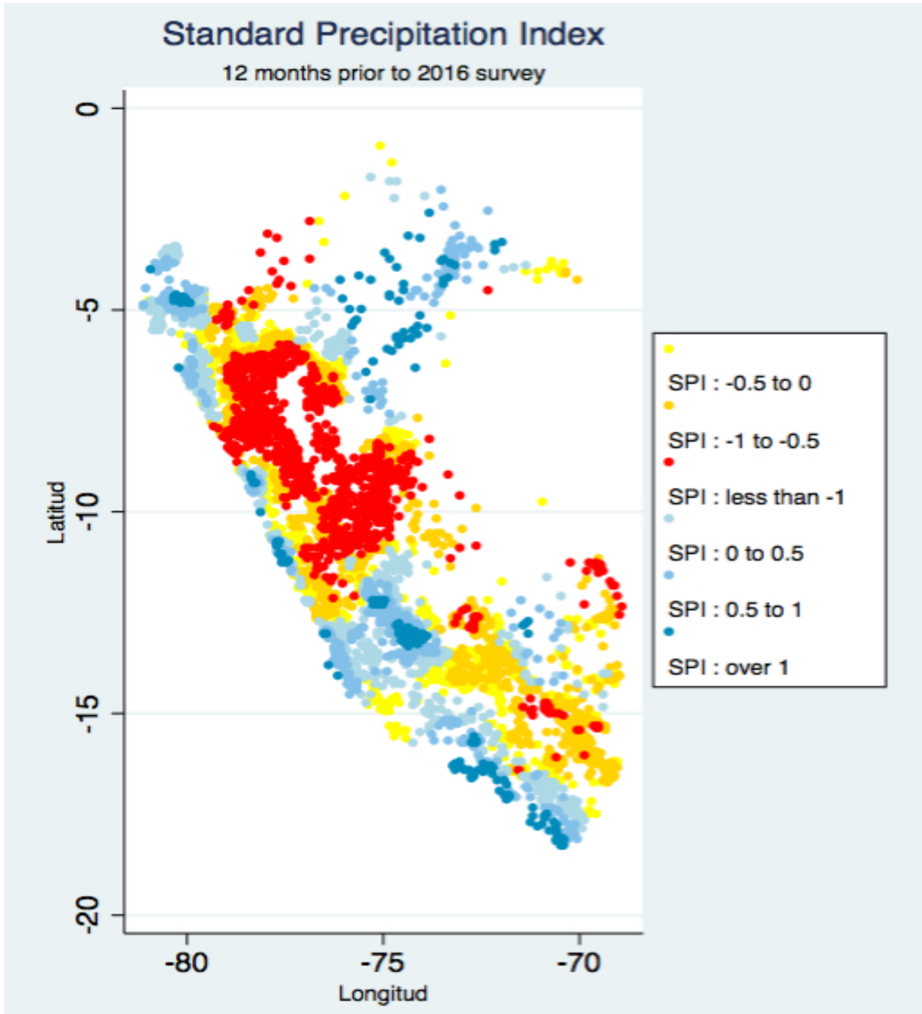




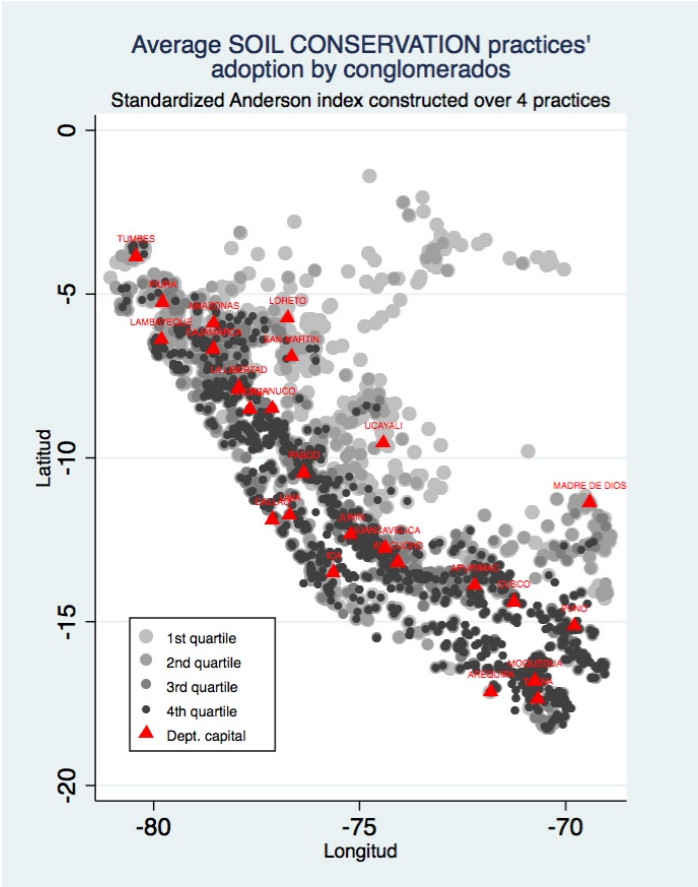
Graph 1: Peruvian farmers' responses to questions on a) whether they perceive their plots to produce less, and b) what is the main perceived reason

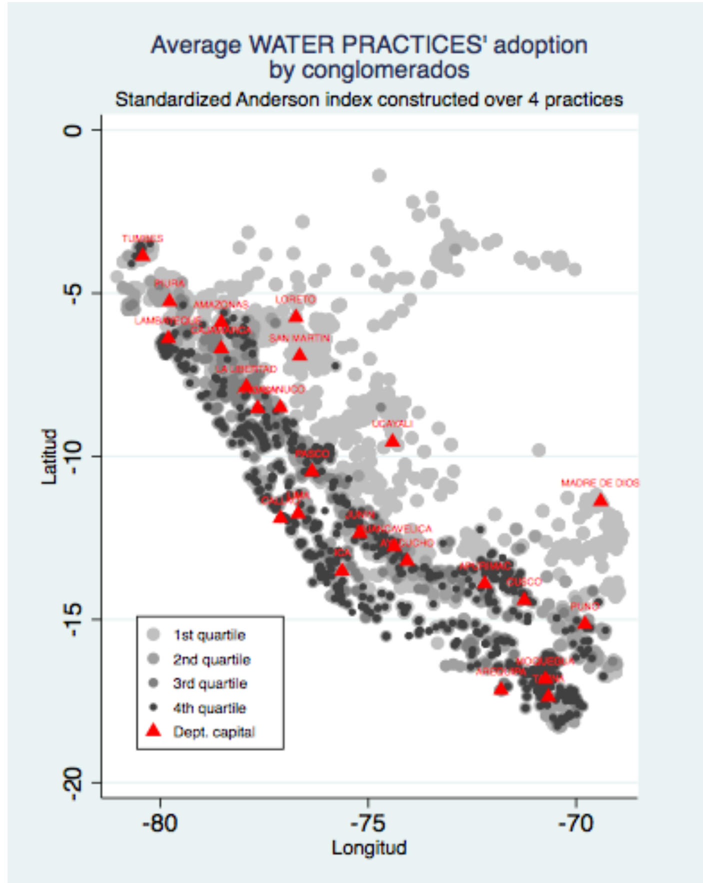


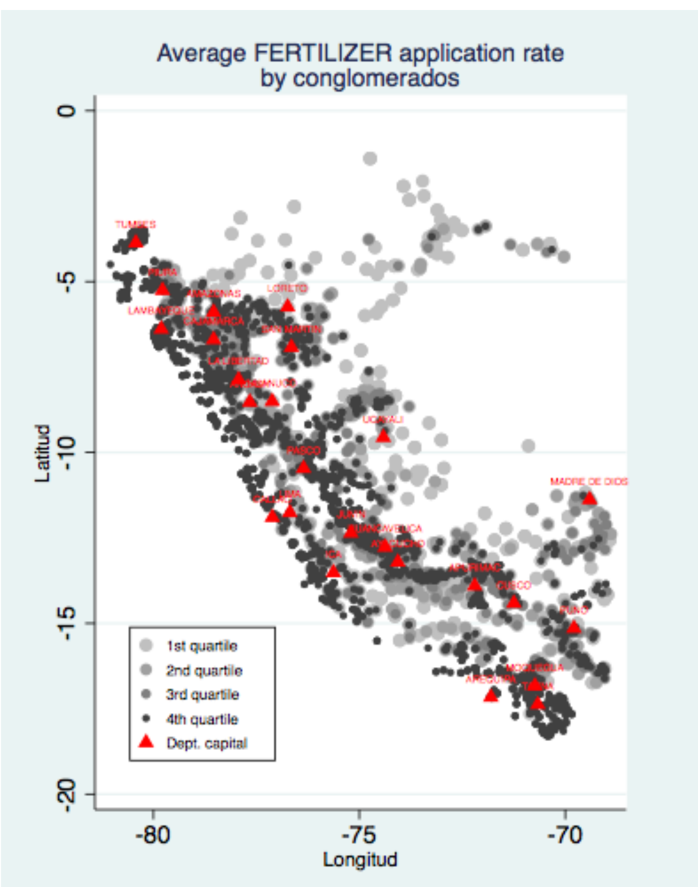
Graph 2: Predicted vs. actual size of landholdings for 2015 and 2016. 2014 data do not include the farm size (area), which for I use regression to predict the sizes using observable characteristics of households. Quantile regression gives the best fit.



Graph 3: Rainfall level shock occurrences across the country in 2016, as defined by a threshold value of a rainfall z-score value below 1.





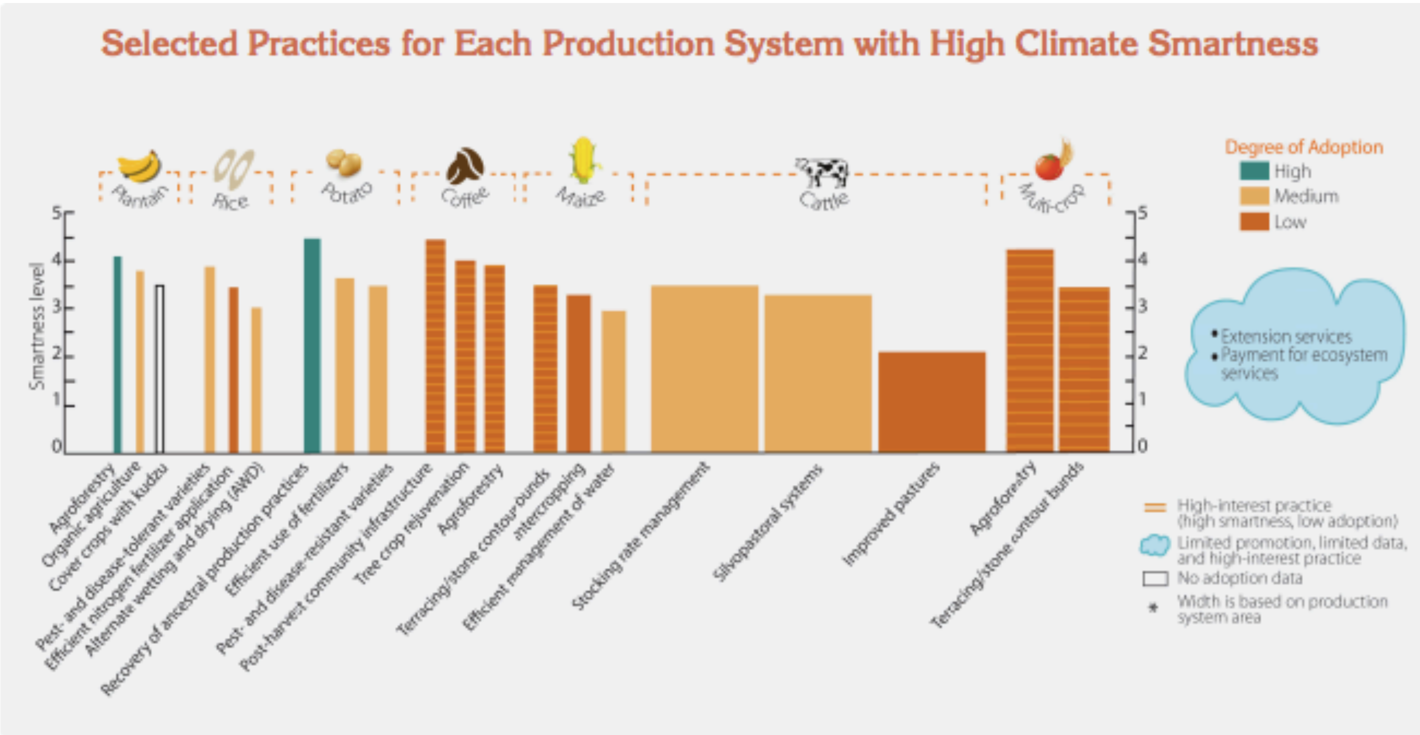


Graphs 4, 5 and 6:
Composite soil practices' adoption rate, composite water practices adoption rate, and rate of fertilizer use, respectively, for each *conglomerado* in 2016.

Part III: Supplemental Materials

CAPÍTULO 300. BUENAS PRÁCTICAS AGRÍCOLAS (PARA LOS CULTIVOS COSECHADOS Y NO COSECHADOS)					
SECCIÓN 300A. BUENAS PRÁCTICAS AGRÍCOLAS NO CONDICIONADAS					
301. ¿UD. APLICA LA PRÁCTICA AGRÍCOLA DE:				Pase a sgte. práctica	302. ¿HACE CUÁNTOS AÑOS LA APLICA? Pase a sgte. práctica
PRÁCTICAS AGRÍCOLAS			SÍ	NO	CANTIDAD
MINIMIZAR DEGRADACIÓN	1	Realizar análisis de suelos?	1	2	
	2	Mezclar la tierra con materia orgánica (rastrojos, estiércol, compost, humus, etc.)?	1	2	
	3	Rotar los cultivos para proteger el suelo?	1	2	
	4	Construir terrazas, zanjas de infiltración o rehabilitación de andenes?	1	2	
LABRANZA DE LA TIERRA	5	Arar o voltear la tierra?	1	2	
	6	Desterronar o desmenuzar la tierra?	1	2	
	7	Nivelar el campo o terreno?	1	2	
	8	Realizar surcos en contorno a la pendiente del terreno?	1	2	
RIEGO	9	Regar con la cantidad de agua que necesita el cultivo?	1	2	
	10	Regar los cultivos con la frecuencia requerida?	1	2	
	11	Medir la cantidad de agua que ingresa a su parcela (Medición con equipos o método empírico)?	1	2	
	12	Realizar el mantenimiento de su sistema de riego?	1	2	
INSUMOS AGRÍCOLAS	13	Usar abonos?	1	2	
	14	Usar fertilizantes?	1	2	
	15	Usar plaguicidas (insecticidas, fungicidas, herbicidas, acaricidas, bactericidas, nematicidas, rodenticidas, molusquicidas, etc.)?	1	2	
	16	Aplicar control biológico?	1	2	
	17	Aplicar manejo integrado de plagas?	1	2	

Suppl. Material 1: Survey instrument. Section 300A: good agricultural practices (basis for indices of soil and water conservation practices). *Peru Istituto Nacional de Estadística e Informática (INEI)*.



Suppl. Material 2: Climate Smart Practices in Peru as evaluated by the World Bank. Also analyzed in my study are: efficient use of fertilizers, recovery of ancestral production practices (rotations, terraces, crop diversity), intercropping, terracing/stone contour bunds, and efficient management of water.

World Bank; CIAT; CATIE. 2015. Climate-Smart Agriculture in Peru. CSA Country Profiles for Latin America Series. 2nd. ed. Washington D.C.: The World Bank Group.