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Empowerment, Adaptation, and Agricultural Production

Evidence from Niger

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ABSTRACT

Located at the heart of West Africa, Niger is a landlocked country with three-quarters of its territory covered by the Sahara Desert. Niger's climate is mostly arid, and it is one of the least developed countries in the world. The vast majority of its population lives in rural areas, and the country is strongly dependent on agriculture. Agriculture is predominantly rainfed and yields rely on one rainy season. Although productivity in Niger has shown a positive trend, agriculture has been strongly affected in recent decades by several crises partly or entirely due to extreme weather events. Farmers pursue a number of strategies in the face of climatic (and nonclimatic) stressors including soil and water conservation methods such as barriers, terracing, and planting pits, and their adaptive capacity is deemed critical for estimating the economic impact of climate change. An understanding of climate change adaptation processes at the farm household level is therefore crucial to the development of well-designed and targeted mitigation policies. In this study, we use new data from Niger and regression analysis to study climate change adaptation through the digging of *zaï* pits and food production and the role of human capital measures therein. We find that adaptation is influenced by the perception that the frequency of droughts has increased and by the availability of financial resources and household labor. Adaptation is also influenced by educational attainment—both formal and Koranic school education. Adaptation of zaï pits is found to play an important role in food productivity. Our counterfactual analysis reveals that even though all households would benefit from adaptation, the effect is found to be significantly larger for households that actually did adapt relative to those that did not, indicating that the prospects of closing the productivity gap through encouraging adaptation in less well-endowed households are limited.

Keywords: soil water conservation methods, smallholders, empowerment, regression analysis, West Africa

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1. INTRODUCTION

Climate change poses potentially large risks for farmers in the developing world, affecting yields, growing seasons, and water availability and increasing weather uncertainties (Nelson et al. 2009). Farmers pursue a number of strategies in the face of multiple stressors—climatic and nonclimatic—including changing to drought-resistant crop varieties, crop diversification, economic diversification, and soil and water conservation methods such as barriers, terracing, and planting pits. The literature suggests that farmers' responses are highly critical for estimating the economic impact of climate change and that understanding adaptation processes is needed for the development of well-targeted policies. There is existing literature on the estimation of the impact of climate change on food production on the country, regional, and global scales (McCarthy et al. 2001; Parry et al. 2004; Stern 2007). Insights from such studies are crucial in appreciating the extent of the problem and designing appropriate mitigation strategies at the global or regional level. The aggregate nature of such studies, however, makes it very difficult to provide insights in terms of effective adaptation strategies at the farm household level.

Although there has been considerable research on farmer behavior, surprisingly there exists little rigorous quantitative analysis on adaptive capacity at the farm household level, especially addressing the complex, forward-looking, and site-specific characteristics of adaptation processes (Below et al. 2012) or how farmers' climate change beliefs influence their plans for the future. Various studies have highlighted the impact of human capital variables on perception formation, on the decision to adapt, and on agricultural productivity. But so far noncognitive ability has not been considered. From a policy perspective, understanding adaptation to climate change is vital. In addition to determining the impact of climatic variables on welfare, it is necessary to understand how the strategies farmers implement in the field in response to long-term changes in environmental conditions are chosen and how they affect productivity or revenues (Di Falco, Veronesi, and Yesuf 2011). A better understanding of farmer perceptions regarding long-term climatic changes, their capacity to adapt, and production outcomes will be important to inform policy for future successful adaptation of the agricultural sector.

In this study, we use new data from Niger and regression analysis to study climate change adaptation through the digging of *zaï* pits and food production and the role of human capital measures therein. We find that adaptation is influenced by the perception that the frequency of droughts has increased and by the availability of financial resources and household labor. Adaptation is also influenced by educational attainment—both formal and Koranic school education. Adaptation of zaï pits is found to play an important role in food productivity. Our counterfactual analysis reveals that even though all households would benefit from adaptation, the effect is found to be significantly larger for households that actually did adapt relative to those that did not, indicating that the prospects of closing the productivity gap through encouraging adaptation in less well-endowed households are limited.

2. CLIMATE VULNERABILITY, PERCEPTION, AND ADAPTATION

Located at the heart of West Africa, Niger is a landlocked country with three-quarters of its territory covered by the Sahara Desert. Niger's climate is mostly arid, with a rainfall gradient ranging from 100 to 700 millimeters of annual rainfall, and it is one of the least developed countries in the world, ranking 186th according to the Human Development Index (UNDP 2013). The vast majority of its population (82 percent) lives in rural areas, and the country is strongly dependent on agriculture, which contributed about 36.4 percent to its gross domestic product in 2015 (World Bank 2016). Agriculture is predominantly rainfed, and yields rely on one rainy season that runs from May to September. Although productivity has shown a positive trend, agriculture has been strongly affected in recent decades by several crises partly or entirely due to extreme weather events (World Bank 2013). There is considerable discussion on how to make agriculture, the main sector in which the poor are involved, and especially smallholder agriculture, more resilient to extreme events as well as adapted to shifts in potential climate conditions (Howden et al. 2007).

Farmers in Niger have always generated their income in a very insecure and unstable natural environment, and households are often diversified in terms of their income sources (Wouterse 2017). That said, in Sahelian Niger, rainfed agriculture is the main activity in terms of land and manpower requirements, but only during the short rainy season (Abdoulaye and Lowenberg-DeBoer 2000). The main cereals are pearl millet (Pennisetum glaucum L. Br.) and sorghum (Sorghum bicolor L. Moench) in the south of the country, both often associated with cowpea as legume (Vigna ungiculata L. Walp). Agriculture is generally managed in an extensive and anti-risk approach. Given the very low inherent fertility of the soils and the high spatial and temporal intra-annual and inter-annual rainfall variability, farmers tend to clear and sow more surface than they can manage and harvest for food security and tenure purposes. Plots are scattered in the *terroir*—the geographical framework of life of a rural society—according to the distance to the village and soil quality mainly and even sometimes on several terroirs.[1] This spatial dispersion of fields helps to mitigate the effects of the rainfall spatial variability on crop yield (Saqalli et al. 2011). In terms of on-farm diversification, dry-season vegetable gardening—onions and to a lesser extent tomatoes—is practiced only in places where wells, marshes, and valleys give access to shallow groundwater. Raising livestock has been a vital component of the farming systems of the Nigerien Sahel for centuries (Saqalli et al. 2011), and most households in the sample held some livestock. About a third of households owned cattle, while two-thirds had some ruminants—goats and, to a lesser extent, sheep. Livestock contribute to household livelihoods through a variety of direct and indirect pathways. Livestock provide financial security and are easily liquidated when cash is required urgently. Impairment of livestock production can also occur as an effect of drought, although livestock-based systems, particularly those based on cattle or camels, or both, tend to be more resilient to drought. In fact, Lamanna et al. (2015) show that the northern Sahel-Saharan zone of Niger, which is mostly reliant on cattle and where dry-season vegetable gardening is more prominent, has a much lower proportion of food-insecure households than the Sahelian zone in which households rely on subsistence crop farming and own smaller ruminants.

Drought is the major climate-related risk for farmers in Niger. Early-season drought is frequently associated with failure of crop plants to emerge, replanting, and an increased workload. Severe drought stress during flowering and grain filling can constrain the crop's ability to develop or fill grains and accelerate leaf senescence and maturity, thus lowering yields (Lamanna et al. 2015). Low soil nitrogen and organic matter contents and limited use of nitrogen inputs further aggravate the impact of drought. In the Tahoua region of Niger, the droughts of 1973, 1984/1985, and more recently 2005 and 2009 have caused severe crises that have rendered it difficult for communities to rapidly adjust their traditional mechanisms of adaptation (Garraud and Mahamane 2012). Although precipitation projections of the

[1] The French word *terroir* is defined geographically—the area managed and exploited by a village community—and socially defined territory containing a set of resources and associated rights to these resources. It is therefore a geographically defined territory with a social interpretation: it is the geographical framework of life of a rural society (Saqalli et al. 2011).

Intergovernmental Panel on Climate Change have indicated likely increases in monsoon precipitation in the region late in the 21st century, addressing drought impacts on crop and livestock production will continue to be a priority in the immediate term. Climate-smart agriculture (CSA)—farming systems that increase productivity, improve farmers' adaptive capacity, and mitigate climate change where possible—has been put forward as a solution to the food and climate challenges Africa faces (Lamanna et al. 2015).

Adaptation Strategies

Adaptations are adjustments or interventions that take place to manage losses or take advantage of opportunities presented by a changing climate. The goal of an adaptive measure should be to increase the capacity of a system to survive external shocks or change. Important adaptation options in CSA include crop diversification, using different crop varieties, changing planting and harvesting dates, and soil water conservation (SWC) methods using shade trees, live barriers, composting, and terracing. Using the CSA Compendium (Rosenstock et al. 2015) in conjunction with the World Bank's Living Standards Measurement Study 2011 household-level database, Lamanna et al. (2015) find for Niger that significant reductions in the proportion of food-insecure households are possible with CSA. Tree coppicing and mulching both reduce the proportion of food-insecure households by roughly 15 percent, whereas SWC strategies such as zaï pits or water harvesting reduce this proportion by about 10 percent. Zaï pits, originally implemented by a farmer in Burkina Faso, are small holes filled with compost and planted with seeds of trees, millet, or sorghum. The holes or pits catch water during the rainy season and, when filled with compost, retain moisture and nutrients through the dry season. By improving soil water holding capacity, zaï pits also help households buffer against drought-induced food shocks, thereby improving resilience.

Less common SWC measures implemented by farmers in Niger are stone bunds, half-moons, and vegetative strips. Stone bunds, established along the contours of the land and where stones or rocks are available, slow water runoff to improve water-catchment capacity. Stone bunds are sometimes combined with zaï pits. Half-moon microcatchments are small, semicircular earth bunds. These are quite common on the desert margins of the Sahel, where they are known as *demilunes*. The half-moons catch water flowing down a slope. Half-moons are particularly helpful to rehabilitate degraded land. A vegetative strip is a strip planted with grass, shrubs, or trees that runs across the slope. It slows down water flowing down the slope, and catches sediment that has been eroded uphill. Over time, soil may build up behind the strip, forming a terrace. One problem with vegetative strips is that they can create alternating bands of fertile and infertile soil. Rich sediment builds up just behind the barrier, so crop yields here are good. Further back from the barrier, though, yields are poorer because the topsoil here has been eroded. These bands may last for some time, until the land between the strips is leveled (Motis, D'Aiuto, and Lingbeek 2013). Zaï pits have been associated with important improvements in yields in particular because they simultaneously address issues of land degradation, soil fertility, and soil moisture. For Niger, therefore, Lamanna et al. (2015) suggest that zaï pits as a strategy to increase productivity and reduce risk exposure will be key for CSA planning for farm-level interventions in the country. It is thus important to understand the driving forces behind climate change adaptation in the form of zaï pits.

Adaptive Capacity

Adaptive capacity, or the factors that enable social systems to respond proactively to environmental change, has emerged as a core domain of global change research (Nelson et al. 2009). SWC investments constitute investments in labor and resources. Digging zaï pits, for example, was found to demand considerable amounts of labor, about 300 person-hours per hectare (Lamanna et al. 2015). For that reason, farmers in Niger were found to treat their fields progressively. Each dry season farmers would rehabilitate some land, but how much they rehabilitated was found to depend on available labor (household or hired labor, or both) and on motivation. Some farmers were found to rehabilitate 0.2 hectare per year while others were found to rehabilitate more. This progressive approach differs from actions planned by SWC projects, which tend to treat blocks of land through collective action using machinery. It is also important to note that a considerable portion of land rehabilitated with zaï pits becomes normal land again after some years. The larger the sand fraction, the quicker the process of conversion to normal land. Farmers rehabilitating gravelly and shallow lateritic soils do maintain zaï on a quasi-permanent basis and just clear the pits when needed (Lamanna et al. 2015). Given that SWC activities require investments, when considering a household's capacity to adapt, one considers first of all their economic feasibility, that is, the on-site land productivity gains obtained from conservation activities. Obviously, the farm household's perceived benefits of conservation and the expected losses due to degradation influence the decision to invest. The functioning of factor markets also plays an important role. Because farmers are assumed economically rational, research has focused principally on detecting socioeconomic barriers to adaptation. However, conclusions of these studies tend to be case-specific and fraught with contradictions (Kessler 2006).

Recent research has explored the socio-cognitive influences on adaptation more fully. In Grothmann and Patt's (2005) socio-cognitive model of private proactive adaptation to climate change, perception is a key variable illustrated as influencing or being influenced by all the model's determinants of adaptive behavior. Perception of hazard risk has long been recognized as a critical determinant of human response to environmental shocks and change, and the understanding of climate perceptions in Africa south of the Sahara has received a large amount of attention in recent years. A large-scale survey of farm households in 11 African countries revealed a strong awareness of temperature and precipitation changes over the last 20 years (Maddison 2007). Similar results were found throughout the literature and revealed a perception of decreasing rainfall shared by more than 70 percent of households (Gbetibouo 2009; Bryan et al. 2013; Mertz et al. 2012; Silvestri et al. 2012). However, studies that have attempted to confront climate change perceptions with meteorological records find only weak evidence that people's perceptions of local weather patterns tally with quantitative measurements from meteorological stations or satellite rainfall estimates in Africa (see Kosmowski, Leblois, and Sultan 2016 for an overview). Modeling adaptation as following directly from climate change perception is therefore likely to lead to biased results. In particular, the use of a Heckman-type selection model in which only households that perceive climate change are included in the analysis of adaptation is misguided.

Frank, Eakin, and López-Carr (2011) find that social identity, assessed through in-depth interviews, mediates between risk perception and adaptation through its influence on motivation. Deci and Ryan (1985) distinguish between intrinsic motivation (doing something because it is inherently interesting or enjoyable) and extrinsic motivation (doing something because a reward is expected). Hence, climate change adaptation cannot be fully explained by models and easily measurable economic and social factors. Decision-making is strongly influenced by nonrational and subjective aspects (for example, intangible factors related to human behavior) (Kessler 2006). Climate change adaptation is thought to require a favorable mental attitude (Leagans 1979) and is influenced by farmers' feelings and aspirations (Giampietro 1997). Empowerment, or the expansion of people's ability to make strategic life choices, particularly in contexts where this ability had been denied to them (Kabeer 1999), could thus play an important role in adaptation decisions. Seymour et al. (2016) use empowerment of women to explain adoption of improved varieties by rural households in Ethiopia, Kenya, and Tanzania and find that though results are mixed as to whether women's empowerment is positively correlated with higher rates of adoption, empowerment is found to be positively correlated with greater participation by women in decisions about the adoption of improved varieties, the acquisition of credit for the purchase of improved varieties, and the acquisition of extension services related to improved varieties.

3. METHODS

The climate change adaptation decision and its implications in terms of an outcome of interest can be modeled in the setting of a two-stage framework (see also Di Falco, Veronesi, and Yesuf 2011 and Abdulai and Huffman 2014). In the first stage, we use a selection model for climate change adaptation where a representative risk-averse farm household chooses to implement climate change adaptation strategies if it generates net benefits. Households in our sample choose between construction of zaï pits and nonconstruction. We represent the net benefit farm household j derives from adaptation to climate change as Y_{jA} and the net benefit from nonadaptation as Y_{jN}, with net benefits representing cropping output. The two regimes can be specified as follows:

$$Y_{jA} = \mathbf{X}_j \boldsymbol{\beta}_A + u_{jA} \tag{1}$$

and

$$Y_{jN} = \mathbf{X}_j \boldsymbol{\beta}_N + u_{jN}, \tag{2}$$

where $\mathbf{X}_j$ is a vector of fixed factors and farm and household characteristics; β_A and β_N are vectors of parameters; and u_{jA} and u_{jN} are independent and identically distributed random variables. The household will normally choose the technology if the net benefits obtained by doing so are higher than results obtained when not using the technology, that is, $Y_{jA} > Y_{jN}$ (Pitt 1983). Although the preferences of the household, such as perceived net benefits of implementation, are unknown to the researcher, the characteristics of the farm household and the attributes of the technology are observed during the survey period. We can therefore represent the net benefits derived from climate change adaptation by a latent variable D_j^*, which is not observed but can be expressed as a function of the observed characteristics and attributes, denoted as $\mathbf{Z}$, in a latent variable model as follows:

$$D_j^* = \boldsymbol{\gamma}' \mathbf{Z_j} + \varepsilon_j, D_j = 1[D_j^* > 0] \quad , \tag{3}$$

where D_j is a binary variable that equals 1 for households that implement zaï pits, and zero otherwise, with $\boldsymbol{\gamma}$ denoting a vector of parameters to be estimated. Thus the farmer adopts the technology only if the perceived net benefits are positive. The error term ε with mean zero and variance σ_ε^2 captures measurement errors and factors unobserved to the researcher but known to the farmer. Variables in $\mathbf{Z}$ include factors that influence the decision to adapt such as farm-level and household characteristics, including perception of increased drought.

4. DATA

Data to estimate our model were collected by the author during April–May 2015 for 500 randomly sampled households (and 769 adult individuals in those households) in 35 villages situated in three communes (Doguéraoua, Malbaza, and Tsernaoua) in the Maggia valley of the Birni N'Konni department in the Tahoua region.[2] Birni N'Konni is situated in the southern part of Niger and belongs to the Sahelo-Sudanese environment, which allows for rainfed agriculture. Household-level data were collected using a standard agricultural household survey, while individual-level data were collected using the Women's Empowerment in Agriculture Index (WEAI) survey. The WEAI survey tool collects data on five domains that make up empowerment: (1) decisions about agricultural production, (2) access to and decision-making power about productive resources, (3) control of use of income, (4) leadership in the community, and (5) time allocation (Alkire et al. 2013).

Farming systems in the Maggia fossil valley of Birni N'Konni can be largely characterized as extensive agropastoral millet, sorghum, and legume based. In our sample, about a fifth of households had dug zaï pits. Less common SWC measures are stone bunds, half-moons, and vegetative strips. Farm and household descriptives by zaï adaptation status are given in Table 4.1. The table shows that output—the quantity of cereals and leguminous crops measured in grain-equivalents and harvested during the 2014 agricultural season—is much higher for households that had put in place zaï pits. As these households also have larger landholdings, we computed yield (not reported) and find that this is also significantly higher for households with zaï pits on their plot(s). Table 4.1 also shows that households that adapted had a more valuable herd and more valuable equipment. These households were also found to be significantly larger, more likely to be headed by a male, to have older heads who are more likely to be literate, to contain more experienced adults, and to have received more education both in terms of formal and Koranic schooling. However, empowerment levels of adapting and nonadapting households are not significantly different.

Table 4.1 Farm and household descriptives

Descriptive	Adapter	Nonadapter	t-test
Household level			
Output in grain-equivalents (kilograms)	2,053 (1,712)[a]	1,307 (1,231)	-5.00
Landholdings (hectares)	5.36 (4.78)	4.01 (3.43)	-3.89
Plots (number)	2.08 (1.36)	1.75 (1.23)	-2.32
Lagged value of herd (FCFA)	743,395 (738,785)	504,667 (606,904)	-3.38
Lagged value of equipment (FCFA)	52,823 (71,132)	36,498 (64,207)	-2.74
Household size (number of members)	6.86 (6.04)	5.58 (2.87)	-4.27
Sex of the household head (1 = male)	0.88 (0.33)	0.72 (0.45)	-2.29
Age of the household head (years)	54.92 (10.79)	52.68 (9.91)	-3.25
Literacy of household head (1 = yes)	0.44 (0.50)	0.32 (0.47)	-2.62
Experience of adults (years)	28.16 (11.96)	26.62 (10.95)	-2.26
Schooling of most educated adult (years)	3.55 (3.17)	2.73 (3.39)	-2.29
Koranic schooling of adult (1 = yes)	0.59 (0.50)	0.29 (0.45)	-6.27
Empowerment (WEAI)	0.70 (0.14)	0.69 (0.15)	-0.11
Perceives increased drought	0.79 (0.41)	0.67 (0.47)	-2.46
Village level			
High participation in migration	0.71 (0.45)	0.54 (0.50)	-3.25
Distance to minibus stop (kilometers)	7.61 (9.84)	5.10 (8.17)	-2.64
Number of observations	101	387	

Source: Author's survey.
Note: FCFA 225 = US$1 (purchasing power parity for 2015) (World Bank 2016). FCFA = CFA franc; WEAI = Women's Empowerment in Agriculture Index. [a] Standard deviation in parentheses.

[2] Twelve households were excluded from the analysis due to missing data.

Estimation Issues

Households normally factor in outcomes such as potential net benefits when making decisions on adaptation of SWC measures. Measures that are implemented therefore need to be taken into account when analyzing outcomes such as output. When the selection of a measure, the zaï pit in our case, is not taken into account, results may be biased because farm households that would obtain lower than average output from the new technology, given prices and fixed factors, choose not to implement and thus truncate the observed technology profit distribution (Pitt 1983). The bias arises because there may be unobservable factors, such as the innate managerial and technical abilities of farmers in understanding and using new technologies, that influence the error terms in both the technology choice equation (ε) and the outcome equation (u), thus resulting in correlation of the error terms of these two equations, with $\mathrm{corr}(\varepsilon, u) = \rho$ (Abdulai and Huffman 2014).

When examining the impacts of an SWC measure, we cannot just attribute the differences in the outcome between those that put into place zaï pits and those that did not. Given that we have at our disposal cross-section data only, and thus no information on the counterfactual situation, and that we have an actual interest in examining the determinants of household-level climate change adaptation through the digging of zaï pits, we follow Di Falco, Veronesi, and Yesuf (2011) and Abdulai and Huffman (2014) and employ the endogenous switching regression model developed by Lee (1982) to account for the selection bias in our estimation of impact of zaï pits on farm outcomes. The endogenous switching regression approach as a generalization of Heckman's selection correction approach accounts for selection on unobservables by treating selectivity as an omitted-variable problem (Heckman 1979). In the switching regression approach, households are classified according to their status as adapters and nonadapters in order to capture the differential responses of the two groups.

Given that farmers choose to dig zaï pits or not, the observed net benefits take the following values:

$$\begin{aligned}&\text{Regime 0 (Not adapt): } Y_{jN} = \mathbf{X}'\boldsymbol{\beta}_{jN} + u_{jN} \text{ if } D_j = 0,\\ &\text{Regime 1 (Adapt): } Y_{jA} = \mathbf{X}'\boldsymbol{\beta}_{jA} + u_{jA} \text{ if } D_j = 1,\end{aligned} \tag{4}$$

where Y_{jA} and Y_{jN} are the outcome variables for those that adapt and those that do not, respectively, $\mathbf{X}'$ is a vector of fixed factors and farm-level and household characteristics. The vectors $\boldsymbol{\beta}$ in (4) and $\boldsymbol{\gamma}$ in (3) are the associated parameters that have to be estimated. Although the variables in the vectors $\mathbf{X}$ in equation (4) and $\mathbf{Z}$ in equation (3) may overlap, it is important to note that accurate identification requires that at least one variable in $\mathbf{Z}$ does not appear in $\mathbf{X}$. In particular, for the model to be identified we use as exclusion restrictions not only those automatically generated by the nonlinearity of the selection model of adaptation (3) but also other variables that directly affect the selection variable but not the outcome variable. Our selection instruments are a binary variable that takes the value of 1 if the household perceives increased frequency of drought over the five years preceding the survey and two village-level variables that capture dedication to agriculture and lagged availability of financial resources. The former measures the distance from the center of the village to the nearest minibus stop, while the latter is a binary variable that takes the value of 1 when more than 50 percent of households participated in short-term migration in the dry season (exode) 10 years ago. Descriptives for these instruments are given in Table 4.1. We establish the admissibility of these instruments by performing a simple falsification test: if a variable is a valid selection instrument, it will affect the adaptation decision but it will not affect the quantity produced among farm households that did not adapt. The results from the falsification test (not reported) reveal that drought sensitivity, remoteness, and past labor availability can be considered as jointly statistically significant drivers of the decision to adapt or not to climate change.[3]

[3] A potential endogeneity problem may arise with the drought-sensitivity variable due to omitted-variable bias—for example, more conscientious households that are more drought sensitive and also more likely to have dug zaï pits. However, we lack suitable instruments to control for this potential bias and we will refrain from any causal inference as to the relation between drought sensitivity and adaptation.

Self-selection into the adapter or nonadapter categories may lead to nonzero covariances between the error terms of the adaptation equation and the outcome equation. The three error terms ε, u_A and u_N are assumed to have a trivariate normal distribution with mean vector zero and the following covariance matrix:[4]

$$cov(u_A, u_N, \varepsilon) = \Sigma = \begin{bmatrix} \sigma_A^2 & \sigma_{AN} & \sigma_{A\varepsilon} \\ \sigma_{AN} & \sigma_N^2 & \sigma_{N\varepsilon} \\ \sigma_{A\varepsilon} & \sigma_{N\varepsilon} & \sigma_\varepsilon^2 \end{bmatrix}, \tag{5}$$

where $\mathrm{var}(u_A) = \sigma_A^2$, $\mathrm{var}(u_N) = \sigma_N^2$, $\mathrm{var}(\varepsilon) = \sigma_\varepsilon^2$, $\mathrm{cov}(u_A, u_N) = \sigma_{\mathrm{AN}}$, $\mathrm{cov}(u_A, \varepsilon) = \sigma_{\mathrm{A}\varepsilon}$, and $\mathrm{cov}(u_N, \varepsilon) = \sigma_{\mathrm{N}\varepsilon}$. For this reason, the error terms in equation (4), conditional on the sample selection criterion, have nonzero expected values, and ordinary least squares (OLS) estimates of coefficients $\boldsymbol{\beta}_A$ and $\boldsymbol{\beta}_N$ suffer from sample selection bias (Lee 1982). The expected values of the truncated error terms $(u_A|D = 1)$ and $(u_N|D = 0)$ are then given as

$$E(u_N|D = 0) = E(u_N|\varepsilon \leq -\mathbf{Z}'\boldsymbol{\gamma}) = \sigma_{N\varepsilon}\frac{-\varphi(\mathbf{Z}'\boldsymbol{\gamma}/\sigma)}{1-\Phi(\mathbf{Z}'\boldsymbol{\gamma}/\sigma)} \equiv \sigma_{N\varepsilon}\boldsymbol{\lambda}_N \tag{6}$$

and

$$E(u_A|D = 1) = E(u_A|\varepsilon > -\mathbf{Z}'\boldsymbol{\gamma}) = \sigma_{A\varepsilon}\frac{-\varphi(\mathbf{Z}'\boldsymbol{\gamma}/\sigma)}{1-\Phi(\mathbf{Z}'\boldsymbol{\gamma}/\sigma)} \equiv \sigma_{A\varepsilon}\boldsymbol{\lambda}_A, \tag{7}$$

where φ and Φ are the probability density and cumulative distribution function of the standard normal distribution, respectively. The ratio of φ and Φ evaluated at $\mathbf{Z}'\boldsymbol{\gamma}$ is referred to as the inverse Mills ratio λ_A, λ_N (selectivity terms). The selectivity terms are incorporated into equation (4) to account for selection bias (see also Di Falco, Veronesi, and Yesuf 2011).

The estimation of the model proceeds in two stages. The first stage involves a probit regression of the determinants of the probability of the digging of zaï pits and thus estimation of the parameter $\boldsymbol{\gamma}$ given in equation (3). These estimates are then used to calculate the selectivity terms (λ_A, λ_N) according to equations (6) and (7). The drawback of this two-step approach is that it generates residuals that are heteroskedastic and as a result cannot be used to obtain consistent standard errors without cumbersome adjustments (Lokshin and Sajaia 2004). The full information maximum likelihood method suggested by Lokshin and Sajaia (2004) overcomes the problem through a simultaneous estimation of the two equations, that is, the adaptation and outcome equations. Of particular interest are the signs and significance levels of the correlation coefficients (ρ) from the estimates.

The effect of climate change adaptation on farm outcomes can be examined by first specifying the expected values of the outcome. The outcome that we consider here is farm output of cereals and leguminous crops in grain-equivalent kilograms. For a household that has adapted to climate change with characteristics $\mathbf{X}$ and $\mathbf{Z}$, the expected value of the outcome Y_{jA} is given as

$$E(Y_{jA}|D = 1) = \mathbf{X}\boldsymbol{\beta}_{jA} - \sigma_{A\varepsilon}\lambda_A. \tag{8}$$

Sample selection is taken into account in the last term, indicating that households that have adapted may behave differently from an average household with identical characteristics due to unobserved factors (Maddala 1986). The expected output had the household chosen not to adapt to climate change is given as

$$E(Y_{jN}|D = 0) = \mathbf{X}\boldsymbol{\beta}_{jN} - \sigma_{N\varepsilon}\lambda_N \quad . \tag{9}$$

[4] The subscript j denoting the household has been dropped for notational clarity.

The change in the outcome due to adaptation can then be specified as the difference between adaptation and nonadaptation. Thus the expected outcomes from equations (8) and (9) are used to obtain unbiased estimates of the effects of adaptation. These estimates represent the average treatment effect on the treated (TT) (Lokshin and Sajaia 2004):

$$TT = E[Y_{jA}|D = 1] - E[Y_{jN}|D = 1] = \mathbf{X}(\boldsymbol{\beta}_{jA} - \boldsymbol{\beta}_{jN}) + (\sigma_{AE} - \sigma_{NE})\lambda_{\mathrm{A}}. \quad (10)$$

Similarly, we can calculate the effect of treatment on the untreated (TU) for the farm households that did not adapt to climate change as:

$$TU = E[Y_{jA}|D = 0] - E[Y_{jN}|D = 0] = \mathbf{X}(\boldsymbol{\beta}_{jA} - \boldsymbol{\beta}_{jN}) + (\sigma_{AE} - \sigma_{NE})\lambda_{N}. \quad (11)$$

In equations (10) and (11), σ represents the covariance of the error terms and λ the inverse Mills ratio. We can also use the expected outcomes to calculate heterogeneity effects. For example, farm households that adapted may have produced more compared with farm households that did not adapt irrespective of the fact that they decided to adapt but because of unobservable characteristics (Di Falco, Veronesi, and Yesuf 2011).

$$BH_A = E[Y_{jA}|D = 1] - E[Y_{jA}|D = 0] = \mathbf{X}(\boldsymbol{\beta}_{jA} - \boldsymbol{\beta}_{jN}) + \sigma_{AE}(\lambda_A - \lambda_N). \quad (12)$$

Similarly, for the group of households that decided not to adapt, "the effect base heterogeneity" is formulated as

$$BH_N = E[Y_{jN}|D = 1] - E[Y_{jN}|D = 0] = \mathbf{X}(\boldsymbol{\beta}_{jA} - \boldsymbol{\beta}_{jN}) + \sigma_{NE}(\lambda_A - \lambda_N). \quad (13)$$

An issue that needs to be addressed in estimating both the adaptation and outcome specification is the potential endogeneity problem that may arise with the empowerment variable. If there are unobserved factors that are correlated with empowerment and the adoption of zaï pits and farm output, then the coefficients in the adaptation or outcome equations, or both, will be biased due again to omitted variables. In other words, there could be innate unobserved differences across individuals in their personality, and these could influence adaptation and productivity. Such innate unobserved heterogeneity could cause a correlation between empowerment and the errors in the determinants of the likelihood of adaptation to climate change and farm output. To account for these potential endogeneity problems, we employ the Rivers and Vuong approach (1988), since one of our dependent variables is dichotomous. The estimation is carried out by first specifying the potential endogenous variable as a function of all other explanatory variables given in the adaptation equation, in addition to a set of instruments in the first-stage regressions. That is, the specification used is

$$T_i = \gamma\mathbf{Z}_{ij} + \psi\mathbf{V}_{ij} + \zeta_{ij}, \quad (14)$$

where T_i is the potentially endogenous variable, empowerment in this case, $\mathbf{Z}_{ij}$ is as described previously, and $\mathbf{V}_{ij}$ is a vector of instruments that is correlated with the given endogenous variable but uncorrelated with the error terms in equations (3) and (4) and is therefore excluded in estimating equation (3). Rather than using the predicted values from the first-stage equation as in a habitual two-stage estimation approach, the approach involves specifying the adaptation equation in (3) as

$$D_{ij}^* = \beta\mathbf{Z}_{ij} + \varphi\mathbf{T}_i + \mathbf{R}_{ij} + \upsilon_{ij}, \quad (15)$$

where $\mathbf{Z}_{ij}$ and $\boldsymbol{T}_i$ are as defined previously and $\mathbf{R}_{ij}$ is a vector of the residual terms from the first-stage regressions of the endogenous variables. The probit estimates of the potential endogenous variables in $\mathbf{Z}_{ij}$ are then consistent (Wooldridge 2002). To ensure identification in the estimation of the adoption specification, some of the variables included in the first-stage estimation (11) are excluded from the adoption equation (12). A suitable identification strategy is to employ a variable that strongly influences empowerment but does not influence the decision to adapt to climate change or farm output. In particular, we postulate that empowerment can be explained by the difference in the ability to be interviewed alone between the primary male and female and access to generic information transmitted via the radio. These variables are expected to explain average empowerment but should not themselves be correlated with either the decision to adapt to climate change or farm output. First-stage estimation results are given in Table A.1.

5. ESTIMATION RESULTS

We present the estimates of the determinants of adaptation and the impact of the adaptation of zaï pits on cropping output in Tables 5.1 and 5.2. As indicated previously, the full information maximum likelihood approach estimates both the adaptation and the outcome equations jointly. Table 5.1 reports the estimates of the endogenous switching regression model estimated by full information maximum likelihood with robust standard errors and community fixed effects. The first column presents the estimation by OLS of the net cropping output function with no switching and with a binary variable equal to 1 if the farm household decided to adapt to climate change and 0 otherwise. The second column presents the estimation using instrumental variables (IV) of the cropping output function in which empowerment is treated as endogenous. The third, fourth, and fifth columns present, respectively, the estimated coefficients of the selection equation (1) to adapt or not adapt to climate change, and of the net cropping output functions (4) for farm households that did and did not adapt to climate change.

The results of the estimation of equation (3) suggest that our three selection variables—increased drought perception, distance to the minibus stop, and high participation in short-term migration during the dry season at the village level—explain climate change adaptation. If the household perceives that the drought frequency has increased over the five years preceding the survey, the more likely this household is to have put in place zaï pits. The further the minibus stop is from the center of the village, the lower is the probability of engagement in activities outside own-farm agriculture and the greater is therefore the dedication to agriculture, increasing the probability that a household has dug zaï pits. Similarly, the greater was the village-level participation in migration 10 years before the survey took place, the larger the influx of resources in the village through remittances, and the more likely it is that households invested in zaï pits. Other variables that explain adaptation are the value of the household's herd, a relatively liquid asset, which points to the importance of the availability of financial resources, and household size, which indicates that the availability of household labor—in the context of a missing labor market—may partly determine the capacity to adapt. The human capital variables of both formal and Koranic school education are also both positively associated with adaptation (see also Maddison 2007), although empowerment is not.

We now turn to the productive implications of adaptation. The simplest approach to investigate the effect of adaptation on production consists of estimating an OLS model of output that includes a binary variable that takes the value of 1 if the farm household implemented zaï pits and 0 otherwise. Estimation results in the first right-hand-side column of Table 5.1 show that output is explained by the various fixed inputs though not a household's endowment of labor proxied by household size. In the OLS specification, empowerment is the only human capital variable that is positively and significantly correlated with output, while when we treat empowerment as endogenous (second right-hand-side column) we see that the age and the sex of the household head also explain output, with older, male heads being more productive. When we break down empowerment by its various indicators, we see that in particular the ability to speak in public—or confidence—relates strongly to staple cropping output.

Results in the first two right-hand-side columns of Table 5.1 also reveal that there is significant difference in output between farm households that adapted and those that did not adapt. This approach, however, assumes that adaptation to climate change is exogenously determined, while it is a potentially endogenous variable. In this case, the estimation via OLS would yield biased and inconsistent estimates. In addition, OLS estimates do not explicitly account for potential structural differences between the production function of farm households that adapted to climate change and the function of farm households that did not adapt. The estimates presented in the last two columns of Table 5.1 account for the endogenous switching in the cropping income function. Both the estimated coefficients of the correlation terms ρ_j are not significantly different from zero (Table 5.1, bottom row) indicating that the hypothesis of absence of sample selectivity bias may not be rejected. However, the output function of farm households that adapted to climate change is significantly different (at the 1 percent statistical level) from the function of farm households that did not adapt. In particular, returns to land are much larger for households that adapted, and returns to empowerment are positive and significant only for households that did not adapt. Again, breaking down empowerment into its various indicators reveals that confidence and group membership are strongly correlated with staple cropping output of households that did not adapt. These differences in the coefficients of the cropping output equation between farm households that adapted and those that did not adapt illustrate the presence of heterogeneity in the sample.

Table 5.1 Endogenous switching regression results for adoption and impact of adoption on net returns

Variable	OLS cropping output (kg)	IV cropping output (kg)	Adaptation	Zaï = 0 cropping output (kg)	Zaï = 1 cropping output (kg)
Zaï (1 = yes)	341.15	326.41			
	(123.81)[b]**	(124.48)[b]**			
Landholdings (hectares)	72.48	70.73	-0.00	57.95	101.45
	(13.78)**	(13.73)**	(0.01)	(10.52)**	(17.70)**
Plots (number)	381.93	389.12	0.03	350.97	444.39
	(53.32)**	(52.77)**	(0.07)	(52.66)**	(91.54)**
Lagged value of herd	2.99	2.92	0.00	3.11	0.89
(FCFA*10,000)	(0.86)**	(0.84)**	(0.00)*	(1.00)**	(1.62)
Lagged value of equipment	28.13	27.62	0.00	28.70	49.27
(FCFA*10,000)	(12.34)**	(12.08)**	(0.02)	(11.19)**	(15.78)**
Household size (number of	-14.89	-12.55	0.05	-36.11	27.72
members)	(19.00)	(18.43)	(0.03)*	(24.72)	(36.85)
Sex of the household head	165.80	213.76	0.19	35.46	438.48
(1 = male)	(106.51)	(122.28)*	(0.20)	(121.66)	(311.79)
Age of the household head	11.75	11.93	0.01	6.76	18.19
(years)	(13.01)	(4.90)**	(0.01)	(6.57)	(9.63)
Literacy of household head	151.50	167.74	-0.10	234.27	-19.43
(1 = yes)	(120.07)	(119.40)	(0.18)	(138.54)*	(227.66)
Experience of adults (years)	4.45	3.84	0.01	5.47	15.94
	(4.21)	(4.24)	(0.01)	(5.06)	(8.83)*
Schooling of most educated adult	11.75	8.70	0.04	6.93	61.58
(years)	(13.01)	(13.72)	(0.02)*	(15.95)	(35.50)*
Koranic schooling of adult	-149.76	-133.80	0.83	-235.31	-482.03
	(116.22)	(115.41)	(0.17)**	(154.66)	(265.79)*
Empowerment[a]	1,086.47	1,825.81	0.05	1,308.65	-289.91
	(321.52)**	(817.84)**	(0.55)	(350.23)**	(822.42)
Perceives increased drought			0.34		
			(0.21)*		
Village level					
High participation in migration (lagged)			0.75		
			(0.20)**		
Distance to minibus stop			0.04		
			(0.01)**		
σ_i				929.66	927.73
				(87.08)**	(65.94)**
ρ_j				-0.40	-0.03
				(0.72)	(0.35)
R-squared	0.56	0.45			

Source: Author's survey.
Note: FCFA 225 = US$1 (purchasing power parity for 2015) (World Bank 2016). Commune fixed effects are not reported. FCFA = CFA francs; OLS = ordinary least squares; IV = instrumental variables kg = kilograms. [a] Predicted from first-stage regression. [b] Robust standard errors in parentheses. ** Significant at 5% level. * Significant at 10% level.

Table 5.2 presents the expected quantity produced per hectare under actual and counterfactual conditions. Cells (a) and (b) represent the expected quantity produced observed in the sample. The expected quantity produced by farm households that adapted is about 2,141 kilograms, while it is about 1,293 kilograms for the group of farm households that did not adapt. This simple comparison, however, can be misleading and drive the researcher to conclude that on average the farm households that adapted produced about 848 kilograms (or 66 percent) more than the farm households that did not adapt. The last column of Table 5.2 presents the treatment effects of adaptation on food productivity. In the counterfactual case (c), farm households who actually adapted would have produced almost 1,000 kilograms (about 87 percent) less had they not adapted. In the counterfactual case (d) that farm households that did not adapt adapted, they would have produced about 287 kilograms (or about 22 percent) more if they had adapted. These results imply that adaptation to climate change significantly increases food productivity. The transitional heterogeneity effect is positive and significant—that is, the effect is significantly larger for the farm households that actually did adapt relative to those that did not adapt. The last row of Table 5.2 adjusts for the potential heterogeneity in the sample and shows that farm households that actually adapted would have produced significantly less than farm households that did not adapt in the counterfactual case (c). This finding highlights, in contrast to findings of Di Falco, Veronesi, and Yesuf (2011) for rural Ethiopia, that adapters are not "better producers" compared with those that did not adapt irrespective of the issue of climate change. Finally, in the counterfactual case (d) that the nonadapted households had adapted, they would produce significantly more compared with farm households that actually adapted.

Table 5.2 Impact of zaï pits on output

	Decision stage		
Impact	**To adapt**	**Not to adapt**	**Treatment effects**
Farm households that adapted	(a) 2,140.83	(c) 1,142.00	998.83
	(160.67)	(116.59)	(64.74)***
Farm households that did not adapt	(d) 1,579.59	(b) 1,292.50	287.09
	(60.97)	(42.21)	(31.24)***
Heterogeneity effects	561.24	-150.50	711.75
	(36.65)***	(36.59)***	(73.23)***

Source: Author's survey
Note: Standard errors in parentheses. FCFA 225 = US$1 (purchasing power parity for 2015) (World Bank 2016). FCFA = CFA francs. *** Significance at the 1 percent level.

6. CONCLUSION

In this paper, we looked at the adaptive capacity of rural households in Niger and the implications of the implementation of zaï pits for agricultural production. We used a recent household- and individual-level database to estimate a simultaneous equations model with endogenous switching to account for unobservable factors that influence food productivity and the decision to adapt. We also explicitly incorporate empowerment as a noncognitive dimension of human capital in both the adaptation and the production function. At the household level, we find that adaptation is influenced by the perception that the frequency of droughts has increased in the five years preceding the survey and by the availability of resources, in terms of herd size (a relatively liquid asset) and household size (which proxies for labor availability in the context of a missing market for labor). Adaptation is also influenced by educational attainment both in terms of formal and Koranic school education but does not seem to be related to empowerment. Results for the village-level variables confirm the importance of availability of financial resources emanating, for example, from migration, in the context of a missing market for credit, but also the important role of dedication to agriculture, which is hypothesized to be greater the more remote is the village.

As to the effect of climate change adaptation on food security, we cannot reject the hypothesis of absence of sample selectivity bias. We find that adaptation to climate change through the digging of zaï pits increases food productivity. We do, however, find important heterogeneity effects. Farm households that actually adapted tend to produce less than farm households who did not adapt in the counterfactual case. We also find that the impact of adaptation on food productivity is larger for the households that did actually adapt than for the households that did not adapt in the counterfactual case that they adapted. These findings suggest that even though all households would benefit from adaptation, the effect is significantly larger for households that actually did adapt relative to those that did not, indicating that the prospects of closing the productivity gap through encouraging adaptation in less well-endowed households are limited. Rather, the results in Table 5.1 show that less productive nonadapters would greatly benefit from interventions directed at enhancing empowerment through, for example, encouraging group membership or leadership training.

APPENDIX: SUPPLEMENTARY TABLES

Table A.1 First-stage regression for empowerment

Land holdings (hectares)	0.002 (0.001)[a]
Plots (number)	-0.012 (0.007)*
Lagged value of equipment (FCFA*10,000)	-0.000 (0.001)
Lagged value of herd (FCFA*10,000)	0.000 (0.000)
Household size (number of members)	-0.003 (0.003)
Sex of the household head (1 = male)	-0.120 (0.018)**
Age of the household head (years)	-0.000 (0.001)
Literacy of household head (1 = yes)	-0.028 (0.016)*
Experience of adults (years)	0.001 (0.001)
Schooling of most educated adult (years)	0.005 (0.002)**
Koranic schooling of adult	-0.011 (0.015)
Difference in ability to be interviewed alone between primary male and female	-0.076 (0.012)**
Access to generic information via the radio	0.037 (0.014)**
R-squared	0.20
Adjusted R-squared	0.19
Kleibergen-Paap Wald rk F statistic	25.36
Stock-Yogo critical values	
10% maximal IV relative bias	19.93
15% maximal IV relative bias	11.59
20% maximal IV relative bias	8.75
Hansen J-statistic (p-value)	0.03 (0.95)
Durbin (score) $\chi^2(1)$ (p-value)	1.21 (0.27)
Number of observations	488

Source: Author's survey.
Note: Commune fixed effects are not reported. FCFA 225 = US$1 (purchasing power parity for 2015) (World Bank 2016). FCFA = CFA francs; IV = instrumental variables. [a] Robust standard errors are in parentheses. * Significant at 10 percent. ** Significant at 5 percent.

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