Diversification Strategies and Adaptation Deficit: Evidence from Niger

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Diversification Strategies and Adaptation Deficit: Evidence from Niger

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Abstract
This paper provides fresh empirical evidence on the adaptation process to face climate changes through the analysis of original cross-sectional data collected at household-level in Niger merged with detailed geo-referenced climatic information. In particular, we identify the main drivers and barriers of crop and labour diversification, which constitute two livelihood strategies in mitigating the adaptation deficit by employing a Seemingly-Unrelated Regression (SUR) model, which accounts for potential interdependence among different diversification practices. Secondly, the effectiveness of diversification practices is assessed by means of three complementary welfare measures, namely income changes, food security and the poverty gap using quantile regression and instrumental variable strategy. We find that, aside from climate shocks, the diversification level varies in response to the educational level of household members and spatial location as well as the adoption of ICTs. The impacts of diversification appear differentiated. While labour diversification is always positively associated with all the three welfare measures, positive coefficients of crop diversification are significant only when associated to food security. Robust causal inference confirms that anomalies in rainfall patterns and droughts in particular, induce adaptation responses, which result in welfare gains limited by a richer calorie intake, while the effects on income and severity of poverty appear detrimental.

JEL Classification: Q01, Q12, Q16, Q18
Keywords: diversification, adaptation, welfare, climate change, Niger

1 Introduction

There is overwhelming consensus on the fact that global climate change is altering the variability of rainfall, temperature and other climatic parameters and that such modifications will likely lead to an increase in the incidence of environmental disasters (e.g., IPCC, 2012; Olson *et al*., 2014; Parry *et al*., 2004). Adaptation processes to face extreme climate events often emerge as effective strategies to be undertaken by the most exposed communities (Adger *et al*., 2003). Among the different contributions that have analysed the impact of climate change on adaptation strategies in sub-Saharan Africa (SSA) countries, Niger - one of the most vulnerable countries - has surprisingly received very little attention. Niger constitutes an interesting case for analysis, since it represents a critical area for climate variation and, at the same time, a highly vulnerable country in terms of potential capabilities to face climatic events and economic shocks (IPCC, 2014). Figure 1 and 2 plot density functions of average rainfall level registered in each month of the growing season and provide a clear picture of long-run changes occurring between 1983-2000 and 2001-2012 periods. At the spatial level (Figure 3), the distribution of rainfalls over Niger in the growing season (May-September) appears to be strongly heterogeneous. Most precipitations concentrate in southern areas, while the northern territories accumulate on average less than 40 mm of monthly rain.

Different factors can potentially make Nigerien communities particularly reluctant to implement effective adaptation measures, including low migration levels, high presence of nomadism phenomena, extensive rain-fed subsistence agriculture, very low education rates and a lack of policy supports. Such elements constitute tangible and intangible barriers to adopt adaptation practices, generating adaptation lock-in which may lead to 'wait and see' or reactive approaches, low cognitive learning, misperception, and insufficient awareness of climate risks with inefficient individual response to face extreme events (Le Dang *et al*., 2014; Baird *et al*., 2014). In some cases, such barriers can also lead to competing behaviours of indigenous traditions versus modern and more effective adaptation strategies (Baird and Gray, 2014).

In light of this, our contribution to the existing literature is threefold. Firstly, our analysis uses a comprehensive large national representative household level survey with rich socio-economic information, merged with detailed geo-referenced climatic information. The combination of these data allows us to assess the role of weather in determining farmers' diversification decisions, and consequently, the impact on welfare. We explicitly consider the possibility of farmers' choosing a mix of diversification options using a seemingly unrelated regression (SUR) model, which accounts for potential interdependence among different diversification practices. The impact of these latter is estimated through different welfare indicators and conditioned to different levels of the welfare distribution by means of quantile regression. Secondly, we also estimate the causal impact of crop diversification on different measures of welfare using instrumental variables techniques (IV).

2 Data and empirical strategy

In order to determine the drivers of diversification practices as well as to test whether, and to what extent, those practices are effective responses to guarantee sufficient livelihood conditions in the presence of climate shocks, we exploit original cross-sectional data

(ECVM/A, 2011) deriving from different sources. The survey was implemented by the Niger National Institute of Statistics with technical and financial assistance from the World Bank. The ECVM/A envisages two visits, the first one during the planting season, and the second one during the harvest season. A total of 25,116 individuals grouped in 3,968 households, with information from either the first or second visit or both visits, characterized the final dataset. The ECVM/A has been designed to have national coverage, including both urban and rural areas all the regions of the country, with a fine spatial breakdown (270 enumerator areas divided by urban areas, rural areas, and within the rural areas, agricultural zones, agro-pastoral zones and pastoral zones). We combine this valuable socio-economic dataset with detailed information on precipitation collected at enumerator area level, every ten days (decadal), from 1983 to 2012. Weather data derive from the Africa Rainfall Climatology Version 2 (ARC2) database and cover the 1983-2012 period. Given the specific focus of this paper on the diversification practices as a possible livelihood strategy for the most vulnerable communities, the final dataset only includes 2396 rural Nigerien households, observed in 2011 and distributed across 139 enumerator areas[1] and eight administrative regions. In testing the drivers of diversification and their effect on household welfare, we apply a sequential empirical procedure. The first step aims at determining the most important diversification drivers (Section 2.1), with a stronger emphasis on climate factors. Once such drivers are identified, in the second step we estimate the impact of diversification on a set of three welfare measure (Section 2.2). In addition, we also address potential endogeneity deriving from the reverse causality of crop diversification and welfare conditions by estimating instrumental variable techniques (Section 2.3).

2.1 Determinants of diversification

Our econometric modelling of the determinants of diversification takes into account a series of issues. First, given that the diversification strategies result in a variety of practices affecting different income sources, we first distinguish between diversification in crop species and labour diversification. However, despite excluding income diversification and focusing the analysis on rural households, the two diversifications considered can still be linked in some cases[2]. Thus, when investigating the drivers of diversification, it is important to take into account both specific and common factors which can affect at the same time and in different directions the two types of diversification, depending on the degree of their complementarity or substitutability.

In terms of econometric modelling, separate estimations would not capture this correlation and would not exploit the information deriving from the entire set of common regressors. In order to address the previous issues, for the analysis of diversification determinants we employ a Seemingly-Unrelated Regression model (SUR) (Zellner, 1963). In particular, the iterative two-stage generalized least square estimator allows the SUR model to provide efficient estimations by combining information on different equations and accounts for

[1] More than 40% per cent of the sample lies in desert regions.

[2] Livestock activities are included in labour diversification. We intentionally do not consider income diversification in our analysis since this implies the availability of relevant capital stocks in heterogeneous activities, a situation unlikely to be found in rural households.

potential correlation in the error terms. According to the theoretical framework previously discussed and considering the data limitations, we specify a two-equation SUR model, in which the dependent variables measuring the degree of diversification are regressed over a set of common predictors, while the error terms are assumed being correlated. More formally, for each i=1,..,N household, the two-equation model in compact notation is given by:

$$\boldsymbol{D}_{i,j} = \boldsymbol{\beta}_0 + \boldsymbol{\Psi}_{i,j}\beta_i + \boldsymbol{\varepsilon}_{i,j}$$

where N=2396 and j=1,2 indexes, respectively, the equation for crop and labor diversification. The errors $\boldsymbol{\varepsilon}$ are assumed to be correlated within individuals and uncorrelated across individuals, with the overall variance-covariance matrix given by $\Omega = E(\varepsilon\varepsilon') = \sum\otimes I_N$. The vector of dependent variable $\boldsymbol{D}$ measures the degree of diversification, whose metrics deserves some explanation. A common method for assessing the degree of diversification is the calculation of a vector of income shares related to different income sources (Lay *et al*., 2008 and Davis *et al*., 2010 among others). Such a method puts directly into the relationship diversification activities and income changes but, on the other hand, a relevant part of information related to different aspects of diversification is neglected. Accordingly, our first diversification measure is constituted by the Shannon-Weaver index as suggested by Duelli and Obrist (2003). In addition, robust directions on the impacts of diversification determinants are also derived by testing in our model the Margalef index (measuring the simple richness) and the Berger-Parker index (measuring the relative abundance). For agricultural diversification, the indices consider the number of cultivated crop species adjusted by land size at plot level, and for labour diversification, we calculated the number of different work activities by distinguishing from 11 different jobs, divided by skilled and unskilled workers[3] aged between 14 and 65 and resulting in 22 labour differentiations.

The set of independent variables, common to the two equations and represented by the vector $\boldsymbol{\Psi}$ include *Climate shocks* variable. Our data allows us to map long-run weather anomalies in order to identify climate shocks in the single period of interest, i.e. 2011, with finer spatial and temporal breakdown than in previous studies (Ersado, 2003; Nhemachena and Hassan, 2007; Dimova and Sen, 2010). In order to identify long-run climate anomalies on the basis of the available data, we rely on the Standard Precipitation Index (SPI). The SPI is a widely used indicator, which allows detection of significant variations in precipitations with respect to the long-run mean. To this aim, raw precipitation data are fitted to a gamma or Pearson Type III distribution, which is then transformed to a normal distribution (see Guttman, 1999 for further details). The use of the SPI presents some advantages with respect to other methods. First, in order to identify climate anomalies such as drought or excessive rainfalls, only time-series data on precipitation are required. Moreover, the SPI is an index based on the probability of recording a given amount of precipitation. Since the probabilities are standardized, a value of zero indicates the median precipitation amount, thus the index is negative for drought, and positive for wet conditions. As the dry or wet conditions become more severe, the index becomes more negative or positive, ranging within a commonly-used scale from -2.5 and +2.5 (WMO, 2012). The characteristic of being standardized thus

[3] We assume that household members can choose between investing in skilled or unskilled activities.

provides a straightforward interpretation and allows for a fully indexed comparison over time and space. In addition, the SPI can be computed for several time scales, ranging from one to 24 months, capturing various scales of both short-term and long-term anomalies. In order to compute our climate shock variables, we first calculate the SPI at 12 months for the reference year 2011. Once the long-run climate anomalies are detected by using the interpretation table provided in WMO (2012), we identify drought and rainfall shocks with dummy variables corresponding to SPI values ranging from less than -2 to more than +2, respectively. Thus, a SPI value of -2.0 or less signals a drought shock while values of +2.0 or more indicates extremely wet conditions[4].

We also include in the model proxies of spatial position, access to markets and infrastructures. In order to account for the access to main infrastructures, our dataset is augmented with information on the road density within a radius of 15 km and with the average distance to main infrastructures calculated as the simple mean of the distance from the household and the nearest postal office, bank and hospital as a proxy of market and credit access; We also include proxies of technology, knowledge and education level such as average household educational level considering all the family members and, as a proxy of knowledge absorption capacity, we include the level of technology endowment by calculating the count of ICT assets as the total number of mobile phones, TVs, radios, cameras, video cameras and computers owned by each households. We also included household endowments such as livestock ownership, non-technological agricultural and technological assets, the presence of market and crop shocks d and the adoption of modern varieties (MVs) among others.

2.2 Effects of diversification

Our multidimensional picture of households' welfare conditions relies on a set of three indicators, which capture different aspects and issues to be taken into account when the analysis of wellbeing is under scrutiny. Namely, our dependent variables consider the total household income expressed in US dollars as a basic measure of welfare. In addition, the Dietary Energy Supply (DES) expressed in per-capita calories per day, as well as the Severity of Poverty (SP) calculated as the squared of the poverty gap index[5], also provides information on food security and inequality among the poor, respectively.

Preliminary statistics signal that the degree of diversification changes according to the welfare status and endowment level. In the case of income (Figure 4), labour diversification measured by the Margalef index follows a reverse U-shaped curve, suggesting that the diversification level is higher in middle-income rural households. On the contrary, when the same diversification is measured through the Shannon-Weaver index (Figure 5), which accounts for the evenness, a monotonic trend appears. At empirical level, this evidence not only suggests measuring the impact of diversification conditioned to different welfare ranges, but also justifies the choice of using different diversification measures. In order to capture

[4] In order to capture the specific impact of long-run weather anomalies on the rural households, the SPI is calculated by including only the months falling in the growing season (i.e. from May to September).

[5] Poverty line at 1.25 2005 PPP US Dollars (World Bank, 2015).

heterogeneity due to the differentiated impacts on the households' welfare, we employ a quantile regression model (Koenker and Hallock, 2001; Koenker, 2005).

The uncorrelated effect of each type of diversification is captured by employing fitted values of dependent variables deriving from the SUR model estimation as welfare predictors in the quantile model, although in adopting such a procedure we do not support any causality claim. In estimating the quantile model, the diversification impact is conditioned to three sections of the distribution (i.e., $q = \{0.25, 0.5, 0.75\}$) of the dependent variable, namely income, DES and SP. It is worth mentioning that the potential bias deriving from the sequential empirical procedure here proposed is minimized by using bootstrapping replications for estimating the quantile model with corrected standard errors. For the i-th household, the welfare equation of the quantile model is given by:

$$W_i = \beta_{0,i} + \beta_1 \widehat{D_i^1} + \beta_2 \widehat{D_i^2} + \beta_3 \lambda_i + \beta_4 \delta_i + \beta_5 \tau_i + \epsilon_i$$

in which W represents the welfare level and $\widehat{D^1}$, $\widehat{D^2}$, are the fitted values measuring crop and labor diversification, respectively. In addition, a series of specific variables and controls directly related to the welfare status are also included, and namely: the sum of total non-technological assets λ owned by each household, the age of household head δ, and the number of family members δ to control for household size. ε represents the idiosyncratic error component. The model estimation is repeated with three different welfare measures (income, DES and SP), thus providing a comprehensive picture of the households living conditions. We also employ an instrumental variable approach to control for potential endogeneity problem associated with diversification decision.

[Figure 4 & 5 - about here]

3 Results

3.1 Determinants of diversification

The outcomes obtained by the SUR model are presented in Table 1, in which columns 1, 2 and 3 report the estimates for Shannon-Weaver, Margalef and Berger-Parker diversification indexes, which represent, respectively, our dependent variables.

As a general and most important result (column 1), we obtain that both crop and labour diversification are significantly affected by weather shocks, these being expressed as dummy variables signalling extreme deviations of the SPI values. This evidence allows us to hypothesize a causal response of households in consequence of extreme climate fluctuations, the latter inducing diversification behaviour as an adaptive strategy. In the case of crop diversification, such a hypothesis will be further scrutinized and confirmed in Section 3.3 by means of the instrumental variables technique.

[Table 1 - about here]

Further interesting results derive from the analysis of other diversification determinants. In particular, households that are more educated enrich their portfolio of practices and are more prone to adopt diversification strategies. As in the previous variables, the positive effect of education is robust to other diversification measures (column 2 and 3). With respect to the access to infrastructures, our variable of interest (the distance to main facilities) is always associated to negative and significant coefficients for crop diversification, thus households living far from main urban areas seem to be more prone to adopt crop diversification behaviour. Higher distances should imply difficulty in accessing the main markets as well as lower chances for socially interacting with more organized communities in search of business opportunities. However, while higher distances act as barriers for crop diversification performances, in the case of labour diversification they have not univocal direction. In fact, higher values of labour diversification should be related to efficient labour markets characterized by higher information levels and the latter, in turn, should benefit from lower distances to urban agglomerations where most business takes place. Nevertheless, our estimates signal that potential benefits deriving from social interactions are not fully captured. This may reveal the existence of individual barriers which may lead to social lock-in that negatively impact the household capacity to access the labour market and enrich the portfolio of job activities.

A further spatial impact significant in all three model specifications is given by the geographical location of households, which confirms the hypothesis that those households living in desert regions and that likely constitute the most vulnerable communities are more prone to adopt diversification practices. The impact is larger for crop diversification, suggesting that the enrichment of crop species variety constitutes a more effective livelihood response in households living in areas subject to drought shocks.

According to our model, higher TLU values are negatively associated with crop diversification and seem to favour labour diversification, although this relation is significant only when diversification is measured by the Margalef index (column 2). Interesting aspects also emerge from the assessment of technology assets. Namely, households with higher endowments of ICT devices (such as mobile phones, smartphones, computers, radio and other devices that favour the communication among individuals) are more likely to experience a higher level of labour diversification, and this relation is consistent across the three diversification measures. On the other hand, the correlation between ICT endowment and crop diversification is negative and significantly differs from zero only when measured through the Berger-Parker index (column 3). Moreover, ICTs enhance the communication process and facilitate social interaction, thus allowing households to capture pieces of knowledge such as job offers and other opportunities, which are functional to higher levels of labour diversification. On the other hand, the hypothesis that ICTs would play an effective role in informing people on local weather forecasts, thus enhancing the awareness on the risks due to extreme weather events, cannot be confirmed in our analysis of diversification determinants.

We find a positive and significant correlation between the amount of irrigated cultivated land and the level of labour diversification, while the relation is so far significant in the case of crop diversification (column 2 and 3). This result is coherent with the geography of Niger, since the extent of lands that benefit from irrigation systems is very little[6]. On the other hand, the effects on crop diversification conditioned to the amount of rainfed land are characterized by significantly positive relationships, which is also consistent across the three diversification measures (column 2 and 3). However, the relation is not univocal for labour diversification, whose positive and significant sign associated with the Shannon-Weaver index (column 1)

[6] The share of irrigated cultivated land over the total cultivated land is 6.8%.

turns out to be negative and weaker when diversification is measured by the Margalef index (column 2). This signals that in presence of rainfed land, households prefer to adopt crop diversification instead of labour diversification. In line with the empirical agronomic literature, farmers utilize rainfed land for subsistence purposes and there are local landraces that are demonstrated to be more resistant to water and climatic stressors. Traditionally, landraces are cultivated in a rich mixed cropping system so as the rainfed land is *per se* an asset linked with the strategy of crop diversification. On the contrary, on irrigated land, modern agricultural technologies may be applied in order to cultivate major and cash crops, which require higher level of water, and in an optimal intensification approach, a mono-cropping farming that may result in a diversity reduction (Bellon, 2004; Lipper and Cooper, 2008). Such a hypothesis is first tested by including a dummy variable indicating the presence of modern varieties (MV). In addition, we interact the MV-dummy with the amount of irrigated cultivated land. The variable of adoption of modern varieties (MV) seems to be negatively correlated to both crop and labour diversification practices, and this result also holds when diversification is measured both with Margalef and Berger-Parker index. From the negative and significant coefficient of the interacted variable, we can infer that when land is allocated to cultivate modern varieties, the intensification process takes place at the expense of the variety of crop species, although this result shows less significance in the estimations using the Margalef and Berger-Parker indices (column 2 and 3).

3.2 Impacts of diversification

In this section, we present the results of the impact of diversification[7] on a set of three dependent variable measuring different aspects of household welfare status, namely total income, DES and SP. Table 2 presents quantile estimation results in the three welfare measures.

[Table 2 - about here]

The impacts of diversification in rural households are heterogeneous, varying across the different welfare classes and depending on the different dimensions of welfare measurement. However, some consistent patterns can be identified across the distributions of the three welfare measures. First, we find a negative relationship between crop diversification and income, although being significant only in higher classes of the income distribution (column 1). On the contrary, labour diversification is strongly and significantly associated with all classes of income and the poverty index (SP). Regarding food security, the DES is negatively correlated with labour diversification only for households having high calorie intake (column 2). Such evidences support the hypothesis that labour diversification constitutes a more complete and effective livelihood strategy with respect to crop diversification, although this latter concentrates its impacts on the food security. Not surprisingly, the household's assets measured with the number of non-technological durable goods owned by households are significantly and consistently associated with higher welfare status in all the welfare indicators employed. However, a weaker relationship emerges in the case of income (column 1). An interesting result derives from the analysis from the coefficient associated with the

[7] Our results are consistent across the three diversification measures (Shannon-Weaver, Margalef and Berger-Parker indices).

average e age of household head, which is not significantly associated only with mid- and low-income classes (column 1). The inconsistency existing in the impact of age on income and food supply may reveal, *ceteris paribus*, a decoupling effect between income accumulation and the capacity to transform this later into proportional food security, although such evidence cannot be confirmed here since it would require panel data analysis.

Since our first welfare measure is given by total family income, the inclusion of the household size as a control is necessary. In the case of income (column 1), larger households are significantly associated with higher incomes and such an effect is consistent across all the income classes. On the contrary, when considering the amount of food consumed as well as the severity of poverty index, the relationship assumes the opposite sign (column 2 and 3). Building on these results, we may infer that a higher number of family members may imply more people at work and a higher income when considering the household as a whole. At the same time, this may also entail more need for food, which is often self-produced within the family unit, in particular in rural and marginalized households. The resulting balance may envisage net income gains but also lower food per capita where households have difficulty in accessing other food sources.

3.3 Results with instrumental variables

To control for potential endogeneity problem of the diversification decision, we also employ the Instrumental Variable (IV) regression model[8], estimated by implementing a two-stage least square (2SLS) estimator[9]. We focus on weather fluctuations as our identifying instruments, which, we argue, generate uncertainty about expected climatic conditions and induce households to adopt diversification strategies. Additionally, we assume that the level of urban infrastructures characterizing the household living area is a fixed factor, which may induce diversification while not directly affecting household welfare. Given the complexity in choosing a valid set of instruments, we focus the analysis on crop diversification and we are quick to point out that our candidate variables may not be perfect. Nevertheless, we will try to demonstrate that the test statistics support the idea that our instruments are valid[10].

The results deriving from IV estimations and presented in Table 3 appear, largely, to be consistent with those obtained by relying on the quantile model[11]. Most importantly, the negative impact of crop diversification on household income (column 1-3) is robust to different measures of diversification and to different model specifications (e.g., with results presented in Table 2), with a stronger effect when the Margalef index is employed (column 4-6). On the contrary and consistently with the results presented in Table 2, crop diversification represents a very good means to increase the food security of rural households, with the DES

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[8] We estimate the models with the *ivreg2* command using the Stata software, v. 13.1.

[9] Our results are robust to the use of alternative estimators such as GMM and are available upon request. It is worth noting that if the model is exactly identified, the efficient GMM and traditional IV/2SLS estimators coincide. For further details, see Hayashi (2000).

[10] We assess the quality of our instruments by using an F-test of the joint significance of the excluded instruments. We also perform overidentification tests of the model. All the results are showed in Table 3.

[11] Given the aim of the IV model, only the impact of crop diversification can be compared to the results obtained from the quantile model reported in Table 2.

being positively and strongly significantly associated with crop diversification in all the three indices (column 4-6). In addition, crop diversification also assumes an effective role in reducing the poverty gap, although this effect is less significant than that on income and DES (column 7-9). By combining the previous results with those obtained through IVs, we find robust evidence of the negative role of crop diversification in terms of income gains and limited capacity to mitigate the severity of poverty. If adapted to our context, such evidence is in line with previous studies, which relate production performances to the degree of crop diversification (Di Falco *et al*., 2010; Di Falco and Chavas, 2009). In our case, rural households represent the most marginalized communities, which rely on crop diversification as a mere adaptation strategy. In support of this hypothesis, it is worth considering that Niger is characterized by imperfect markets and weak policy support, which make difficult access to complementary agricultural inputs and food purchasing. Thus, diversifying households cannot capture complementary welfare benefits such as income gains, deriving from richer crop diversity; they rely on diversification mainly as an adaptive response able to guarantee sufficient food supply.

Regarding the variables related to specific households' characteristics, we observe that higher educational level correspond to slightly higher incomes (column 1-3) and lower values of severity of poverty (column 7-9). We also find confirmation on the negative performances of female-headed households both in terms of income changes (column 1-3), while no significant impact is found with respect to food security and severity of poverty (columns 4-6 and 7-9). The size of family is significantly and positively associated to higher incomes (column 1-3), but also implies more need for food and more income allocated to the latter (column 4-6 and 7-9). Hence, the size of family produces differentiated impact across the three welfare dimensions here analysed, a result consistent with the previous results reported in Table 2. With respect to the spatial factors, we observe that the average distance to main facilities shows no significant effects on welfare status. Living in desert regions represents a significant welfare reduction factor, since such a negative impact holds across the three welfare dimensions on all diversification measures. Interesting results can also be observed when the household assets are analysed. One relevant and interesting effect is due to the role of ICT devices, which allow households to capture a higher level of technical knowledge, more accurate weather forecasts and other pieces of knowledge that are key for implementing effective crop diversification strategies. ICTs produce strongly significant and positive impacts not only in terms of income (column 1-3) but also in the amount of food calories (columns 4-7) as well as in reducing the poverty gap (columns 7-9). Moreover, such effects are robust to the three diversification measures. Regarding the importance of agricultural assets, a significant role is assumed by the non-technology ones which, together to the amount of irrigated cultivated land, are functional to producing higher incomes (columns 1-3) and also to mitigating the severity of poverty (columns 7-9). On the other hand, households that own rain-fed lands are not significantly affected by any welfare variations.

[Table 3 - about here]

4 Conclusions

In this paper, we aim to identify the drivers and effects of two diversification activities, namely crop and labour diversification, in rural Nigerien households. Our analysis of diversification determinants confirms the hypothesis that anomalies in rainfall patterns result in adaptation responses measured through the adoption of diversification practices. The inducement effect of climate factors is consistent for both crop and labour diversification and across the three indices of diversification employed, namely Shannon-Weaver, Margalef and Berger-Parker.

Besides, the main `push' factors given by the drought shocks, the level of crop diversification is positively associated to other significant catalysts such as the educational level of household members, the spatial location, and different sets of household endowments. On the other hand, main limitations to crop diversification derive from the amount of livestock owned, from the presence of female-headed households and from excessive rainfalls. The combined effect of adopting MVs with cultivated irrigated land signals the potential presence of agricultural intensification processes which is detrimental to richer degrees of crop diversification.

Regarding the labour diversification, the infrastructural level and the distance from main facilities imply opposite diversification behaviour. While crop diversification benefits from longer distances and from a denser road pattern, labour diversification seems to be negatively affected by these factors. On the other hand, labour diversification positively responds to higher levels of household ability to capture pieces of knowledge and information from ICT devices. In addition, in line with the results obtained for crop diversification, living in desert areas induces households to allocate labour in a richer way. Additional beneficial effects for labour diversification are signalled by the interaction of the MV variable with the one indicating the amount of irrigated cultivated land as well as by the amount of both technological and non-technological agricultural assets owned by households.

The second part of our analysis focuses on the impacts of diversification, which are scrutinized on a set of three welfare indicators. Largely the quantile model confirms our descriptive evidence of differentiated effects across different classes of the different welfare indicators. More in detail, labour diversification is significantly and positively associated with income and negatively with the severity of poverty, particularly in the higher welfare classes. However, a weakly significant correlation is also found in the case of higher classes of DES. On the contrary, a richer calorie intake is always and strongly significantly associated with crop diversification, while the latter is negatively correlated with income and more severe poverty. As in the previous estimations, the instrumental variable approach also shows that impacts of diversification significantly affect the level of welfare with differentiated impacts. Namely, crop diversification is confirmed to reduce the income level and to increase the severity of poverty, but its role is key for sustaining households with larger caloric intake. This supports the hypothesis that most marginalized farmers are more responsive to crop-diversification as a risk-minimization strategy and that such a strategy is actually effective in increasing their food security.

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Table 1 - Drivers of diversification (Comparison across indices) - SUR estimations.

	(1) Shannon-Weaver		(2) Margalef		(3) Berger-Parker	
	Crop	Labour	Crop	Labour	Crop	Labour
Drought shocks (SPI≤ -2)	0.265***	0.125**	0.0355**	0.0720*	0.313***	0.0930**
	(3.42)	(2.09)	(2.51)	(1.69)	(2.73)	(2.27)
Rainfall shocks (SPI$\geq +2$)	-0.127***	0.00857	-0.0175***	0.00123	-0.223***	-0.00704
	(-3.83)	(0.33)	(-2.88)	(0.07)	(-4.54)	(-0.40)
Educational level (years)	0.00480*	0.00368*	0.000808*	0.00616***	0.0105***	0.00238*
	(1.84)	(1.82)	(1.69)	(4.29)	(2.72)	(1.72)
Female headed (dummy=1)	-0.0794**	-0.0253	-0.0127*	-0.0123	-0.122**	-0.0145
	(-2.12)	(-0.87)	(-1.84)	(-0.59)	(-2.20)	(-0.73)
Avg. distance to main facilities (km)	-0.00326***	0.000874**	-0.000565***	-0.000480*	-0.00416***	0.000168
	(-6.21)	(2.15)	(-5.86)	(-1.66)	(-5.34)	(0.60)
Road density (15km radius)	0.00144***	-0.000972***	0.000196***	-0.00115***	0.00361***	-0.000808***
	(3.69)	(-3.21)	(2.74)	(-5.33)	(6.22)	(-3.90)
Desert region (dummy=1)	0.0539**	0.0477**	0.0463***	0.00561	0.106***	0.0324**
	(2.10)	(2.40)	(9.83)	(0.40)	(2.79)	(2.38)
TLU	-0.0139***	-0.00102	-0.00253***	0.00385**	-0.0247***	-0.000297
	(-5.01)	(-0.47)	(-4.99)	(2.52)	(-6.01)	(-0.20)
N° of technology assets	-0.0132	0.0244***	0.0000752	0.0260***	-0.0536***	0.0144**
	(-1.25)	(2.98)	(0.04)	(4.46)	(-3.41)	(2.57)
N° of agricultural tech. assets	0.0319	0.191***	-0.0143*	-0.0279	-0.147**	0.147***
	(0.69)	(5.33)	(-1.68)	(-1.09)	(-2.14)	(5.97)
N° of agricultural non-tech. assets	0.0326***	0.00764***	0.00623***	0.0295***	0.0459***	0.00383**
	(10.63)	(3.22)	(11.08)	(17.45)	(10.09)	(2.35)
Irrigated cultivated land (hectars)	0.149***	0.0592***	-0.000457	0.0142	-0.0454	0.0293**
	(5.69)	(2.92)	(-0.10)	(0.98)	(-1.17)	(2.11)
Rainfed cultivated land (hectars)	0.0183***	-0.00701**	0.00285***	0.0151***	0.0195***	-0.00276
	(4.83)	(-2.39)	(4.10)	(7.21)	(3.47)	(-1.37)
Crop disease shocks (dummy=1)	0.0542	-0.0230	0.00936	-0.0179	0.0938*	-0.0110
	(1.56)	(-0.86)	(1.47)	(-0.94)	(1.82)	(-0.60)
Input price shocks (dummy=1)	0.0629	-0.0208	0.00361	0.0265	-0.0455	-0.0315
	(1.27)	(-0.54)	(0.40)	(0.97)	(-0.62)	(-1.20)
MV adoption	0.265***	-0.0333	0.0439***	0.0358	0.378***	-0.0186
	(4.94)	(-0.80)	(4.47)	(1.21)	(4.75)	(-0.66)
MV interacted with cultivated land	-0.0174**	0.0200***	-0.00308*	0.000612	-0.0172	0.0104**
	(-1.98)	(2.93)	(-1.91)	(0.13)	(-1.32)	(2.22)
_cons	1.398***	1.180***	0.0748***	0.199***	1.595***	1.140***
	(30.35)	(33.10)	(8.86)	(7.85)	(23.34)	(46.67)

N= 2396, *t* statistics in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. SUR model, correlation matrix. Breusch-Pagan test of independence (H0: correlation across equations): Model (1): $\chi 2$=0.156, Pr=0.6927, Model (2): $\chi 2$=7.532, Pr=0.0061, Model (3): $\chi 2$=4.661, Pr=0.0308.

Table 2 - Effects of diversification (Shannon-Weaver index) on income, DES and SP

	(1) Income			(2) DES			(3) SP		
	q25	q50	q75	q25	q50	q75	q25	q50	q75
Crop divers. (fitted on Shannon index)	130.8	-181.7*	-719.7***	487.5***	697.2***	745.5***	0.0120***	0.0268***	0.0348***
	(1.49)	(-1.93)	(-4.17)	(6.83)	(12.11)	(7.57)	(2.92)	(3.66)	(3.68)
Labour divers. (fitted on Shannon index)	1403.5***	2533.0***	3961.4***	30.86	-20.04	-592.3***	-0.111***	-0.230***	-0.303***
	(5.83)	(7.40)	(5.43)	(0.20)	(-0.11)	(-3.13)	(-6.59)	(-9.54)	(-8.31)
Total non-tech. durable assets	1.299	19.56*	65.09**	10.39**	24.02***	33.20***	-0.00403***	-0.00840***	-0.0103***
	(0.20)	(1.76)	(2.55)	(2.08)	(4.86)	(3.24)	(-10.20)	(-13.99)	(-7.60)
Age of household head	2.091*	3.048*	-1.678	1.162	1.342	-0.0630	-0.0000774	-0.00000974	-0.000154
	(1.76)	(1.65)	(-0.42)	(0.90)	(0.82)	(-0.03)	(-0.84)	(-0.06)	(-0.76)
Household size	52.54***	94.97***	156.7***	-151.2***	-203.8***	-231.1***	0.0117***	0.0234***	0.0292***
	(7.53)	(6.73)	(7.33)	(-26.13)	(-28.04)	(-29.98)	(14.94)	(20.68)	(23.70)
Constant	-1747.0***	-2433.4***	-2626.1***	2086.1***	2570.0***	3957.2***	0.0985***	0.234***	0.383***
	(-5.05)	(-5.94)	(-3.02)	(9.06)	(12.52)	(21.34)	(4.57)	(7.79)	(8.53)

N=2396. *t* statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Quantile estimations with 100 bootstrap replications.

Table 3 - Welfare effects of crop diversification on three different diversification indices (Shannon-Weaver, Margalef and Berger-Parker)

	(1) Income	(2) Income	(3) Income	(4) DES	(5) DES	(6) DES	(7) SP	(8) SP	(9) SP
Crop diversification (Shannon)	-874.1*			597.6***			0.0928***		
	(-1.83)			(3.07)			(2.96)		
Crop diversification (Margalef)		-6396.1*			4471.3***			0.673***	
		(-1.80)			(3.02)			(2.78)	
Crop diversification (Berger-Parker)			-494.3**			235.3**			0.0638***
			(-2.01)			(2.46)			(3.88)
Educational level (years)	23.03**	24.37**	24.17**	2.122	1.106	2.672	-0.00130*	-0.00143**	-0.00156**
	(1.97)	(2.03)	(2.13)	(0.51)	(0.25)	(0.68)	(-1.91)	(-1.98)	(-2.32)
Age of household head	-0.368	-0.249	0.532	2.959**	2.909**	2.075*	-0.0000723	-0.0000869	-0.000138
	(-0.13)	(-0.08)	(0.19)	(2.19)	(2.06)	(1.67)	(-0.36)	(-0.41)	(-0.73)
Female headed (dummy=1)	-336.2***	-350.3***	-335.4***	-9.611	1.168	-23.14	0.00759	0.00901	0.00893
	(-2.89)	(-2.83)	(-2.95)	(-0.16)	(0.02)	(-0.41)	(0.81)	(0.89)	(0.94)
Household size	49.46***	48.55***	51.71***	-204.9***	-204.1***	-208.1***	0.0236***	0.0237***	0.0236***
	(2.69)	(2.63)	(2.97)	(-30.66)	(-28.53)	(-33.79)	(20.95)	(19.96)	(21.70)
Avg. distance to main facilities (km)	0.830	0.0499	1.343	-1.383	-0.788	-2.302***	0.0000601	0.000139	0.0000680
	(0.31)	(0.02)	(0.58)	(-1.35)	(-0.66)	(-2.61)	(0.38)	(0.73)	(0.48)
Desert region (dummy=1)	-260.4***	-10.20	-255.2***	-183.9***	-359.4***	-178.1***	0.0364***	0.0101	0.0348***
	(-2.58)	(-0.06)	(-2.60)	(-4.63)	(-4.54)	(-4.67)	(5.48)	(0.79)	(5.31)
TLU	85.98***	81.88***	85.31***	7.670	10.70*	5.776	-0.00232***	-0.00190**	-0.00199**
	(3.96)	(3.76)	(4.00)	(1.46)	(1.77)	(1.19)	(-2.66)	(-2.05)	(-2.37)
N. of technology assets	163.9***	180.5***	154.5***	30.43*	18.79	34.71**	-0.0215***	-0.0233***	-0.0203***
	(3.43)	(3.65)	(3.22)	(1.84)	(1.01)	(2.20)	(-7.63)	(-7.86)	(-7.46)
Total non-tech. durable assets	65.69***	61.71***	60.65***	21.54***	24.35***	23.52***	-0.00733***	-0.00691***	-0.00663***
	(3.54)	(3.25)	(3.30)	(3.22)	(3.35)	(3.70)	(-6.84)	(-6.00)	(-6.14)
N. of agricultural tech. assets	528.3**	410.1	418.6*	-63.25	19.07	-7.399	-0.0404***	-0.0279**	-0.0266***
	(2.12)	(1.63)	(1.80)	(-0.83)	(0.24)	(-0.13)	(-3.76)	(-2.45)	(-2.81)
N. of agricultural non-tech. assets	103.4***	114.9***	97.09***	17.43*	8.883	27.47***	-0.00676***	-0.00794***	-0.00672***
	(4.10)	(3.79)	(4.61)	(1.94)	(0.75)	(3.96)	(-4.66)	(-4.16)	(-5.56)
Irrigated cultivated land (ha)	318.3*	186.0	162.5	-103.0**	-12.41	-2.809	-0.0362***	-0.0222***	-0.0190***
	(1.90)	(1.31)	(1.21)	(-2.25)	(-0.38)	(-0.09)	(-3.98)	(-3.09)	(-2.86)
Rainfed cultivated land (ha)	-14.76	-12.22	-20.66	-6.183	-8.257	0.677	-0.000108	-0.000357	0.000207
	(-0.91)	(-0.70)	(-1.49)	(-0.86)	(-1.02)	(0.11)	(-0.09)	(-0.26)	(0.19)
Crop disease shocks (dummy=1)	-202.4*	-190.1	-203.4*	-43.19	-52.62	-31.29	0.0261***	0.0248**	0.0249***
	(-1.81)	(-1.61)	(-1.87)	(-0.87)	(-0.96)	(-0.68)	(2.73)	(2.45)	(2.66)
Input price shocks (dummy=1)	-137.7	-169.9	-220.0	-173.3***	-151.5**	-125.1**	-0.0162	-0.0128	-0.00658
	(-0.90)	(-1.07)	(-1.49)	(-2.66)	(-2.29)	(-2.00)	(-1.23)	(-0.95)	(-0.51)
MV adoption	156.1	203.8	114.9	-47.43	-84.62	23.22	-0.0207	-0.0255	-0.0210
	(0.67)	(0.80)	(0.54)	(-0.48)	(-0.77)	(0.27)	(-1.25)	(-1.39)	(-1.36)
MV interacted with cultivated land	14.34	10.07	20.81	5.089	8.337	-1.542	0.000792	0.00123	0.000349
	(0.49)	(0.32)	(0.73)	(0.40)	(0.57)	(-0.13)	(0.34)	(0.49)	(0.15)
Constant	1791.0**	1053.2***	1360.2***	2729.2***	3223.3***	3228.1***	-0.0789	0.000117	-0.0556*
	(2.31)	(2.67)	(2.74)	(8.50)	(18.76)	(16.04)	(-1.54)	(0.00)	(-1.65)
r2	0.0467	0.0188	0.0929	0.353	0.276	0.407	0.169	0.0842	0.185

N=2396. Robust t statistics in parentheses, ∗ $p < 0.1$, ∗∗ $p < 0.05$, ∗∗∗ $p < 0.01$. F-test of excluded instruments: Model (1), (2), (3): F=19.32; Model (4), (5), (6): F=11.16; Model (6), (7), (8): F=37.51. Overidentification test of all instruments (Hansen J statistics): Model (1): χ2 = 0.87, p = 0.641, Model (2): χ2 = 8.82, p = 0.022; Model (3) χ2 = 18.52, p = 0.001; Model (4): χ2 = 0.897, p = 0.638; Model (5): χ2 = 8.17,p = 0.016; Model (6): χ2 = 17.17,p = 0.000; Model (7): χ2 = o.26,p = 0.876; Model (8): χ2 = 14.179,p = 0.000; Model (9): χ2 = 12.576,p = 0.001. Endogeneity test (H0: regressors tested are exogenous): Model (1): χ2 = 7.26, p = 0.007; Model (2): χ2 = 8.16, p = 0.004; Model (3): χ2 = 7.55, p = 0.006; Model (4): χ2 = 4.97, p = 0.025; Model (5): χ2 = 9.44, p = 0.002; Model (6): χ2 = 6.85, p = 0.008; Model (7): χ2 = 7.16, p = 0.007; Model (8): χ2 = 4.39, p = 0.036; Model (9): χ2 = 12.663, p = 0.000.

Figure 1 – Density functions on average precipitations in growing season, 1983-2000.

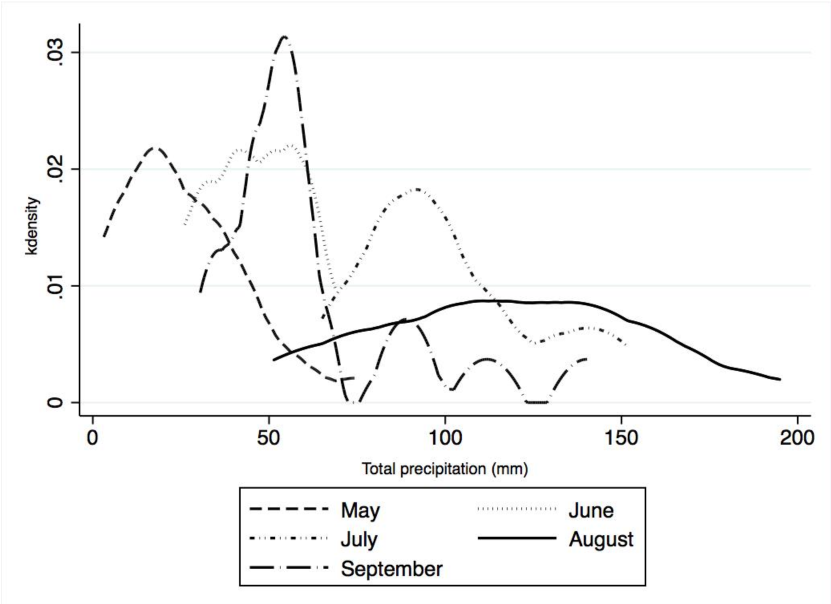
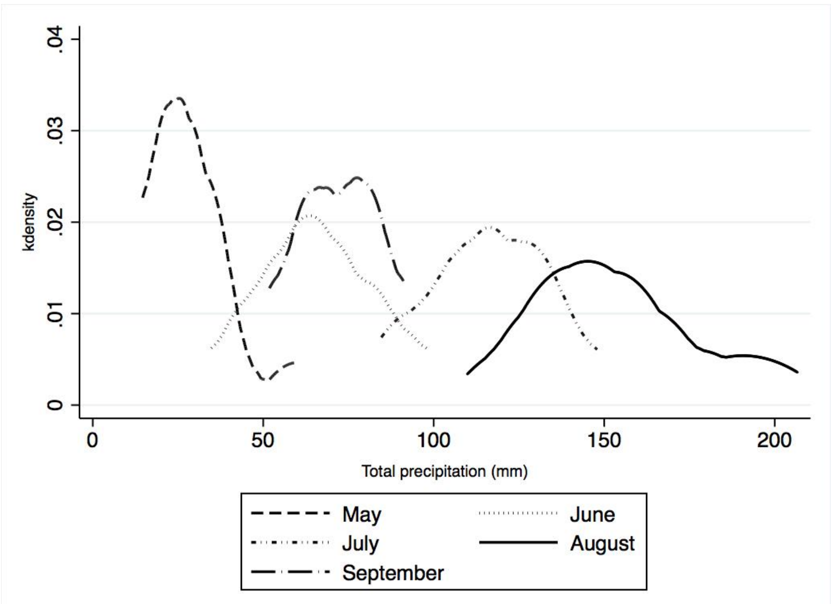


Figure 2 – Density functions on average precipitations in growing season, 2001-2012.



Source: authors' elaborations based on ARC2 database.

Figure 3 – Spatial distribution of precipitations in the growing season (May-September) over the period 1983-2012.

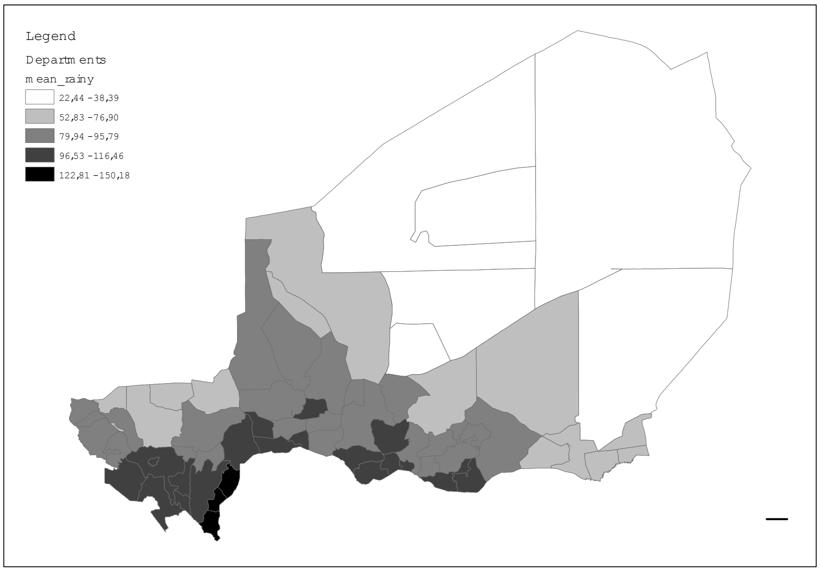


Figure 4 – Diversification degree (with Margalef index) vs. per-capita income.

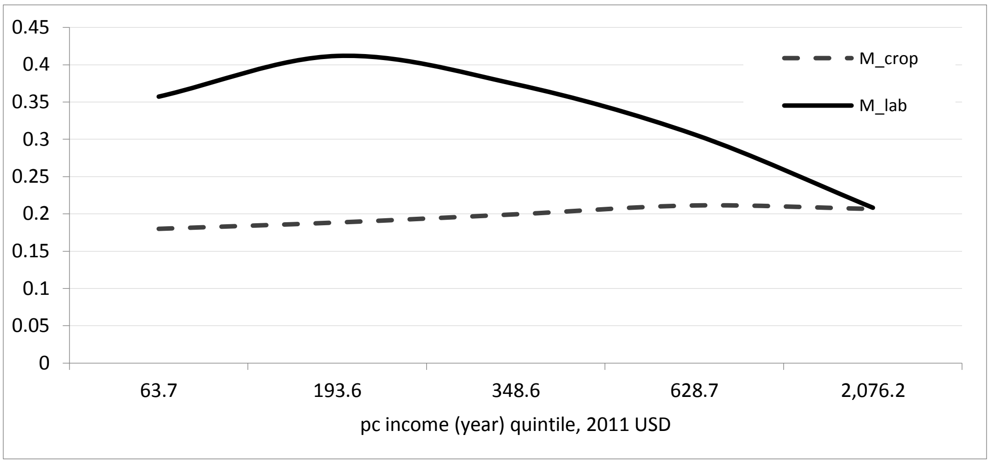


Figure 5 – Diversification degree (with Shannon-Weaver index) vs. per-capita income