Food and Agriculture
Organization of the
United Nations

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FAO AGRICULTURAL DEVELOPMENT ECONOMICS
WORKING PAPER 18-06

ISSN 2521-1838

November 2018

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Food and Agriculture Organization of the United Nations

Rome, 2018

Required citation:

Asfaw, S., Maggio, G. & Palma, A. 2018. *Climate resilience pathways of rural households: evidence from Ethiopia.* FAO Agricultural Development Economics Working Paper 18-06. Rome, FAO. 36 pp. Licence: CC BY-NC-SA 3.0 IGO.

ISBN 978-92-5-131140-0

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Abstract

Climate variability and extreme events continue to impose significant challenges to households, particularly to those that are less resilient. By exploring the resilience capacity of rural Ethiopian households after the drought shock occurred in 2011, using panel data, this paper shows important socio-economic and policy determinants of households' resilience capacity. The analysis shows that households affected by the shock generally possess more resilience capacity than those not affected, as they tend to develop adaptive capacity. Three policy indications emerge from the analysis. First, government support programmes, such as the Productive Safety Net Programme (PSNP), appear to sustain households' resilience by helping them to reach the level of pre-shock total consumption, but have no impact on the food-consumption resilience. The implementation of such types of programmes, therefore, may be insufficient to support food security of chronic food-insecure farmers after a weather shock. Secondly, the "selling out assets strategy" affects positively households' resilience, but only in terms of food consumption – not total consumption. Policies improving market access, for examples through investing in infrastructure or attracting private investment in the agricultural sector, may represent a strategy enhancing farmers' resilience to weather shocks. Finally, the presence of informal institutions, such as social networks providing financial support, sharply increases households' resilience by helping them to reach pre-shock levels of both food consumption and total consumption. Policies incentivizing the formation of these networks, through the participation of households in agricultural cooperatives, agricultural associations, or community projects, may also help farmers in recovering their consumptions levels after a weather shock.

Keywords: resilience, adaptation, livelihood strategy, food security, climate change, Ethiopia, drought.

JEL codes: Q12, Q18, I32; C130

Acknowledgments

This paper is produced in the context of the programme of work on economic and policy analysis of climate change (EPIC) within FAO's Agricultural Development Economics Division (ESA). We greatly appreciate the inputs, help, reviews, and comments received from Federico Belotti, Alessandro Carraro, Ada Ignaciuk, James Moody, Andrea Piano Mortari, Marco Sánchez Cantillo, Nicholas Sitko and Jakob Skoet. This paper reflects the opinions of the authors and not the institution they represent or with which they are affiliated. We are solely responsible for any errors.

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1 Introduction

Climate change mitigation and adaptation processes constitute two pillars of the ambitious goal of sustainable development (IPCC, 2014). Adaptation assumes a prominent role in developing countries where most of climate risks are concentrated and where the impact of climate change and economic development are increasingly interlinked due to inequitable distribution of resources, institutional barriers, and high birth rates (Kates, 2000; Adger *et al.*, 2003; Garg *et al.*, 2009; McSweeny and Coomes, 2011; Lemos *et al.*, 2013). Given that "climate change is a growing threat to development, sustainability will be more difficult to achieve for many locations, systems, and populations unless development pathways are pursued that are resilient to effects of climate change" (Denton *et al.*, 2014, p. 1110). Consequently, incremental responses are becoming extremely urgent in order to reduce both development deficits and the risk of poverty traps due to resource-dependent economies (Jerneck and Olsson, 2008). According to the UNFCCC (2011), the combination of adaptation and mitigation processes with effective institutions able to reduce vulnerability is key for generating climate-resilient pathways in the developing countries, where the impacts of climate stressors threaten the livelihoods of the most exposed communities.

Resilience analysis is a growing field of investigation in developing countries as its conceptual framework is adaptable to contexts where individual economic performance is measurable and affected by unexpected shocks. Resilience is becoming a flourishing research topic (Tanner *et al.*, 2015; Adger *et al.*, 2011) and a new metrics for policy makers and institutions involved in spurring and assessing the process of climate change adaptation in developing countries (FSIN, 2015). In this context, however, the scientific literature lacks a common definition and a common methodological framework to assess the ability of households to deal with extreme unexpected events. The concept of resilience, for example, is widespread among different sciences and may assume multiple connotations (for a review, see Folke, 2006). This paper draws on engineering where the definition of resilience is based on the idea of equilibrium and perturbation of a system and its capacity to bounce back to normality (Holling, 1996). This is commonly known as 'engineering resilience' and assumes the same features as the property of 'elasticity' (Brand, 2009; Grimm and Wissel, 1997). Such a general definition shows potential applicability in countries affected by weather shocks by assuming resilience as the "capacity that ensures stressors and shocks do not have long-lasting adverse development consequences" (Constas, Frankenberger and Hoddinott, 2014). However, the practical implementation of resilience capacity measurement has been limited by different barriers such as the lack of specific data with information on both type and intensity of the shock as well as on the response strategies, difficulty in identifying shocks and a fragmented methodological approach, among others. Therefore, the establishment of a robust assessment framework still represents an urgent need in the field (Palmer and Smith, 2014). Moreover, a common framework could help policy-makers tackle the disruptive effects of climate change and to "ensure [resilience] does not become the next empty development buzzword" using a tested, approved, and generalized strategy (FSIN, 2015, p. 5).

Even though several resilience frameworks often apply to the dynamics of macroeconomic systems, this paper shifts the attention to 'microeconomic resilience', defined as the ability of a household to minimise welfare losses and reach the pre-shock welfare level (see also Hallegatte, 2014). Following this definition, we propose a methodology, with a theoretical foundation in the new Anticipate, Absorb, Reshape (A2R) framework (UN, 2017), that allows to measure the degree of resilience capacity and its determinants. The analysis considers the severe drought that occurred in Ethiopia in 2011–2012.

The remainder of the paper proceeds as follows. In Section 2, we introduce the conceptual framework and present the particular case of Ethiopia. Section 3 describes the data used in the analysis, and Section 4 describes the research design and the empirical strategy. Significant characteristics of resilience to climate change, together with a review of the state-of-the-art of empirical literature are also included. Section 5 discusses the results. Section 6 discusses the policy implications and concludes.

2 Conceptual framework

2.1 Climate adaptation practices in developing countries

A large body of empirical literature analyses the interaction of vulnerability and shock impacts in developing countries, often focusing on how the adaptive capacity of households enables to recover from shocks of different nature (Dercon, Hoddinott and Woldehanna, 2005; Gray and Mueller, 2012; Hoddinott, 2006; Hoddinott and Kinsey, 2001; Little *et al.*, 2006, among others). Adaptive capacity translates into strategies carried out by households, *ex ante*, in the immediate aftermath of shocks and in a longer perspective. All together, these phases determine the shock's 'transition dynamics' or, in other terms, the resilience capacity as a whole (Carter *et al.*, 2007). The strategies adopted to this aim envisage a wide array of activities and assets that differ across countries, communities and household characteristics (Thiede, 2014; Bohle, Downing and Watts, 1994; Chambers, 2006; Watts and Bohle, 1993; Webb and Reardon, 1992).

Several studies suggest that households rely on internal and external resources during the post-shock recovery phase. Poorer and marginalised households are likely to exploit their own resources such as livestock and other physical assets functional to livelihood activities, which however constitute assets minimizing the risk of falling into the poverty trap (Hoddinott, 2006; Barrett and Carter, 2013; Carter and Barrett, 2006; Zimmerman and Carter, 2003; Carter and Lybbert, 2012). These households, however, are also likely to receive support from the governments through welfare support programmes, which can sustain their levels of income and food security in periods of exceptional stress (Sabates-Wheeler, Lind and Hoddinott, 2013). In contrast, wealthier households have often access to external resources such as insurance schemes, markets, credit institutions, and larger social networks. Since they hold a larger amount of disposable income, asset-rich households are also more likely to adopt conservative asset smoothing behaviours, diversification strategies, and to follow recovery paths that translate into shorter times to readjust (Carter *et al.*, 2007; McPeak, 2004). In this respect, Little *et al.* (2006) found evidence that ex-ante wealthier Ethiopian households experience higher welfare losses than the relatively poorer households, but they contemporaneously show a higher resilience capacity. The authors' underlying hypothesis is that the variability of the adjustment path for most exposed households can be higher given their larger potential capability to smooth consumption, to sell assets in critical periods, and to recover after a shock.

Migration constitutes a further adaptive strategy, both when single members or the household as a whole decides to move (Hugo, 1996; Laczko and Aghazarm, 2009). Migration or relocation of the households, often referred to as maladaptive strategies, allow households to seek new economic and social opportunities elsewhere. In contrast, migration of single household's members is functional to supplement standard incomes with individual remittances and allows members to divide the household's assets in larger shares (Thiede, 2014; Ezra, 2001). Evidence of geographic mobility driven by drought shocks is found in Gray and Mueller (2012) within the rural Ethiopia, or in Gray and Bilsborrow (2013) in the case of Ecuador.

Among other determinants of resilience, knowledge dissemination aimed to increase the awareness level on climate risk, such as alert systems or media diffusion, can represent effective means of uncertainty reduction and prompt response whereby households exploit these knowledge advantages to carry out actions in order to minimise the shock impacts (Below, Schmid and Sieber, 2015).

Finally, an important issue to account for is how the shock affects the household wealth distribution. In some cases, households are beneficiaries of policy support and social networks existing before the adjustment phase. For instance, formal and informal borrowing and transfer arrangements, as documented in Corbett (1988) and De Waal (2005) may give rise to welfare distributional changes within the same community or village.

To summarise, the analysis of the literature suggests that the household resilience capacity is affected both by external and internal factors. Among the first group, for example, formal institutional support may be represented by government support programs and non-government institutions such as NGOs and local commercial institutions provide safety-nets that facilitate the recovery path. In addition to this, informal institutions, such as social networks, can sustain households affected by shocks in their community. The social network constituted by relatives and friends may also represent an effective instrument of support during the adjustment phase. Internal factors may include strategies adopted by households such as crop and labor diversification, selling private assets, and consumption smoothing.

To catalyse and scale-up actions aimed to accelerate resilience capacity, the former UN Secretary- General Ban Ki-moon and 13 members[1] within the UN system at COP21, the Paris Climate Conference, has launched a new Initiative to build climate resilience in 2015, specifically conceived to address the Sustainable Development Goal 13.[2] This new Initiative is A2R – namely Anticipate, Absorb, Reshape - and is aimed to address the need of world's most vulnerable population to face extreme climate events and reduce the risk of climate disasters. [3] The A2R strategy grounds on three thematic pillars: anticipation of hazards, shock absorption and reshaping development to reduce future climate risks (UN, 2017). The specific objectives behind the three lines of action are raising awareness about climatic risk, establishing measurable targets, promoting resilience knowledge and mobilising resources to raise resilience capacity.

The three thematic pillars envisage a series of adaptive and response strategies. Anticipation includes actions aimed at raising awareness and perception of climatic risks such as weather information, early warning and other *ex-ante* deliberate activities and pre-existing conditions able to mitigate the impact of extreme weather events. In this respect, the amount of social, natural and economic assets constitutes the pre-condition belonging to the anticipation phase. Once the shock occurs, the absorption process takes place. This phase includes all the activities carried out to cope with the shock impacts in a short run perspective as, for instance, consumption smoothing strategies, migration or credit. Finally, the rehabilitation process includes activities aimed at reshaping the development pathway with reduced risks and vulnerabilities in a medium- and long-run perspective.

Given the multitude of different contributions and the lack of robust approaches in the resilience literature, the A2R constitutes a suitable and effective basis to develop our conceptual framework. Accordingly, we assume that the resilience process is the result of actions carried out in two different periods, the pre-shock (t) and the after-shock (s) period. The pre-shock period includes only the anticipation phase, while the after-shock period involves both the

[1] The 13 UN entities participating in the Initiative are Food and Agriculture Organization (FAO), United Nations Environment Programme (UNEP), United Nations Framework Convention on Climate Change (UNFCCC), United Nations Human Settlements Programme (UN-Habitat), United Nations International Children's Emergency Fund (UNICEF), United Nations Educational, Scientific and Cultural Organization (UNESCO), United Nations Population Fund, formerly the United Nations Fund for Population Activities (UNFPA), United Nations Office for Project Services (UNOPS), United Nations Office for Disaster Risk Reduction (UNISDR), World Food Programme (WFP), United Nations Office for the Coordination of Humanitarian Affairs (OCHA), World Health Organization (WHO) and World Meteorological Organization (WMO).
[2] "Take urgent action to combat climate change and its impacts".
[3] For more information on this Initiative, see www.a2rinitiative.org

absorption and rehabilitation phases. In our case, a straightforward distinction of these two periods derives from the two years in which the Ethiopian survey waves used for our analysis were carried out (as further explained below), with the first including information collected in 2011 (before the drought shock) and the other including information for the period 2013–2014 (after the shock).

We then assume that, in the pre-shock period t, households are characterised by a series of strategic assets $\boldsymbol{K}_t = \{\boldsymbol{K}_t^N, \boldsymbol{K}_t^H, \boldsymbol{K}_t^F, \boldsymbol{K}_t^S\}$, where $\boldsymbol{K}^N$ stands for natural capital, $\boldsymbol{K}^H$ denotes human capital, and $\boldsymbol{K}^F$, $\boldsymbol{K}^S$ are vectors of financial and social assets, respectively (Scoones, 1998; Bebbington, 1999; Ellis, 2000; Niehof, 2004; Martin and Lorenzen, 2016; Asfaw, Pallante and Palma, 2017; Nguyen *et al.*, 2017). During the pre-shock period, the resilience is expected to be at the minimum level given that households have not experienced any shocks, although they may be aware of future occurrence of potential extreme events.

During the shock, households carry out a set of actions aimed at minimizing the negative impacts (absorption) and, in the after-shock phase, they focus on recovering at the soonest in a more resilient environment (rehabilitation). Differing from the pre-shock period, during this phase the resilience is expected to be at its maximum level. As discussed above, the set of alternative coping strategies $\boldsymbol{R}_s = \{\boldsymbol{R}_s^E, \boldsymbol{R}_s^I\}$ can be divided in two main groups, with the first one including those strategies relying on external help (e.g. policy support measures, received credits) and those internal to the households, as for instance diversification and consumption or asset smoothing strategies (Carter *et al.*, 2007). The household welfare $\boldsymbol{W}_s = f[\rho_s(\boldsymbol{S}_t, \boldsymbol{K}_t); \boldsymbol{K}_t]$, at any time and in a risky environment subject to shocks $\boldsymbol{S}$, could be represented by a random variable, in which ρ indicates the level of resilience that households assume to cope with $\boldsymbol{S}$ experienced in s, and in accordance with $\boldsymbol{K}$ and $\boldsymbol{\varepsilon}$ unobserved factors.

2.2 The case of Ethiopia

IPCC (2014) reports that a relevant part of climate vulnerable countries concentrate in sub-Saharan Africa (SSA). Among these, Ethiopia represents one of the most emblematic cases given the complexity of its geography, the heterogeneous distribution of the population and its resource-dependent economy (Orindi *et al.*, 2006; Stige *et al.*, 2006). According to Carter *et al.* (2007), Ethiopia is a shock-prone country, characterised by recurrent drought events.[4] About 85 percent of the population resides in rural areas and rely on rain fed low-diversified agriculture, making Ethiopian households heavily dependent on weather conditions (Asfaw, 2015; Thiede, 2014; Devereax, 2000; Little *et al.*, 2006). The routinely adverse weather events produce detrimental effects on farm household welfare. Carter *et al.* (2007) estimate a 20 percent reduction in per capita consumption for households subject to a drought shock at least once in the previous five years. Thus, the amount of rainfall and average temperature, as well as other climatic factors, during the growing season are critical to crop yields and food security problems. According to Carter *et al.* (2007), the poorest households in Ethiopia struggle to insure against shocks and often rely on costly and harmful coping strategies.

According to Funk *et al.* (2012), Ethiopia receives most of its rain between March and September. Rains begin in the south and central parts of the country during the Belg (short rainy) season, then progress northward, with central and northern Ethiopia receiving most of their precipitation during the Kiremt (long rainy) season. Rainfall totals of more than 500 mm during these rainy seasons typically provide enough water for viable farming and pastoral

[4] During March 2016, Ethiopia faced a further drought shock. This confirms the high vulnerability of the country and stresses the need for fresh empirical evidence focusing on this important topic.

pursuits. Between the mid-1970s and late 2000s, Belg and Kiremt's rainfall decreased by 15-20 percent across parts of southern, south-western, and south-eastern Ethiopia (Funk *et al.*, 2012). During the past 20 years, the areas receiving sufficient Belg rains have contracted by 16 percent, exposing densely populated areas of the Rift Valley in south-central Ethiopia to near-chronic food insecurity. The same occurred for the Kiremt season. Poor long cycle crop performance in the south-central and eastern midlands and highlands could directly affect the livelihoods of many sectors of the population, while adding pressure to national cereal prices.

Between July 2011 and mid-2012, a severe drought has affected the Horn of Africa. The crisis has involved principally southern Ethiopia, south-central Somalia and northern Kenya. Regional drought has come on top of successive bad rains and rising inflation. It has ramped up a chronic livelihoods crisis into a tipping point of potential disaster by putting extreme pressure on food prices, livestock survival, and water and food availability. Estimates have suggested such an event threatened the livelihood of 9.5 million people (UN OCHA, 2011).

Given the increasing vulnerability level, Ethiopia has experienced a variety of policy responses aimed at enhancing the capacity of farm households to cope with weather volatility and other extreme environmental events. A significant long-term social protection program, known as the Productive Safety Net Programme (PSNP), was established in 2005 in response to a series of drought-related disasters during the late 1990s and early 2000s (Pierro and Desai, 2008). The program is still in force and aims at enabling the rural poor facing chronic food insecurity to resist shocks, create assets and become food self-sufficient. The PSNP provides multi-annual predictable transfers, as food, cash or a combination of both, to help chronically food insecure people. At the time of data collection, the PSNP was in its third phase (PSNP 3) with a total budget of 2.3 billion of US dollars (World Bank, 2012). Other than the PSNP, the Ethiopian government has implemented a set of other food aid and food-for-work programs (Caeyers and Dercon, 2008; Clay, Molla and Habtewold, 1999). However, a common drawback of these arrangements is that they can perpetuate dependence on post-drought government assistance with accompanying moral hazard.

3 Data description

The main data source for the analysis of resilience determinants is the Ethiopian Rural Socio-economic Survey (ERSS), a two-year panel on socio-economic status collected at household level. The ERSS is collaborative project between the Central Statistics Agency of Ethiopia (CSA) and the World Bank, implemented in 2011–12 (first wave) and in 2013–14 (second wave). The ERSS is integrated with the CSA's Annual Agricultural Sample Survey (AgSS) and is designed to be representative of rural and small town areas of Ethiopia. It is based on a two-stage probability sample. The first stage of sampling entailed selecting primary sampling units, which are a sample of the CSA enumeration areas (EAs). The second stage consisted in the selection of households to be interviewed in each EA. The ERSS covers all regional states except the capital, Addis Ababa. It primarily collects information on rural areas, being implemented in 290 rural and 43 small town enumeration areas (EAs). The conceptual framework described in Section 2.1 drives the selection of the model variables.

The welfare function includes the vector of variables related to shock anticipation and a series of controls, all referring to the first wave of interview (pre-shock period). During the anticipation phase, households rely on different assets that constitute their pre-shock endowment. In the $\boldsymbol{K}_t^N$ vector for natural capital, we include a dummy for identifying smallholder farmers and the Tropical Livestock Unit (TLU) as a measure for livestock capital. Higher TLU levels may be associated with a higher number of on-farm activities, such as dairy and butchery and small commercial enterprises (Moll, 2005), which are in competition with mere crop cultivation activities (Teklewold, Kassie and Shiferaw, 2013; Shiferaw *et al.*, 2013). Age and years of education of the household head, together with the household sex ratio, size and a dummy for female headed households, health status before the shock and school attendance of household members characterise the human capital endowments represented in vector $\boldsymbol{K}_t^H$. The information on financial and social assets($\boldsymbol{K}_t^F$ and $\boldsymbol{K}_t^S$) includes: a) the share of households benefitting from microfinance programs at EA level before the shock; b) the geographical distance in kilometres to the nearest population centre with more than 20,000 inhabitants as a proxy for market access (Beck, Demirgüç-Kunt and Honohan, 2009); c) a count of ICT technologies (TVs, mobiles, radios, computers, etc.); and d) a count of transportation assets (e.g. bicycles, cars) owned by households as a measure of social assets and networking capacity. There is robust empirical evidence suggesting that spatial proximity favours market and information access (Lanjouw, Quizon and Sparrow, 2001; Fafchamps Shilpi, 2003; Deichmann *et al.*, 2008; Davis *et al.*, 2010). Moreover, ICTs assume a key role in anticipating weather shocks by providing opportunities for the top-down dissemination of knowledge such as weather forecasts, hazard warnings, market information and advisory services (Noble *et al.*, 2014; Asfaw, Pallante and Palma, 2017). In order to control for physical terrain characteristics, we add a variable capturing information on the average community's altitude, expressed in meters above the sea level together with the vectors of control REG and AEZ, which include, respectively, regional and Agro-Ecological Zones (AEZs) dummies.

During the absorption and rehabilitation phases, households are likely to show their maximum resilience level in order to minimise welfare loss. The set of different activities that households set up to cope with the shock and to rehabilitate in a more resilient environment are captured by the vectors $\boldsymbol{R}^E$ and $\boldsymbol{R}^I$, which disentangle respectively strategies relying on external help and those internal to the household. For all these variables, information is available at household level. According to data availability, the vector of external activities $\boldsymbol{R}^E$ includes a set of variables signalling received credit from NGOs and other non-government institutions, received formal help (from government policies such as the PSNP and other complementary interventions) and received informal help (from relatives and friends which constitute an informal safety-net). It is worth noting that, differing from other variables referring to a short-run shock coping strategy, the variable of financial credit is interpretable as a potential rehabilitation signal, since households may ask for credit in order to rebuild more resilient infrastructures or to invest in new activities less prone to suffer from natural disasters.

The vector of internal activities $\boldsymbol{R}^{I}$ includes dummies for sold assets and smoothing consumption strategies to provide information on the absorption phase. Moreover, a set of dummies signalling the existence of crop diversification, labor diversification and Sustainable Land Management (SLM) practices help to identify strategic rehabilitation activities carried out after that households overcome the acute phase of drought. The set of SLM practices available at household level are the use of mixed crop cultivation, use of fertilisers and adoption of practices to reduce soil erosion. Table 1 provides summary statistics for the selected variables.

In order to identify shocked households, socio-economic households data are merged with detailed information on precipitation collected at EA level (decadal) from 1983 to 2014. Rainfall data derive from the Africa Rainfall Climatology Version 2 (ARC2) database.[5]

Table 1. Descriptive statistics for selected model variables

Variable	Mean	s.d.	min	max
Diff. in total consumption	-1 699.94	1 716.72	-10 105.61	1 863.31
Diff. in food consumption	-93.84	116.52	-730.41	155.52
Natural capital				
Tropical Llivestock Units (TLU)	2.13	2.85	0	41.5
Smallholder (yes=1)	0.47	0.5	0	1
Elevation a.s.l. (mt)	1 847.41	587.08	344	3 311
Irrigation scheme (2011, EA level)	0.56	0.5	0	1
Human capital				
Ave. age of household head	43.28	15.31	0	100
Ave. education of household head	1.78	2.2	0	17
Sex ratio	1.09	0.97	0	8
household size	4.89	2.28	1	14
Female headed household (=1)	0.24	0.42	0	1
Not attending school (=1)	0.39	0.28	0	1
Had health issue (=1)	0.19	0.27	0	1
Financial and social capital				
Microcredit (2011, EA level)	0.2	0.4	0	1
Distance to main pop. center (km)	38.57	33.33	1.8	208.2
Distance to main road (km)	15.65	17.07	0	161.9
Tot. technology durables (count)	0.82	1.4	0	10
Climatic variability				
Standardized Precipitation Index (SPI)<=-1.5 (=1)	0.611	0.48	0	1

[5] The ARC2, an improved version of the ARC1, combines inputs from two sources: i) 3-hourly geo- stationary infrared (IR) data centred over Africa from the European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) and ii) quality controlled Global Telecommunication System (GTS) gauge observations reporting 24-h rainfall accumulations over Africa. For further details, see Novella and Thiaw (2013).

Variable	Mean	s.d.	min	max
Resilience - External help				
Received credit (yes=1)	0.16	0.36	0	1
Received help from government (yes=1)	0.15	0.35	0	1
Received help from rel. and friends (yes=1)	0.02	0.13	0	1
Resilience - Internal help				
Consumption smoothing (yes=1)	0.02	0.12	0	1
Sold assets (yes=1)	0.04	0.19	0	1
Crop diversification (count)	1.98	2.8	0	16
Labor diversification (count)	0.41	0.62	0	3
SLMs Mixed crops (yes=1)	0.49	0.5	0	1
SLMs Fertiliser (yes=1)	0.66	0.47	0	1
SLMs Anti-erosion (yes=1)	0.64	0.48	0	1

Source: Authors' own elaboration.

4 Research design and empirical strategy

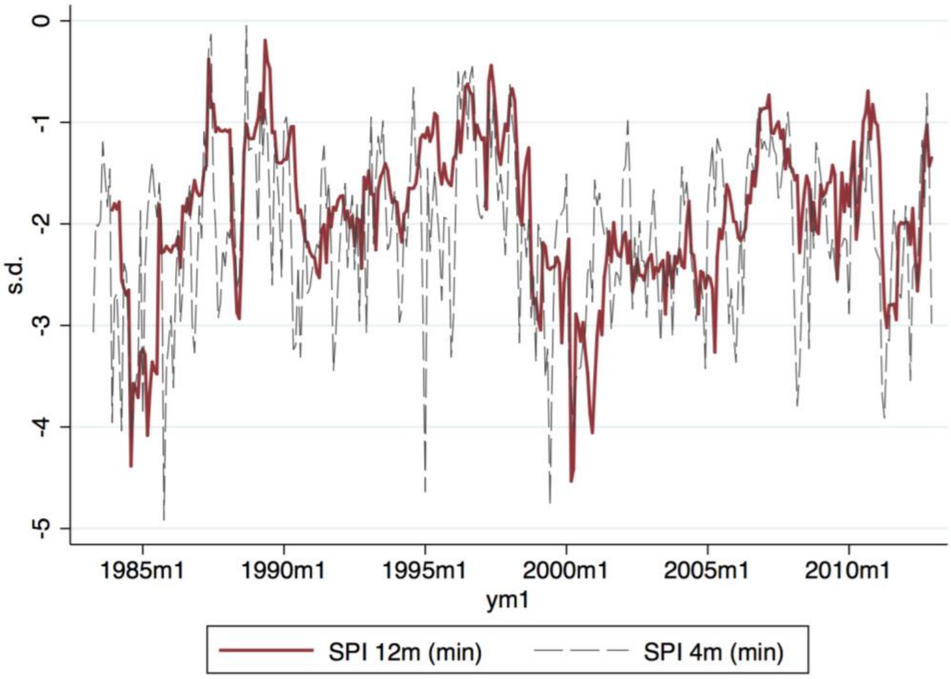
4.1 Shock identification

To identify the set of households hit by the climate shock during 2011 we take advantage of our granular precipitation data to calculate the Standardised Precipitation Index (SPI) as an objective measure of drought.[6] The SPI can be calculated over different rainfall accumulation periods to capture different potential impacts of a meteorological drought. SPIs for short and medium accumulation periods (from three months to 12 months) mostly capture anomalies on soil water conditions and agricultural output, while time scale over 20 months are indicators for reduced stream flow and reservoir storage. Given that we are interested in capturing variations in the short-medium period, we calculate the SPI at nine months over the period 1983–2014. The climate shock dummies are computed by considering the period 2011–2012 (first wave interview) and index values larger than 1.5 standard deviation (s.d.) for precipitation events and lower than -1.5 s.d. for drought shocks that occurred only during the months of growing season.

Figure 1 shows the SPI trend during the period for which precipitation data are available (1983–2012). The SPI trend computed at nine months signals that Ethiopia experienced recurrent drought shocks. Respectively, these latter can be detected during 1985, 2000, 2005 and 2011. The 4-month minimum SPI value, capturing short-term deviations from the historical average signals peaks up to -4 s.d., which correspond to extremely dry conditions experienced by the population.

[6] The SPI is a widely used indicator in climatic science, as it allows detecting significant variations in precipitations with respect to the long-run mean. The SPI fits raw precipitation data to a gamma or Pearson Type III distribution, transformed in a second step into a normal distribution (see Guttman, 1999 for further details). The use of SPI presents some advantages over other methods. First, it allows identifying climate anomalies only through time-series data on precipitation. Moreover, the SPI is an index based on the probability of recording a given amount of precipitation. Since the probabilities are standardised, a value of zero indicates the median precipitation amount (half of the historical precipitation amounts are below the median, and half are above the median), 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 to +2.5 standard deviations (sd) (WMO, 2012). The characteristic of being standardised provides a straightforward interpretation and allows for a fully indexed comparison over time and space.

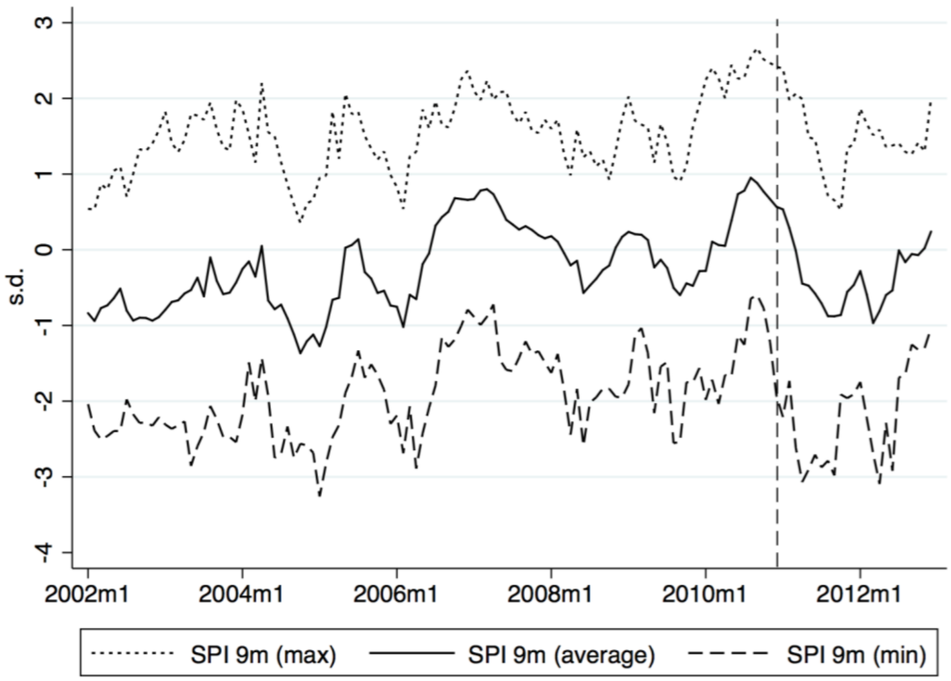
Figure 1. 12-month vs 4-month Standardized Precipitation Index (SPI) comparison, 1983–2012



Source: Authors' own elaboration.

Figure 2 focuses on a more recent perspective, considering the maximum, mean, and minimum value of SPI at 9 months only during the period 2002-2012. Despite SPI's trend at 9 months appears as more stable and less volatile than that depicted in Figure 1, it is still possible to detect shocks during 2005 and for the period 2011-2013.

Figure 2. Standardized Precipitation Index (SPI) trends through 2002 to 2012



Source: Authors' own elaboration.

At national level the number of households that experienced a climate shock corresponds to 51 percent of the sample. Table 2 shows the distribution of climate shocks, based on SPI, in each region of Ethiopia. At regional level the pattern shows substantial variation, with some regions (Afar and Harari) having no population affected by drought. This spatial heterogeneity suggests controlling for agro-ecological and regional physical characteristics when analysing the transitional dynamics of resilience during and after the drought shock.

Table 2. Percentage of shocked households by region

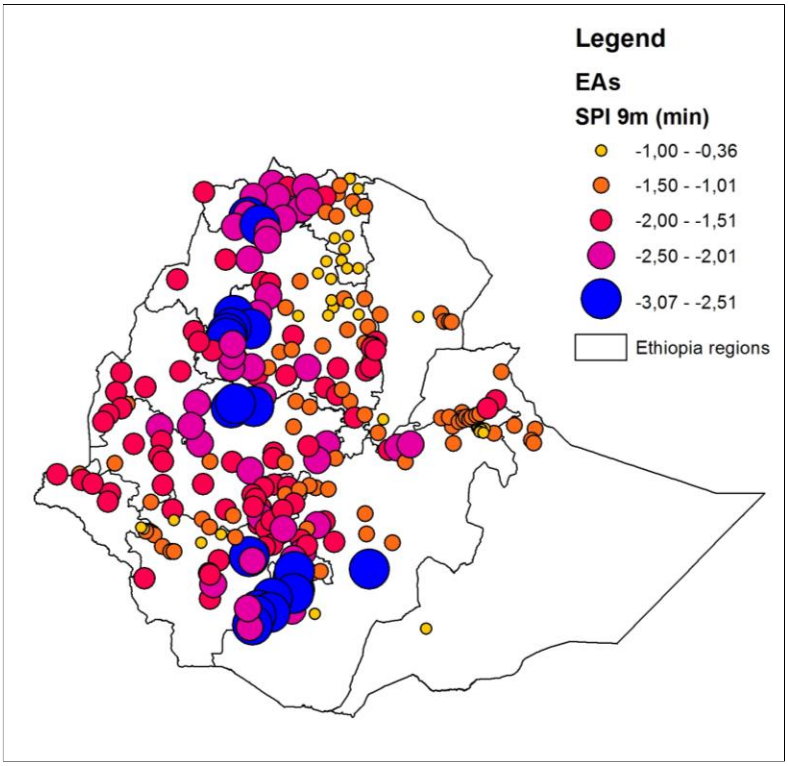
Region	Shocked households (%)
Tigray	49
Afar	0
Amhara	70
Oromia	71
Somalie	60
Benshagul Gumuz	100
SNNP	74
Gambelia	45
Harari	0
Diredwa	21

Notes: The table displays the percentage of shocked households by region. Households are considered shocked when observing a Standardized Precipitation Index (SPI) lower than 1.5.

Source: Authors' own elaboration.

The heterogeneity in the spatial distribution of the drought shock also emerges from Figure 3, which shows the shock intensities measured by the SPI. The spatial distribution of the SPI index shows that the central-north, central, and central-south regions are the ones observing the highest shock intensity (SPI<-2.50). Lower intensity shocks (1.50<SPI<2.50) are observed also in these regions and in the western country, whereas the eastern part does not experience any large SPI variation.

Figure 3. Spatial 9-month Standardized Precipitation Index (SPI) and Enumeration Areas (EAs) distribution in Ethiopia



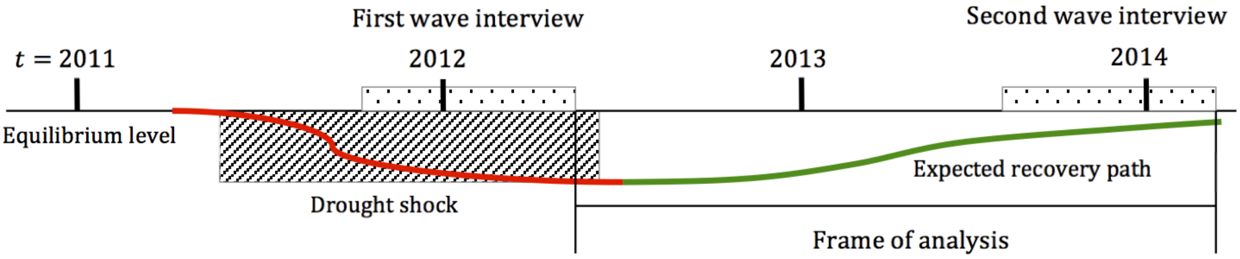
Source: Authors' own elaboration.

In order to guarantee common baseline characteristics, the identification strategy also imposes the exclusion of households declaring to have been hit by any type of shock occurring in the pre-treatment period ($t \leq 2011$), which represents a sort of "equilibrium condition" at the baseline once controlling for household and physical characteristics before the shock. This further restriction is based on self-reported information included in the ERSS and collected at the time of the second interview. Although the use of subjective data has been somehow questioned (Bertrand and Sendhil, 2001, among others), a trade-off exists since those data often provide researchers with precious pieces of information not available in standard observational data. In this respect, Pradhan and Ravallion (2000) and Ravallion (2012) have stressed the need and usefulness of subjective information to facilitate empirical investigation of causal effects.[7]

Figure 4 helps identify the frame of analysis for the events occurring during period 2011–2013 and for which we have research data.

[7] As a matter of fact, subjective information often constitute the only measure in studies assessing the households' response to external shocks in developing countries, together with the use of large-sample surveys (Dercon, Hoddinott and Woldehanna, 2005; Dercon and Krishnan, 2000a, 2000b; Demeke, Keiln and Zeller, 2011; Gray and Mueller, 2012; Noack et al., 2015; Skoufias and Quisumbing, 2005).

Figure 4. Timeline and frame of analysis



Source: Authors' own elaboration.

4.2 Sorting

In an ideal experiment, the treatment and control groups are randomly distributed. Even though this study employs an objective metrics to identify the group of shocked households, and we can reasonably assume that climate shocks occur randomly both in time and space, the hypothesis of self-selection cannot be totally excluded by unconditionally considering the distribution of drought shocks. Endogenously driven mechanisms able to induce households to be 'preferred candidates' for the shock may exist. Especially in panel analyses, households could sort into more or less risky places (or livelihood activities) based on their tolerance to shocks and their differential willingness to pay for risk reductions. Even though most households have limited capacity to move from regions characterised by extreme events toward safer zones of the same region or country, we address this concern by restricting the sample to households not having left the same location during the last two years starting from the first wave interview. Out-migration of single household members also constitutes an effective adaptive strategy for most exposed households (Lucas and Stark, 1985; Rosenzweig and Stark, 1989; Gray and Mueller, 2012; Gray and Bilsborrow, 2013). Since the data contain households' geographical location for each wave, it has been possible to restrict to urban households not moving between the two waves. In this subsample, migration of single household's members involved only 3 households, which were excluded from the final sample.

To summarise, our final estimation sample comprehends rural households observed during both interview waves and that have lived at least for two years in the same location before the drought shock occurred. Moreover, we include households declaring only a drought shock between the first and the second wave. According to these criteria, our final estimation sample consists of 1930 observations, divided into two groups of 1016 shocked households and 914 non-shocked households, respectively.

4.3 Model specification

Scholars have produced several methodological attempts at estimating resilience, whose outcomes are divisible in two distinct literature strains. Some authors have focused on the multidimensional and latent nature of the phenomenon (Alinovi, Mane and Romano, 2010; Alinovi *et al.*, 2010; Tawodzera, 2012), trying to estimate resilience using multistage techniques such as Factorial Analysis (FA) or Principal Component Analysis (PCA). Other authors have emphasised the importance of both the shock and/or the time dimension (Fingleton, Garretsen and Martin, 2012, Bènè, 2013; Hoddinott, 2014; Di Caro, 2014; Alfani *et al.*, 2015).

Alinovi, Mane and Romano (2009) study the resilience capacity of Palestinian households using a single cross section and applying multi stage PCA to reduce the multidimensionality of the phenomenon. The authors identify six relevant dimensions (income and food access, access to public services, social safety nets, assets, adaptive capacity and stability) for the definition of resilience. The process consists in two steps: first, each dimension is identified by means of PCA, then, the authors apply again the PCA on the six dimensions to obtain a single resilience index. The model fits the resulting index as an independent variable in a strategy regressing the level of food consumption on other controls, where it turns out to be positive and significant. While allowing for the identification of common 'latent' factors, PCA is a purely descriptive technique. As for other composite indicators, the goal of PCA is to reduce the number of variables of interest into a smaller set of components. However, PCA provides no information about the aspect of the future data, since it analyses all the variance in the variables and reorganises it into a new set of components. The same applies to other 'data mining' techniques. In this respect, as Alinovi, Mane and Romano (2010) point out, "structural equation models (SEMs) are the most appropriate tools for dealing with [this] kind of model".

In their work, Alfani *et al.* (2015) employ an intuitive definition of resilience: "When a household (or individual) is hit by a shock, the household is resilient if there is very little difference between its pre-shock welfare and the post-shock welfare". Such definition is applied to estimate resilience for countries in the Sahel region. Given the limited data availability, the authors construct an *ad hoc* counter factual measure and compute welfare changes between t and $t + 1$ for both treated and non-treated households. In their framework, resilient households are those whose consumption exceeds a threshold level, compatible with a permanent income/consumption smoothing framework. The proposed methodology led to the identification of three different groups of households: chronically poor, non-resilient and resilient. These groups show significantly different characteristics, with resilience capacity associated to a higher education level and to asset-rich households.

Rasch *et al.* (2016) develop a multi-scale analysis of resilience focusing on the case of communal range system in Thaba Nchu, South Africa. The authors couple a principal agent model of household interaction with a biophysical model of the rangeland to assess the resilience of the socio-ecological system to external shocks. Rasch *et al.* (2016) adopt the Gini coefficient to the herd size of household in the communal livestock production system as a proxy to measure the system resilience, while they measure household resilience using the access to resources and asset poverty. The results show that the experience of a drought shock increases the system's resilience, but also accelerates structural changes at household level.

An alternative vision of resilience is the one proposed by Bènè (2013). The author provides a framework where the total cost of resilience is made up by taking into account the "costs of anticipation" (i.e. the ex-ante investment made by households to overcome, for instance, crop fluctuations), the "impact costs" (i.e. the assets lost because of the shock) and the "costs of recovery activities" (i.e. rebuilding of destroyed assets). Within the proposed framework "resilience can be measured and monitored simultaneously at different levels, for different components of a system, and includes both objective and subjective costs".

Cissé and Barrett (2016) have recently proposed a strategy to estimate resilience at individual and household level. Their work takes as a case study the pastoralist communities in Northern Kenya and relies on two steps. They first estimate a multiple conditional moments of a welfare function, and then aggregate the individual-specific estimates into a decomposable measure that can be operationalized for policy scopes.

In the attempt to sum up the results so far developed, the literature suggests that resilience is an unobservable household trait; hence, it is natural that it appears as a latent variable, one that is not directly observed but rather is inferred through the estimated model. The empirical framework is explained in Annex 1. As noticed therein, the estimated equation is as follows (equation 9 in the Annex 1):

$$\boldsymbol{W}_{i,2014-2011} = \beta + \boldsymbol{X}_{i,t}\boldsymbol{\gamma} + REG_j\boldsymbol{\delta} + AEZ_k\boldsymbol{\zeta} + (\boldsymbol{R'}_{\boldsymbol{i}}\boldsymbol{D_i})\boldsymbol{\psi} + \boldsymbol{v}_i$$

Where, $\boldsymbol{W}_{i,2014-2011}$ denotes the difference in expenditure for food or in total consumption between 2011 and 2014, both expressed in constant 2010 US dollars; β represents the intercept; $\boldsymbol{X}_{i,t}$ is a set of predetermined characteristics and controls as described in Section 3 and $\boldsymbol{\gamma}$ the associated coefficients ; REG_j and $AEZ_k$are, respectively, a set of regional-level and agro-ecological dummies, with $\boldsymbol{\delta}$ and $\boldsymbol{\zeta}$ denoting linked coefficients. The resilience component enters in the specification as a set of interaction terms between dummies for shocked/non-shocked households given by $\boldsymbol{D}$ and the set of dummy variables included in $\boldsymbol{R}$ and presented in Section 3, with $\boldsymbol{\psi}$ representing the resilience parameters to be estimated. Finally, $\boldsymbol{v}$ includes an idiosyncratic term capturing the error component. This equation is estimated with survey data separately for two welfare variables. Both estimates are carried out with robust standard errors clustered at Enumeration Area (EA) level. All variables are expressed in natural logarithms, with the exception of dummy variables.

5 Results

Table 3 and 4[8] present the estimation results, while Figure 5, Figure 6, Figure 7 and Figure 8 report, respectively, the diagrams for resilience scores and density distributions for total and food consumption.

5.1 Consumption function

Table 3 reports the outcomes for variables included in the consumption model. Given that the two outcome variables are expressed as within differences, negative coefficients are interpreted as positively correlated with higher post-shock welfare levels or, alternatively, with lower welfare losses. Among the set of selected variables for natural capital, we do not find a significant association between a reduction in consumption gap and the endowment of livestock as proxied by the Tropical Livestock Unit (TLU) index. The government's implementation of irrigation schemes existing before the drought shock is also not significantly associated to lower consumption differences. In contrast, smallholder farmers show a greater capacity to recover up to previous consumption levels, being the condition of smallholder significantly associated to -0.13 and -0.2 per cent in gap reduction for total and food consumption respectively.

Table 3. Estimation results - Part A

	Model (1) Tot. consumption	Model (2) Food consumption
Age of household head	-0.175***	-0.174*
	(0.047)	(0.078)
Ave. years of education	0.030	0.066
	(0.028)	(0.043)
Sex ratio	0.005	0.017
	(0.018)	(0.030)
household size	-0.007	-0.067
	(0.041)	(0.073)
Female headed household (dummy)	-0.039	-0.026
	(0.047)	(0.070)
Not attending school (1=yes)	-0.020	-0.050
	(0.071)	(0.115)
Had health issues (1=yes)	-0.059	-0.050
	(0.070)	(0.111)
Smallholders (1=yes)	-0.136**	-0.209**
	(0.046)	(0.079)
TLU index	-0.005	-0.023
	(0.021)	(0.033)
Distance to nearest pop. center (km)	-0.046	-0.061
	(0.045)	(0.072)
Distance to nearest major road (km)	0.032	0.062*
	(0.019)	(0.027)
Total technology durables	-0.028	0.023
	(0.036)	(0.061)
Microfinance (EA level)	-0.103	-0.171

[8] Table 3 and 4 refer to a single estimation model. The table is split into two parts to allow for an easier visualisation.

	Model (1) Tot. consumption	Model (2) Food consumption
	(0.069)	(0.124)
Irrigation scheme (EA level)	0.054	0.013
	(0.053)	(0.098)
Altitude	0.278*	0.526**
	(0.123)	(0.195)
AEZ dummies	yes	yes
Regional dummies	yes	yes
Constant	-2.450**	-4.396**
	(0.928)	(1.436)

Notes: N=1930. All variables, excluding dummies, are in logarithms. Standard errors clustered at Enumeration Area (EA) level in parenthesis.

Source: Authors' own elaboration.

A strong and significant role emerges for altitude, which acts as a negative "asset" in recovering the consumption capacity. This result can be economically justified by assuming the altitude where the communities live as a proxy of social and market barriers. The elasticity associated to this factor is quite large, namely 0.28 and 0.52 per cent given a one per cent increase in altitude, respectively for total and food consumption, even though these coefficients show a weaker statistical significance.

As far as the human capital is concerned, household age is found to be a major determinant of lower consumption gaps, with an elasticity of gap reduction of 0.17 per cent for both total and food consumption. However, although similar in magnitude, in the case of food the coefficient is only weakly statistically significant. We do not find significant effects for all the other variables included, namely education, proportion of females within the household, the size of the household and changes in health status. This set of results points to a modest role of human capital in Ethiopian households for recovering to previous consumption levels after the drought shock.

Moving to the results for financial and social assets, we find a minor role of household distance to the major road, which proxies the access to financial and social capital. The coefficient associated with this variable is very low and only weakly significant. Other important proxies of social assets (count of technology assets) and financial assets (distance to major population centres and presence of microfinance programs) are far from being statistical significant.

5.2 Resilience determinants

Table 4 shows the most important results of our analysis, i.e. the factors affecting the resilience capacity at household level. Differently from Table 3, these coefficients have a different interpretation since we look at the statistical distribution of the resilience by modelling its mean. Hence, positive coefficients are associated with a higher resilience capacity and vice-versa.

We first look at the group of variables relating to external help strategies. Both the variables included in the analysis, namely government support and help received from relatives and friends, emerge as strong determinants of the households' resilience. Particularly large is the role of relatives and friends for increasing the resilience capacity for food consumption, with a coefficient two times larger than the one associated with total consumption. The institutional ‘safety net’ provided by the different governmental programs represents a significant resilience driver, but only in the case of total consumption. Moving to the internal resilience strategies, the only significant driver that we find is the variable signalling sold assets, which is associated with a higher resilience capacity only in the case of food consumption. As for the other internal strategies, we do not find significant effects able to increase the household’s resilience capacity.

As expected, the set of results obtained by interacting the resilience drivers with non-shocked households are far from being significant. This suggests that the set of resilience strategies, both those relying on internal and external help, played a significant role only for individuals affected by the drought shock, stressing the latent nature of resilience.[9]

Table 4. Estimation results - Part B

Post-shock resilience drivers (absorption and reshape)	**Model (1) Tot. consumption**	**Model (2) Food consumption**
Shock - Received credit	-0.123	-0.356
	(0.199)	(0.353)
Shock - Consumption smoothing	0.350	0.590
	(0.277)	(0.390)
Shock - Sold assets	0.324	1.392**
	(0.243)	(0.513)
Shock - Received gov. help	0.467**	0.621
	(0.149)	(0.337)
Shock - Help from rel. and friends	0.532**	1.073**
	(0.197)	(0.375)
Shock - Crop diversification (count)	-0.075	0.115
	(0.123)	(0.177)
Shock - Labor diversification (count)	0.192	0.132
	(0.608)	(0.941)
Shock - Soil erosion practices	0.108	0.034
	(0.191)	(0.279)
Shock - Mixed crops	0.017	0.036
	(0.136)	(0.253)
Shock - Fertilizer	-0.225	-0.558
	(0.183)	(0.342)
No shock - Received credit	-0.549	-0.162
	(0.593)	(0.687)
No shock - Consumption smoothing	0.576	0.702
	(0.719)	0.115
No shock - Sold assets	0.096	(1.106)
	(0.679)	-0.244
No shock - Received gov. help	-0.054	(1.131)
	(0.365)	-0.412
No shock - Help from rel. and friends	-0.019	(0.671)
	(0.688)	-0.120
No shock - Crop diversification (count)	-0.354	(1.404)
	(0.413)	0.273
No shock - Labor diversification (count)	-0.756	(0.424)
	(0.796)	-1.502
No shock - Soil erosion practices	-0.296	(1.190)
	(0.405)	-0.455

[9] Regarding the lambda parameter, which represents the contribution of the resilience error component over the total model error, all the estimates show highly significant lambda values, which validate the specification of the resilience drivers in our econometric model.

Post-shock resilience drivers (absorption and reshape)	**Model (1) Tot. consumption**	**Model (2) Food consumption**
No shock - Mixed crops	0.066	(0.497)
	(0.390)	-0.543
No shock - Fertilizer	-0.076	(0.553)
	(0.420)	-0.312
Lambda	0.904***	1.186***
N	1930	1930
Resilience for shocked household ($\boldsymbol{R}$)	0.330	0.703
Resilience for non-shocked household ($R_{shcoked}$)	0.448	0.878
t-test ($R_{shcoked} < \boldsymbol{R}$)	0.000	0.000
t-test ($R_{shcoked} = \boldsymbol{R}$)	0.000	0.000

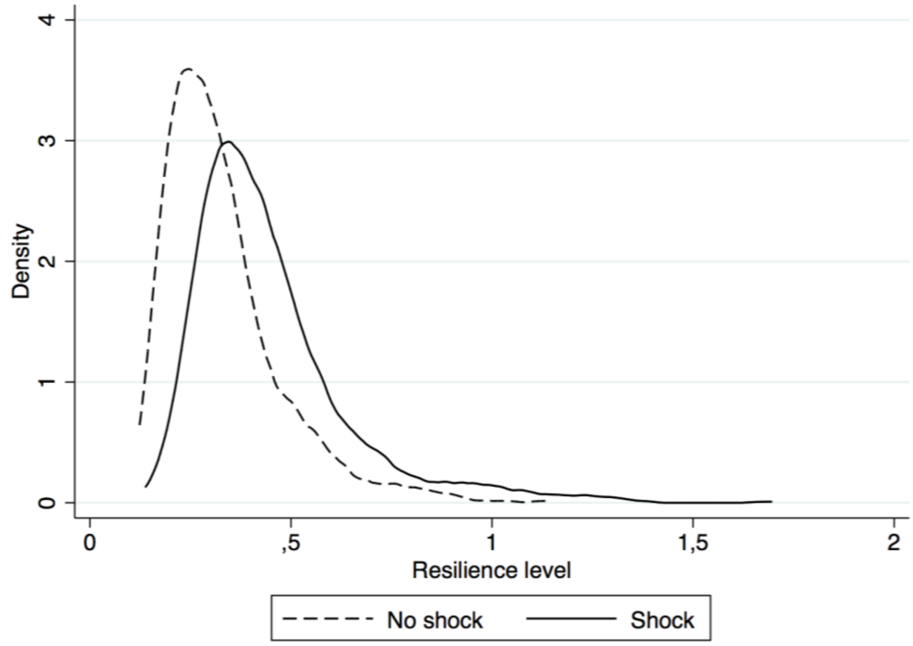
Notes: All variables, excluding dummies, are in logarithms. Standard errors, in parenthesis, are clustered at Enumeration Area (EA) level.

Source: Authors' own elaboration.

5.3 Resilience scores

We find strongly significant differences in the average resilience level when comparing the group of shock vs non-shock households. These differences, for total and food consumption respectively, are clearly depicted in Figure 5 and Figure 6, which show the kernel density functions of the two household groups, for total (Model 1) and food consumption (Model 2) respectively. Moreover, Table 4 reports the results associated to the statistical tests[10].

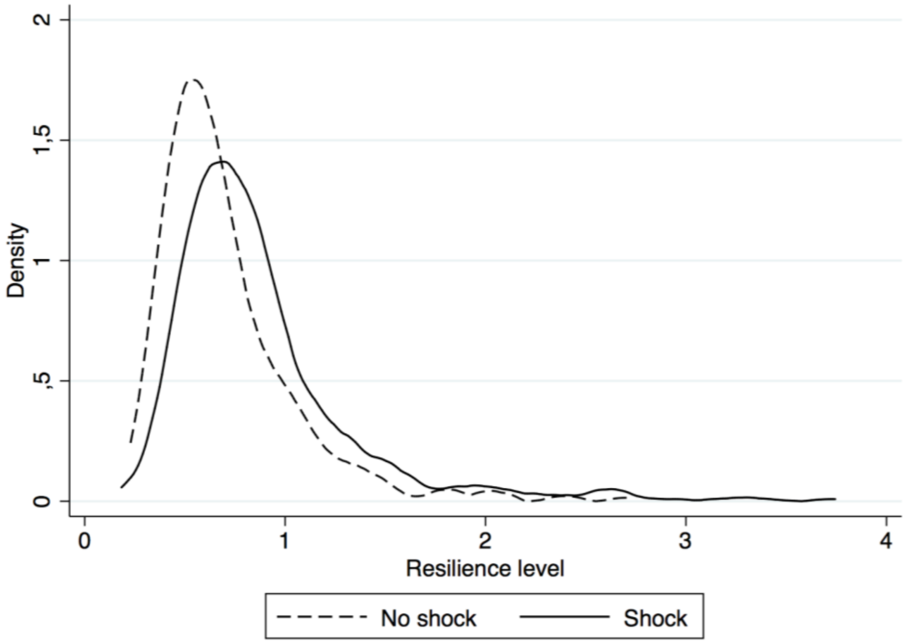
Figure 5. Kernel densities of resilience in total consumption



Source: Authors' own elaboration.

[10] We used the t-test to measure the equality of shocked and non-shocked average resilience.

Figure 6. Kernel densities of resilience for food consumption

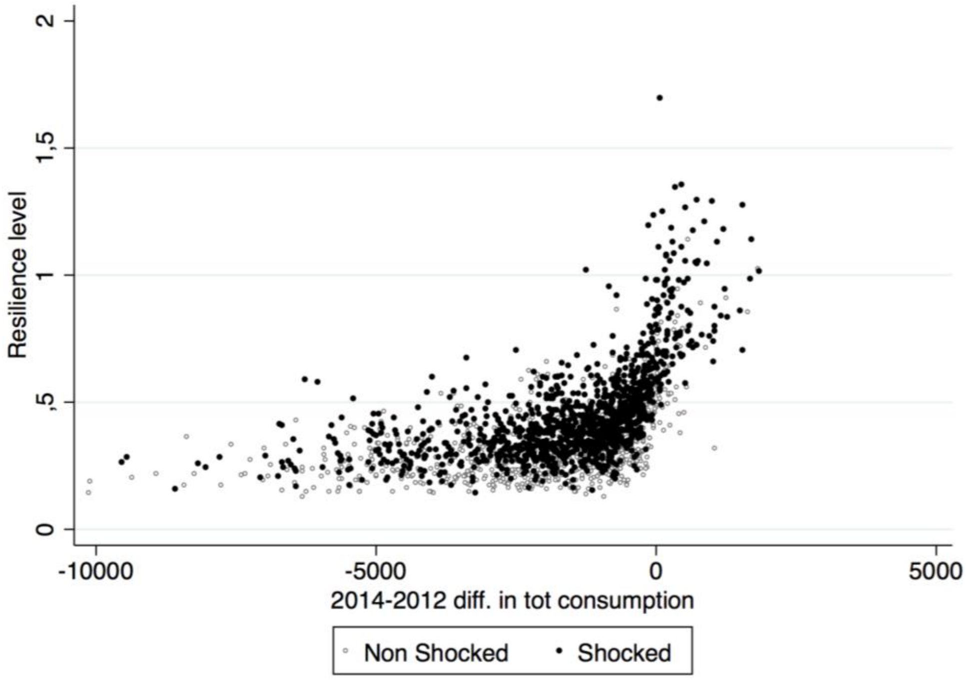


Source: Authors' own elaboration.

In both specifications, total and food consumption, the tests are strongly significant, validating our identification strategy. In the case of total consumption, we find that the shocked group is about 33 percent more effective than the non-shocked group in reaching previous consumption levels. In the case of food consumption, the resilience level is higher than the one for total consumption. This seems reasonable since food consumption represents a primary need and produces more immediate and stronger recovery feedbacks when households are hit by unexpected extreme events. When comparing the group of shocked vs. non-shocked households for the food consumption model, we find a difference of 24 percent in favour of the former group, which again signals a higher resilience for households affected by the drought shock.

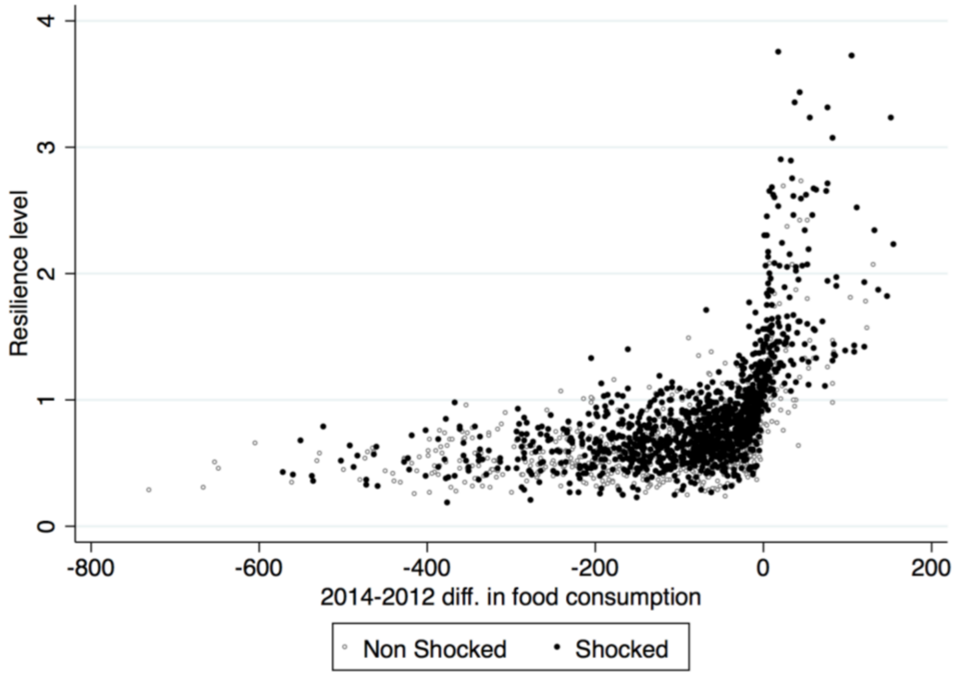
The score diagrams reported in Figure 7 and 8 show the resilience level on the vertical axis and the within welfare differences in the horizontal one. In an optimal recovery framework, higher resilient households are expected to locate all around the zero of the horizontal axis. This, indeed, would suggest that their consumption differences would be around zero and that these resilient households fully recovered to their previous welfare level. In our case, both diagrams show a sharp differentiated pattern when comparing the shocked and non-shocked groups, since the former (represented by filled dots) agglomerate around the zero and on higher resilience levels. In addition, the lowest resilience scores for shocked households all stand above those of the non-shocked group.

Figure 7. Resilience scores for total consumption



Source: Authors' own elaboration.

Figure 8. Resilience scores for food consumption



Source: Authors' own elaboration.

6 Conclusions and policy implications

Empirical results in this paper confirm that resilience is generally higher for households affected by the drought shock in 2011 household vis-à-vis households not affected, with a stronger evidence in the case of food consumption. This is likely to occur because households facing the shock tend to activate stronger resilience mechanisms and recover earlier when their livelihood is directly threatened by an extreme event, suggesting that the observed effect relates to the adaptive capacity rather than a simple welfare effect. When comparing the two groups, shocked households vs non-shocked households, we found that, on average, the former are about 33 percent more effective in recovering from falls in total consumption and 24 percent more effective in the case of food consumption.

Three main policy indications emerge from the analysis. First, government support programmes, such as the PSNP, are able to sustain households' resilience by helping them to reach the level of pre-shock total consumption, but have no impact on the food-consumption resilience. This may suggest considering and redefining these programs so as to include the objective of increasing households' food resilience. From our results, indeed, it emerges that these programs have an inadequate effect in terms of supporting food security of chronic food-insecure farmers. Secondly, the "selling out assets strategy" affects positively households' resilience, but only in terms of food consumption. This suggests that the implementation of policies improving market access in the more remote areas of the country may also affect the resilience capacity of the local households. This can be achieved, for example, by investing in infrastructures, but also by attracting private investment in the agricultural sector. Finally, the presence of informal institutions, such as social networks providing financial support, sharply increases households' resilience by helping them to reach pre-shock levels of food- and total consumption. Supporting the formation of these networks, incentivizing participation of households to agricultural cooperatives, agricultural associations, or community projects, may also help farmers recover their wealth level after a weather shock.

Despite the large number of theoretical studies and empirical attempts to provide methodological frameworks to measure resilience, our study offers important implications for research methods in this field. Our conceptual framework is based on the A2R initiative, which represents a key and comprehensive setting for resilience analysis in developing countries subject to extreme climate events. Moreover, the approach to compare shocked households vs. non-shocked households based on their capacity to choose effective response strategies of different types, can prove useful to understand what populations may be targeted by government support programmes.

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Annex 1. Empirical framework

This annex presents an empirical framework based on a composite error model, in which resilience is a non-observable and strictly positive characteristic.

Let $\boldsymbol{W}$ be the vector of observable outcome variables of interest representing the level of welfare and $\boldsymbol{X}$ a vector of independent variables and controls as conceptualised in Section 2.1 and defined in Section 3. Our composite error model takes the following form:

$$\boldsymbol{W}_i = f(\boldsymbol{X}_i, \beta) \times \exp(\boldsymbol{v}_i) \times \exp(\boldsymbol{r}_i) \tag{1}$$

where $i = 1, .., N$ indicates households, β is a vector of unknown parameters to be estimated, $\boldsymbol{v}$ a standard idiosyncratic component including reporting and other measurement errors and $\boldsymbol{r}$ represents the level of resilience. Assuming a specific functional form for $f(\boldsymbol{X}_i, \beta)$ and taking logs of both sides of equation, we obtain:

$$\ln(\boldsymbol{W}_i) = \ln f(\boldsymbol{X}_i, \beta) + \boldsymbol{\varepsilon_i} \tag{2}$$

where the error component can be disentangled in:

$$\boldsymbol{\varepsilon}_i = \boldsymbol{v}_i + \boldsymbol{r}_i \tag{3}$$

We assume that $\boldsymbol{v}_i \sim \mathrm{iid}$ represents the idiosyncratic components while $\boldsymbol{r}_i \sim \mathcal{N}^+(0, \sigma_r^2)$ is an asymmetric non-negative random variable representing resilience whose mean follows a truncated normal distribution.[11] We further assume that $\boldsymbol{v}_i$ and $\boldsymbol{r}_i$ are distributed independently of each other and of the regressors, implying $Cov(\boldsymbol{v}_i, \boldsymbol{r}_i) = 0$, $Cov(\boldsymbol{v}_i, \boldsymbol{X}_i) = 0$ and $Cov(\boldsymbol{r}_i, \boldsymbol{X}_i) = 0$. The Maximum Likelihood estimation of the unknown parameter vector $\theta = (\beta, \sigma_v^2, \mu, \sigma_r^2)$ does not allow obtaining estimates of the individual specific resilience score ($\boldsymbol{r}_i$). Based on a well-known result from the econometrics literature (Jondrow *et al.*, 1982), we can exploit the information in $\boldsymbol{\varepsilon}_i$ to derive estimates of $\boldsymbol{r}$ for each i. In particular, given the aforementioned distributional assumptions, a point estimate of $\boldsymbol{r}_i$ can be written as:

$$E(\boldsymbol{r}_i | \boldsymbol{\varepsilon}_i) = \sigma_* \left[\frac{\widetilde{\mu_i}}{\sigma_*} + \frac{\phi(\widetilde{\mu_i}/\sigma_*)}{1 - \Phi(-\widetilde{\mu_i}/\sigma_*)}\right] \tag{4}$$

where:

$$\widetilde{\mu_i} = \frac{\sigma_r^2 + \mu\sigma_v^2}{\sigma^2} \tag{5}$$

$$\sigma_*^2 = \sigma_r^2 \sigma_v^2 / \sigma^2 \tag{6}$$

[11] We estimate the model by means of *sfcross* Stata TM command developed by Belotti et al. (2012), which does not allow the use of other statistical distributions when modelling the distributional mean.

and where ϕ and Φ represent the standard normal density and cumulative distribution function respectively. For each $i = 1, \dots, N$ household, our estimation model in compact notation takes the following form:

$$\boldsymbol{W}_{i,2014-2011} = \beta + \boldsymbol{X}_{i,t}\boldsymbol{\gamma} + REG_{j,t}\boldsymbol{\delta} + AEZ_{k,t}\boldsymbol{\zeta} + \boldsymbol{v}_i + \boldsymbol{r}_i \tag{7}$$

in which $\boldsymbol{W}$ is a vector of the two dependent variables represented by within log-differences 2014-2011 of the expenditure for food and total consumption, both expressed in 2010 US dollars. Assuming an 'equilibrium condition' and according to an optimal recovery strategy, we would expect such differences to be nearly zero, since resilient households would be able, at least partially, to 'bounce back' to pre-shock welfare levels. The interpretation of these variables, after controlling for initial conditions and endowment levels, is thus straightforward: the higher the differences, the higher the welfare losses. The resilience term $\boldsymbol{r}$ is included to investigate whether an association exists between welfare losses and resilience capacity level or, in other words, whether the resilience component significantly explains these welfare changes.

To this aim, we explicitly model the resilience level in the after-shock period through a double-component error, which includes an idiosyncratic term $\boldsymbol{v}$ capturing reporting errors and other classic noises, and the $\boldsymbol{r}$ term, which represents the resilient component and captures deviations from the initial equilibrium. The latter follows a truncated normal distribution, whose mean is a function of $\boldsymbol{R} = \{\boldsymbol{R}^E; \boldsymbol{R}^I\}$ as described in Section 3, and of a vector of unknown parameters ψ to be estimated (see also Larson and León, 2006).

While before the drought shock all households are potentially in equilibrium,[12] once the shock occurs the group of shocked households starts to recover and activates their resilience capacity by following one, or a combination of, the set of strategies included in $\boldsymbol{R}$.By contrast, those households that have not been hit by the shock are not expected to significantly alter their resilience level.

To disentangle the different resilience capacity during the absorption and rehabilitation phases in the two household groups, the identification strategy employs an interaction term between a dummy for shocked/non-shocked households given by $\boldsymbol{D}$ and the set of dummy variables included in $\boldsymbol{R}$. This simple identification technique allows to obtain a statistical test and quantification of systematic resilience differences between shocked and non-shocked households during and after the shock. The resilience equation employed is as follows:

$$\boldsymbol{r_i} = (\boldsymbol{R'}_{\boldsymbol{i}}\boldsymbol{D_i})\boldsymbol{\psi} \tag{8}$$

By combining equation 7) and 8), the complete estimation model is as follows:

$$\boldsymbol{W}_{i,2014-2011} = \beta + \boldsymbol{X}_{i,t}\boldsymbol{\gamma} + REG_{j,t}\boldsymbol{\delta} + AEZ_{k,t}\boldsymbol{\zeta} + (\boldsymbol{R'}_{\boldsymbol{i}}\boldsymbol{D_i})\boldsymbol{\psi} + \boldsymbol{v}_i \tag{9}$$

[12] The concept of 'equilibrium' refers here to a situation in which a household is not affected by any external shock. This condition is satisfied by applying the sample restriction described in Section 4.1.

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ISBN 978-92-5-131140-0
9 789251 311400
CA2653EN/1/11.18