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Climate Resilience Pathways of Rural Households. Evidence from Ethiopia

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Climate resilience pathways of rural households. Evidence from Ethiopia.

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Abstract

This paper explores the resilience capacity of rural Ethiopian households after the drought shock occurred in 2011. The work develops an original empirical framework able to capture the policy and socio-economic determinants of households' resilience capacity by making parametric statistical assumption on the resilience distribution. To this end, the analysis employs a two-wave representative panel dataset aligned with detailed weather records while controlling for a large set of household- and community-level characteristics. The analysis shows that the majority of these factors affects significantly resilience capacity only in the group of households affected by the drought shock, suggesting that the observed effect relates to the adaptive capacity enabled by these factors, rather than a simple welfare effect. Three policy indications emerge from the findings of the empirical model. First, government support programmes, such as the 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. Secondly, the "selling out assets strategy" affects positively on households' resilience, but only in terms of food consumption. 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. Policies incentivizing the formation of these networks, through the participation of households to agricultural cooperative, agricultural associations, or community projects, may also help farmers in recovering their wealth level after a weather shock.

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

JEL codes: Q12, Q18, I32; C130

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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; McSweeney 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 of a common definition and of 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 article 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 developing studies affected by climatic shocks by assuming resilience as the “capacity that ensures stressors and shocks do not have long-lasting adverse development consequences” (Constas et al., 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 to 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 (HH) 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 A2R framework (UN, 2017), that allows to measure the degree of resilience capacity and its determinants. The work models resilience as the latent HH’s capacity to combine diverse coping strategies to recover to the pre-shock welfare levels. This methodological framework identifies the most significant determinants HHs’ response under a set of parametric assumptions on their statistical distribution. Using two national representative survey waves collected during 2011-2012 and 2013-2014, we test the above methodological approach to total and food consumptions of HHs experiencing the severe droughts occurred in Ethiopia between 2011 and 2012. The analysis complements these data with granular precipitation information at village level.

The findings show that the resilience level is higher for the group of shocked HHs, particularly for the case of food consumption. This is because shocked households tend to activate stronger resilience feedbacks and recover earlier when their livelihood is under threat of extreme events, suggesting that the observed effect relates to the adaptive capacity rather than a simple welfare effect. Diverse policy indications emerge from the analysis. First, government support programmes sustain households' resilience by helping them to reach the level of pre-shock total consumption. Secondly, disinvestment strategies are only effective for food consumption. Finally, informal institutions, such as social networks providing financial support, support households' resilience for both food and total consumptions.

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 them to recover from shocks of different nature (Dercon et al., 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 et al., 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 to protect to avoid the risk of falling in 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 *et al.*, 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 HHs 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 HHs, but they contemporaneously show a higher resilience capacity. The authors' underlying hypothesis is that the variability of the adjustment path for most exposed HHs 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 HH as a whole decides to move (Hugo, 1996; Laczko and Aghazarm, 2009). Migration or relocation of the households, often referred as maladaptive strategies, allow households to seek new economic and social opportunities elsewhere. In contrast, migration of single HH's members is functional to supplement standard incomes with individual remittances and allows members to divide the HH'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 others 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 HHs exploit these knowledge advantages to carry out actions in order to minimise the shock impacts (Below et al., 2015).

Finally, an important issue to account for is how the shock affects the HH wealth distribution. In some cases, HHs 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. Analysing this aspect, Thiede (2014) who finds in Ethiopia equalising effects on within-community livestock inequality and a non-significant effect on the asset inequality, with regional heterogeneity in both cases.

To summarise, the analysis of the literature suggests that the HH resilience capacity is affected both by external and internal factors. Among the first group, for example, formal institutional support may be represented 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 HHs affected by shocks in their community. The social network constituted by relatives and friends may also represents an effective instrument of support during the adjustment phase. Internal factors may include strategies adopted by HHs such as crop and labour diversification, selling private assets, and consumption smoothing.

To catalyse and scale-up actions aimed to accelerate resilience capacity, the UN Secretary- General Ban Ki-moon and 13 members¹ 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 no. 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 with 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 mid- 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 ground 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 absorption and rehabilitation phases. In our case, a straightforward distinction of these two periods derives from the two years in which the survey waves were carried out, 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*, HHs are characterised by a series of strategic assets $\mathbf{K}_t = \{\mathbf{K}_t^N, \mathbf{K}_t^H, \mathbf{K}_t^F, \mathbf{K}_t^S\}$, where \mathbf{K}^N stands for natural capital, \mathbf{K}^H denotes human capital, and \mathbf{K}^F , \mathbf{K}^S are vectors of financial and social assets, respectively (Scoones, 1998; Bebbington, 1999; Ellis, 2000; Niehof, 2004; Martin and Lorenzen, 2016; Asfaw et al., 2017; Nguyen et al., 2017). During the pre-shock period, the resilience is expected to be at the minimum level given that HHs have not experienced any shocks, although they may be aware of future occurrence of potential extreme events.

1 The 13 UN entities participating in the Initiative are FAO, UNEP, UNFCCC, UN-Habitat, UNICEF, UNESCO, UNFPA, UNOPS, UNISDR, WFP, OCHA, WHO, and WMO.

2 "Take urgent action to combat climate change and its impacts".

3 For more information on this Initiative, see <http://www.a2rinitiative.org>

During the shock, HHs 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 $\mathbf{R}_s = \{\mathbf{R}_s^E, \mathbf{R}_s^I\}$ 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 HH welfare $W_s = f[\rho_s(\mathcal{S}_t, \mathbf{K}_t); \mathbf{K}_t]$, at any times and in a risky environment subject to shocks \mathcal{S} , could be represented by a random variable, in which ρ indicates the level of resilience that HHs assume to cope with \mathcal{S} experienced in s , and in accordance with \mathbf{K} and ε unobserved factors.

2.2 The case of Ethiopia

IPCC (2014) reports that a relevant part of climate vulnerable countries concentrate in the 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% 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 HH welfare. Carter et al. (2007) estimate a 20% reduction in per capita consumption for HHs 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 HHs in Ethiopia struggle to insure against shocks and often rely with 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 pursuits. Between the mid-1970s and late 2000s, Belg and Kiremt 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 the 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 at its third

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.

phase (PSNP 3) with a total budget of 2.3 billion of US dollars (World Bank, 2012). Other than the PSNP, Ethiopian government has implemented a set of other food aids and food-for-work programs (Caeyers and Dercon, 2008; Clay et al., 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 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 designed to be representative of rural and small town areas of Ethiopia and 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, involving 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, HHs rely on different assets that constitute their pre-shock endowment. In the \mathbf{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 to 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 et al., 2013; Shiferaw et al., 2013). Age and years of education of the HH head, together to the HH sex ratio, size and a dummy for female headed HHs, health status and school attendance of HH members characterise the human capital endowments represented in vector \mathbf{K}_t^H . The information on financial and social assets (\mathbf{K}_t^F and \mathbf{K}_t^S) includes: a) the share of HHs benefitting of 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 et al., 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 HHs as a measure of social assets and networking capacity. There is robust empirical evidence suggesting that spatial proximity favours market and information access (Lanjouw et al., 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 et al., 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 to the vectors of controls REG and AEZ , which includes, respectively, regional and Agro-Ecological Zones (AEZs) dummies.

During the absorption and rehabilitation phases, HHs are likely to show their maximum resilience level in order to minimise welfare loss. The set of different activities that HHs set up to cope with the shock and to rehabilitate in a more resilient environment are captured by the vectors \mathbf{R}^E and \mathbf{R}^I , which disentangle respectively strategies relying on external help and those internal to the HH. For all these variables, information is available at HH level. According to data availability, the vector of external activities \mathbf{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 HHs 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 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, labour diversification and Sustainable Management Land (SLM) practices help to identify strategic rehabilitation activities carried out after that HHs overcome the acute phase of drought. The set of SLM practices available at HH 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 model selection variables.

In order to identify shocked HHs, socio-economic HHs 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

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).

Table 1 - Descriptive statistics for selected model variables.

Variable	Mean	s.d.	min	max
Diff. in total consumption	-1699.94	1716.72	-10105.61	1863.31
Diff. in food consumption	-93.84	116.52	-730.41	155.52
<i>Natural capital</i>				
TLU	2.13	2.85	0	41.5
Smallholder (yes=1)	0.47	0.5	0	1
Elevation a.s.l. (mt)	1847.41	587.08	344	3311
Irrigation scheme (2011, EA level)	0.56	0.5	0	1
<i>Human capital</i>				
Ave. age of HH head	43.28	15.31	0	100
Ave. education of HH head	1.78	2.2	0	17
Sex ratio	1.09	0.97	0	8
HH size	4.89	2.28	1	14
Female headed HH (=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
<i>Financial and social capital</i>				
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
<i>Climatic variability</i>				
SPI<=-1.5 (=1)	0.611	0.48	0	1
<i>Resilience - External help</i>				
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
<i>Resilience - Internal help</i>				
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
Labour 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

4. Research design and empirical strategy

4.1 Shock identification

To identify the set of HHs 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 s.d. for precipitation events and lower than -1.5 s.d. for drought shocks that occurred only during the months of growing season. Again, we look at the drought event occurred in 2011-2012 by considering HHs that do not change residence over the period of analysis as this help to control for sorting from drought shocks.⁷

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 sd, which correspond to extremely dry conditions experienced by the population.

Figure 1 - 12-month vs. 4-month SPI comparison, 1983-2012.

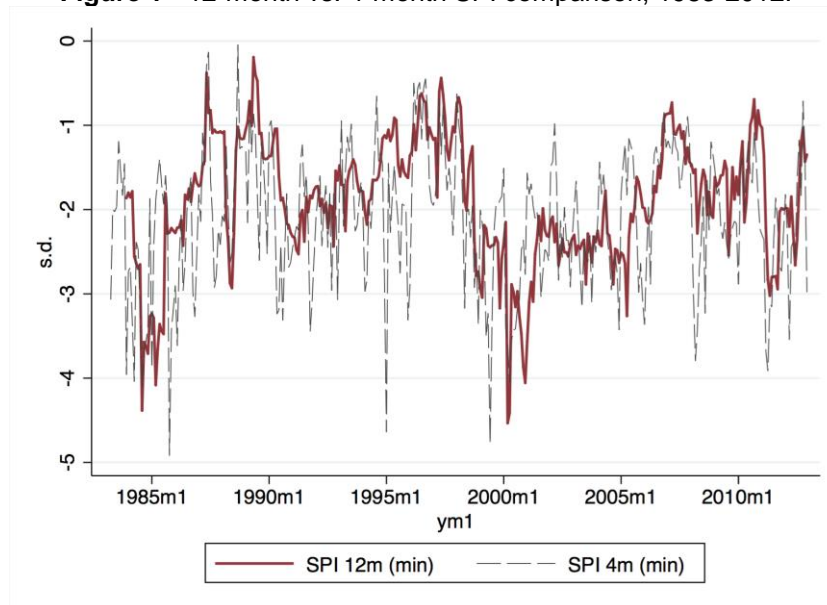
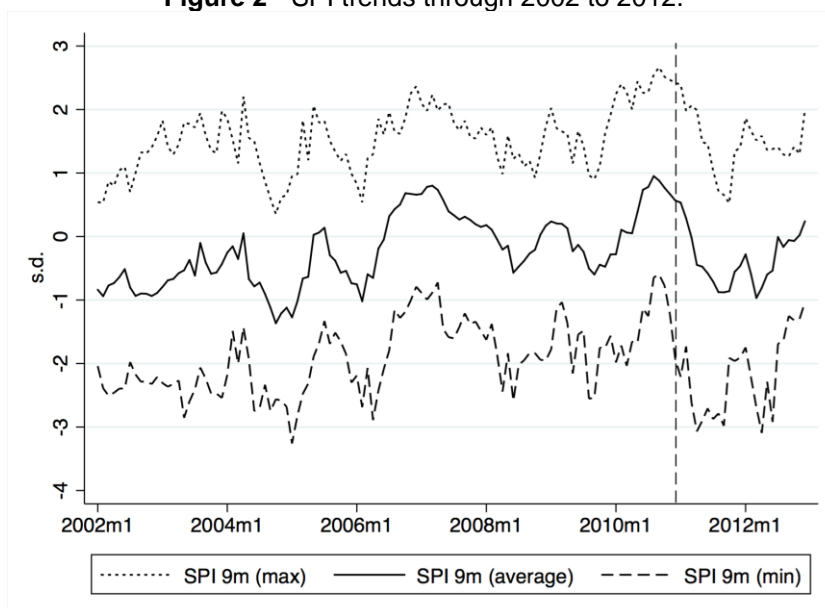


Figure 2 focuses on a more recent perspective, considering the maximum, mean, and minimum value of SPI at 9 months only during the period 2002-2012. Despite SPI's trend at 9 months appears as more stable and less volatile than in Figure 1, it is still possible to detect shocks during 2005 and for the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

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.

⁷ Also considering the data limitations, this allows to rule out potential endogeneity for sorting of HHs that geographically adapt to recurrent shocks (that is, that occur over larger spatial heterogeneity). HH before the drought in 2011-2012 are those declared not to have been subject to both climate and other shocks that is in a sort of "equilibrium". The climate data since 1985 are necessary in order to calculate deviations (by means of the SPI) from the mean of the historical climate distribution.

Figure 2 - SPI trends through 2002 to 2012.



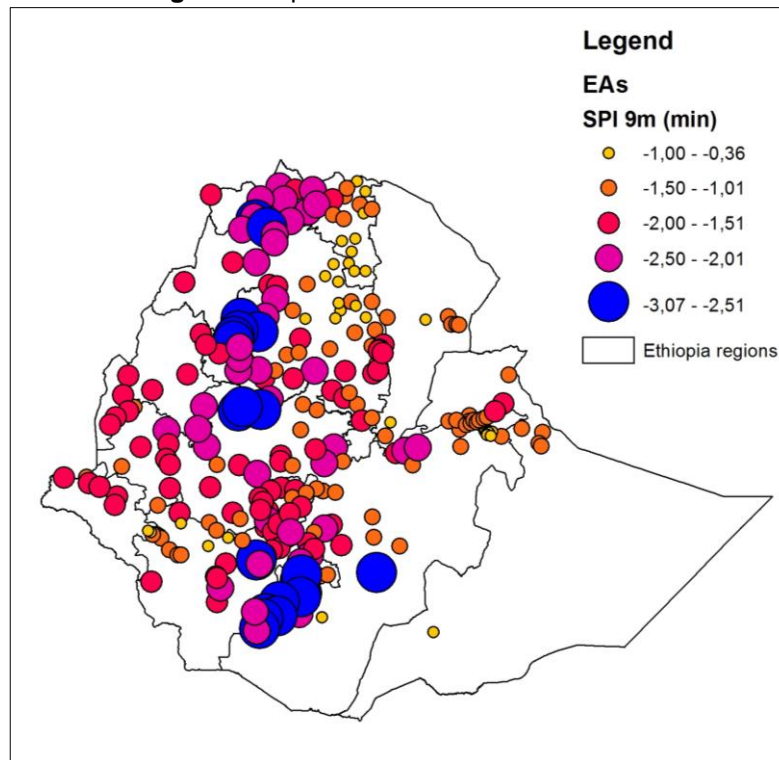
At national level the number of HHs that experienced a climate shock corresponds to 51 percent of the sample. This number gives the proportion of the severe drought borne by the population and its large extension. Table 2 shows the distribution of climate shocks, based on SPI, in each region of Ethiopia. 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 - Shocked HHs by region based on 9-month $SPI \leq -1.5$ s.d.

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

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 east part does not experience any large SPI variation.

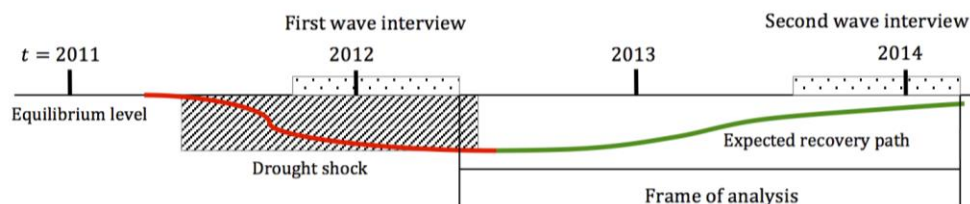
Figure 3 - Spatial 9-month SPI distribution.



In order to guarantee common baseline characteristics, the identification strategy also imposes of excluding HHs declaring to have been hit by any type of shock occurred in the pre-treatment period ($t \leq 2011$), which represents a sort of “equilibrium condition” at the baseline once controlling for HH and physical characteristics before the shock. This further selection 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 effects⁸.

Figure 4 helps identifying the frame of analysis for the events occurred during period 2011-2013 and for which we have research data.

Figure 4 - Timeline and frame of analysis.



⁸ 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 et al., 2005; Dercon and Krishnan, 2000a; 2000b; Demeke et al., 2011; Gray and Mueller, 2012; Noack et al., 2015; Skoufias and Quisumbing, 2005).

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 HHs, 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 HHs to be 'preferred candidates' for the shock may exist. Especially in panel analyses, HHs could sort into more or less risky places (or livelihood activities) based on their tolerance for shocks and their differential willingness to pay for risk reductions. Even though most HHs 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 limiting the sample to HHs not having left the same location during the last two years starting from the first wave interview. Out-migration of single HH members also constitutes an effective adaptive strategy for most exposed HHs (Lucas and Stark, 1985; Rosenzweig and Stark, 1989; Gray and Mueller, 2012; Gray and Bilsborrow, 2013). However, once selected only urban HHs and those not moving during the previous two years, migration of single HH's members include only 3 observations, which were excluded from the final sample.

To summarise, our final estimation sample comprehends rural HHs 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 HHs declaring only a drought shock between the first and the second wave. According to these criteria, our final estimation sample counts 1930 observations, divided in two groups of 1016 shocked and 914 non-shocked HHs, respectively.

4.3 Model specification

Scholars have produced several methodological attempts of 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 et al., 2010a; Alinovi et al., 2010b; 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 et al., 2012, Bèné, 2013; Hoddinott, 2014; Di Caro, 2014; Alfani et al., 2015).

Alinovi et al. (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 et al. (2010a) 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 applies to estimate resilience for countries in the Sahel region. Given the limited data availability, the authors construct an ad hoc counterfactual 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 HH 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 HH in the communal livestock production system as a proxy to measure the system resilience, while they measure HH 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 HH level.

An alternative vision of resilience is the one proposed by Bèné (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 an econometric 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 households' trait, hence it is natural to model it as a latent variable. Following this line, in this section we present an empirical framework based on a composite error model, in which resilience is a non-observable and strictly positive characteristic.

Let W be the vector of observable outcome variable of interest representing the level of welfare and 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:

$$W_i = f(X_i, \beta) \times \exp(v_i) \times \exp(r_i) \quad (1)$$

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

$$\ln(W_i) = \ln f(X_i, \beta) + \varepsilon_i \quad (2)$$

where the error component can be disentangled in:

$$\varepsilon_i = v_i + r_i \quad (3)$$

We assume that $v_i \sim iid$ represents the idiosyncratic components while $r_i \sim \mathcal{N}^+(0, \sigma_r^2)$ is an asymmetric non-negative random variable representing resilience whose mean follows a truncated normal distribution.⁹ We further assume that v_i and r_i are distributed independently of each other and of the regressors, implying $Cov(v_i, r_i) = 0$, $Cov(v_i, X_i) = 0$ and $Cov(r_i, X_i) = 0$. 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 (r_i). Based on a well known result of the econometric literature (Jondrow et al., 1982), we can exploit the information in ε_i to derive estimates of r for each i . In particular, given the aforementioned distributional assumptions, a point estimate of r_i can be written as:

$$E(r_i | \varepsilon_i) = \sigma_* \left[\frac{\tilde{\mu}_i}{\sigma_*} + \frac{\phi(\tilde{\mu}_i/\sigma_*)}{1 - \Phi(-\tilde{\mu}_i/\sigma_*)} \right] \quad (4)$$

⁹ 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.

where:

$$\tilde{\mu}_i = \frac{\sigma_r^2 + \mu\sigma_v^2}{\sigma^2} \quad (5)$$

$$\sigma_*^2 = \sigma_r^2 \sigma_v^2 / \sigma^2 \quad (6)$$

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:

$$\mathbf{W}_{i,2014-2011} = \beta + \mathbf{X}_{i,t}\boldsymbol{\gamma} + \text{REG}_{j,t}\boldsymbol{\delta} + \text{AEZ}_{k,t}\boldsymbol{\zeta} + \mathbf{v}_i + \mathbf{r}_i \quad (7)$$

in which \mathbf{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 being 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 since negative values are associated to welfare losses. The resilience term \mathbf{r} is included to investigate whether exists an association between welfare losses and resilience capacity level or, in other terms, 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 \mathbf{v} capturing reporting errors and other classic noises, and the \mathbf{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 $\mathbf{R} = \{\mathbf{R}^E; \mathbf{R}^I\}$, as described in Section 3, and of a vector of unknown parameters $\boldsymbol{\psi}$ to be estimated (see also Larson and León, 2006).

While before the drought shock all HHs are potentially in equilibrium,¹⁰ once the shock occurs the group of shocked HHs starts to recover and activates their resilience capacity by following one, or a combination of, the set of strategies included in \mathbf{R} . On the contrary, those HHs 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 HH groups, the identification strategy employs an interaction term between a dummy for HHs affected by the shock represented by \mathbf{D} and the set of dummy variables included in \mathbf{R} . This identification allows obtaining a statistical test and quantification of systematic resilience differences between shocked and non-shocked HHs during and after the shock. The resilience equation employed is as follows:

$$\mathbf{r}_i = (\mathbf{R}'_i \mathbf{D}_i) \boldsymbol{\psi} \quad (8)$$

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

$$\mathbf{W}_{i,2014-2011} = \beta + \mathbf{X}_{i,t}\boldsymbol{\gamma} + \text{REG}_{j,t}\boldsymbol{\delta} + \text{AEZ}_{k,t}\boldsymbol{\zeta} + (\mathbf{R}'_i \mathbf{D}_i) \boldsymbol{\psi} \quad (9)$$

For the two dependent variables, we carry out separate cross-sectional estimates, which provide, respectively, results for differences in total consumption (Model 1) and food consumption (Model 2). We estimate both models with robust standard errors clustered at EA level. All variables are in natural logarithms, with the exception of dummy variables.

¹⁰ The concept of 'equilibrium' refers here to a situation in which a household does not experience any external shock. This condition holds by applying the sample restriction described in Section 4.1.

5. Results

Table 3 and 4¹¹ present the estimation results, while Figure 5-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 lower post-shock welfare levels or, alternatively, with higher welfare losses. Among the set of selected variables for natural capital, we do not find significant association between reduction in consumption gap and the endowment of livestock as proxied by the 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 lower 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.

It also emerges a strong and significant role of elevation as a positive factor in recovering the consumption capacity, most likely given by the fact that elevation represents a mitigation factor during drought conditions. The elasticity associated to this factor is quite large, namely 0.28 and 0.52 per cent given a one per cent increase in elevation, respectively for total and food consumption, even though these coefficients show a weaker statistical significance.

As far as the human capital is concerned, the major barrier for lower consumption gap is found in the HH age, with younger HH heads associated with lower welfare loss. For both total and food consumption outcomes, we find an elasticity of gap reduction of 0.17 per cent. However, although similar in magnitude, in the case of food the coefficient is only weakly statistically significant. We do not find significant effects in all the other variables included, namely education, proportion of females within the HH, the size of the HH and for changes in health status. This set of results point to a modest role of human capital in Ethiopian HHs to recover up to the previous consumption levels after the drought shock.

Moving to the results for financial and social assets, we find a minor role of HH distance to the major road, which proxies the access to financial and social capital. The coefficient associated to 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 pop. centre and presence of microfinance programs) are far from being statistical significant.

¹¹ Table 3 and 4 refer to a single estimation model. The table consists of two parts to allow for an easier visualisation.

Table 3 - Estimation results - Part A

	Model (1) Tot. consumption	Model (2) Food consumption
Age of HH head	-0.175*** (0.047)	-0.174* (0.078)
Ave. years of education	0.030 (0.028)	0.066 (0.043)
Sex ratio	0.005 (0.018)	0.017 (0.030)
HH size	-0.007 (0.041)	-0.067 (0.073)
Female headed HH (dummy)	-0.039 (0.047)	-0.026 (0.070)
Not attending school (1=yes)	-0.020 (0.071)	-0.050 (0.115)
Had health issues (1=yes)	-0.059 (0.070)	-0.050 (0.111)
Smallholders (1=yes)	-0.136** (0.046)	-0.209** (0.079)
TLU (2012)	-0.005 (0.021)	-0.023 (0.033)
Distance to nearest pop. center (km)	-0.046 (0.045)	-0.061 (0.072)
Distance to nearest major road (km)	0.032 (0.019)	0.062* (0.027)
Total technology durables	-0.028 (0.036)	0.023 (0.061)
Microfinance (EA level)	-0.103 (0.069)	-0.171 (0.124)
Irrigation scheme (EA level)	0.054 (0.053)	0.013 (0.098)
Elevation	0.278* (0.123)	0.526** (0.195)
AEZ dummies	yes	yes
Regional dummies	yes	yes
Constant	-2.450** (0.928)	-4.396** (1.436)

N=1930. All variables, excluding dummies, are in logarithms. Standard errors clustered at EA level in parenthesis.

5.2 Resilience determinants

Table 4 shows the most important results of our analysis, i.e. the factors affecting the resilience capacity at HH 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 received help from relatives and friends, emerge as strong determinants of the HHs' resilience. Particularly large is the role of relative 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 to 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 HH's resilience capacity.

As expected, the set of results obtained by interacting the resilience drivers with non-shocked HHs 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. 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.

Table 4 - Estimation results - Part B

<i>Post-shock resilience drivers (absorption and reshape)</i>	Model (1)	Model (2)
	Tot. consumption	Food consumption
Shock - Received credit	-0.123 (0.199)	-0.356 (0.353)
Shock - Consumption smoothing	0.350 (0.277)	0.590 (0.390)
Shock - Sold assets	0.324 (0.243)	1.392** (0.513)
Shock - Received gov. help	0.467** (0.149)	0.621 (0.337)
Shock - Help from rel. and friends	0.532** (0.197)	1.073** (0.375)
Shock - Crop diversification (count)	-0.075 (0.123)	0.115 (0.177)
Shock - Labour diversification (count)	0.192 (0.608)	0.132 (0.941)
Shock - Soil erosion practices	0.108 (0.191)	0.034 (0.279)
Shock - Mixed crops	0.017 (0.136)	0.036 (0.253)
Shock - Fertiliser	-0.225 (0.183)	-0.558 (0.342)
No shock - Received credit	-0.549 (0.593)	-0.162 (0.687)
No shock - Consumption smoothing	0.576 (0.719)	0.702 (1.106)
No shock - Sold assets	0.096 (0.679)	-0.244 (1.131)
No shock - Received gov. help	-0.054 (0.365)	-0.412 (0.671)
No shock - Help from rel. and friends	-0.019 (0.688)	-0.120 (1.404)
No shock - Crop diversification (count)	-0.354 (0.413)	0.273 (0.424)
No shock - Labour diversification (count)	-0.756 (0.796)	-1.502 (1.190)
No shock - Soil erosion practices	-0.296 (0.405)	-0.455 (0.497)
No shock - Mixed crops	0.066 (0.390)	-0.543 (0.553)
No shock - Fertiliser	-0.076 (0.420)	-0.312
Lambda	0.904***	1.186***
N	1930	1930
Resilience for shocked HH (R)	0.330	0.703
Resilience for non-shocked HH ($R_{shocked}$)	0.448	0.878
t -test ($R_{shocked} < R$)	0.000	0.000
t -test ($R_{shocked} = R$)	0.000	0.000

All variables, excluding dummies, are in logarithms. Standard errors are clustered at EA level.

5.3 Resilience scores

We find strongly significant differences in the average resilience level when comparing the group of shock vs non-shock HHs. These differences, respectively for total and food consumption, are evident 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 tests¹².

Figure 5 - Resilience in total consumption.

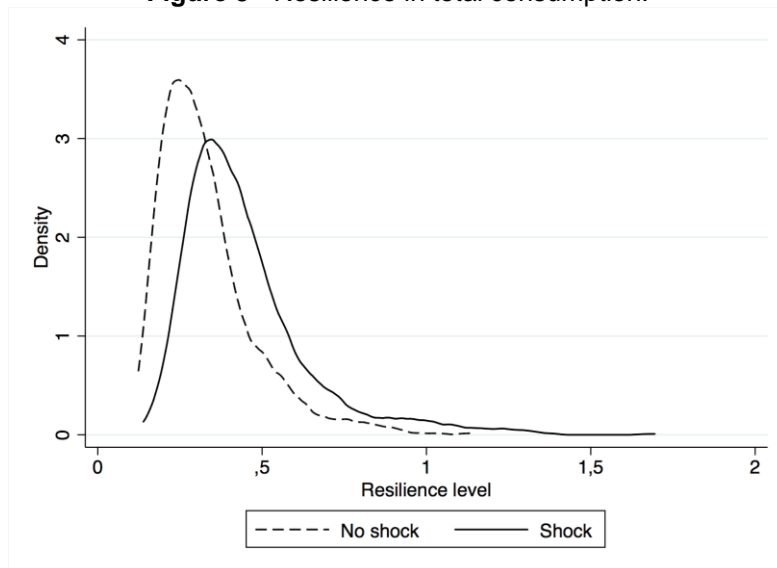
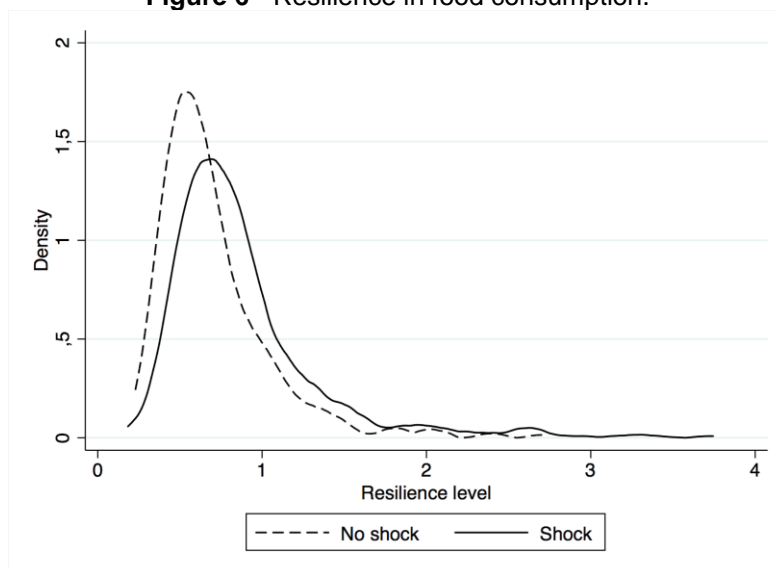


Figure 6 - Resilience in food consumption.



In both Model (1) and (2), the tests are strongly significant, straightening our identification strategy. In the case of total consumption (Model 1) we find that the shocked group is about 33% more effective than the non-shocked group in reaching previous consumption levels. In the case of food consumption (Model 2), the resilience level is higher than the one for total consumption. This seems reasonable since food consumption represents a primary need and produces immediate and stronger recovery feedbacks when households experience unexpected extreme events. When comparing the group of shocked to non-shocked HHs for food consumption model, we find a difference of 24% in favour of the former group, which again signals a higher resilience for HHs affected by the drought shock.

The score diagrams reported in Figure 7 and Figure 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 HHs are expected to locate all around the zero of the horizontal axis. This signals that no consumption differences exist before and after the shock and that HHs fully recovered or even improved their previous

¹² We used the t-test to measure the equality of shocked and non-shocked average resilience.

welfare level if their score is positioned beyond the ideally zero line. 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 HHs all stand above those of the non-shocked group.

Figure 7 - Resilience scores for total consumption.

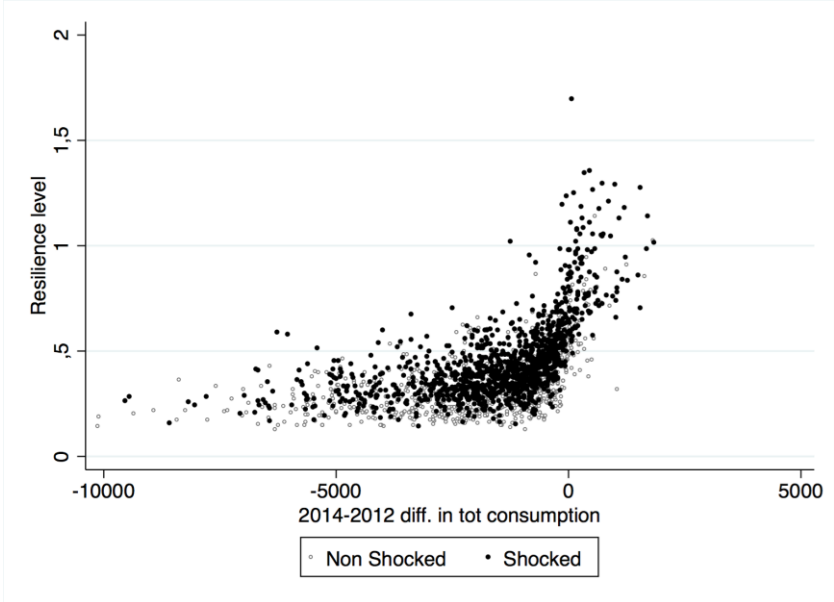
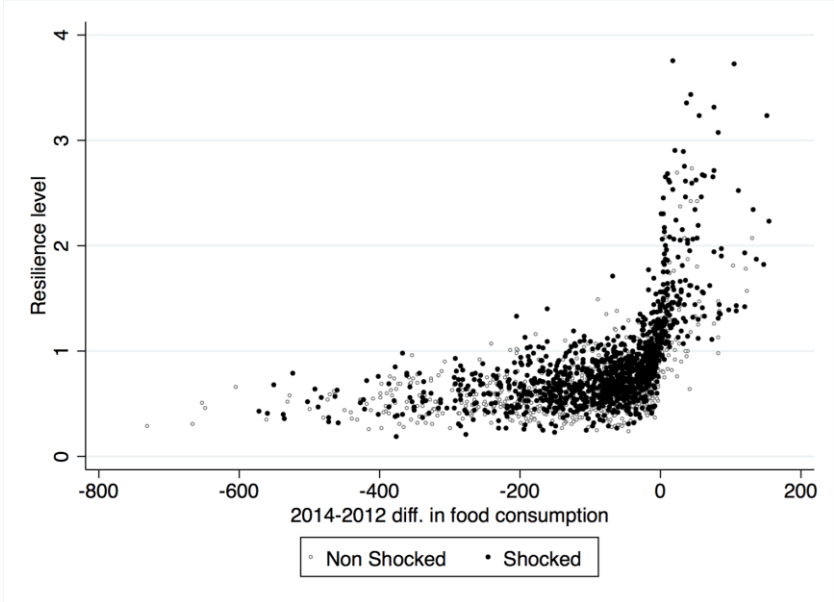


Figure 8 - Resilience and diff. in food consumption.



6. Conclusions and policy implications

This paper provides a conceptual and methodological framework measuring the resilience capacity of rural HHs subject to unexpected and severe shocks. We assume and model the resilience concept as the latent HH's capacity to be effective in combining different strategies to 'bounce back' to previous welfare levels. By making a set of parametric assumptions on its statistical distribution, the methodological

framework allows to identify the most significant determinants HHs' response. We test this methodology to the case of severe drought occurred in Ethiopia between 2011 and 2012, and evaluate the different factors affecting the capacity of shocked HHs to recover to previous consumption levels, namely total and food consumption. We employ representative data from two survey waves, 2011-2012 and 2013-2014, which provide a richness of socio-economic information at HH level. The analysis complements these data with granular precipitation information at EA level in order to identify the group of shocked HHs by means of SPI.

The results confirm that the resilience level is higher in the group of shocked HHs, with a stronger evidence in the case of food consumption. This is likely to occur because shocked households tend to activate stronger resilience feedbacks 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, we find that, on average, shocked households are about 33% more effective in recovering from falls in total consumption and 24% more effective in the case of food consumption.

Three main policy indications emerge from the findings of the empirical model. 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. The effectiveness of these policies, therefore, may depend on the wealth level of the targeted population, as for instance it can be insufficient to support food security of chronic food-insecure farmers, but can help food secure households to recover their normal consumption path. 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 is achievable, for example, by investing in infrastructures, but also toward 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 cooperative, agricultural associations, or community projects, may also help farmers to recover their wealth level after a weather shock.

Considering the growing number of empirical attempts to provide methodological frameworks to measure resilience, our study offers important implications for research methods in this field. Our conceptual framework grounds on the recent A2R initiative, which represents a key and comprehensive setting for resilience analysis in developing countries subject to extreme climate events. Moreover, the econometric approach provides a *vis-à-vis* comparison of shocked vs. non-shocked HHs based on their capacity to choose effective response strategies of different types and timing.

Despite its innovative nature, our contribution also presents some limitations. First, we model resilience as a strictly positive characteristic, limiting the distributional assumptions made on it. This implies that all HHs in the estimation sample assume a non-zero level of resilience capacity. Although this does not undermine the probative value of our analysis, further research may improve the empirical methodology here proposed. Second, the limited longitudinal component of our panel sample limits the observation of readjustment period, which most likely translates in a downward bias of resilience level. Moreover, a potential estimation approach based on panel analysis would suffer from the well-known incidental parameter problem given the short panel at hand. To investigate further the complex process of resilience, longer panel datasets with more environmental information would constitute precious research assets.

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