What is the Role of Improved Technologies on Farmers' Resilience to Food Insecurity on the Face of Adverse Shocks? Evidence from Ethiopia Using Panel Data

by Wubneshe Dessalegn Biru, Tim K. Loos, and Manfred Zeller

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Wubneshe Dessalegn Biru[1], Tim K. Loos[2], Manfred Zeller[1]

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Abstract

Ethiopia's smallholder farmers are prone to recurring and unanticipated shocks caused by weather and climate related hazards that cause substantial welfare loss. Recently, the concept and measure of household resilience capacity in poorer countries and its role to food security has been given much attention by scholars and international organizations that proposed an empirical measure of resilience capacity from a food security perspective. By using four rounds of household level panel data collected between 2012 and 2019, this paper aims to identify the determinants of household resilience to food insecurity and assess the role played by technology adoption on improving household resilience and thus food security. The household resilience index is estimated by combining factor analysis and structural equation modeling. While addressing the endogeneity problem, we estimate the causal link between resilience capacity index and food security indicators with technology adoption and shocks. The results reveal that assets take the highest share in building the resilience index. We find that adoption is significantly and positively associated with the resilience index. The higher the initial level of the resilience score the higher the current level of resilience and thus food security status. Drought shock significantly reduces the growth of the resilience index. The findings also reveal the level of adoption does not shield households from the negative effects of shocks. Based on our research findings we recommend that policy interventions should exert much effort not only in promoting technology adoption but also in building household resilience accompanied by improved infrastructure for smallholders.

Keywords: Ethiopia; panel data; resilience index; shock; technology adoption

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✉ Wubneshe Dessalegn Biru
wubneshed.biru@uni-hohenheim.de

Tim Loos
tim.loos@giz.de

Manfred Zeller
zellerm@uni-hohenheim.de

[1]University of Hohenheim, Institute of Agricultural Sciences in the Tropics (Hans-Ruthenberg-Institute) (490), Rural Development Theory and Policy (490a)

[2] Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ), Bonn

Abstract

Ethiopia's smallholder farmers are prone to recurring and unanticipated shocks caused by weather and climate related hazards that cause substantial welfare loss. Recently, the concept and measure of household resilience capacity in poorer countries and its role to food security has been given much attention by scholars and international organizations that proposed an empirical measure of resilience capacity from a food security perspective. By using four rounds of household level panel data collected between 2012 and 2019, this paper aims to identify the determinants of household resilience to food insecurity and assess the role played by technology adoption on improving household resilience and thus food security. The household resilience index is estimated by combining factor analysis and structural equation modeling. While addressing the endogeneity problem, we estimate the causal link between resilience capacity index and food security indicators with technology adoption and shocks. The results reveal that assets take the highest share in building the resilience index. We find that adoption is significantly and positively associated with the resilience index. The higher the initial level of the resilience score the higher the current level of resilience and thus food security status. Drought shock significantly reduces the growth of the resilience index. The findings also reveal the level of adoption does not shield households from the negative effects of shocks. Based on our research findings we recommend that policy interventions should exert much effort not only in promoting technology adoption but also in building household resilience accompanied by improved infrastructure for smallholders.

1 Introduction

Households in developing countries particularly smallholder farmers are one of the most vulnerable social groups to shocks caused by changes in weather patterns, climatic, economic, and human-induced shocks (Dercon, 2004). As it is in most of African countries, smallholder farmers in Ethiopia are disproportionately affected by weather-related shocks such as drought, flooding as well as several other human-induced shocks including conflict /political instability, animal diseases, high input prices, and imperfect product market (Carter et al., 2007). The United Nations Framework Convention on Climate Change (UNFCCC, 2014) categorized Ethiopia among the top most vulnerable countries to the adverse impacts of climate variability in sub-Saharan Africa. The effects of shocks, even small in magnitude, may have persistent negative effects because rural households in the country have limited capacity and resources to absorb their adverse consequences. According to (Carter et al., 2007), for instance, every Ethiopian rural household was exposed to drought at least once in the previous five years. The extent of harm, however, varies from household to household depending on the different household or community characteristics. Studies indicate that the poorest households are the most affected and often struggle to cope with shocks (Dercon, 2004; Dercon et al., 2005). This group of households mostly practice costly and harmful coping strategies such as desperate sales that in turn potentially risked them entering the poverty trap.

The concept of economic resilience which is defined as "the household's ability to absorb the negative effects of adverse shocks" (Adger, 2000) has become an important research and policy issue especially in developing countries where a significant proportion of their population are vulnerable. Household resilience capacity is hypothesized to reduce the adverse effects of idiosyncratic and covariate shocks that the households may experience. Resilience is a multidimensional concept determined by several indicator variables known as resilience pillars. Investment in agricultural technologies can be one of the important determinants of resilience capacity that may have a considerable role in building resilience and thus reducing food insecurity. The use of agricultural technologies boosts agricultural productivity and yield thereby improving sales income that also ensures higher food consumption (Shiferaw et al., 2014), leading to an overall improvement of household welfare and vulnerability to adverse shocks (Kassie et al., 2011).

The measurement of resilience and its determinants has not been adequately explored partly as the field is relatively new in the context of economic resilience. The measurement of resilience in the food security context is first explored by Alinovi et al. (2008, 2010). The authors estimated the resilience index by using a two stage factor analysis where in the first stage the resilience pillars are estimated using observable indicator variables and in the second stage they use the predicted values of the pillars to estimate the resilience index. The authors use cross sectional data and also shocks are not explicitly explored in their model. Recently, others attempted to assess the determinants of the change in welfare over time using short term panel data (Vaitla et al., 2012). Using the FAO RIMA II approach (d'Errico and Pietrelli, 2017; FAO, 2018) estimated the resilience index and attempted to explore its determinants over time as well as its role in reducing the negative impact of shocks and thereby improve food security indicators. The RIMA II approach is a resilience measurement approach proposed by the FAO Resilience Measurement Technical Working Group (RMTWG) (FAO, 2018) which is evolved from the RIMA I approach applied by Alinovi et al. (2010). The RMTWG also defined resilience as "the ability of a household to keep with a certain level of well-being (i.e. being food secure) by withstanding shocks and stresses".

None of these authors, however, explicitly considered the role adoption of agricultural technologies may play in building the resilience capacity and thus improve the food security indicators and also in reducing the adverse effects of shocks. This paper explores the link between household welfare represented by resilience capacity index (RCI), household dietary diversity (HDD), and food consumption with the adoption of chemical fertilizer and improved seed including their joint adoption and shocks (drought and flooding) over time. Furthermore, we analyzed the differential effect between adoption and shocks on the outcome variables. The two technologies are chosen mainly because of their complementarity and are also often recommended to be used as packages (Dorfman, 1996; Marra et al., 2003). The analysis allows us to measure the level of resilience capacity and its determinants as well as how livelihoods change over time that assists public intervention as well as gives insights for further research. Moreover, the study highlights the determinants of resilience and how is household resilience composed. This article is organized into five sections, including the introduction. The next section provides a general concept of resilience and its measure, while section three presents the methodology and data sources. Section four presents the statistical and econometric results and discussion of the main outputs. The conclusions and recommendations of the study are presented in section five.

2 The Concept and Measure of Resilience and Shocks

2.1 The Concept and Measure of Resilience

Recently researchers and humanitarian agencies have given much emphasis on the concept of resilience and its measure, mainly because of the increase in the frequency and severity of adverse shocks and exposure of vulnerable households (Barrett and Constas, 2014, Hallegatte, 2014). Thus, several attempts have been made to define and measure economic resilience. However, both the definitions and methodology used to measure is heterogeneous which raises the question of whether they measure one identical concept with the different methods used. In terms of the definition of resilience, according to Ellis (1998) it is defined as “the ability of a system to absorb change”. Similarly, Adger (2000) defined resilience as “the ability of groups or communities to cope with external stresses and disturbances as a result of social, political and environmental change”. But the most recent definition of resilience in food security context is from the FAO by Alinovi et al. (2008). According to them resilience is the capacity of households to ensure that adverse shocks and stressors do not have long-lasting development consequences (Alinovi et al., 2010, 2008; Barrett and Constas, 2014; FAO, 2018). With regard the empirical estimation of the resilience index, the FAO Resilience Measurement Technical Working Group (RMTWG) (FAO, 2018) proposed an advanced methodology the Resilience Index Measurement and Analysis (RIMA II) evolved from the RIMA I (Alinovi et al., 2010). The RMTWG also defined resilience as “the ability of a household to keep with a certain level of well-being (i.e. being food secure) by withstanding shocks and stresses”. Other alternative approaches were also proposed by (Frankenberger et al., 2012). As we aim to measure the resilience capacity of households to food insecurity and explore its effect on future household food security in the face of adverse shocks along with other determinants of resilience including technology adoption. The estimation of resilience capacity in this paper is estimated by employing the RIMA II approach.

The concept of resilience considers both ex-ante actions that reduce the risk of households becoming food insecure and ex-post actions that help households cope after a crisis occurs indicating that the analysis of resilience requires the use of panel data. The use of panel data helps us to capture the change in household welfare and the factors determining the change over time. Resilience is not also easily observed or is considered as latent that its measure requiring the use of several indicator variables called resilience pillars. These resilience pillars are unobservable themselves. Thus, resilience is created using composite indices which are computed by combining the important indicator variables and create the resilience scores (Krishnakumar, 2007). Note that the measure of resilience and vulnerability is quite different where vulnerability is measured using a single indicator variable such as income or consumption expenditure that shows the susceptibility of people to damage when exposed to particular adverse shocks (Biru et al., 2020). Resilience, on the other hand, is a multidimensional concept measured by several indicator variables. Regarding the number of components building resilience, the RMTWG listed nine resilience pillars used to construct the household resilience index (FAO, 2018). Seven out of the nine dimensions fall under the physical category which includes: income and food access; access to basic services; assets; enabling institutional environment; climate change; agricultural practices and technology; and social safety nets. The remaining two dimensions represent the capacity category and include sensitivity and adaptive capacity. In this study, four out of the nine resilience pillars are considered (see Appendix Table A1). Agricultural technology and experience to shocks, however, are not considered in the construction of the resilience index in our case as these variables are the main covariates of our regression models.

Households may experience shocks that have a substantial adverse impact on their regular consumption as well as welfare. When a shock hits, households employ several coping strategies, mainly consumption smoothing, asset smoothing, and adoption of new livelihood strategies such as the adoption of improved seed, in our case. Household resilience capacity which is constituted from the different pillars also contributes to absorb and cope with shocks and helps households to bounce back to their previous state of well-being. Thus, the effects of shocks results in the long term increase or decrease in food security. This leads to the aftershock state level of food security which can also be obtained using the different resilience pillars or time variant and time invariant household characteristics. In this chapter, we adopted the FAO RIMA II approach to estimate the resilience capacity score. We aim to measure the resilience capacity of households to food insecurity and explore its effect on future household food security in the face of adverse shocks along with other important determinants of resilience including technology adoption. The estimation of resilience capacity in this paper is estimated by employing the RIMA II approach.

2.2 Estimation of Resilience

To estimate the resilience score, we employed a two-step procedure adopted from the RIMA II approach (FAO, 2018). In the first stage, the latent variable representing each pillar is estimated separately using the different observable variables by employing factor analysis (FA), and in the second stage Structural Equation Modeling -Multiple Indicators Multiple Cause (SEM-MIMIC) model is used to estimate the RCI by using the predicted values of each of the four pillars. In the MIMIC model, the two variables representing food security household HDD and food consumption are assumed to be the achievements of resilience capacity and are observable. Figure 4.1 presents the path diagram of the resilience of the household model. The circles represent latent variables and the rectangles represent the observable variables.

The explanation and estimation of the four pillars[2] and their respective observable indicator variables used as well as the estimation of the RCI is presented as follows:

Access to Basic Services (ABS): access to basic services represent the ability of a household to make basic needs, and access and use of basic public services; includes, access to infrastructure, health centers, periodic markets, agricultural extension services, and schools. Important public services including the source of drinking water; the main source of lighting; the proximity of a household (minutes taken using the usual mode of transportation) from the closest hospital, periodic market, agricultural extension center, woreda office were included under this pillar. With regard to its estimation, standard methods of factor analysis assume that the variables are continuous and follow a multivariate normal distribution. In this case, the variables are mixed (i.e. continuous and dummy), and using the simple factor analysis gives biased estimates. To solve this problem, we use a user written command (polychoric) to estimate the factor scores. With regard to the sign of the indicators variables, as expected, source of lighting and the main toilet facility as well as source of quality water have a positive correlation with the first factor. On the other hand, the distance of the household from the periodic market and agricultural extension office is negatively correlated with the first factor. Therefore, the first factor seems to have the expected signs with the original variables and appears to be the one that explains access to basic services best. As a result, we retained the first factor in predicting the *ABS* latent variable.

Assets (AST): the assets ownership pillar comprises of both durable and non-durable assets that reflect the wealth status of the household. The observable variables used to represent assets include the number of habitable rooms (excluding kitchen and toilet), type of roof material, agricultural land owned (ha), and livestock ownership in Tropical Livestock Unit (TLU). The entire indicator variables used to represent assets is expected to have a positive association with the latent variable measuring the asset component of resilience. This is true with the first factor where all the variables are directly related with a factor loading of greater

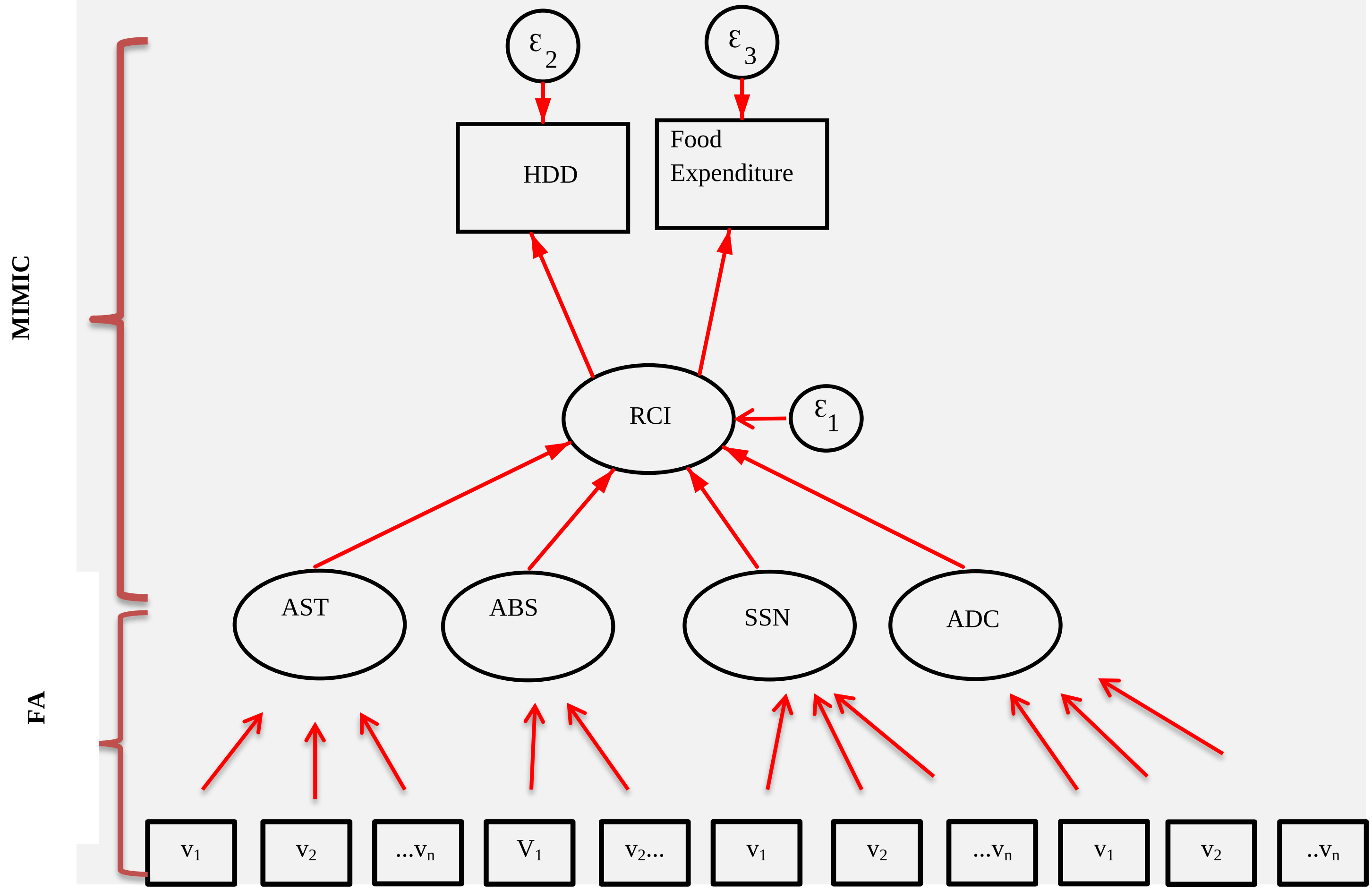
[2] All observed variables used to estimate the pillars are listed in the Appendix along with their Eigen values and factor loadings

than 0.4 following the Kasier criterion. As a result the first factor is retained and used for the estimation of the resilience index.

Social Safety Nets (SSN): social safety is the measure of the household's ability to get assistance from institutions as well as help from relatives and friends in case of need. *SSN* helps households to satisfy their basic needs and household consumption and this resilience to food insecurity (Andrews et al., 2018). Informal institutions which are comprised of strategies used for risk sharing involving social networks, norms, trust, and reciprocities such as credit networks, food, and labor sharing networks play an important role in helping households in times of shock in Ethiopia (Dejene, 2010). These arrangements help communities from adverse livelihood shocks and uncertainties. According to Dejene (2010), local informal institutions in Ethiopia are known to play important roles in assisting the poor and food insecure. In our case, social safety net is represented by membership in institutions such as credit, mahber, iqub and idirr. The first factor has the expected signs with the latent variable measuring SSN. Therefore, we retained the first factor in predicting this pillar.

Adaptive Capacity (ADC): adaptive capacity is the ability of a household to adapt to a new situation and develop new strategies of livelihood (Folke, 2006) cited by (Alinovi et al., 2010) which is linked with the existence of institutions and networks that enable the household to acquire knowledge or learn so that they are able to adjust while changes are taking place, so as to retain the same livelihood functions. According to Gallopín (2006), the capacity of adapting to perturbations and shocks is strictly connected with being able to learn from technological progress. Variables representing *ADC* component are literacy of the household head (read and write), whether the household has another source of income/remittance as well as the irrigation dummy representing whether the household uses irrigation technology. Other technology adoption-related variables that may be relevant to this pillar are not included here as our main objective is to assess the causal link between technology adoption and shocks with resilience to food insecurity. Other variables such as the demographic structure of the household affect adaptive capacity (Vincent, 2007), but as they are included as explanatory variables in our regression models, they are excluded from use in the estimation of RCI. The eigenvalues and the factor loadings of the first stage resilience estimation (FA) is reported in Table A1 of the Appendix in this chapter.

As depicted in Figure 4.1 the MIMIC model has two components (Bollen et al., 2010). The first component causes (pillars) and the RCI (latent) and in the second component the RCI in turn determines food security indicator variables represented by HDD and food consumption which are observable. In this model food security is represented by real per capita[3] food consumption expenditure and HDD.



Source: adapted from (FAO, 2018)

Figure 1 Path diagram of the RCI estimation of a household model

FA assumes that the residual errors are uncorrelated with each other, whereas the SEM-MIMIC approach relaxes this assumption and allows such correlation. The *RCI* is the predicted score of the four pillars (Asset, ABS, SSN and ADC) MIMIC model. It assumes that all the estimated components are normally distributed with mean 0 and variance 1. The resilience scores created using the MIMIC model, however, are unit less. Therefore, to make interpretation of the regression coefficients simple, we rescale into values ranging from 0 to 1. The transformation is executed using the min-max scaling based on the simple formula:

$$\left(x_i^* = (x - x_{min}) / x_{max} - x_{min} \right).$$

[3] Food consumption expenditure in ETB is deflated using 2010 as base year

The food security indicator variables employed here are HDD and real per capita food consumption expenditure. The two components of the MIMIC model, namely the measurement component Eq. (1) - indicate the link between RCI and the food security indicators and the structural component Eq. (2), which links the estimated pillars to the RCI. Empirically, the relationship can be written as:

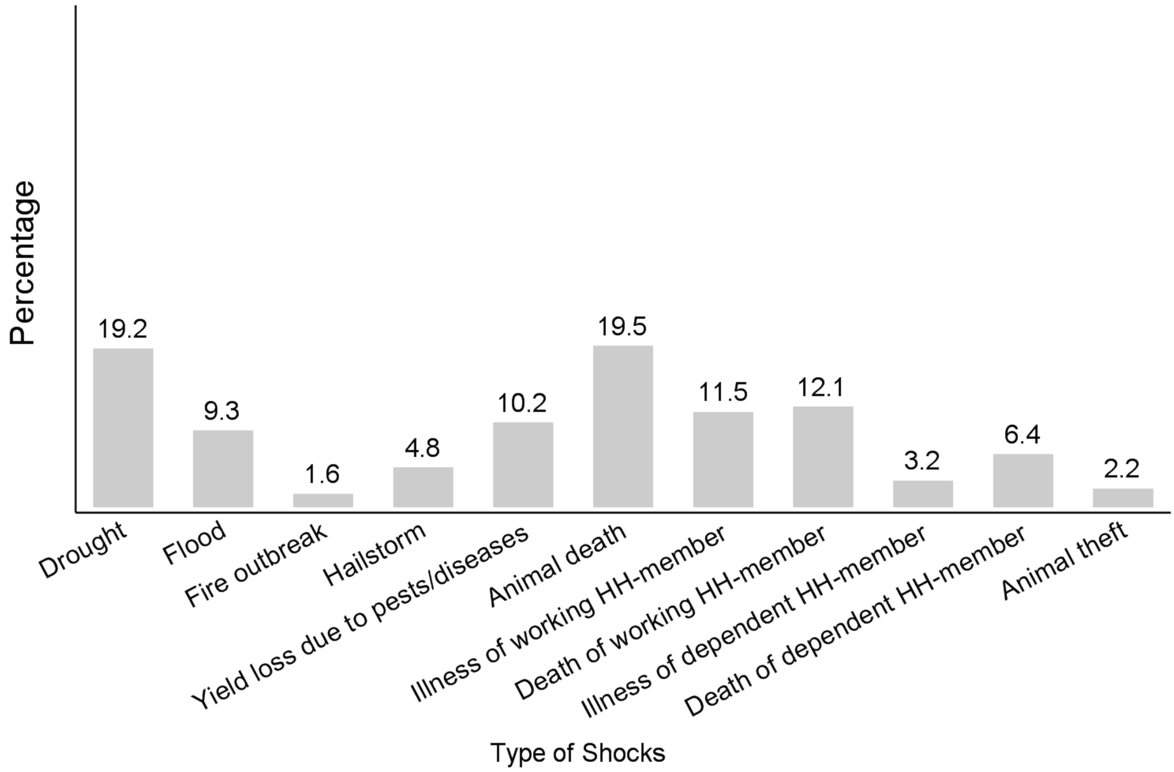
$$\begin{bmatrix} Food\ Expenditure \\ Household\ Dietary\ Diversity \end{bmatrix} = [\gamma_1, \gamma_2][RCI] + [\varepsilon_1, \varepsilon_2] \tag{1}$$

$$[RCI] = [w_{ABS}, w_{AST} w_{SSN}, w_{AC}] + \begin{bmatrix} AST \\ ABS \\ AC \\ SSN \end{bmatrix} + [\varepsilon_3] \tag{2}$$

Where *Where, RCI*=resilience capacity index; *ABS* =access to basic services; *AST*= asset index; *SSN*=social safety nets; and *ADC*= adaptive capacity, w_k the weight for the k^{th} block in defining resilience; and e_i=error term. There, the RCI_{it} is the predicted score of the five pillars mentioned above using SEM, considering that all the estimated components are normally distributed with mean 0 and variance 1. The MIMIC model does not solve endogeneity issues if it is detected in the model. Therefore, this analysis using the MIMIC approach is more of descriptive showing the relationship between resilience and its pillars. In this paper, the causal inference is dealt in the subsequent regression analysis.

2.3 The Occurrence of Shocks

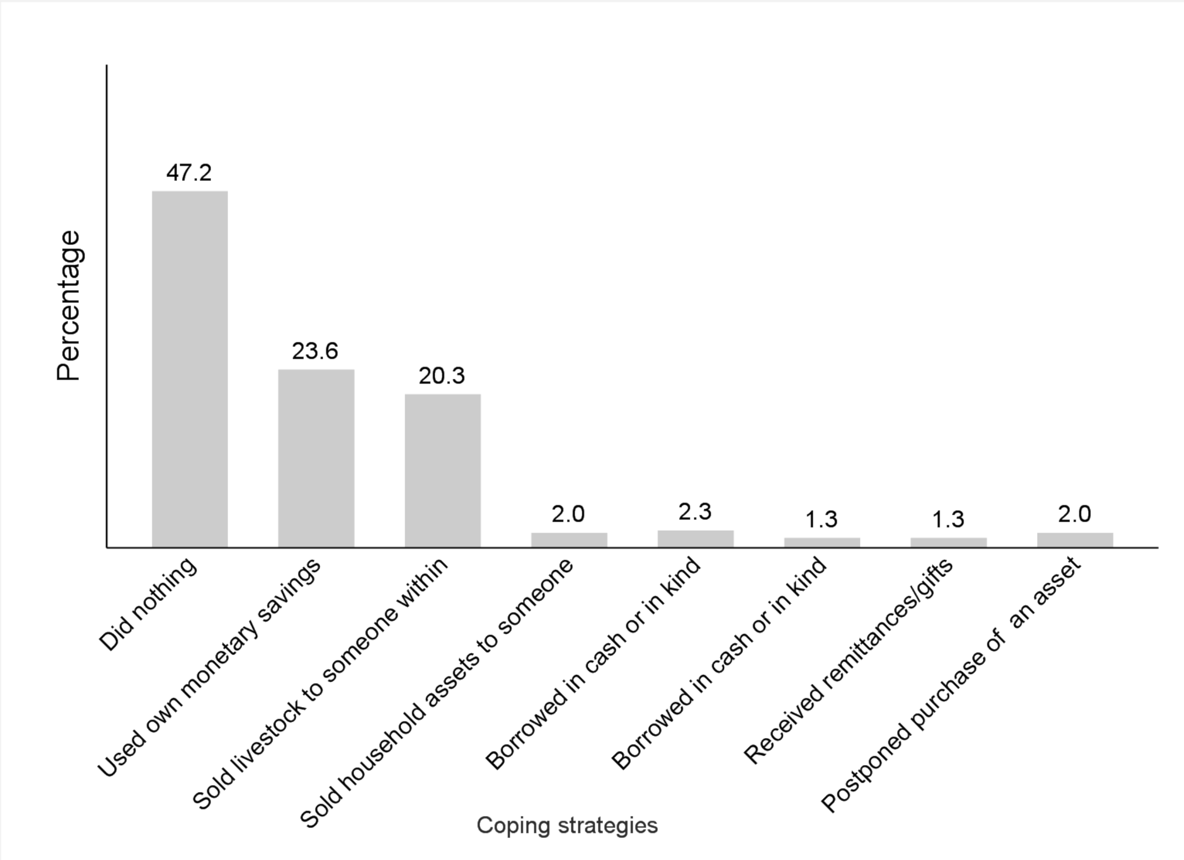
Shocks: in this sub-section, we describe the types of shocks reported in our sample households. Shocks are defined as adverse events that lead a substantial loss of household income, a reduction in consumption, and/or a loss of productive assets (Dercon et al., 2005). Household resilience capacity can be substantially reduced by shocks (Dercon, 2004; Dercon et al., 2005; Hoddinott, 2006) and this welfare deterioration along with its other determinants can be measured using panel datasets. Recurrent drought is one of the most common causes of crop failure and food shortages in the SSA, particularly Ethiopia (Shiferaw et al., 2014). Regarding the types of shock data, respondents were asked if shock events have happened in the past five years and if those shocks lead the household to a substantial loss or substantial reduction in their food and regular non-food consumption. In terms of shock categories, shocks are divided into a number of broad categories such as natural, market, agricultural, political, criminal shocks. The most common types of shocks reported in our sample households are drought, flooding, agricultural production and marketing related shocks. Very few households reported the same type of shock that occurred more than once in the previous five years. Regarding the proportion of households reported shocks, using the pooled data of 2014, 2016 and 2019 about 30% of the sample households reported to have experienced at least one type of shock. Figure 2 presents the different types of shocks reported by the sample households using the pooled data of 2014, 2016 and 2019. It can be seen that drought and animal death are the most reported shocks (19%) followed by the death of working household member (12%) and illness of working HH members (11.5%).



Source: Own computation (DFG-Ethiopia data)

Figure 2 Households reporting adverse shocks between 2014 and 2019

The ability of households to withstand shocks or stresses depends on the available livelihood options and on how well households are able to handle risks. Figure 3 reports the most important coping strategies households used to cope the reported shocks. The majority (47%) of the households did nothing to cope with the shocks and about 23% and 20% of those affected by adverse shocks reported that they have used own monetary saving and sale of livestock, respectively. Other coping strategies that are reported are selling of assets, borrowing and postponing the purchase of assets.



Source: Own computation (DFG-Ethiopia data)

Figure 3 Households reporting coping strategies between 2014 and 2019

3 Methodology and Data

3.1 Data and study area

A household-level panel data collected in four rounds collected in 2012, 2014, 2016 and 2019 are used in this study. The household survey is collected in a random sample of 373 farm households from 29 Kebeles[4] selected in fifteen woredas (districts) of Southwestern Ethiopia, each differing in their climatic and agro-ecological characteristics (see, Biru et al., 2020). This is a follow up survey from which the sample woredas are drawn from a nationally representative baseline survey conducted in 2012 by the International Food Policy Research Institute (IFPRI) and the Agricultural Transformation Agency (ATA) of Ethiopia. Our follow-up surveys conducted in 2014, 2016 and 2019 considering the South Western parts of Ethiopia covering Oromia and SNNP regions of Ethiopia. Because of logistical and budget reasons, the sample woredas were limited to those baseline Woredas located in the specified region.

The data collection was carried out in September for the baseline survey and between March and June for the last consecutive three rounds. The household surveys were carried out using computer-assisted personal interviewing (CAPI) that ensured superior data quality through built-in consistency checks and other correction methods. The household level questionnaire collects information on demographic characteristics, asset ownership, technology and input use, consumption, production, health, risk and ambiguity. Moreover, community level data including access to infrastructure such the household’s proximity to the nearest dry weather road, clean water, hospital, clinic, agricultural extension offices. The sample households were also asked to report in the previous three years if they have experienced any type of adverse shock that lead to a substantial welfare loss. Regarding tracking the sample households over the four long rounds was quite good. The attrition rate is 0% between 2012 and 2014, 2.5% between 2014 and 2016, (4%), and 2% between 2016 and 2019.

3.2 Conceptual Framework

Households may face both endogenous and exogenous shocks. However, we assumed the shocks considered here as exogenous that are theoretically beyond the control of the farmer. Further, we assumed that the shocks themselves are not inter-correlated. The effect of shocks on welfare can, therefore, be estimated using single equation models with the assumption that welfare indicators and exposure to shocks are linearly associated. However, estimating the

[4] The smallest administrative unit of Ethiopia

causal link between adoption and the welfare indicator variables using single equation models could lead to biased estimates because of the potential presence of endogeneity problems caused by unobserved heterogeneities (Tittonell et al., 2007).

Farmers' adoption and non-adoption decision is related to the expected net returns of adoption or non-adoption. A household adopts a technology set that maximizes the expected profit, where its returns are also dependent on several factors such as factor markets and the production function of the specific technology (Feder et al., 1985). In developing countries, household production and consumption decisions are non-separable that needs to be considered in our impact analysis. Smallholders in Ethiopia operate under a thin or missing factor and product market as well as households production and consumption decisions are non-separable. With this regard, to investigate the welfare impact of adoption, we apply a non-separable recursive household model. For simple conceptualization, suppose that *A* represents adoption (chemical fertilizer and improved seed including joint adoption), the adoption equation can be written as:

$$A=f(X,L,Z,V) \tag{3}$$

Where *X* represents variables determining the household's ability to adopt the technology choice sets, *L* is household demographic characteristics including labour endowment, *Z* is agro-ecological characteristics and *V* represents community characteristics.

The next step is linking technology adoption with the welfare indicators. Technology adoption improves resilience capacity and thus food security. Here we formulate the household welfare equation in a utility framework such that

$$W=f(A, S, L,V) \tag{4}$$

Where *W* represents household welfare (i.e. RCI, HDD, food consumption) *S* represents shocks (drought and flooding) and other variables are as previously defined. We hypothesized that the adoption of the two inputs accompanied with other complementary soil and water conservation practices increases the level of food security for adopters and potentially reduces the negative impacts of shocks.

3.3 Empirical Approach

Estimation of Multiple Technology Adoption

To assess the effects of adoption and shocks on household resilience to food insecurity and the role adoption may play in averting the adverse effects of these shocks, we first estimate the adoption equation of two commonly practiced complementary inputs: chemical fertilizer and improved seed. Starting from Eq. (3) in our conceptual framework we specify the following:

$$A_{it} = \alpha + \beta_1 x_{it} + \beta_3 HH_{it} + \beta_4 V_{it} + \beta_5 T_t + \mathcal{E}_{it} \qquad (5)$$

x_{it} represents variables determining technology adoption, HH_{it} household characteristics, V_{it} represents spatial or agro-ecological characteristics, T_t denotes year dummy. $\mathcal{E}_{it}$ is a compound error term consisting of unobserved time-invariant factors, c_i, and unobserved-time variant shocks, v_{it}, that affect technology adoption. In estimating Eq. (5) we used MNL model and include all exogenous variables, year and community dummies, as well as the means of time-varying variables to control for unobserved heterogeneity. This correlated random effects model relaxes the strong assumption of no correlation in a standard random-effects model (Wooldridge, 2010).

Estimating the Impact of Adoption and Shocks on the Resilience Index

The impact analysis of technology adoption on the RCI and food security indicators and its role in reducing the adverse impact of idiosyncratic and covariate shocks is the main objective this study. As outlined in the conceptual framework, we can formulate the following simplified relationship:

$$W_{it} = \eta A_{it} + \delta S_{it} + \beta' HH_{it} + \beta_4 V_{it} + \beta_5 T_t + \theta(A_{it} * S_{it}) + \alpha_i^* + \varepsilon_{it} \qquad (6)$$

Where W_{it} welfare indicator (RCI, HDD and food consumption), A_{it} technology adoption sets, S_{it} shock, X_{it} is the community and household level socio-economic characteristics, α_i^* household fixed effects and ε_{it} the idiosyncratic error term. θ captures the differential effect of technology adoption and shocks. This model suffers from three potential sources of endogeneity. The first potential source of endogeneity comes from unobserved heterogeneity. Time-invariant household characteristics which are unobserved may be correlated both with adoption and with our welfare measure. The second potential source of endogeneity is selection bias, where some households, depending on wealth status, risk preference, and ability/skill are tend to adopt new technology while also having a higher welfare level. Third, the current resilience score and food security indicator variables may heavily depend on past resilience scores and the food security indicator variables causing omitted variable bias. As a result, the inclusion of a lagged dependent variable and also lagged values of some of the independent variables, in our model, is theoretically required (Wooldridge, 2012). Empirically, Eq.(6) can be re-written as follows:

$$W_{it} = \rho W_{i,t-1} + \eta A_{it} + \delta S_{it} + \beta' HH_{it} + \beta_4 V_{it} + \beta_5 T_t + \theta(A_{it} * S_{it}) + \alpha_i^* + \varepsilon_{it} \quad (7)$$

$W_{i,t-1}$ is the lagged dependent variable (first-order lag), other variables are as defined in Eq.(6). This type of model can be estimated by first differencing within the transformation, as in one-way fixed effects models, or by taking first. This type of econometric relationships is estimated using dynamic panel data (DPD) models. Although the use of lagged dependent variables in DPD models allow for partial adjustment of the model, it causes a bias arising from the demeaning process that subtracts an individual's mean values of the dependent and each of the independent variables including the lagged dependent variable from each of the respective variable creating a correlation between regressor and error according to Nickell (1981). To resolve this issue, one prominent econometric model has been proposed by (Hsiao and Anderson, 1981) and extended by (Arellano and Bond, 1991). This model is commonly known as growth model (Dercon et al., 2009) and can be estimated using the first difference Generalized Method of Moments(GMM) model estimation. The difference GMM model uses the difference between the outcome variables at period *t* and *t-1* as the dependent variable for the period. The GMM estimates of the (Arellano and Bond, 1991) model can be written as:

$$\Delta W_{it} = \rho \Delta y W_{i,t-1} + \Delta A_{it} + \Delta S_{it} + \beta' \Delta X_{it} + \theta \Delta(A_{it} * S_{it}) + \Delta\varepsilon_{it} \quad (8)$$

Where Δ is the change in the variables from the baseline over time, and the rest is as previously defined. The model is designed for cases in which is at least equal to 3 and the number of observations is large (small T and large N) (Arellano and Bond, 1991). Furthermore, the GMM estimation all the independent variables that are assumed to be endogenous and the lagged values of the outcome variable are instrumented using lagged values of the same variable. Compared to RE and FE models, AB estimation weaken the exogeneity assumption for a subset of regressors, thereby providing consistent estimates even if reverse causality is present.

In summary, in estimating the impact of shocks and technology choice sets including their interaction, first we estimate the adoption equation using MNL model as previously outlined.

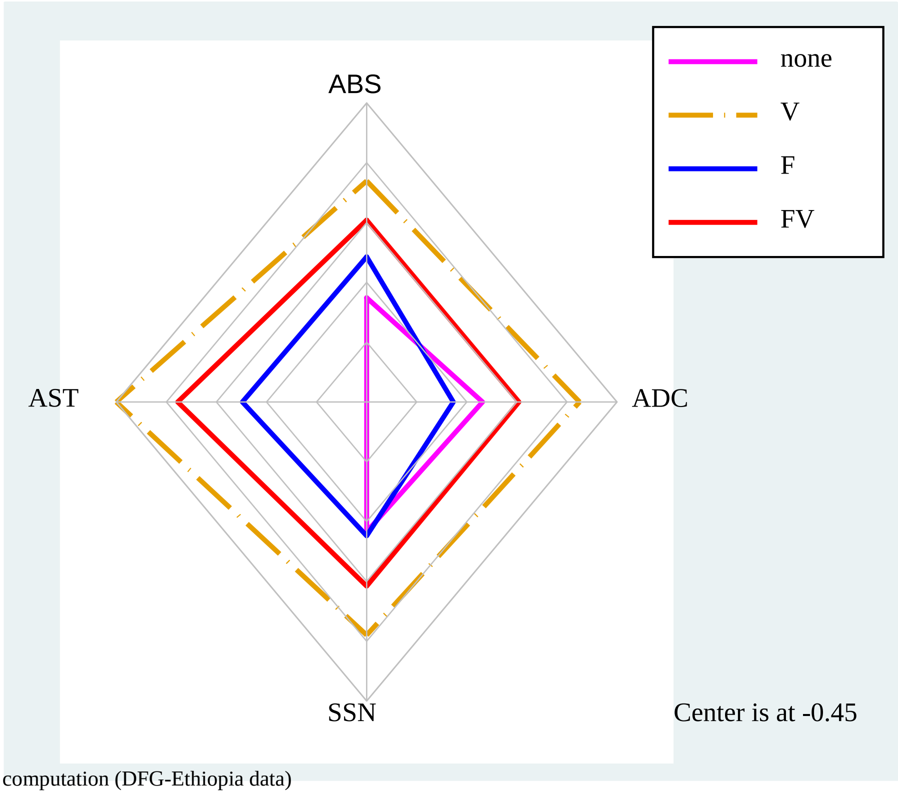
Secondly, we execute the predicted probabilities from the MNL model. Finally, we estimate the welfare equation using the GMM growth model as well as IV model by instrumenting with their lagged values of the RCI and the predicted values of adoption from the MNL model. Similarly, the two other outcome variables representing food security: food consumption and HDD are estimated using the same procedure. In this case we hypothesized that the lagged values of the RCI influences the current food security status of a household.

4 Results and Discussion

This section presents descriptive results of the outcome variables (RCI, HDD, food consumption) and the covariates both the endogenous (adoption dummies) and the exogenous variables included in the regression model. We estimated the RCI by combining the FA and SEM-MIMIC model. In the MIMIC model HDD and food consumption are considered to be influenced by the resilience capacity and are directly observable and indirectly associated with the remaining four pillars (FAO, 2018).

4.1 Descriptive Results

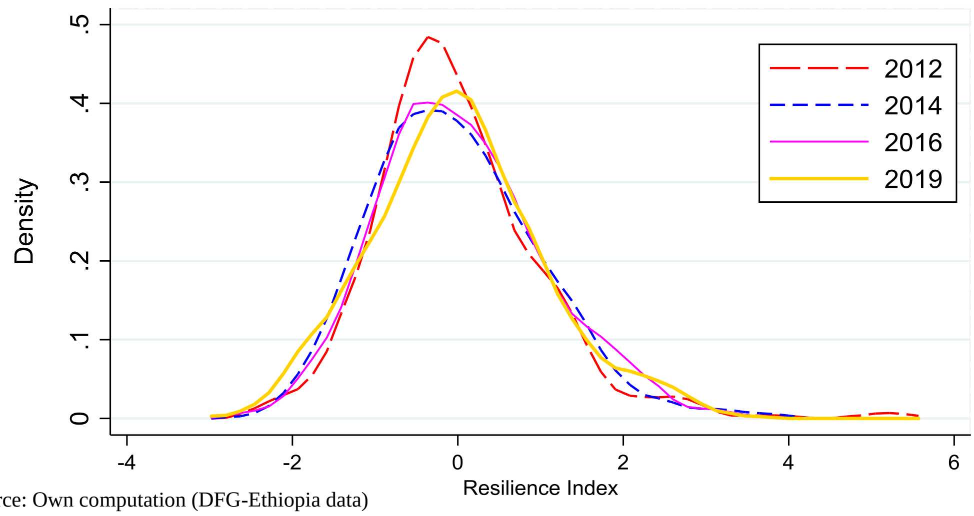
Figure 4 shows the radar graph for the resilience index and its pillars by the adoption status of households (i.e. single or joint adoption of chemical fertilizer and improved seed) including non-adopters where none of the technologies or their combinations is adopted. The analysis of the resilience score and its components for the different periods also reveals that the importance of the drivers is dynamic throughout the survey rounds. It is shown that households that adopted only improved seed appear to have the highest RCI even higher than those who adopted both technologies jointly. But this is only a descriptive result that does not necessarily show a causal link. It is shown that non-adopters scored less in all of the pillars and RCI except SSN and ADC where non-adopters have a higher score compared with the fertilizer-only adopters.



Source: Own computation (DFG-Ethiopia data)

Figure 1 Radar graph of the resilience pillars by adoption status of households

Figure 5 shows the Kernel density plot used to visualize the distribution of the resilience index over the four survey rounds. The figure shows a slight difference in the resilience distribution between the first three rounds and the last round (2019). However, there is no clear difference in the means of the resilience index between the first three rounds.



Source: Own computation (DFG-Ethiopia data)

Figure 2 Kernel density distribution of resilience index by survey (2012-2019)

The SEM-MIMIC results presented in Table 1 shows that all the five pillars are statistically significant determinants of the RCI. This table also shows that the two most important drivers of resilience capacity are asset ownership (AST) and adaptive capacity (ADC). The estimated value of RCI is unitless. Therefore, a scale is defined by constraining the food consumption variable loading (γ_1) to be 1.

Table 1 Estimation of RCI using MIMIC: coefficients of structural and measurement components

	Coeff.	**sig**	
Structural			
Assets (AST)	0.19	***	(0.02)
Access to Basic Services (ABS)	0.12	***	(0.03)
Social Safety Nets (SSN)	0.05	***	(0.014)
Adaptive Capacity (ADC)	0.06	***	(0.015)
Measurement			
Per capita food consumption expenditure (log)	1		
Household dietary diversity (HDD)	2.60	***	(.04)
$\chi 2$	**11.94**		
P-value	**0.007**		
Obesrvations	**1164**		

Table 2 presents the differences in the household characteristics by the resilience index and its pillars. The t-statistics for the pair-wise comparison among the means of the independent variables including shock categories and input combinations are also presented in this table. The pairwise comparison and the t-statistics with the technology choice sets is always compared with the non-adopters.

In terms of differences by adoption status, adopters who used at least one of the technologies have a statistically significantly higher resilience score compared to non-adopters. The same applies to the pillars where non-adopters have lower mean scores all the four pillars compared with adopters. Regarding food consumption and dietary diversity, adopters appear to have a higher mean per capita food consumption and HDD.

With regard to experience to shocks, households have no statistically significant differences in the resilience score and its pillars except in SNN score where households who did not report any shock have a higher SSN compared with those who have experienced at least one type of shocks during the study period. Specifically, there is no statistical difference in the resilience index and its pillars between households who reported drought and those who did not report. Concerning household headship, male-headed households have a higher and statistically significant resilience index compared with female-headed households. Male-headed households have higher and statistically significant scores in all of the resilience pillars but ABS compared with female-headed households. Regarding changes on the resilience score over time, we compared the mean levels of the resilience index and its score with that of the baseline (2012). The pairwise comparison shows a slight increase in the resilience index between 2012 (-0.03) to 2014 (-0.02) and in 2016 (0.04) and then dropped in 2019 (0.001). The pairwise comparison of the difference in RCI between the baseline 2012 and the last wave 2019 is not statistically significantly different from zero.

Overall, adopters of the different technology combinations including single technology adoption show a higher resilience score. However, the resilience scores more or less remains constant over time.

Table 2 Differences in household characteristics by the RCI and its building blocks

	Mean values of the RCI and its building blocks				
Variables	**RCI**	**ABS**	**AST**	**ADC**	**SSN**
F_0V_0	-0.45	-0.08	-0.46	-0.04	-0.06
F_0V_1	0.44***	0.36***	0.47***	0 .13	0.48***
F_1V_0	-0.06***	-0.04	-0.03***	-0.16*	-0.01
F_1V_1	0.26***	0.05**	0.23***	0.20***	0.12***
HHs reported shock	0.03	0.01	0.01	-0.09	-0.12
HHs reported no shock	-0.05	-0.003	0.002	0.03	0.07***
HHs reported drought	-0.01	0.11	-0.002	0.20	0.01
HHs with no drought experience	0.01	-0.01	0.03	0.01	0.01
Female headed households	-0.38	.055***	-0.26	-0.75	-0.15
Male headed households	0.07***	-0.01*	0.05***	0.14***	0.03***
2012	-0.03	-0.01	-0.03	-0.01	-0.01
2014	-0.02	-0.07	-0.14	0.08	-0.23
2016	0.04	0.02	0.01	0.01	0.32
2019	0.001	0.06	0.13	-0.10	-0.06
N					1116

Note: *, **, *** indicate significant differences at α = 0.10, α = 0.05, α = 0.01, respectively. F and V represent chemical fertilizer and improved seed respectively; subscript “0” denotes non-adoption while “1” denotes adoption.

Table 3 presents the changes in household food security indicators over the last three panel waves. Considering only the three waves, we computed proportion of households that experience a loss in the two food security indicator variables. About 38% of the sample households experienced a decline in HDD between 2014 and 2016 and a little less (35%) experienced a decline in HDD between 2016 and 2019. Out of those households who experienced a decline in HDD, 43% of them were able to recover in 2019. In terms of food consumption, the proportion of households experiencing a decline in food consumption between 2014 and 2016 is quite high (60%) compared to the proportion of households experienced decline food consumption between 2016 and 2019 (36%). Only 20% of the households were able to recover from the loss of food consumption on 2019.

Table 3 Changes in food security status between two periods

Changes in food security status		
HDD	N	%
Households experienced a decline between (2014 -2016)	149	38
Households experienced a decline between (2016-2019)	140	35
Households recovering from loss (2014 and 2019)	106	43
Per capita food consumption		
Households experienced a decline between (2014 -2016)	236	60
Households experienced a decline between (2016-2019)	143	36
Households recovering from loss (2014 and 2019)	106	28

The means and standard deviations for resilience and its building blocks by survey year is given in Table 4. As explained, the main objective of this paper is to analyze the impact of adoption and adverse shocks as well as their differential effects on the welfare outcome variables. Using the two inputs (chemical fertilizer and improved seed), four possible combinations including non-adoption where none of these technologies are adopted can be constructed. Thus, adoption is represented by four dummy variables (F_0V_0, F_0V_1, F_1V_0, F_1V_1). Shocks and Household demographics such as gender, age, household size, and dependency ratio that are not used to construct the resilience pillars are included in our regression models.

The descriptive results show that the resilience index increased in the first three rounds and then somehow dropped in the last round. On the contrary, the joint adoption of chemical fertilizer and improved seed shows an increasing trend over time (26%, 33%, 39%, and 40% in 2012, 2014, 2016, and 2019, respectively). On average, the proportion of non-adopters remains constant between 2012 and 2014 (24%) but then decreased to 16% in 2016 and again increased to 21 % in 2019. Concerning the demographic characteristics of households, the average size of the household is more or less the same (on average 6) throughout the survey rounds. The dependency ratio which is 47% and gender household head did not also change over the survey rounds. The proportion of non-adopters of the two technologies or their combinations is the same between 2012 and 2014 and constantly decreased between 2014 and 2019. The proportion of households adopting only improved seed only adopters decreased from 9% to 4% and 3% for the first three rounds and again slightly increased to 4% in the last round. On the other hand, the proportion of fertilizer only adopters which is the highest technology choice set in our sample is the same throughout the survey rounds (40%). The proportion of households adopting chemical fertilizer and improved seed variety jointly (F_1V_1) consistently increased over the four survey rounds.

The different types of shocks including drought, flooding, animal death, death of a family member, high input price and low sales price are included in the regression model. In terms of the frequency of reported shocks, more households reported adverse shocks in 2019 followed by the 2014 round. The proportion of households that reported at least one type of shock for the previous three years decreased between 2014 and 2016 (29% versus 23%) but then increased to 36% in the 2019. Out of the households who reported shocks in 2014, 2016, and 2019, on average, 2%, 11%, and 2% were affected by droughts, respectively. Moreover, a significant proportion of households 29% in 2014, 22% in 2016, and 36% in 2019 have reported flooding shocks. Households took about six months to recover to their normal welfare level. Regarding the reduction of food or regular consumption, about 19%, 13%, and 22% reduced their food consumption in 2014, 2016, and 2019 due to shocks, respectively. Likewise, 18%, 14%, and 19% of households were forced to reduce their regular consumption in 2014, 2016, and 2019, respectively.

Table 4 The descriptive statistics if the variables in the regression model

Variable	Description	2012		2014		2016		2019		Pooled	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
RCI	Resilience Capacity Index (Standardized , 0 to 1)	0.33	0.11	0.34	0.12	0.35	0.12	0.34	0.13	0.34	0.12
HDD	Household Dietary Diversity	6.88	1.4	6.51	1.7	6.50	1.7	6.67		6.64	1.6
Household size	Number of family members	6.25	2	6.4	2.2	6.5	2.3	6.4	2.3	6.4	2.3
Gender	Dummy, 1= if the household head is male	0.84		0.83		0.83		0.83		83.4	
Dependency ratio	The ratio of working to non-working hh members	0.48	0.2	0.47	0.2	0.46	0.2	0.47	0.2	0.47	0.2
Age	Age of the household head in years	45	14	46	14	49	13.7	50	14.3	47.5	14
F_0V_0	None adopters of chemical fertilizer and improved seed	0.24		0.24		0.20		0.16		0.21	
F_0V_1	Proportion of households adopted high yielding variety	0.09		0.04		0.03		0.04		0.05	
F_1V_0	Proportion of households Fertilizer and improved seed	0.40		0.38		0.38		0.39		0.39	
F_1V_1	Proportion of households adopted chemical fertilizer	0.26		0.33		0.39		0.40		0.34	
Shock exp.	HHs reported shocks past three years			0.29		0.23		0.36		0.29	
Drought	Drought experience the past three years			0.02		0.11		0.02		0.05	
Flooding	Proportion of households experienced shock			0.29		0.22		0.36		0.29	
Hailstorm	Proportion of households reporting hailstorm			0.03		0		0.02		0.01	
Yield Loss	Proportion households reported yield loss			0.05		0.002	8	0.03		0.03	
Animal death	Proportion of households reporting animal death			0.04		0.013		0.11		0.05	
Recovery months	Number of months the hh took to recover to normal			4.6	6	3	5	8	10	6	7.5
Regular Cons.	Proportion of households reduced regular consumption			0.18		0.14		0.19		0.17	
Food consumption	Proportion of households reduced food consumption			0.19		0.13		0.22		0.18	
N					**372**					**1116**	

Note: *, **, *** indicate significant differences at α = 0.10, α = 0.05, α = 0.01, respectively.

F and V refer to chemical fertilizer and improved seed, respectively; subscript “0” denotes non-adoption while “1” denotes adoption

4.2 Impact Assessment on the Resilience Capacity Index and Food Security

The assessment of the impact of technology adoption and shocks on welfare is undertaken by representing welfare by RCI, HDD, and per capita food consumption. We employed the GMM model following (Arellano & Bond, 1991) to estimate the impact of adoption and shocks on resilience growth. Furthermore, we executed the instrumental variables (IV) regression model instrumenting the technology dummies with their lagged values and the predicted probabilities of adoption from the first stage MNL adoption equation. As a robustness check for the IV model estimates, we also executed mixed Tobit model regression, but, by using only data from the last three rounds; due to the lack of shock information in the baseline survey.

Table 5 presents the GMM estimator (column 1), IV (column 2), and the mixed Tobit (column 3) model estimates. In terms of the model results, the signs of both the endogenous and exogenous variables have the expected signs and are qualitatively similar to that of the IV and mixed Tobit results. However, very few variables seem to be significant in the difference GMM consistent with the descriptive results which show a negligible change in resilience capacity over the survey rounds. The results indicate drought has a statistically significant negative impact on the household on the growth of the resilience capacity index. Family size increases the growth of the resilience score statistically significantly. It is also shown that growth in 2016 was significantly higher compared to the other survey rounds. Our findings (Column 2 of Table 4.5) show that the initial value of the resilience capacity, the technology choice sets (F_0V_1 and F_1V_1), gender of the household head, household size, age of the household head are statistically significant determinants of the resilience index. Specifically, male-headed households have a statistically significant and higher level of resilience index compared to female-headed households. Household size statistically significantly increases the RCI. A unit increase in the initial value of the RCI increases the current RCI[5] by 0.5 points. Age has a statistically significant negative impact on the resilience index. The adoption of F_0V_1 significantly leads to a higher resilience score. Overall, Our findings show initial resilience index, technology dummies (F_0V_1 and F_1V_1), gender of the head, household size, age of the household head determine resilience index significantly. Drought appears to significantly decrease the growth resilience score.

[5] In this paper the terms resilience index and resilience capacity or RCI are used interchangeably.

Table 5 Impact of adoption and shocks on resilience capacity index

Variables	**Description**	**(1) GMM**			**(2) IV**			**(3) Tobit**		
RCI_{t-1}	Initial resilience capacity	0.05		(0.07)	0.51	***	(0.05)	0.561	***	(0.02)
HH size	Number of household members	0.006	***	(0.003)	0.005	**		0.003	***	(0.002)
Gender	Sex of the household head	0.02		(0.02)	0.02	**	(0.01)	0.02	***	(0.01)
F_0V_1	Dummy=1, if HH adopted only improved seed	0.007		(0.04)	0.50	*	(0.30)	0.10	***	(0.02)
F_1V_0	Dummy=1, if HH adopted only fertilizer	0.003		(0.01)	0.04		(0.04)	0.02	**	(0.01)
F_1V_1	Dummy=1, if adopted both improved seed and chem. Fertilizer	0.002		(0.02)	0.06	**	(0.03)	0.05	***	(0.01)
Drought	Dummy=1, HH reported drought shock	-0.04	*	(0.02)	0.02		(0.05)	-0.01		(0.03)
Flood	Dummy=1, HH reported flood shock	-0.02		(0.02)	-0.01		(0.02)	-0.0004		(0.02)
Age	Age of the HH head (years)	-0.0003		(0.001)	-0.001	***	(0.00)	-0.001	***	(0.001)
Drought* F_0V_1	Interaction term drought and improved seed	-0.01		(0.06)	-0.42			-0.02		(0.05)
Drought* F_1V_0	Interaction term drought and chemical fertilizer	-0.001		(0.02)	-0.03		(0.06)	-0.01		(0.04)
Drought* F_1V_1	Interaction term drought and improved seed and fertilizer	-0.02		(0.03)	-0.01		(0.05)	-0.01		(0.04)
SNNPRs	Dummy=1, if SNNPRs region									
2016	Dummy=1, if 2016 survey round	0.01	*	(0.01)	0.015		0.01	0.020	**	
2019	Dummy=1, if 2019 survey round	0.004		(0.01)	-0.01		0.009	-.001		
R^2 or Log-likelihood					0.26					
Sample size		**1,116**			**1,116**			**746**		

Note: *, **, *** indicate significant differences at α = 0.10, α = 0.05, α = 0.01, respectively.
F and V refer to chemical fertilizer, improved seed, respectively; subscript “0” denotes non-adoption while “1” denotes adoption. In the GMM model, F_0V_1, F_1V_0 and F_1V_1 were instrumented with their lagged values and all the lagged explanatory variables included in the model.

Table 6 reports the IV regression model executed by instrumenting the resilience index and technology dummies with their lagged values (Column 1 and 3). The OLS and mixed Tobit estimates for robustness check are also presented in Columns 2 and 4. The outcome variables in these models are represented by real per capita food consumption expenditure and HDD.
As indicated in column 1, demographic characteristics of the household such as family size and gender of the household head are statistically significant determinants of consumption. The higher the household size the higher the household per capita food consumption. Regarding, technology adoption, chemical fertilizer only or improved seed only, or their joint adoption is positively and significantly related to food consumption. In terms of shocks, drought statistically and significantly decreases food consumption. This significant and negative sign confirms our hypothesis that shocks reduce household assets and production, thus reducing household food insecurity. Although, not statistically significant the interaction terms between the technology dummy and drought ($Drought*F_1V_1$) is positive indicating the role of adoption of multiple technologies in smoothing the negative impact of shocks.

Column 2 of Table 6 presents the estimates of the IV regression model on the impact of adoption and shocks HDD as the outcome variable. The results indicate that household characteristics such as gender of the household head and household size affect dietary diversity positively and significantly. The adoption of chemical fertilizer and improved seed including their joint adoption also significantly increases household dietary diversity. The interaction terms of the technology bundles and drought representing shock are not statistically significantly different from zero in this model.

Overall, the results reveal that the adoption of chemical fertilizer and improved seed including their joint adoption increases food consumption and HDD. Although the adoption of chemical fertilizer and improved seed including their joint adoption increases the resilience capacity index as well as the food security indicators, there is limited evidence on its impact in averting the adverse impacts of shocks.

Table 6 Impact of adoption and shocks on food consumption and HDD

		Food Consumption						HDD					
		(1) IV			**(2) Tobit**			**(3) IV**			**(4) Tobit**		
RCI_{t-1}											3.3	***	(0.42)
Age	Age of the HH head (years)	0.0003		(0.001)	0.0001		(0.0004)	-0.01		(0.01)	-0.01		(0.01)
Gender	Sex of the household head	0.002		(0.02)	0.01		(0.01)	0.58	**	(0.23)	0.58	***	(0.22)
Household size	Number of household members	0.01	***	(0.003)	0.01	***	(0.002)	0.10	***	(0.04)	0.11	***	(0.04)
F_0V_1	Dummy=1, HH adopted only improved seed	0.47	*	(0.25)	0.13	***	(0.03)	0.90		(0.57)	0.90	*	(0.55)
F_1V_0	Dummy=1, if HH adopted only fertilizer	0.28	**	(0.12)	0.07	***	(0.02)	0.67	*	(0.36)	0.67	*	(0.35)
F_1V_1	Dummy=1, adopted improved seed and. Fert	0.23	***	(0.08)	0.06	***	(0.02)	1.04	***	(0.35)	1.04	***	(0.33)
Hailstorm	Dummy=1, HH reported Hailstorm shock	-0.06		(0.04)				-2.66	*	(1.61)	-2.66	*	(1.55)
Yield loss	Dummy=1, HH reported yield loss shock	-0.05	*	(0.03)	-0.04		(0.05)	-0.31		(0.96)	-0.32		(0.92)
Animal death	Dummy=1, HH reported animal death shock	-0.03		(0.02)				-0.19		(0.73)	-0.18		(0.70)
Drought	Dummy=1, HH reported drought shock	-0.04	**	(0.02)	-0.03		(0.03)	-0.11		(0.57)	-0.11		(0.55)
Drought * F_0V_1	Interaction term drought and F_0V_1	-0.05		(0.06)	-0.05		(0.06)	0.59		(1.04)	0.59		(0.99)
Drought*F_1V_0	Interaction term drought and F_1V_0	-0.001		(0.04)	-0.01		(0.04)	-0.46		(0.70)	-0.45		(0.67)
Drought*F_1V_1	Interaction term drought and F_1V_1	0.02		(0.04)	0.02		(0.04)	-0.08		(0.69)	-0.08		(0.67)
R^2 or log-likelihood		**0.14**			**965**			**0.03**			**2140**		
Sample size		**1116**											

Note: *, **, *** indicate significant differences at α = 0.10, α = 0.05, α = 0.01, respectively.
F and V refer to chemical fertilizer and improved seed; subscript “0” denotes non-adoption while “1” denotes adoption.

5 Conclusion and Recommendation

Smallholder farmers in developing countries particularly in Ethiopia are disproportionately affected by natural shocks such as drought, flooding as well as several other human-induced shocks including conflict, political instability, and inflation. This often results in significant welfare deterioration since smallholders in these regions have a minimal absorptive capacity. Investment in agricultural technologies plays important role in building resilience capacity and potentially reducing food insecurity. This study uses panel data collected between 2012 and 2019 to identify the determinants of household resilience to food insecurity and assess the role of chemical fertilizer and improved seed including their joint adoption on the resilience capacity and food security of smallholders and the role these inputs may play in reducing the adverse effects of shocks.

The four resilience pillars used to construct resilience capacity appear to be significant determinants of the resilience capacity index and assets take the highest share. It is also indicated that adopters have a significantly higher resilience index compared with non-adopters. The findings also reveal that adopters and non-adopters have no significant differences in terms of their proneness to shocks. The findings reveal that joint or single use of chemical fertilizer and improved seed are significant determinates of resilience capacity index, household dietary diversity, and food consumption. Drought is negatively and statistically significantly linked with the growth of the resilience capacity index. Other variables determining household dietary diversity and consumption expenditure are household size, gender, and age of head. The results also show that the initial value of the resilience capacity index is a significant determinant of the resilience capacity index. We find that adoption has a limited role in protecting households from the adverse impacts of shocks. Based on our research findings we recommend that policy interventions should exert much effort not only in promoting technology adoption but also in building resilience accompanied by improved infrastructure for smallholders.

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Appendix

Table A1 The eigenvalues and factor loadings of the resilience pillars used to estimate the RCI

Pillars	Variable	Factor loadings	
		Factor1	Pillars' correlation with the var.
ABS	Source of light	0.50	0.30
	Type of toilet	0.42	0.27
	Distance from market	-0.66	-0.42
	Distance from agricultural extension office	-0.67	-0.42
	Source of drinking water	0.50	0.31
AST	Livestock (TLU)	0.60	0.3
	Land (ha)	0.49	0.27
	Number of rooms	0.80	0.42
	Corrugated iron roof	0.76	0.42
SSN	Iqub	0.69	0.56
	Iddir	0.52	0.43
	Mehaber	0.37	0.31
	Credit	0.56	0.46
ADC	Education	0.75	0.65
	Other income	0.72	0.62
	Irrigation	0.25	0.22

Source: Own computation from DFG-Ethiopia data

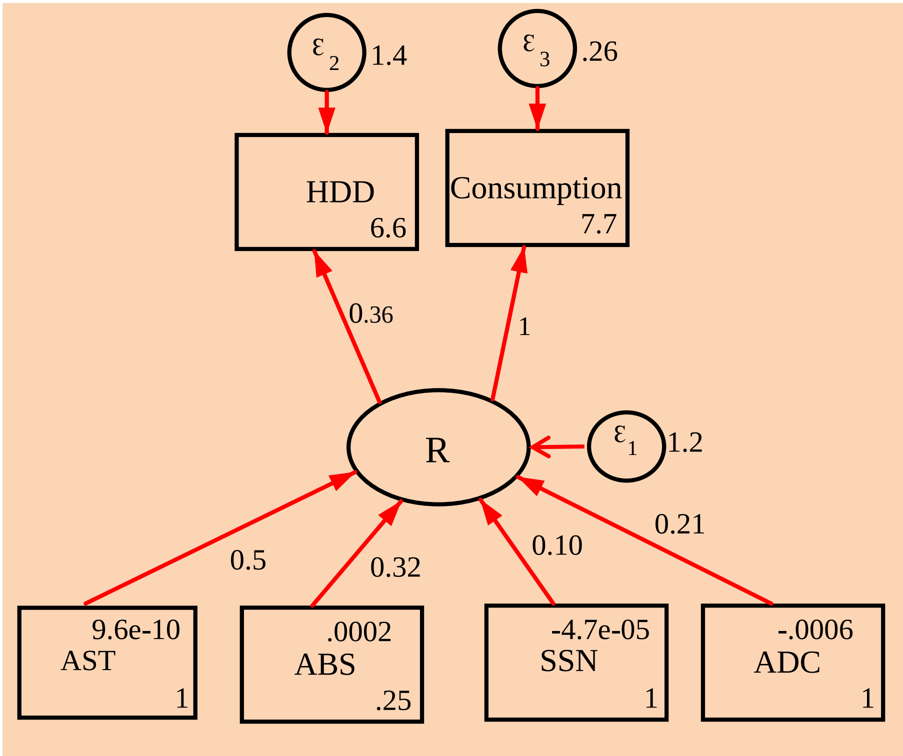

Figure A1 Resilience path diagram