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Crops in crises: Shocks shape smallholders' diversification in rural Ethiopia

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ABSTRACT

Crop diversity plays a central role in smallholder farmers' ability to cope with and adapt to shocks. Shifting crop varieties and diversifying the crop portfolio are common risk reduction strategies. This paper addresses the influence of covariate climate shocks and idiosyncratic socioeconomic shocks on crop variety use and crop species diversification by smallholder farmers using nationwide balanced panel data (2011/12, 2013/14, & 2015/16) from rural households in Ethiopia combined with village-level historical monthly rainfall and temperature data. We apply correlated random effects models, which control for time-invariant household unobservables. Past exposure to drought shocks increased the use of improved seed varieties in general and for wheat, while long-term average rainfall and lagged flood shocks enhance crop species diversity. Lagged temperature shocks increase improved seed use and crop species diversity. However, recurrent drought exposure and exposure to relatively more severe drought shocks significantly reduced overall agricultural activity. Idiosyncratic shocks, to a much lesser degree, influenced seed use and crop diversification decisions compared to covariate drought shocks. Heterogeneity analysis revealed that drought shock exposure on farmers with less than average farm sizes and other assets - compared to those better-off – increased their relative reliance on local seed use, reduced crop diversification, and reduced improved seed use. The results are robust to various sensitivity checks. Our findings are relevant for policy responses aiming to strengthen smallholders' ability to cope with and adapt to shocks: farmers' seed-based risk reduction strategies rely on access to seeds from both formal and informal seed systems, but policies addressing economic inequality are needed to enhance access to improved seeds and crop diversity for resource-poor socioeconomic groups.

1. Introduction

Seeds are essential assets in smallholder farmers' portfolio of coping and adaptation strategies during periods of environmental and socioeconomic stress. With access to a wide variety of seeds, farmers can choose crop varieties suited to local conditions. Farmers may also diversify their portfolios and reduce production risk by growing a broader range of local and improved crop varieties. Therefore, access to seed is considered an essential aspect of seed, food, and livelihood security in the wake of both acute and chronic stress situations (Bezner, 2022; Howden et al., 2007; McGuire & Sperling, 2013; Mortimore & Adams, 2001; Sperling, 2020).

Livelihoods in Sub-Saharan Africa are vulnerable to both covariate and idiosyncratic shocks. Covariate shocks universally affect many households living in the same geographic location (e.g., climate shocks and epidemics), while idiosyncratic shocks affect specific households and one household's experience is not related to the experience of neighboring households, such as illness, death, or loss in employment (Dercon 2004, 2005; Pradhan & Mukherjee, 2018). Agriculture is a key pillar in rural livelihoods, and exposure to both types of shocks are common and affects access to agricultural inputs and thereby coping and adaptation strategies. For instance, the COVID-19 pandemic has disrupted access to key inputs by farmers (including seed) and increased logistical, administrative, and transaction costs for farmers (Sperling, 2020). The pandemic has thus added to already struggling agri-food systems in the region. Understanding how farmers cope and adapt to shocks is important to develop evidence-based policy responses to improve their seed, food, and livelihood security.

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A meta-study for the Intergovernmental Panel on Climate Change Assessment Report (IPPC AR5) tested the relative adaptation effect of a range of on-farm adaption measures and found cultivar adjustment to be one of the most effective methods (Challinor et al., 2014; IPCC 2014). The most recent IPCC report (AR6) furthermore emphasizes the adaptation potential in crop diversification (IPCC 2022). Other studies have found greater crop diversity to be associated with enhanced livelihood outcomes, including higher temporal food production stability at both the household (Asfaw, Scognamillo, Caprera, Sitko, & Ignaciuk, 2019; Bozzola & Smale, 2020; Di Falco, Bezabih, & Yesuf, 2010; Makate, Wang, Makate, & Mango, 2016; Mulwa & Visser, 2020) and national levels (Renard & Tilman, 2019). However, for such crop-based adaptation methods to be effective, farmers need to be seed secure.

Seed security entails that farmers have access to quality seeds of well-adapted varieties that meet their needs and preferences (FAO 2018; Sperling, 2020). Farmers access seeds through seed systems, which encompass the chains of actors, institutions and activities involved in the development, distribution, and use of seeds (Almekinders, Louwaars, & De Bruijn, 1994; Sperling, Cooper, & Remington, 2008). In developing countries, the formal seed system delivering seeds of improved varieties released by plant breeders and certified by seed inspection authorities supplies only a small share of the total volume of seeds used while informal sources such as seed saving from own harvest, sourcing through social networks and local markets supply the bulk of seeds used (Louwaars & de Boef, 2012). Thus, crop-based adaptation to climate change relies on well-adapted varieties (technology) as well as well-functioning seed systems (institutions).

The uptake of improved varieties' remains low in many parts of SSA, although it has increased over time (Sheahan & Barrett, 2017). In their review of adoption studies Acevedo et al. (2020) have shown that unavailability of improved seeds, inadequate information, lack of complementary farming inputs, and high seed prices are common barriers to adoption of climate-resilient crops. Moreover, farmer preferences for traits not present in modern varieties could explain some of the low adoption rates (Fisher et al., 2015), but adoption studies rarely explore the reason for growing other varieties than the improved ones. This is a research gap since improved varieties, and formal seed systems supply only a small share of the seeds used by smallholders in developing countries (Coomes et al., 2015). The study of local crop varieties (i.e., varieties of local origin, selected by farmers) has typically been the domain of a branch within crop science. This literature on genetic resources and seed systems has shown that local varieties sourced through informal seed systems play a role in the coping behavior and adaptation to various stressors (Abay, Waters-Bayer, & Bjørnstad, 2008; Mekbib, 2007) and that farmers often mix local and improved varieties to serve different needs and to minimize risks in their households (Bellon & Hellin, 2011; Westengen, Ring, Berg, & Brysting, 2014). There is thus a need for more knowledge about how smallholder farmers' seed use, including seeds of both local and improved varieties, is influenced by shocks.

Smallholder farmers may respond to shocks by diversifying their livelihood strategies both on– and off-farm (Asfaw et al., 2019; Morton, 2007; Mulwa & Visser, 2020). In a risky context with imperfect input and output (food) markets, it is assumed that low-income families can minimize their exposure to future shocks by diversifying their activities and growing enough food for subsistence (Fafchamps, 1992; Kurosaki & Fafchamps, 2002). Economic theories that study farmer behavior under risk, such the state-contingent theory of adaptation by Chambers and Quiggin (2000) are useful for explaining farmers' responses to previous shock exposure. The state-contingent theory of adaptation assumes that farming households make production decisions to maximize anticipated utility of returns in different states of nature, e.g., states with and without climate shocks (Holden & Quiggin, 2017). Therefore, production risks and shocks, farmers' perceptions of those risks based on shock experiences as well as risk preferences, influence farming decisions. Emerging studies that incorporate climate shocks and risk attitudes and behavior have shown that lagged climate shock exposure leads to higher uptake of improved (drought-tolerant) varieties, and more so by more risk-averse farmers (Holden & Quiggin, 2017; Katengeza, Holden, & Lunduka, 2019). Employing the state-contingent theory of adaptation, this study evaluates the influence of lagged shock exposure on variety use and crop diversification practices in rural Ethiopia. We analyze a panel data set compiled from three rounds (2011/12, 2013/14, and 2015/16) of the Living Standards Measurement Study-Integrated surveys on Agriculture (LSMS-ISA) for Ethiopia. More specifically, this study aims to answer the following research questions: (i) How does exposure to covariate and idiosyncratic shocks influence the types of seeds used by farmers and the extent of crop diversification? (ii) How does household diversity in asset wealth endowments, land size holding, and access to social safety nets mediate the influence of covariate shock exposure on seed use and diversification decisions in rural Ethiopia?

The rest of the article is organized as follows. Section 2 briefly discusses the Ethiopian context, while section 3 lays out the conceptual framework. Section 4 describes the methodology and presents descriptive statistics. Section 5 presents the results, while section 6 discusses them. Section 7 concludes and presents policy implications.

2. The Ethiopian context

Agriculture is a key source of employment and income in low and middle-income countries, including Ethiopia. Due to environmental and cultural diversity and heterogeneity, Ethiopia is the centre of origin and diversity of various food crops, and farmers also today grow multiple crops for both consumption and commercial purposes (Dessie, Abate, Mekie, & Liyew, 2019). Food production is dominated by smallholders, as they cultivate approximately 96 % of the total area devoted to food production (Taffesse, Dorosh, & Gemessa, 2012). There are two main rainy seasons (Meher and Belg) and hence two cropping seasons. The Meher season is the most important season for crop production, with more than 90 % of total cereal production. Five major cereal crops are at the core of Ethiopia's agriculture and food production economy: teff, maize, sorghum, wheat and barley.

The current Ethiopian seed policy promotes an integrated seed sector development that recognizes the complementarity between the country's different seed systems (MoA 2019). The national seed policy and Pluralistic Seed System Development Strategy, (released in 2013 and adopted in 2017) (MoA and ATA 2017), provides the legal basis for the co-existence of formal and informal seed systems. It also includes provisions to support interventions in both formal and informal systems and promote an emerging 'intermediate' system. The intermediate seed system has grown considerably under the new strategy and includes Seed Producer Cooperatives (SPC) producing Quality Declared Seeds (QDS) of improved varieties (Sisay, Verhees, & van Trijp, 2017). Informal seed systems provide the bulk of the seeds used by farmers in the country (Thijssen, Bishaw, Beshir, De Boef, & (eds)., 2008), but for some crops, including vegetable seeds, hybrid maize and wheat, the formal system supplies a significant share of the certified seeds of improved varieties (Alemu & Bishaw, 2015; Erenstein & Kassie, 2018).

Ethiopia, as with many developing regions is not spared for recurrent shock exposure. Common shocks in history include covariate weather shocks (drought, flood, and other weather shocks), covariate economic shocks (price shocks in input and output markets), conflicts, and idiosyncratic shocks such as illness, death, family break-ups, loss of formal employment, loss of livestock to theft and predation (Dercon, 2004; Porter, 2012). Several shocks have been experienced in different parts of Ethiopia for the study period (2011–2016) and afterward. According to the International disaster database (EM-DATA[1]), major recent shocks include: a major drought of 2011 which was experienced in most parts of the country (e.g., Dire Dawa, Gambela, Harari, Oromia, SNNP, Somali and Addis Ababa) and affected approx. 1 million people; the El Nino drought of 2015/2016 seasons (experienced in Afar, Somali, Oromia, Amhara, and SNNP) which affected about 10.2 million people; flash floods (in Wolayita district in SNNP region, and Bale district in Oromia region) which affected close to half a million people in 2016. More recent examples include the locust outbreak which started in November 2019 (experienced in Afar, Amhara, Oromia, Somali, Tigray regions), the ongoing Covid-19 pandemic, and the civil war (since November 2020).

Both covariate and idiosyncratic shocks affect livelihoods and are usually linked to a reduction in assets, fall in incomes, and a significant reduction in consumption. However, smallholder farming households usually find it easier to cope with idiosyncratic household shocks than to covariate weather shocks (Dercon, 2005; Nguyen, Nguyen, & Grote, 2020).

Since 2005, there has been growing political momentum around social protection and cushioning of the most vulnerable from the impacts of shocks in Ethiopia. Safety net programs such as the Productive Safety Net Program (PSNP) introduced in 2005 have been very important for household food security, in particular in areas with chronic food insecurity. These programs represent the main source of insurance against shocks and household food insecurity and include food-for-work, cash-for-work, and free food distribution outside the main growing season for eligible households and communities. The PSNP program was designed to serve three main purposes: (a) smoothing food consumption for the poor and food-insecure through food or cash transfer during periods of stress, (b) cushioning household asset depletion due to shocks and other socioeconomic stressors, and (c) building community assets using the public works component (food or cash-for-work) that has been focused on building village and feeder roads(Debela, Shively, & Holden, 2021; Dejene & Cochrane, 2021).

Moreover, until recently economic progress in Ethiopia has reduced poverty and enhanced resilience to shocks. High economic growth, combined with continued population growth, has resulted in a rapid rural transformation process in Ethiopia, with fast-growing rural towns and larger cities and diversification of the economy (Bezu & Holden, 2014; Holden & Tilahun, 2020; Masters et al., 2013). Also, farm sizes have reduced over time, resulting in agriculture intensification (Masters et al., 2013).

3. Conceptual framework

Farmers' seed-related adoption decisions under risk may be analyzed within the state-contingent framework of Chambers and Quiggin (2000). Within this framework, smallholder farmers make input decisions before weather conditions are revealed. Production decisions under uncertainty are made to maximize average utility of returns in different states of nature (Holden & Quiggin, 2017). We assume that the vulnerability of households is closely associated with their resource poverty. Their most important resources are their availability of land and labor endowments relative to their consumption needs. Land- and labor-poor households are therefore assumed to be more vulnerable to shocks. We also assume that it is more difficult to use social networks to protect oneself against covariate shocks than against idiosyncratic shocks, making interventions such as the safety net programs more important as protection against covariate shocks such as droughts. Furthermore, drought shocks have direct effects on the performance of the crops and varieties grown and on market prices and the availability of essential commodities. Improved varieties may or may not perform better than the local varieties in different environments and under different states of nature.

Shocks may alter the household's farming activities in heterogeneous ways. The literature distinguishes between *ex-post* risk coping mechanisms (what farmers do after exposure to shocks) and what they do before exposure (*ex-ante* risk management) (Angelsen & Dokken, 2018). Characteristics of the rural settings such as over-reliance on agriculture, lack of functional insurance markets, and the dire consequences of a bad season (Dercon, 2005; Rose, 2001) complicate both *ex-post* and *ex-ante* response to shocks. Households may switch from selling food in years with good rainfall and becoming net buyers in years with poor rainfall. Covariate risk implies that such rainfall shocks occur simultaneously to households in large geographical areas with the consequence that most of them are net sellers in good years, and most are net buyers of food in bad years. Therefore, poor market integration leads to low food prices when they are net sellers and high food prices when they are net buyers. Holden and Shiferaw (2004) found that the indirect price effects were stronger than the direct production loss effects of such shocks in Ethiopia. Households may resort to the selling of livestock and assets as a coping mechanism after shock exposure and, they may engage in the diversification of income portfolios to prepare themselves for future shocks (Dercon & Christiaensen, 2011; Dercon, 2005). For instance, Gebregziabher and Holden (2011) found that in Tigray, Ethiopia, when households exhaust selling their assets, they distress rent out their land after shock exposure to get urgent cash. Gebru, Holden, and Alfnes (2021) used household panel data to study the adoption of improved wheat and drought-tolerant teff in northern Ethiopia and found that higher rainfall in the previous year was associated with more adoption of drought-tolerant teff.

This paper focuses on understanding smallholder farmers' behavioral responses in their seed use decisions to climate variables, particularly previous shock exposure. Different crop varieties may perform differently with and without shocks, and farmers exposed to shocks are likely to discover and learn the different benefits associated with different varieties. We consider long-term climate variables, lagged idiosyncratic and covariate shocks as our main test variables.

We, however, take cognizant that the behavior of farmers and their preferences will be related to resource endowments (wealth, education) and other household characteristics. Therefore, we control for household resource endowments, such as household tropical livestock units, farm size, access to productive safety nets, and asset wealth. We also control household characteristics, such as the number of literate household members, household dependency ratio, age, gender, and marital status of the household head.

Following the literature on agricultural household modelling (De Janvry, Fafchamps, and Sadoulet (1991)), sustainable livelihoods literature (Ellis, 2000) and the agricultural adoption literature (Acevedo et al., 2020; Takahashi, Muraoka, & Otsuka, 2020), farmer's decisions to choose a given farming practice or technology also market-related factors. For instance, responding to market imperfections and failure (resulting in large price bans between selling and purchasing prices), farmers may grow a combination

[1] The EM-Data is a global database on natural and technological disasters(shock s), capturing the occurrence of disasters in the world from 1900 to the present. The EM-DAT is maintained by the Centre for Research on the Epidemiology of Disasters (CRED) at the School of Public Health of the Université catholique de Louvain located in Brussels, Belgium. The data is accessible online via the following link(https://www.emdat.be/).

of varieties or diversify crop production to cover the household's consumption needs (Alobo Loison, 2015). Hence, we control for variables that proxy market access, including distance to markets and distance to nearest paved road.

The impact of shocks is likely to be heterogeneous on farmers with different vulnerability levels, which possibly shape 'farmers' responses to seed variety use and diversification decisions. Poorer farmers (farmers less endowed with assets) and farming households who lack formal insurance options tend to be more vulnerable to shock exposure (Dercon & Christiaensen, 2011; Dercon, 2005). The behavioral impact of shocks on disadvantaged households often takes the form of adopting low-risk activities as risk management strategies at the expense of lower mean returns and incomes. To test for heterogeneity in the behavioral response to shocks, we also test the effect of interaction effects. We consider (i) land size inequality, (ii) access to social safety nets, and (iii) asset wealth inequality in assessing conditioned impacts of drought shocks. This study, therefore, seeks to answer the research questions by testing the following hypotheses:

First, we hypothesize that past exposure to adverse rainfall shocks increases the use of improved seeds and crop diversification through both push and pull factors. Past exposure to rainfall shocks can affect households' ability to produce and save their own seed, thus acting as a push factor increasing their propensity to access improved seed through the formal seed systems and/or diversify the crop portfolio in the following year. On the other hand, past exposure to drought shocks may also promote learning on the performance of varieties hence pulling them towards improved varieties and more diverse cropping to adapt farming to future shock exposure.

*Second, we hypothesize that farmers in disadvantaged positions (*e.g., *the poor) to a lesser degree than better-off farmers use improved varieties and/or diversify their cropping portfolio post-exposure*. Farmers in disadvantaged positions (i.e., those with poor assent endowments) and those without access to formal insurance options are more vulnerable to shock exposure (Dercon & Christiaensen, 2011; Dercon, 2005).. Hence, we expect poorer farmers to be more likely to be pushed towards less costly crop use options (e.g., use of local seeds) as *ex-post* risk management strategies.

4. Data and methods

4.1. Data

The study uses of a rich panel data set from three rounds of the Ethiopian Socioeconomic Survey (ESS) combined with monthly weather data (rainfall and temperature) for the period 1980 to 2017. The ESS is administered by the Ethiopian Central Statistical Agency in collaboration with the World Bank's Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) project. Three-panel rounds of the data for Ethiopia are publicly available on the World Bank website.[2] We construct a three-year balanced household panel of 2 398 rural households interviewed successively in three-panel rounds (2011/12, 2013/14, 2015/16). The three-year household panel for Ethiopia started with 3 969 households, of which 3 466 (87 %) were rural in 2011/12. We trace rural households successively interviewed in all three rounds, with consistent household identification information, and usable data on agricultural activities, including seed use information to construct a balanced panel. The ESS data is representative at the national and regional level for rural areas and the four largest regions in Ethiopia: Oromia, Amhara, Tigray and Southern Nations, Nationalities, and People's Region (SNNP) (Aguilar, Carranza, Goldstein, Kilic, & Oseni, 2015).

The historical climate data are from WorldClim (Fick & Hijmans, 2017; Masarie & Tans, 1995), and were used to define historical rainfall and temperature variables and lagged shock variables. We link survey data with historical climate data by using geo-referenced data available at the Enumeration Area (EA) level, which is the smallest sampling unit (the village) for LSMS-ISA data. Further details on LSMS-ISA data descriptions and on how we processed weather data, generated lagged shock variables, and merged it with household-level data are given as part of the Supplementary material (appendix).

4.2. Model and variable specification

We model the farmers' decisions to select and or adopt crop varieties and diversify cropping portfolios using limited dependent variable models (Wooldridge, 2010). We assume the farmer aims to maximize overall welfare from their decisions, which implies that they choose seed type and farming practices that maximize anticipated utility or minimize production risks subject to constraints. Farmers' seed and diversification decisions are based on several factors as given in the conceptual framework and these may include weather expectations for that season, resources available, and characteristics of the farming technology or practice (Ding, Schoengold, & Tadesse, 2009; Katengeza, Holden, & Lunduka, 2019). To evaluate the impact of shock exposure on farming household's seed use decisions and diversification, we, therefore, apply appropriate limited dependent variable models within the Correlated Random Effects (CRE) approach, which controls for time-invariant household unobservables in a similar way as household fixed effects do when continuous dependent variables are used (Wooldridge, 2019). For seed use (dummies) and intensity of use (quantities), we use CRE logit and Tobit models, while for crop count and Simpson indices of crop diversification we use CRE Poisson and Tobit models respectively. We share more details on the CRE approach including its merits in the next section (Model estimation and justification).

Farmers' decisions to use improved or local seed are modeled, first as binary decision variables, and second as a censored outcome variable measuring the intensity of use as shown in Equations (1) and (2).

Binary decision variables (logit model):

$$P(Q_{it} = 1|C_{vt}, S_{it}, H_{it}, YR_t, \sigma_i) = \mathrm{F}(\theta_0 + \theta_1 C_{vt} + \theta_2 S_{it} + \theta_3 H_{it} + \theta_4 YR_t + \sigma_i + \varepsilon_{it}), \tag{1}$$

Censored outcome variables (Tobit model):

$$Q_{it} = \max(0, \gamma_0 + \gamma_1 C_{vt} + \gamma_2 S_{it} + \gamma_3 H_{it} + \gamma_4 YR_t + \sigma_i + \epsilon_{it}) \tag{2}$$

Count outcome variables (Poisson model):

$$E(Q_{it}|C_{vt}, S_{it}, H_{it}, YR_t, \sigma_i) = \sigma_i \exp(\beta_0 + \beta_1 C_{vt} + \beta_2 S_{it} + \beta_3 H_{it} + \beta_4 YR_t + \sigma_i + \varrho_{it}) \tag{3}$$

For seed use type decisions, Q_{it} is the dependent variable and represents different values for the use and intensity of use decisions. In the first stage, seed use estimation (use decision) Q_{it} is a dummy variable equal to one if household i used improved (local) seed in year t, and zero otherwise. This practice is done in general for all crops (improved seed and local seed) and specifically for maize and wheat, which are important cereal crops in the Ethiopian basket of food crops (Rashid & Minot, 2010). For the intensity of local and improved seed use, Q_{it} is measured as the quantity of local and improved seed used by the household (self-reported),

[2] The data sets are publicly available on https://surveys.worldbank.org/lsms.

respectively. Seed use intensity variables are all log-transformed to reduce heteroscedasticity and make our data more normally distributed.

For crop diversification, we use the count and the Simpson indices of diversity and model the respective crop outcome variables as shown in equations (2) and (3). The crop count index measures the number of cultivated crops (richness), and it is based on the assumption that all crops contribute equally to the household crop portfolio, which is not often the case (Tesfaye & Tirivayi, 2020). The Simpson index overcomes the weaknesses of the count index as it measures not only richness but the relative abundance of each species (evenness).

C_{vt}, and S_{it} are respectively, vectors of covariate and idiosyncratic shock variables. In the vector of idiosyncratic shocks (S_{it}), we include major loss of livestock and loss of formal employment by a household member in the recent past. In the vector (C_{vt}), we include objective measures of covariate climate shocks. We follow related studies, for example Katengeza, Holden, & Lunduka (2019),[3] and measure one and two-year lag measures of climate shock exposure in the *Meher* season. The *Meher* season is the most important season for agricultural production, with more than 90 % of total cereal production in Ethiopia (Taffesse et al., 2012). We follow studies by Michler, Baylis, Arends-Kuenning, and Mazvimavi (2019), and Ward and Shively (2015) and define temperature and rainfall shocks as normalized deviations in a single season's climate variable (rainfall and temperature) from the expected seasonal climate variable, as defined by its historical average. We define rainfall and temperature shocks accordingly as follows:

a) $Rainshock_{vt} = \left[\frac{rain_{vt} - \bar{rain}_v}{\sigma_{rain_v}}\right]$, where $Rainshock_{vt}$ is a rainfall shock measure for a cluster(village) (v), in the year (t), and $rain_{vt}$ is the observed amount of rainfall for the defined period (season), $\bar{rain}_v$ is the average seasonal rainfall for the village(v) over the 38 years (1980–2017), and, σ_{rain_v} is the standard deviation of rainfall during the same period.

We follow the same approach and define temperature shocks as follows:

b) $Tempshock_{vt} = \left[\frac{temp_{vt} - \bar{temp}_v}{\sigma_{temp_v}}\right]$b), where $Tempshock_{vt}$ is a temperature shock measure for a cluster (village) (v), in the year (t), and $temp_{vt}$ is the observed temperature for the defined period (season), $\bar{temp}_v$ is the average seasonal temperature for the village(v) over the 38 years (1980–2017), and, σ_{temp_v} is the village-level standard deviation of temperature during the same period.

These two measures are symmetric in the way that higher than normal rainfall or temperature having have the same effects – just with the opposite sign - as lower rainfall or temperature. Given our interest in testing for the influence of drought shocks (negative Z-scores) we split the rainfall shock variable in (a) into positive and negative rainfall deviations (Z-scores) and term the negative Z-scores drought shock. Our measure of drought shock is hence defined and split as follows:

c)

$$Droughtshock_{vt} = \left\{ \left[\frac{rain_{vt} - \bar{rain}_v}{\sigma_{rain_v}}\right] \textit{ if } rain_{vt} < \bar{rain}_v, \textit{ and } 0 \textit{ otherwise} \right.c),$$

where σ_{rain_v} is the village-level standard deviation of the cumulative rainfall for the months May-September over the 38-year period from 1980 to 2017. The resultant drought shock will have negative rainfall Z-scores ranging from - x to 0 and is summarized in Figure 2. To facilitate direct and more intuitive interpretations of results on the influence of drought shocks (negative Z-scores) on seed use and diversification decisions, in all our regressions we take the absolute value of the negative drought shocks measured as Z-scores. For all the shock measures in (a, b, and c), we measure 1 and 2-year lags from the reference season. We specifically define all the climate variables for two periods: the *Meher* season and the early season of the *Meher* season (May to July). We use the latter to test for early season shocks in our regressions, given that such shocks can have more drastic effects on crop production (Elagib, 2015). We first test for the effects of general temperature and rainfall shock variables, and then we specifically test for drought shocks.

We merge shock variables to household data based on the year (reference season) in which agricultural data for households was collected. We also include the historical mean of rainfall and temperature (1981–2017) of the early season for the *Meher* season in all our regressions. We include temperature variables in our regression to avoid potential omitted variable bias if we exclude temperature, given that crop production responds both to rainfall and temperature. The vectors for covariate shocks (C_{vt})(rainfall and temperature shocks) and idiosyncratic shocks (S_{it}) (losing livestock & formal employment) represent our key "treatment" variables in a natural experiment approach. Hence, we treat them as exogenous variables and discuss their impacts rather than only assess their correlations with seed use and diversification decisions.

We control for other household socioeconomic variables (H_{it}) in our seed use and diversification equations, including household wealth variables (e.g., agricultural asset index[4] and farm size), human capital variables (e.g., education), access to social safety nets (e.g., Productive Safety Net (PNSP) program), and other field related characteristics. We control for additional covariates mainly as a robustness check to our main findings. The vector YR_t represents year dummies, and the year 2011/12 is used as the reference. Finally, σ_i, captures individual household time-invariant effect while $\varepsilon_{it}, \epsilon_{it}$, and ϱ_{it} are the idiosyncratic error terms.

4.3. Model estimation and justification

Parameters in equations (1), 2, and 3 are estimated using the correlated random effects (CRE) model, as proposed by Mundlak (1978) and Chamberlain (1984). In line with the CRE approach, we assume that the unobserved heterogeneity can be replaced with its linear projection onto the time averages of all household level regressors (Chamberlain, 1982; Mundlak, 1978). Hence, in estimating equations (1), 2, and 3, we add the means (across years) of variables in the vector of socioeconomic variables (H_{it}) as additional controls. The CRE approach is preferred over the traditional random effects (RE) model because it relaxes the stringent exogeneity assumption of the RE approach by allowing an arbitrary correlation between the unobserved effect or household-specific heterogeneity (σ_i) and the explanatory variables. CRE also avoids the incidental parameters problems associated with fixed effects in models with limited dependent variables (Wooldridge, 2019). As highlighted in Wooldridge (2010), the CRE can be applied to commonly used models, such as unobserved effects probit, Tobit,

[3] Katengeza et al. (2019b) uses the state-contingent theory to explain decision-situations and decisions in such recursive models and how risk and risk perceptions influence decisions.

[4] To come up with the household asset wealth index, we combine information on household ownership of durable non-land assets (e.g., agricultural equipment and machinery) captured in Ethiopia LSMS-ISA data to create the household asset wealth index, using Principal Components Analysis(PCA) (Filmer & Pritchett, 2001).

and count models (Wooldridge 2010, 2019). Average Partial Effects (APEs) are presented to help interpret the economic and not just the statistical significance of variables.

This study, therefore, models the binary use decisions (i.e., use of local seed variety and improved seed varieties for all crops and specifically for maize and wheat), using a CRE logit estimator and report odds ratios. The decision on seed use intensity (amount of local or improved seed used per household) is modeled using a CRE Tobit estimator to account for those who do not use the seed variety. We run separate regressions for the two crop diversification indices. For crop count (richness), CRE Poisson regression is used,[5] while for the Simpson index, a CRE Tobit estimator is used to account for left censoring on the index.[6] In running our model specifications, we first estimate simple models where we control only for the test variables of interest (S_{it}, C_{vt}), and then secondly, we add additional controls as a robustness check.

4.4. Heterogeneity analysis

There is heterogeneity in Ethiopia in agro-ecological conditions and cropping patterns (Beyene, Gibbon, & Haile, 2006). More so, farming households are diverse in resource endowments (land labor and capital) and access to markets, government support, and other institutional services. We, therefore, assess the conditioned impacts of shocks. We do this by using interaction terms of covariate drought shock variables and indicator variables for (i) low agricultural asset endowments (elaborated below), (ii) households with less than average land size holdings (elaborated below), and (iii) households with access to social safety nets. We define low asset wealth (farm size) endowments as dummy variables (1 = yes) for households in the bottom 40 % of the sample asset wealth index (farm size) distribution. We start by defining five quintile categories (1 (=lowest), to 5 (highest)) for each variable (asset wealth and farm size), and then assign one to households with quintile categories 1 and 2, and 0 otherwise. Our indicator variables hence measure relative household asset endowments. The model specification involving interaction terms takes the following form:

$$Q_{it} = \eta_0 + \eta_{1*}(C_{vt} \times Div\_int) + \eta_2 S_{it} + \eta_3 H_{it} + \eta_4 YR_t + \sigma_i + \mu_{it} \quad (4)$$

where $(C_{vt} \times Div\_int)$ is the interaction between the covariate shock variable and the indicator variable for relevant household characteristics described prior. We test for interaction effects in all our dependent variables (seed use and intensity, and crop diversification indices). η_{1*} is the vector of coefficients linked to interaction terms between indicators of socioeconomic diversity and covariate shock exposure. We consider covariate drought shocks (lagged drought shock variables) only in the analysis of interaction effects. The interaction effects of shock exposure and household diversity indicators are performed in three separate equations (one for each indicator variable). However, we take cognizant of the fact that access to safety nets is non-random. Hence, our results on the interaction effects of rainfall shock exposure and access to safety nets should be interpreted cautiously. As much as we can control for the unobserved heterogeneity at the household level for a set of time-varying household socioeconomic variables (H_{it}), we cannot fully account for unobserved time-varying characteristics at the household level, which are potentially correlated with the allocation or access to productive safety nets.

[5] An alternative to model count data would be the negative binomial model, however, the Poisson model is used because it is robust to both over and under dispersion which is not the case with the negative binomial model. The negative binomial model is robust only with over-dispersion (Gardner, Mulvey, & Shaw, 1995).

[6] About 6% of farmers in the pooled sample had zero (0) values for diversification for the Simpson crop diversification index.

4.5. Robustness checks

We explore the robustness of our results by: (i) controlling for additional covariates (in addition to key test variables), (ii) using alternative econometric estimation methods, (iii) using a different weather data source, and (iv) testing and controlling for possible attrition bias.

We run our main results with and without additional controls. To assess the consistency of the primary study outcomes, we also apply the conditional mixed process (CMP) framework proposed by Roodman (2011). The underlying rationale is that we often want to jointly estimate two or more equations with linkages among their error terms. For instance, equations for local and improved seed varietal use could have correlated errors, as farmers can use both local and improved varieties as complementary strategies. Also, seed use decisions and the decision to diversify could have correlated error terms as the use of different crop varieties relates to diversification. The CMP adopted here is based on Zellner (1962) concept of the seemingly unrelated regression (SUR) estimator. Its main advantage is that if there are meaningful correlations between error processes of individual equations for seed use decisions, SUR estimates take account of these correlations and yield more efficient estimates than those derived from single equations. We also estimate seed use and intensity decisions in alternative CRE Craggit Double Hurdle models[7] (Cragg, 1971), and crop count and Simpson indices of diversification using CRE negative binomial, and CRE fractional probit models[8] (Wooldridge, 2010) as robustness analyses.

Besides, we also reproduce our main tables using a different weather data source. It may be possible that properties of weather data may drive results used, such as the selection of weather stations, bias correction methods used, spatial resolutions of data, imputation of missing data, among other factors (Auffhammer, Hsiang, Schlenker, & Sobel, 2013; Letta, Montalbano, & Tol, 2018). For robustness analysis, we use data from NASA's Modern-Era Retrospective analysis for Research and Applications, version 2 (MERRA-2) (Gelaro et al., 2017), to define weather variables and shocks.

Lastly, we also check the robustness of our main results to possible attrition bias in the analyzed panel. First, we estimate an attrition probit model with a dummy dependent variable for households not observed in the follow-up survey 2013/14, using household characteristics at baseline as explanatory variables. Second, we construct an Inverse Mills Ratio (IMR) from the attrition Probit models. Third, following the procedure of the Heckman model, we use the constructed IMR to test and control for the potential attrition bias effect by including it as an additional explanatory variable in our correlated random effect models. Adjusting for attrition bias in all our equations does not alter our main conclusions, showing that our findings are robust to attrition bias.

We present results from the various robustness checks in the Supplementary material (Table B-W).

[7] Craggit Double Hurdle (DH) models are used as an alternative modelling framework for seed use decisions (use and intensity). In the DH models the first hurdle involves estimating a probit model that determines the probability that the farming household uses a certain seed type (1=yes; 0= no), while the second hurdle involves estimating a truncated regression model to determine the intensity of seed use.

[8] Given that the Simpson Index (SI) can be read as fractions, defined, and observed only on an interval scale of $0 \leq SI \leq 1$, we can also model the SI index of crop diversification, using a fractional probit estimator (Papke & Wooldridge, 2008). We hence implement the CRE fractional probit models as an alternative to CRE Tobit model of crop diversification using the Simpson index. Fractional regression models such as the fractional probit implement quasi-maximum likelihood estimators to constrain the predicted value between zero and one (Papke & Wooldridge, 2008; Wooldridge, 2011).

5. Potential study limitations

Our study's approach is not without limitations. First, we rely on self-reported data on household cropping activities, including the classification of improved and local varieties. While local varieties are commonly understood as traditional varieties (aka 'landraces'), farmers sometimes refer to locally developed improved varieties as local and sometimes also refer to exotic improved varieties as local after 'recycling' seeds as farm-saved seeds for a few seasons (Westengen, Jeppson, & Guarino, 2013). In fact, even national and international agricultural research organizations classify improved wheat varieties recycled more than five seasons as local (Yirga, Mohammad, Kassie, & Groote, 2013). The point in our study is, however, not to assess the performance of different types of crops but to understand how a diversity of crop varieties are used as coping and adaptation strategies, thus the self-reported categories improved, and local are useful proxies for diversity below the species level. Second, our data allows us to understand the impact of past shock exposure and vulnerability on current farmer actions (*ex-post*), not what they do before exposure (*ex-ante* risk management). However, we believe that studying the impacts of past exposure on current farmer practices can shed light on future exposure to shocks and farmers' responses in coping with them.

The strength of the data used is that it is representative, covering the same households over multiple seasons. Hence, we can understand the responses of farmer's seed use and diversification decisions to shocks in Ethiopia from large data sets, and we can understand the dynamics of the effect as opposed to static effects mainly explored in literature. Hence, we feel that our study gives relevant insights for policy despite noted possible concerns.

5.1. Descriptive statistics

5.1.1. Outcome variables by year

Households mainly rely on local seed varieties in their crop production, as shown in Table 1. Use rates for local seed varieties range from 97 to 99 % of the households over the three seasons. A considerable proportion - about 20 % - of the farmers also use improved seed. From 2011/12 through 2015/16, the use of improved seeds increased modestly from 18 % to 21 %. In terms of the quantity of seed used per household (averaged for all crops), much higher amounts of local seeds are used compared to improved seeds. On average, 16 to 17 kg of improved seeds is used per year per household in the studied period. More than four times as much local seeds were used on average.

Crop diversification is also common, with, on average, rural households growing about 8 different crops in a given year (season). The Simpson index of crop evenness also shows high crop diversification levels in rural Ethiopia, as the average index ranges from 0.71 to 0.73.

Maize is an important cereal for Ethiopians, and 61 to 64 % of our sampled rural households grow maize. In the middle panel of Table 1, descriptive statistics for local and improved varietal use for maize growers are reported. Like for other crops, rural farmers rely mostly on local maize seed. About 90 % of the farmers used local maize seed in 2011/12, but the share decreased slightly to 85 and 84 % in 2013/14 and 2015/16. This is mirrored by an increase in improved maize seeds, from 19 % of the households in 2011/12 to 24 % (2013/14) and 25 % (2015/16). On average, about three times more local maize seeds (58 kg) are used compared to improved seeds (19 kg). Thus, although local seeds dominate, maize cultivation has a relatively higher use of improved seeds compared to other crops.

Wheat is also an important cereal grown in selected high potential areas in Ethiopia. About 26–27 % of the sampled farmers grow wheat (Table 1). Among wheat growers, the use of improved seed has been between 10 and 13 %, with no clear time trend. Over 91 % of the wheat growers relied on local wheat varieties. The heavy reliance on local varieties for wheat growers is also underscored by the much higher average quantities of local wheat seeds (123–147 kgs) than for improved seeds (15–19 kgs). Wheat has less use of improved varieties compared to maize. The ratio of local to improved wheat varietal use (for wheat growers) is about 8, thus twice the average across crops.

5.1.2. Key explanatory variables by year

Table 2 presents descriptive statistics for key explanatory variables selected to explain seed use decisions and diversification. From Table 2, we can see that, on average, the one-year lag for rainfall shock is dominated by flood shocks (positive Z-scores), while the 2-year lag is dominated by drought shocks

Table 1
Descriptive statistics of selected outcome variables used in the analysis.

Variable definitions	2011/12	2013/14	2015/16
	Mean(s.d.)	Mean(s.d.)	Mean(s.d.)
All crops (N = 2398)			
Improved seed use (1 = yes; 0 = otherwise)	0.18(0.39)	0.21(0.41)	0.21(0.41)
Quantity of improved seeds used per household	16.13(67.30)	16.40(54.68)	17.65(68.39)
Local seed use (1 = yes; 0 = otherwise)	0.97 (0.16)	0.98(0.15)	0.99(0.12)
Quantity of local seeds used per household	60.78(107.78)	78.59(127.01)	69.96(111.36)
Grow maize (1 = yes; 0 = otherwise)	0.64(0.48)	0.61(0.49)	0.62(0.49)
Grow wheat (1 = yes; 0 = otherwise)	0.26(0.44)	0.27(0.45)	0.27(0.44)
Number of crops grown per household	8.77(4.77)	8.66(4.66)	8.48(4.63)
Simpson index of crop diversity	0.73(0.21)	0.72(0.21)	0.71(0.22)
Maize growers (N = 1539)			
Improved maize seed (1 = yes; 0 = otherwise)	0.19(0.39)	0.24(0.43)	0.25(0.43)
Quantity of improved maize seed used per household	17.69(74.08)	18.34(55.89)	21.04(73.20)
Local maize seed use (1 = yes; 0 = otherwise)	0.90(0.30)	0.85(0.36)	0.84(0.37)
Quantity of local maize seeds used per household	54.62(96.18)	61.47(106.55)	59.07(102.14)
Wheat growers (N = 628)			
Improved wheat seed (1 = yes; 0 = otherwise)	0.12(0.33)	0.13(0.34)	0.10(0.29)
Quantity of improved wheat seed used per household	18.79(82.86)	14.60(53.10)	19.30(90.37)
Local wheat seed use (1 = yes; 0 = otherwise)	0.90(0.29)	0.91(0.29)	0.94(0.23)
Quantity of local wheat seeds used per household	123.39(151.03)	147.24(177.15)	149.61(150.84)

Notes: Summary statistics are not weighted, standard deviations (s.d) in parentheses.

Table 2
Descriptive statistics of explanatory variables(test variables) used in the analysis.

Variables	2011/12	2013/14	2015/16
	mean	mean	mean
Rainfall shock 1-year lag (Z-score)	0.053	0.183	0.027
Rainfall shock 2-year lag (Z-score)	−0.450	−0.028	0.360
Temperature shock 1-year lag (Z-score)	0.416	0.117	0.826
Temperature shock 2-year lag (Z-score)	2.177	0.594	0.797
Livestock loss in the previous year (1 = yes) †	0.067	0.038	0.071
Formal employment loss (off-farm) by a household member last year(1 = yes) †	0.007	0.006	0.008
Observations	2398	2398	2398

Notes: summary statistics are not weighted, † denotes dummy variable: Shock variables shown in the table are for the period May-July (early season of the Meher season).

(negative z-scores). In terms of drought shocks, we also see that, on average, the drought shock is severe for the two-year lag compared to the one year-lag (Figure 2). For temperature shocks, positive Z-scores dominate for both 1 and 2-year lags, suggesting an overall increase in temperatures. We show the distribution of rainfall and temperature shocks (Z-scores) in Figure 1.

On average, 6 % of households in the pooled sample lost some of their livestock due to death or theft (1-year lag); about 6.7, 3.8, and 7.1 % of farmers lost their livestock in 2011/12, 2013/4, and 2015/16. Also, losing formal employment (1-year lag) was only experienced by about 1 % of respondents in the pooled sample and all survey years (Table 2).

Descriptive statistics for other rainfall and temperature measures considered, including long-run mean rainfall and long-run mean temperature, are shown together with other control variables considered in the Supplementary material.

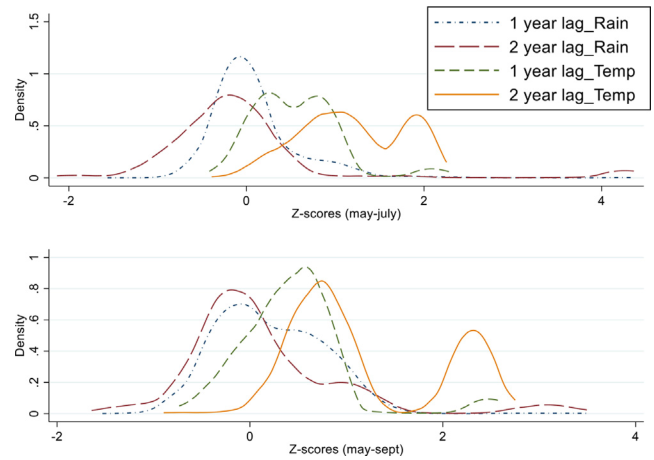

Figure 1. Distribution of rainfall and temperature shocks for the Meher season (may-sept) and early season (may–July) of the Meher in the pooled sample.

6. Results

This section presents the main findings from our regression analyses. In Tables 3-6 we report results from seed use equations while in tables 7-8 we report results from crop diversification equations. The results presented are estimated within the Correlated Random Effects (CRE) framework. We first present naïve regression results (where we include only the key treatment variables of interest (C_{vt}, S_{it}) and year dummies (YR_t) but without control variables (H_{it})). Second, we show results where we control for additional controls (and their means across years). For brevity we only report coefficients of our key test variables.

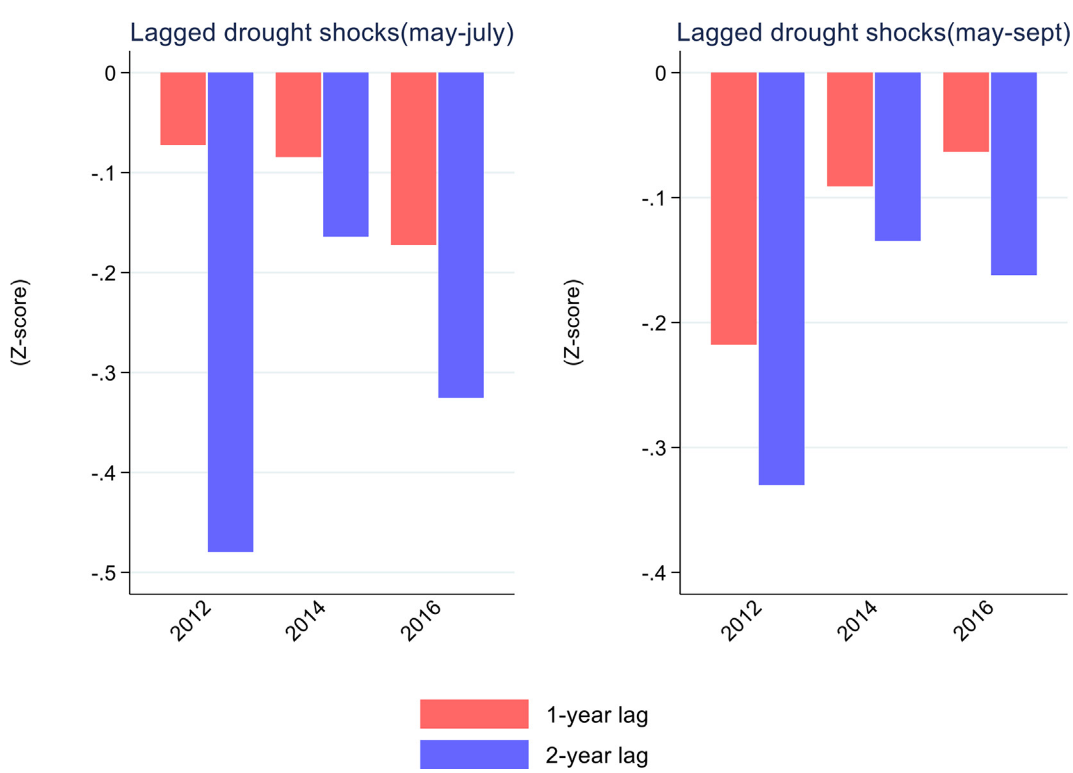

Figure 2. Drought shocks (rainfall shortage) for the Meher season and early season (May-July) of the Meher season in the pooled sample.2012,2014, and 2016 represents 2011/12, 2013/14, and 2015/16 survey rounds of Ethiopia Socioeconomic Survey (ESS).

Table 3
Impact of shocks on household seed use decisions (all crop model) in rural Ethiopia.

	Improved seed		Local seed	
	Use	INT	Use	INT
	(OR)	(APE)	(OR)	(APE)
Models without additional controls				
Rainfall shortage 1-year lag	3.645***	2.233***	0.636	0.316***
	(1.1541)	(0.5564)	(0.3659)	(0.0999)
Rainfall shortage 2-year lag	0.354***	−1.738***	4.965***	−0.054
	(0.0548)	(0.2736)	(2.4025)	(0.0432)
Temperature shock 1-year lag	1.016	0.084	0.391***	−0.213***
	(0.0980)	(0.1717)	(0.0771)	(0.0283)
Temperature shock 2-year lag	1.836***	1.093***	4.652***	0.138***
	(0.2797)	(0.2704)	(0.8771)	(0.0396)
Historical mean temperature (1980–2017)	0.959*	−0.114***	0.927**	−0.091***
	(0.0223)	(0.0434)	(0.0314)	(0.0100)
Historical mean rainfall (1980–2017)	1.003***	0.005***	1.000	0.001***
	(0.0002)	(0.0004)	(0.0004)	(0.0001)
Livestock loss†	0.904	−0.061	1.919	0.021
	(0.1804)	(0.3487)	(0.9172)	(0.0597)
Job loss (off-farm)†	0.998	0.101	0.587	0.036
	(0.4923)	(0.8609)	(0.5247)	(0.1639)
Year dummies	Yes	Yes	Yes	Yes
Other controls	No	No	No	No
Observations	7194	7194	7194	7194
Models with additional controls				
Rainfall shortage 1-year lag	2.740***	1.723***	0.448	0.265***
	(0.8786)	(0.5491)	(0.2594)	(0.0929)
Rainfall shortage 2-year lag	0.418***	−1.414***	3.790***	0.014
	(0.0659)	(0.2722)	(1.8145)	(0.0414)
Temperature shock 1-year lag	1.097	0.221	0.471***	−0.196***
	(0.1064)	(0.1701)	(0.0928)	(0.0269)
Temperature shock 2-year lag	1.662***	0.858***	4.432***	0.104***
	(0.2521)	(0.2643)	(0.8464)	(0.0374)
Historical mean temperature (1980–2017)	0.959*	−0.124***	0.937	−0.104***
	(0.0239)	(0.0449)	(0.0381)	(0.0078)
Historical mean rainfall (1980–2017)	1.003***	0.005***	1.000	0.0001**
	(0.0003)	(0.0005)	(0.0004)	(0.0001)
Livestock loss†	0.962	0.041	1.324	−0.037
	(0.1928)	(0.3428)	(0.6348)	(0.0557)
Job loss (off-farm)†	0.875	−0.063	0.972	0.072
	(0.4314)	(0.8468)	(0.9032)	(0.1532)
Year dummies	Yes	Yes	Yes	Yes
Other controls + their means across years	Yes	Yes	Yes	Yes
Observations	7194	7194	7194	7194

Notes: Cluster robust standard errors at EA level in parenthesis; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; INT = intensity. APE = Average partial effects, OR = odds ratios. Improved and local varieties are first measured as dummy variables for use and then secondly as continuous variables indicating the intensity of use (kgs of seed used). We model use and intensity of use (INT) equations using Correlated Random Effects logit and Tobit, respectively. †denotes a dummy variable.

6.1. Impact of shocks on seed use decisions

6.1.1. Full sample

.This paper focuses on how shocks affect access and the use of local and improved seeds and crop diversification. Table 3 and Table 4 show that the one-year lag of drought shock increases the use of improved seeds in general and improved wheat in particular. However, the two-year lag of drought shock exposure is shown to have a contrasting effect, as it reduces the chances and intensity of improved seeds and improved maize use while increasing the chances and intensity of using local seeds and local maize. The contrasting effects of the two lags of drought shock seem to suggest that it is the most recent drought shocks (1-year lag) that trigger adaptive behavioral responses by farmers in their seed use decisions and that the relatively more intense and distant drought shocks (e.g., the 2-

Table 4
Impact of shocks on maize and wheat seed use decisions in rural Ethiopia.

	Improved maize		Local maize		Improved wheat		Local wheat	
	Use	INT	Use	INT	Use	INT	Use	INT
	(OR)	(APE)	(OR)	(APE)	(OR)	(APE)	(OR)	(APE)
Models without additional controls								
Rainfall shortage 1-year lag	1.428	0.336	0.546	0.063	7.369***	7.002***	0.343	−0.625**
	(0.6650)	(0.6111)	(0.2568)	(0.1701)	(4.4500)	(2.1868)	(0.2497)	(0.2974)
Rainfall shortage 2-year lag	0.193***	−2.206***	7.104***	0.435***	1.011	−0.139	0.928	−0.289
	(0.0451)	(0.3083)	(1.9030)	(0.0733)	(0.3877)	(1.3331)	(0.4103)	(0.1829)
Temperature shock 1-year lag	1.200	0.352*	1.211	0.029	1.276	0.846	0.878	−0.020
	(0.1924)	(0.2120)	(0.2112)	(0.0552)	(0.2646)	(0.7315)	(0.2159)	(0.0964)
Temperature shock 2-year lag	1.379	0.536*	1.019	0.053	2.794**	3.541***	0.573	−0.368***
	(0.3163)	(0.3147)	(0.2283)	(0.0747)	(1.1492)	(1.3541)	(0.2254)	(0.1279)
Historical mean temperature (1980–2017)	0.781***	−0.380***	1.188***	−0.015	1.086*	0.289*	0.887**	−0.072***
	(0.0332)	(0.0589)	(0.0471)	(0.0159)	(0.0473)	(0.1531)	(0.0453)	(0.0227)
Historical mean rainfall (1980–2017)	1.004***	0.006***	0.998***	−0.000	1.000	−0.001	1.000	0.000
	(0.0004)	(0.0005)	(0.0003)	(0.0001)	(0.0004)	(0.0013)	(0.0004)	(0.0002)
Livestock loss†	1.191	0.378	1.255	0.240**	0.664	−1.246	1.018	−0.097
	(0.3374)	(0.3704)	(0.4006)	(0.1093)	(0.2828)	(1.4527)	(0.4637)	(0.1828)
Job loss(off-farm)†	0.951	−0.075	2.040	0.363	1.167	0.177	0.573	−0.373
	(0.6442)	(0.8715)	(1.5992)	(0.2946)	(1.3884)	(4.2408)	(0.6956)	(0.5576)
Models with additional controls								
Rainfall shortage 1-year lag	0.987	−0.078	0.640	−0.010	5.603**	5.510**	0.911	−0.200
	(0.4659)	(0.6032)	(0.3057)	(0.1637)	(3.7960)	(2.2085)	(0.7994)	(0.2737)
Rainfall shortage 2-year lag	0.226***	−1.935***	6.049***	0.433***	1.270	0.920	0.845	−0.055
	(0.0540)	(0.3047)	(1.6576)	(0.0723)	(0.5297)	(1.3455)	(0.4168)	(0.1733)
Temperature shock 1-year lag	1.227	0.337	1.157	0.035	1.312	0.893	0.808	−0.125
	(0.1961)	(0.2071)	(0.2004)	(0.0539)	(0.2933)	(0.7263)	(0.2177)	(0.0916)
Temperature shock 2-year lag	1.195	0.289	1.034	−0.002	2.799**	3.042**	0.634	−0.201*
	(0.2718)	(0.3044)	(0.2311)	(0.0730)	(1.2516)	(1.3378)	(0.2759)	(0.1210)
Historical mean temperature (1980–2017)	0.770***	−0.407***	1.224***	0.002	1.044	0.104	0.904*	−0.100***
	(0.0360)	(0.0626)	(0.0526)	(0.0158)	(0.0515)	(0.1578)	(0.0541)	(0.0201)
Historical mean rainfall (1980–2017)	1.004***	0.005***	0.998***	−0.000***	1.000	−0.002	1.000	−0.001***
	(0.0004)	(0.0005)	(0.0003)	(0.0001)	(0.0004)	(0.0013)	(0.0005)	(0.0002)
Livestock loss†	1.318	0.479	1.101	0.146	0.760	−0.677	0.902	−0.084
	(0.3770)	(0.3639)	(0.3529)	(0.1050)	(0.3495)	(1.4601)	(0.4557)	(0.1690)
Job loss†	0.846	−0.142	3.020	0.536*	1.307	0.666	0.653	−0.129
	(0.5792)	(0.8580)	(2.4233)	(0.2831)	(1.5805)	(4.0002)	(0.8213)	(0.5173)
Other controls + their means across years	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4479	4479	4479	4479	1937	1937	1937	1937

Notes: In parenthesis are cluster robust standard errors at EA level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; INT = intensity. APE = Average partial effects, OR = odds ratios. Improved and local varieties for both maize and wheat are first measured as dummy variables for use. Secondly, continuous variables indicate the intensity of use (kgs of seed used). We model use and intensity (INT) of use equations using Correlated Random Effects logit and Tobit, respectively, †denoted dummy variable.

year lag) limit use of improved seeds while increasing use of local seed varieties.

Also, we found that the probability and intensity of using improved seeds increase with historical mean rainfall. In contrast, the chances of using local maize and wheat varieties decrease with historical mean rainfall (Table 3 and Table 4). These results could point to the fact that areas with higher rainfall historically (agronomically favorable areas) have higher use of improved seeds while more marginal areas have less.

Furthermore, we see that temperature shocks (both one and two-year lags) are positively associated with improved seed use (including improved wheat and maize). Lagged temperature shock variables do not show consistent effects on local seed use decisions. Additionally, the historical mean temperature is negatively associated with the intensity of both improved and local variety use (Table 3 and Table 4).

Additionally, Table 4 shows the loss of a formal job by a household member to enhance the chances and intensity of using local maize varieties. We also observe that in most of our models, our

Table 5
Interaction effects of drought shocks and household diversity indicators on household seed use decisions (all crop model) in rural Ethiopia.

	Improved seed		Local seed	
	Use	INT	Use	INT
Rainfall shortage (interactions)	(OR)	(APE)	(OR)	(APE)
Rainfall shortage 1-year lag × Rainfall shortage 2-year lag	0.254***	−2.226***	0.187***	0.143**
	(0.0682)	(0.4495)	(0.0903)	(0.0652)
All other baseline controls	Yes	Yes	Yes	Yes
Observations	7194	7194	7194	7194
Small farm size				
Rainfall shortage 1-year lag × LFS	2.325	1.271	0.205**	0.283**
	(1.2013)	(0.9405)	(0.1366)	(0.1442)
Rainfall shortage 2-year lag × LFS	0.592**	−0.822**	3.291**	0.026
	(0.1279)	(0.3832)	(1.7196)	(0.0557)
All other baseline controls	Yes	Yes	Yes	Yes
Observations	7194	7194	7194	7194
Asset poor households				
Rainfall shortage 1-year lag × poor	1.241	0.314	0.739	0.344***
	(0.5489)	(0.7733)	(0.5687)	(0.1236)
Rainfall shortage 2-year lag × poor	0.496***	−1.204***	2.738*	−0.110**
	(0.0949)	(0.3322)	(1.5747)	(0.0491)
All other baseline controls	Yes	Yes	Yes	Yes
Observations	7194	7194	7194	7194
Received Social Safety Nets				
Rainfall shortage 1-year lag × SSN	8.602***	4.070***	0.421	0.368*
	(5.8657)	(1.1738)	(0.5232)	(0.1941)
Rainfall shortage 2-year lag × SSN	0.520	−0.958	2.408	0.230**
	(0.2132)	(0.7073)	(2.5710)	(0.1020)
All other baseline controls	Yes	Yes	Yes	Yes
Observations	7194	7194	7194	7194

Notes: Cluster robust standard errors at EA level in parenthesis; * p < 0.10, ** p < 0.05, *** p < 0.01; INT = intensity. APE = Average partial effects, OR = odds ratios. LFS = indicator variable for Low farm size; SSN = Indicator variable for having received Social Safety Nets; Improved and local varieties are first measured as dummy variables for use and then secondly as continuous variables indicating the intensity of use (kgs of seed used). We model use and intensity (INT) of use equations using Correlated Random Effects logit and Tobit, respectively, †denotes dummy variable.

test variables' crude effects (effects without additional controls) are comparable to the adjusted effects (effect after controlling for additional controls), indicating that our results are robust to adding additional controls.

6.1.2. Heterogeneity analysis

We perform heterogeneity analysis using interaction terms to understand the conditioned effects of lagged drought shock exposure. We start by interacting one and two-year lags of drought shocks and assess the influence of recurrent drought exposure on our dependent variables. We then perform interaction effects analysis of indicator variables for household socioeconomic diversity (small farm size, low agricultural asset endowment, and access to social safety nets) with lagged drought shocks and report results in Tables 5-6. We only show an extract of results from the interaction effects analysis for brevity. Results show that recurrent drought shock exposure discourages the use of improved varieties while enhancing the use of local seed varieties (Table 5 and Table 6).

The results also show that drought shock exposure for households with less than average farm sizes significantly reduces their chances of using improved seeds and improved maize and increases their chances of using local seed varieties in general and specifically for maize and wheat.

Further, results show that drought shock exposure for smallholder farming households in the low-agricultural asset category significantly increases their chances and intensity of local seed variety use in general (Table 5) and particularly for local maize (Table 6) and reduces chances of using improved seed (in general) and improved maize.

Also, interacting lagged drought shock exposure with the reception of Social Safety Nets (SSN) reveals that access to SSN with exposure enhances the use and intensity of improved seeds and improved maize and the intensity of local seed (in general) and local wheat. However, when interacting with a more severe and distant drought shock (2-year lag), social safety nets significantly reduce the use and intensity of improved varieties.

6.2. Impact of shocks on crop diversification decisions

6.2.1. Full sample

The impact of shocks on crop diversification decisions is shown in Table 7. We report results on the two indices considered: crop count (richness) and the Simpson index (evenness). We show both crude (without additional controls) and adjusted (with additional controls) effects of climate variables and shocks on crop diversification decisions in Table 7.

Table 7 shows that historical mean rainfall is positively associated with crop diversity, both in terms of species richness and evenness while historical mean temperatures have the opposite effect on crop diversity. However, drought shocks are associated with a reduction in the number of crops grown (Table 7), and flood shocks experienced in the recent past encourage crop

Table 6
Interaction effects of shocks and household diversity indicators on maize and wheat seed use decisions in rural Ethiopia.

	Improved maize		Local maize		Improved wheat		Local wheat	
	Use	INT	Use	INT	Use	INT	Use	INT
	(OR)	(APE)	(OR)	(APE)	(OR)	(APE)	(OR)	(APE)
Rainfall shortage (interactions)								
Rainfall shortage 1-year lag × Rainfall shortage 2-year lag	0.286***	−1.521***	1.416	0.314***	0.396**	−2.644*	2.091	0.416**
	(0.1193)	(0.5224)	(0.5709)	(0.1149)	(0.1697)	(1.3715)	(1.0290)	(0.1731)
All other baseline controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4479	4479	4479	4479	1937	1937	1937	1937
Low farm size								
Rainfall shortage 1-year lag × LFS	2.355	0.364	0.349	−0.364	4.061	4.909	0.295	−0.299
	(1.8819)	(1.0917)	(0.2668)	(0.2697)	(4.3822)	(3.6207)	(0.3489)	(0.5147)
Rainfall shortage 2-year lag × LFS	0.218***	−1.932***	5.873***	0.364***	0.925	−0.021	2.645*	0.291
	(0.0774)	(0.4539)	(2.2895)	(0.1030)	(0.4369)	(1.5419)	(1.5246)	(0.2024)
All other baseline controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4479	4479	4479	4479	1937	1937	1937	1937
Asset poor households								
Rainfall shortage 1-year lag × poor	0.695	−0.367	0.999	0.165	1.486	1.133	1.135	−0.043
	(0.4352)	(0.8265)	(0.6498)	(0.2202)	(1.3811)	(2.9627)	(1.3198)	(0.3451)
Rainfall shortage 2-year lag × poor	0.433***	−1.167***	3.351***	0.197**	0.688	−0.888	1.435	0.231
	(0.1180)	(0.3521)	(1.0985)	(0.0846)	(0.2913)	(1.3495)	(0.7106)	(0.1673)
All other baseline controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4479	4479	4479	4479	1937	1937	1937	1937
Received Social Safety Nets								
Rainfall shortage 1-year lag × SSN	7.395*	3.562**	0.054***	−0.597*	5.767	5.152	0.836	−0.051
	(8.4166)	(1.5184)	(0.0560)	(0.3592)	(6.4709)	(3.7186)	(1.2045)	(0.5291)
Rainfall shortage 2-year lag × SSN	0.283*	−1.554*	2.377	0.479**	0.433	−2.443	2.696	0.700***
	(0.2082)	(0.9411)	(1.6449)	(0.1941)	(0.2922)	(2.1521)	(2.2696)	(0.2544)
All other baseline controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4479	4479	4479	4479	1937	1937	1937	1937

Notes: In parenthesis are cluster robust standard errors at EA level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; INT = intensity. APE = Average partial effects, OR = odds ratios. LFS = indicator variable for Low farm size, SSN = Indicator variable for having received Social Safety Nets, Improved and local varieties for both maize and wheat is first measured as dummy variables for use and secondly as continuous variables indicating the intensity of use (kgs of seed used). We model use and intensity (INT) of use equations using Correlated Random Effects logit and Tobit, respectively. †denoted a dummy variable.

diversification (Supplementary material Table J). Besides, historical mean temperature discourages crop diversification.

Also, we found that crop diversification is positively associated with temperature shocks. Further, livestock loss within the household is negatively associated with crop diversification, while job loss within the household is positively associated with the number of crops grown (Table 7).

Results also show that controlling for additional variables does not significantly alter the interpretation of results on the impact of covariate and idiosyncratic shocks on crop diversification. Our results are hence robust to the addition of additional controls.

6.2.2. Heterogeneity analysis

We also assessed the impacts of recurrent drought shock exposure and how heterogeneity in household socioeconomic conditions influences the impact of shocks on diversification. The results (Table 8) show recurrent drought shock exposure to reduce the number of crops grown. Also, interacting drought exposure on households with low farm size discourages crop diversification. Besides interacting, lagged drought shocks with an indicator variable for asset-poor households negatively associates with the number of crops grown by the household.

Further, we see that drought shock exposure on households who accessed social safety nets promotes crop diversification (Table 8).

7. Discussions

Our study evaluated (i) whether past exposure to covariate shocks and idiosyncratic shocks significantly influence seed variety use and diversification of cropping portfolios, and (ii) whether effects of shocks are heterogeneous by households' land size holding inequality, agricultural asset endowment inequality, and access to social safety nets. We discuss key findings for each of these two research questions below.

7.1. Impact of shocks on seed use decisions and crop diversification

Several findings emerged from our analyses. First, drought shock exposure increases the likelihood of farmers using improved seeds, in particular improved wheat, and reduces the likelihood of local wheat seed use. We learned that the most recent drought shocks (1-year lag) are more influential on crop seed use compared to more distant drought shocks (2-year lag). Relatively more severe and long-term drought shocks (2-year lag), and recurrent drought shock exposure (1-year lag*2-year lag) reduce the likelihood and intensity of using improved seeds while enhancing the likelihood and intensity of using local seeds. Also, lagged temperature shocks enhance the likelihood and intensity of using improved seeds in general and for wheat and maize. Second, recurrent drought shock exposure discourage crop diversification, while flood shocks and temperature shocks promote crop diversification. Third,

Table 7
Impact of shocks on crop diversification decisions in rural Ethiopia.

	No additional covariates		With additional covariates	
	Crop Count	Simpson Index	Crop Count	Simpson Index
	(APE)	(APE)	(APE)	(APE)
Rainfall shortage 1-year lag	−0.033	0.005	−0.061*	−0.001
	(0.0321)	(0.0136)	(0.0321)	(0.0132)
Rainfall shortage 2-year lag	0.038***	0.006	0.012	−0.005
	(0.0144)	(0.0059)	(0.0147)	(0.0059)
Temperature shock 1-year lag	−0.022**	−0.005	−0.006	−0.004
	(0.0091)	(0.0038)	(0.0091)	(0.0037)
Temperature shock 2-year lag	−0.006	0.018***	−0.021	0.016***
	(0.0138)	(0.0054)	(0.0138)	(0.0053)
Historical mean temperature (1980–2017)	−0.035***	−0.017***	−0.018***	−0.010***
	(0.0047)	(0.0012)	(0.0044)	(0.0012)
Historical mean rainfall (1980–2017)	0.0005***	0.0002***	0.0004***	0.0002***
	(0.000047)	(0.000014)	(0.000045)	(0.000013)
Livestock loss†	0.009	−0.021**	0.001	−0.021**
	(0.0191)	(0.0082)	(0.0191)	(0.0080)
Job loss(off-farm)†	0.093*	0.002	0.078	−0.005
	(0.0529)	(0.0222)	(0.0527)	(0.0216)
Year dummies	Yes	Yes	Yes	Yes
Other controls + their means across years	No	No	Yes	Yes
Observations	7194	7194	7194	7194

In parenthesis are cluster robust standard errors at EA level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; APE = Average partial effects, we model crop count and Simpson diversity equations using Correlated Random Effects Poisson and Tobit, respectively, †denotes dummy variable.

idiosyncratic household shocks have a less significant role in explaining seed use and crop diversification decisions when compared to covariate rainfall (or temperature) shocks.

The finding that improved seed use is positively associated with experiencing drought shock in the previous season can be explained by both push and pull factors. First, given that smallholder farmers in Ethiopia rely mainly on informal seed sources, including farm-saved seeds, farmer to farmer seed exchange, and local markets (Thijssen et al., 2008), prior exposure to a bad season probably reduces seed supply from the informal sources. Hence, past exposure to a bad season pushes farmers to move from their default position (use of local seeds) towards using off-farm sourced improved seeds. In the longer term, exposure to drought in a rural economy dependent on rain-fed agriculture is likely to intensify poverty (Dercon, 2004) and this may explain why we found 2-year lag drought shocks to reduce crop diversification, and recurrent drought shock exposure (drought shock 1 and 2-year lag interactions) to reduce improved seed use and enhance local seed use. Liquidity constraints following a bad season (or even worse: recurrent bad seasons) can be severe amongst smallholder farmers. Hence, acquiring improved seed from the formal seed system and implementing a diversified crop portfolio become more expensive and outside their reach if the households experience intensified poverty.

Second, the choice of improved varieties at the expense of local varieties after exposure to drought shocks could also reflect the pull factor of learning. Farmers may have learned from their past experiences that improved varieties perform better under low rainfall conditions, and this might also explain the increased use of improved varieties at the expense of local varieties when faced with drought shocks. In such a case, farmers may increase the use of improved varieties as a form of insurance to future anticipated shocks. For instance, Katengeza, Holden, & Lunduka (2019) found that past exposure to drought shocks improves the probability of using improved drought-tolerant maize varieties in Malawi. Based on the same data, Holden and Quiggin (2017) found that more risk-averse farmers were more likely to adopt such varieties as well as local maize at the expense of other improved varieties. In addition, past shock exposure enhanced the use of drought-tolerant maize and discouraged the use of local maize. Preferences may therefore interact with learning through exposure to shocks in the adaptation process. This idea is further supported by literature that alludes to the fact that rural households switch from their business-as-usual practices to practices that increase their mutual insurance to shocks to better cope with shocks (Angelsen & Dokken, 2018; Takasaki, 2011).

The positive effects of lagged flood shocks on crop diversification show more opportunities than constraints associated with abundant rainfall. Abundant rainfall in the previous year may translate into good harvests, which could relax liquidity constraints and lead to higher farming activity and crop diversification.

Furthermore, the finding that smallholder farmers' seed use and crop diversification decisions consistently respond to most recent shocks compared to long-term shocks likely reflect that smallholder farmers are more likely to build their weather expectations for the coming seasons based on their most recent weather shock experiences. Our results here are in line with previous studies (e.g., Katengeza, Holden, and Fisher (2019)) that found more recent weather shocks to be more influential in shaping farmers' weather expectations compared to more distant, long-term weather shocks. However, there could be more competing explanations for the contrasting effects of shocks (immediate vs distant shocks), leaving room for future research to explore the mechanisms that could lead to differential responses to immediate and distant weather shocks.

Idiosyncratic shocks minimally explain seed use and crop diversification decisions when compared to covariate rainfall shocks.

Table 8
Interaction effects of shocks and household diversity indicators on crop diversification decisions in rural Ethiopia.

	Crop diversification indices	
	Crop Count	Simpson Index
Rainfall shortage (interactions)		
Rainfall shortage 1-year lag × Rainfall shortage 2-year lag	−0.080***	0.008
	(0.0250)	(0.0093)
All other baseline controls	Yes	Yes
Observations	7194	7194
Small farm size		
Rainfall shortage 1-year lag × LFS	−0.277***	−0.048**
	(0.0574)	(0.0205)
Rainfall shortage 2-year lag × LFS	−0.012	0.013
	(0.0208)	(0.0079)
All other baseline controls	Yes	Yes
Observations	7194	7194
Asset poor households		
Rainfall shortage 1-year lag × poor	−0.170***	−0.022
	(0.0431)	(0.0177)
Rainfall shortage 2-year lag × poor	−0.024	−0.002
	(0.0175)	(0.0070)
All other baseline controls	Yes	Yes
Observations	7194	7194
Received Social Safety Nets		
Rainfall shortage 1-year lag × SSN	0.358***	0.048*
	(0.0742)	(0.0278)
Rainfall shortage 2-year lag × SSN	0.013	0.021
	(0.0375)	(0.0145)
All other baseline controls	Yes	Yes
Observations	7194	7194

In parenthesis are cluster robust standard errors at EA level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; APE = Average partial effects, we model crop count and Simpson diversity equations using Correlated Random Effects Poisson and Tobit, respectively, †denotes dummy variable.

Losing livestock assets and formal employment within the household minimally explains seed use and diversification decisions. Losing livestock assets and income from formal work reduces household income and asset endowments, further hurting farming investments. Livestock is an essential source of wealth and manure to fertilize the soil and draft power to cultivate the Land for farming households (Thornton & Herrero, 2015). Hence, losing livestock reduces the availability of crucial inputs, which may minimize crop diversification on the farm. However, smallholder farming households usually find it easier to cope with idiosyncratic household shocks than to covariate weather shocks (Dercon, 2005; Nguyen et al., 2020), which can explain why idiosyncratic shocks were less important in explaining seed use and diversification decisions.

7.2. Conditioned effects of drought shocks

Heterogeneity analyses show that drought exposure among farmers with small farm sizes and low agricultural assets reduces reliance on improved seeds, increases reliance on local varieties (in general and for maize and wheat), and reduces crop diversification. On the other hand, access to productive safety nets enhances the likelihood that the farmers will use improved seeds and diversify their crop portfolio following a drought.

Uninsured climate shocks usually lead to fluctuations in household welfare, and may lead to transient (temporary) poverty. This might, however, be avoided if effective safety nets are in place (Dercon, 2005). We found access to social safety nets to significantly alter the effects of drought shock exposure on seed use and diversification decisions. Access to social safety nets enables households to maintain agricultural activity and crop diversification and improve their use of improved seeds. However, relatively more intense drought shocks reduce improved seed use and crop diversification and enhance local seed use. Access to productive safety nets does not significantly alter this relationship for relatively more intense drought shocks. However, given that we cannot fully account for unobserved time-varying characteristics at the household level, which are potentially correlated with access to productive safety nets our results on the interaction effects of rainfall shock exposure and access to productive safety nets must be regarded as correlations and not implying any causal relations.

The adverse effects of recurrent drought shocks on cropping decisions could reflect the effects of temporal poverty induced by drought shock exposure. The effects of drought shock exposure are worse among poorer households (Deressa, Hassan, & Ringler, 2008). This notion possibly explains why farmers with less than average farm sizes and households lowly endowed with agricultural assets were found to intensify on local seed use and reduce diversification post-exposure to drought shocks.

Further, the use of improved varieties may appear a risky venture for the farmer when weather conditions are uncertain. This point to shock exposure also having behavioral impacts, where households faced with risks and with limited insurance substitutes are pushed towards risk management strategies that include low-risk activities (e.g., use of local seeds) but also with lower returns (Dercon 2005, 2002, 2004). This finding is in line with earlier studies: poor households who face production shocks become less likely to engage in beneficial activities that are considered risky (Dercon & Christiaensen, 2011; Gebremariam & Tesfaye, 2018).

8. Conclusions

Crop diversification and varietal change are important strategies for buffering production risk in smallholder agriculture and, hence, rural development (Asfaw et al., 2019; Bozzola & Smale, 2020; Di Falco et al., 2010; Katengeza & Holden, 2021; Tesfaye & Tirivayi, 2020). This study gives important insights into the drivers and constraints involved in farmers decision to use different types of seeds and to diversify their crop portfolio. The bulk of the seeds used by Ethiopian farmers are local. However, improved seed use for all crops and specifically for maize shows a slightly increasing trend over the study period. Furthermore, cropping portfolios at the household level are highly diversified in rural Ethiopia.

We found that more rainfall is associated with more use of improved seeds as well as higher crop diversity. Exposure to drought shocks increases households' use of improved seeds in general and specifically for wheat. However, one and two-year lags of drought shocks have heterogenous effects on seed use and diversification decisions. The most recent weather shocks (one-year lags) appear more influential than more distant weather shocks (two-year lags) in shaping farmers' weather expectations which influence seed use and diversification. Recurrent and severe drought shocks significantly reduce agricultural activity, including improved seed use and crop diversification. Besides, loss of livestock within the household reduces resources available and hence prospects to diversify. Also, losing off-farm work by a household member enhances reliance on local maize seed. Overall, shock exposure poses heterogeneous impacts on seed use and crop diversification in rural Ethiopia. Low-income households and those with less than average farm size significantly intensify local seed use and reduce reliance on improved seed use following covariate shocks. The implication is that socioeconomic disadvantages (e.g., poor asset endowments) and drought shocks make households more seed insecure.

The negative interaction between poverty and shock exposure for the crop-based adaptation activities is significantly lowered when households have access to social security nets. However, in Ethiopia, the productive safety net program only reaches 8 % of the Ethiopian population (Berhane, Gilligan, Hoddinott, Kumar, & Taffesse, 2014; Duru, 2016). In such context, one would expect that farmers have incentives to diversify crop and variety choices as a strategy to buffer risks. And, previous studies have found that crop diversification and improved seed use indeed directly enhance food security under and after shocks. However, our results indicate that recurrent exposure to adverse shocks reduces farming returns and intensifies liquidity constraints, and possibly enhances poverty, hindering farmers from effectively implementing adaptation actions to such shocks, thus hindering the realization of the positive welfare outcomes highlighted in the previous literature.

To avoid negative climate responses for agricultural development by smallholder farmers, up-scaling sustainable and affordable insurance and effective social safety nets is needed. Moreover, given the significance of both improved and local seeds in the face of shocks, farmer's seed systems must co-exist and work in harmony with efforts to increase access to both improved and local varieties. For the less land and asset endowed and those without access to the public social security program, local seeds are an essential part of their de facto safety nets. The informal seed systems supplying local seeds must thus at a minimum be allowed the legal space to exist, but they should also be considered an important entry point for supporting farmers' seed security through such measures as farmer-group seed production and decentralized seed quality control. Hence, our results lend support to Ethiopia's pluralistic seed system development strategy (which recognizes formal, informal, and intermediate seed systems) as an institutional approach to enhance farmers' adaptative capacity (MoA and ATA 2017; Mulesa, Dalle, Makate, Haug, & Westengen, 2021). If well implemented, the pluralistic seed system development strategy can improve farmers' chances to access sufficient quality seed of preferred crops and varieties both in normal seasons and post-shock exposure.

Crop diversity at both species and varietal level is key for adapting to the effects of climate change and other risks faced by smallholder farmers in SSA. We have shown that Ethiopian rural households indeed respond to shocks by making changes in their crop portfolios in subsequent seasons, but that the nature and intensity of those changes depend on their socioeconomic status and their access to social safety nets. Policy measures aimed at reducing vulnerability through increasing seed security must thus address the seed systems farmers rely on for access to these vital resources as well as social inequalities in seed access.

CRediT authorship contribution statement

Clifton Makate: Conceptualization. **Arild Angelsen:** Conceptualization, Supervision. **Stein Terje Holden:** Conceptualization, Supervision. **Ola Tveitereid Westengen:** Conceptualization, Supervision, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.worlddev.2022.106054.

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