Smallholder Agriculture Commercialization Dynamics Under Changing Climate: Evidence from Rural Ethiopia

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Abstract

Smallholder crop commercialization, which implies the engagement of farmers with output markets, has been for long a popular development policy for alleviating rural poverty in many countries in Sub-Sahara Africa. The success of smallholder crop commercialization initiatives lies in developing robust value chains that link farmers to inputs and outputs markets, by so doing improving their welfare from the consequent market-based exchanges. However, the development of these value chains must overcome systemic investment risks. One such risk is climate risk, particularly rainfall, temperature variability, and shocks (e.g., drought and heat stress). Commercialization dynamics under changing climate remain largely under-explored in extant literature. This study explores how smallholder commercialization decisions and outcomes are evolving under elevated climate risk exposure and other socioeconomic challenges affecting smallholders in Ethiopia. Precisely, we evaluate the dynamics of the influence of long-term climate variability and recurrent climate shocks in driving crop output market participation in Ethiopia. The study uses longitudinal household panel data for Ethiopia spanning seven years (2012-2019), complemented with historical climate data for over 30 years (1980-2018). We rely on measures of the degree of participation in output markets as indicators of agricultural commercialization. We apply appropriate latent variables models in a Correlated Random Effects framework, which helps us address the potential endogeneity problem associated with output market participation decisions emanating from unobservable household heterogeneity. Results reveal recurrent climate variability and specific shocks (drought, flood, and heat stress) to strongly influence crop output commercialization. Also, investments in commercial input purchases offer resilience to farmers and help sustain output market participation under climate variability and stress. Efforts to upgrade smallholder agricultural value chains should be in tandem with steps toward protecting production from climate risks.

Keywords: crop output commercialization; climate risk; resilience; smallholder farmers; Ethiopia

1. Introduction

The commercialization of smallholder agriculture has been a popular development policy instrument for alleviating rural poverty in Sub-Sahara Africa. In a broad sense, a smallholder farm household is viewed as commercialized if it purchases some of its inputs and sells a fraction of its output. Therefore, the process of commercialization is associated with a rise in the share of marketed output and purchased inputs per unit of output(Jones Govereh & Nyoro, 1999; Strasberg et al., 1999; Gebre-ab, 2006; Jaleta, Gebremedhin, & Hoekstra, 2009). Given that smallholder farmers constitute the majority of people living in abject poverty, commercialization is seen as a means to bring the welfare benefits of market-based exchanges to this group and is, therefore, central to an inclusive development process (Gebremedhin & Tegegne, 2012). It initiates a virtuous cycle that raises household income, thus improving consumption, food security, and nutritional outcomes in rural households (Carletto, Corral, & Guelfi, 2017). This idea is especially true for rural smallholder farmers in marginal areas who have relatively little interaction with markets(Sharp, Ludi, & Gebreselassie, 2007). Proponents of this view contend that enhancing the extent of smallholder commercialization in this part of society has more impact on alleviating poverty than promoting a few large ventures(Amsalu, 2014).

While smallholder agriculture offers an indispensable pathway out of poverty, it is also a major source of vulnerability to poverty and food insecurity, mainly due to climate change, asset poverty, and market imperfections(Barrett, 2008; Alem, Bezabih, Kassie, & Zikhali, 2010). Scientific evidence indicates that the global climate is changing and rather important for agriculture, with consequent rising average temperatures and altered rainfall amount and distribution(IPCC, 2022). These phenomena profoundly dictate the types and distributions of cultivation, including the viability of these endeavors(Newsham, Kohnstamm, Naess, & Atela, 2018). There is growing evidence that agro-meteorological hazards, such as drought, have become commonplace in much of Sub-Saharan Africa, with disproportionate effects on smallholders who predominantly rely on rainfed agriculture and are characteristically resource-constrained(Belay, Recha, Woldeamanuel, & Morton, 2017; IPCC, 2022). Given the highly climate-sensitive nature of agricultural production, climate change has obvious and important ramifications for agricultural commercialization, which has a bearing on poverty(Newsham et al., 2018).

While extant literature abounds with the determinants and effects of agriculture commercialization in developing countries, including SSA (see, for example, Boka (2017b), Boka (2017a); Getahun (2020) and for recent reviews), various caveats remain that call for further studies. For instance, in this type of literature, little is known in the context of Ethiopia on how smallholder farmer commercialization decisions are evolving under recurrent rainfall and temperature shock exposure linked to climate change. Besides, in the general climate change literature relating climate variability to yields and demand for farming inputs(Mendelsohn, 2009; Kurukulasuriya & Rosenthal, 2013; Nordhagen & Pascual, 2013; Mendelsohn & Wang, 2017; Makate, Angelsen, Holden, & Westengen, 2022), the effects of climate change on agricultural decision-making remain ambiguous as the results reported in the literature are not uniform across different contexts. For example, in Tanzania, the decision to use commercial inputs such as fertilizer was found to be positively associated with both rainfall (amount) and rainfall variability (Heisse & Morimoto, 2019, 2023), while in some parts of Ethiopia, rainfall variability was found to reduce both the probability and intensity of commercial fertilizer use (Alem et al., 2010; Dercon & Christiaensen, 2011). Additionally, in Nigeria, a study by Takeshima and Nkonya (2014) also found low rainfall to be associated with enhanced adoption and the extent of adoption of chemical fertilizers. In addition, it is also evident from the literature that climate change results in increased uncertainty in the form of extreme climate events(drought, floods, landslides, cyclones), which translate to production risks associated with crop failure, low productivity, and undesirable agricultural production outcomes (Kurukulasuriya & Rosenthal, 2013; Mendelsohn & Wang, 2017).

Although we derive key insights from this literature, we focus on linking climate shocks to specific household commercialization decisions (e.g., selling of produce) and not necessarily on production decisions (e.g., using specific inputs and producing output).

Moreover, although the literature linking climate variables (rainfall and temperature) and general variability is vast, the literature testing for specific shocks (e.g., drought, flood, and heat stress shocks is emerging but still scarce(Bora, 2022; Makate et al., 2022) -a caveat which we also explore in the context of crop output commercialization decisions in Ethiopia. Testing for the effects of specific shocks on agricultural commercialization decisions enhances our understanding of the dynamics and can help proffer specific adaptation actions. Also, most of the studies in the literature (except for a few) have used cross-sectional data collected from small and regional samples(Pender & Alemu, 2007; Asfaw, Shiferaw, Simtowe, & Haile, 2011; Gebremedhin & Tegegne, 2012; Tufa, Bekele, & Zemedu, 2014; Hailua, Manjureb, & Aymutc, 2015; Abafita, Atkinson, & Kim, 2016; Hagos & Geta, 2016), which limits comprehension of long-term relationships and the external validity of findings. Therefore, our study adds important insights to the currently available literature on climate change, household vulnerability, and smallholder agricultural commercialization decisions in the presence of specific agriculture production risks.

Against this background, the study investigates how long-term climate variability (rainfall and temperature coefficient of variation) and recurrent climate shock exposure (drought, flood shocks, heat stress) influence crop output market participation among smallholder food crop producers in rural Ethiopia. Furthermore, we assess how investing in commercially purchased inputs (seed and fertilizer) earlier in the season helps sustain crop output market participation and intensity decisions under specific shocks (drought, flood, and heat stress) post-harvest. The rest of the paper is structured as follows: Section 2 gives the Ethiopian context on the studied theme, while Section 3 briefly explains the theoretical framework used to formulate study hypotheses. Section 4 briefly discusses this study's research contributions, while Section 5 describes data sources and the research methodology. Section 6 presents and discusses the main findings from the study, and finally, Section 7 concludes the paper and proffers policy recommendations.

2. Ethiopian Context

Though the commercialization of smallholder agriculture is central to Ethiopia's development agenda, its potential is largely untapped; the process is still in its infancy and varies in different parts of the country (Getahun, 2020). Recent studies also reveal marked disparities in agriculture commercialization across regions, gender of household head, distance to markets, wealth, and other socio-demographic factors. The general trend, though, is that of an increase in the rate of crop commercialization without evident changes in crop mix (Getahun, 2020; Minot, Warner, Dejene, & Zewdie, 2021).

Even though input support programs can be traced back to the Minimum Package Program Initiative of the early 1970s, concerted government smallholder commercialization policy efforts started in 2005, as outlined in the government's second Poverty Reduction Strategy Paper (Alem et al., 2010; Louhichi, Temursho, Colen, & y Paloma, 2019). Ever since, Ethiopian agricultural policy has shifted from an emphasis on increased productivity for poverty reduction to a more market-oriented approach that seeks to facilitate agricultural commercialization and diversification into high-value crops to raise income and improve the welfare of rural households (Minot et al., 2021). Agricultural commercialization is core to the government's two consecutive five-year growth plans (GTP-I and GTP-II), intending to achieve growth, build livelihood assets, and eradicate poverty through intensifying agricultural production(Getahun, 2020). The recent launch of the Agricultural Commercialization Cluster (ACC) initiative by the Ethiopian Agricultural Authority is also a testament to that (Louhichi et al., 2019).

However, a plethora of factors continues to cast a dark shadow over the prospects of smallholder commercialization in Ethiopia. Smallholder agriculture is still dominantly characterized by low output, insecure tenure and poor access to land, poor access to inputs, low technical knowhow, underdeveloped irrigation infrastructure, poor market infrastructure, underdeveloped support institutions, and climate change (Gebre-ab, 2006; Jaleta et al., 2009; Tilaye, 2010; Gebremedhin & Tegegne, 2012; Boka, 2017b). Al-Hassan, Sarpong, and Mensah-Bonsu (2006) pointed out that access to both input and output markets is not always smooth, and this is often augmented by volatile prices that pose challenges for smallholders to effectively participate in the markets. With 95% of cropped area and national annual crop production largely dominated by subsistence-oriented, natural resource-intensive, low input, low output, rainfed smallholder farming systems, Ethiopia is frequently cited as one country that is highly vulnerable to climate variability (Tesfaye, Seid, Getnet, & Mamo, 2016; Belay et al., 2017). Long-term records indicate repeated rainfall failure, and since 1980, the country has suffered seven major droughts, five of which led to famine in addition to several local droughts (Tesfaye et al., 2016; Belay et al., 2017). These cycles of droughts create poverty traps for many households, constantly hampering efforts to increase incomes and build up assets (Dercon, 2004). Like many SSA countries, farmers are rarely insured against climate risk, as conventional crop insurance schemes are impractical under such circumstances. Evidence on the potential effects of climate variability on smallholder commercialization efforts remains sparse and mixed.

This study seeks to contribute to the limited empirical literature that empirically assesses the role of climate risk in shaping agricultural commercialization outcomes among smallholder food producers in Ethiopia. To achieve these study objectives, the study uses nationally representative longitudinal household panel data for Ethiopia covering the period 2011/12-2018/19. While smallholder commercialization implies engagement with both input and output markets, Pingali (1997) illustrated that commercialization on the input side is likely to proceed in tandem with the degree of participation on output markets. Participation in the output market is, therefore, the lynchpin of the smallholder commercialization concept (Leavy & Poulton, 2007). For conceptual brevity, we focus our analysis more on the output side and assess the potential mediatory role played by input commercialization in supporting output commercialization under a changing climate. We rely on measures of the degree of participation in output markets as indicators of agricultural commercialization. We adopt panel data methods that address the endogeneity of output market participation to study agricultural commercialization under climate stress in Ethiopia. Given that we study both the probability and intensity of commercialization decisions, we employ the flexible Cragg (1971) Double Hurdle Models (CDHM) estimated in a Correlated Random Effects (CRE) framework that addresses possible endogeneity associated with household farming decisions by eliminating unobserved household effects using panel data(Wooldridge, 2019). Our study bears important implications for upgrading agricultural commercialization efforts under increasing climate and socioeconomic risk in agro-based rural economies.

3. Theory and Hypotheses

Theory: Climate risk can influence the engagement of farm households with markets in several ways. Following behavioral theories under risk (e.g.,Binswanger and Rosenzweig (1986)) and Chambers and Quiggin (2000) the general risk-coping literature in agriculture (e.g.,Dercon (2004, 2005)) climate risk can pose heterogeneous effects on agricultural commercialization motives. First persistent climate risk exposure can influence the learning of the benefits of different technologies and other agricultural commercialization decisions with or without climate risks, leading to farmers preferring farming technologies or decisions that benefit them in dealing (adapting or coping) with climate risk.

Second, climate risk could be severe enough to intensify poverty and offset positive behavioral responses toward using modern inputs to advance agricultural commercialization in smallholder farming(Dercon, 2004; Holden & Quiggin, 2017). For instance, elevated climate risk (shocks) can undermine returns from farming and intensify liquidity constraints, leading to smallholder farmers selling productive assets and forgoing using modern inputs(Kakota, Nyariki, Mkwambisi, & Kogi-Makau, 2011; Kirsten, Mapila, Okello, & De, 2013), especially when they lack access to formal insurance. In settings with perfect financial and insurance markets, households can borrow credit to finance external input access and trade away the risk of crop failure in the insurance market(Alem et al., 2010; Yu & Hendricks, 2020). However, given imperfections in factor and insurance markets typical of most rural areas(Markelova & Mwangi, 2010), farmers encounter serious constraints in coping with production risks and make input use decisions that minimize exposure to such risks. On the output side, constrained input use and the direct negative effects of varying rainfall and temperature over time mean declining and cyclical fluctuations in farm output in ways that farmers cannot control(Orr et al., 2021). Taken together with household consumption decisions, this has obvious implications on the degree to which farmers participate in output markets. In addition, previous literature alludes climate risk as a significant factor influencing not only agricultural production outcomes such as yield (Kurukulasuriya & Rosenthal, 2013) but also agricultural production decisions, including the demand and use of commercial inputs (Nordhagen & Pascual, 2013; Mendelsohn & Wang, 2017; Asfaw, Scognamillo, Caprera, Sitko, & Ignaciuk, 2019; Makate & Makate, 2022).

Also, the general risk coping literature that distinguishes *ex-ante* (income smoothing) and *ex-post* (consumption smoothing) risk management strategies (Dercon, 2004, 2005) provides an analytical framework for the comprehension of smallholder commercialization decisions and responses to climate risks. According to this literature, the *ex-ante* mechanisms target risk reduction through altering production decisions which might include purchasing climate-resilient inputs (fertilizer and seed), diversifying inputs (mixing local and external inputs[1]), or diversifying crop production and livelihood income sources in general in anticipation of future shock exposure. These strategies ensure the smallholder farmer hedges against future income losses (hence income smoothing). On the other hand, *ex-post* strategies deal with coping with losses due to shock exposure after the event. For example, negative shocks such as drought or floods could reduce production and income from farming, reducing investment in productive inputs in the following seasons by households. Hence, lowering external input purchases or output sales post a drought or a flood shock can be regarded as an *ex-post* coping response. With the availability of nationally representative household panel data that captures farmers' input and output commercialization decisions over time, as in this study, we can test these hypotheses in the context of Ethiopia.

[1] Examples might include mixing farmer saved seeds (local input) with improved drought tolerant seeds (external input) or combining the use of organic fertilizers(local) with chemical fertilizers(external).

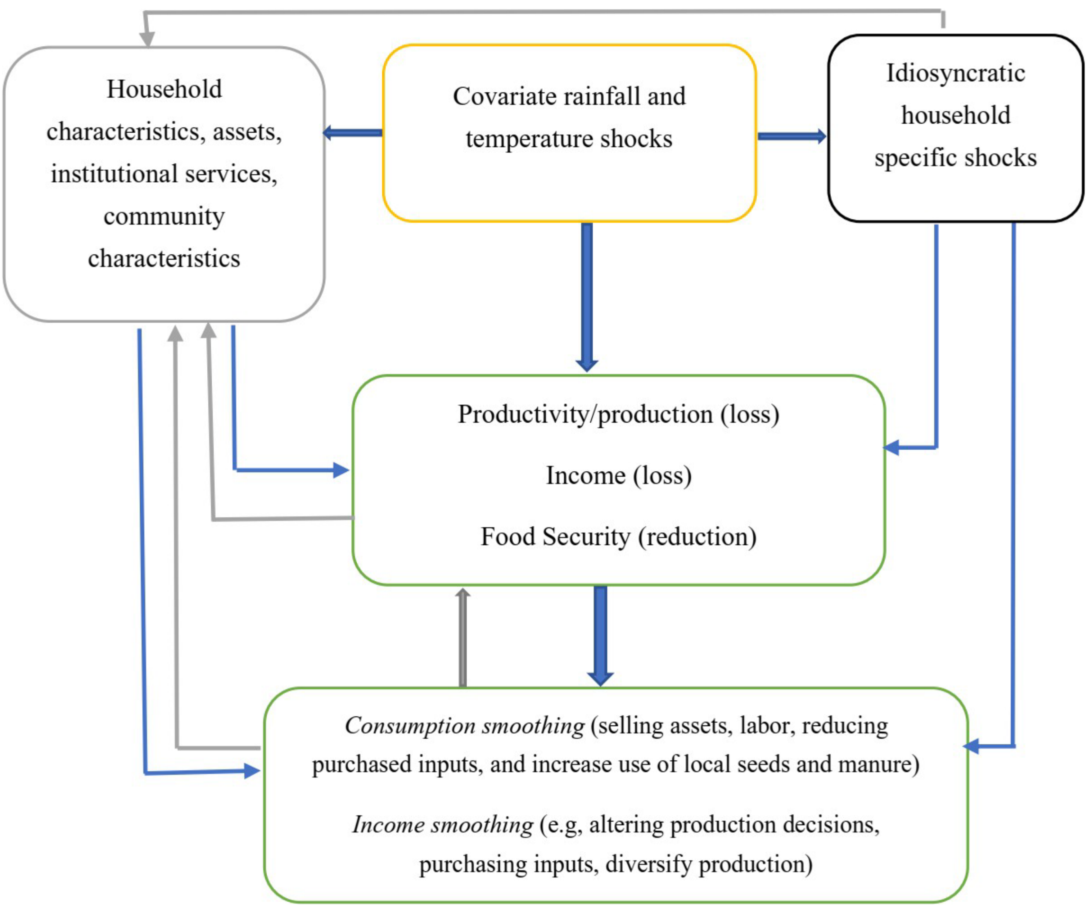

Figure 1: Simplified framework linking shocks, agriculture outcomes, and response strategies.

Figure 1 shows a simplified diagram showing the pathways through which covariate shocks might influence agricultural commercialization outcomes. Covariate shock exposure will affect agricultural livelihood outcomes, particularly crop yields, post-harvest decisions (e.g., crop sales), farm income, and food security. The household's vulnerability to shocks in smallholder farming settings depends on their underlying characteristics, asset resource endowments, social networks, community linkages, and institutional support (e.g., access to safety nets), among other factors. Post-exposure to shocks, depending on vulnerability and adaptive capacity (which determines the extent of negative impacts of shocks), triggers immediate ex-post coping strategies (consumption smoothing) and distant risk-reduction strategies in preparation for future shocks (income smoothing). The relationships are not static but dynamic, as decisions and outcomes in one season impact decisions and outcomes in the following seasons. For example, drastic changes in household composition and/or assets may lead to idiosyncratic shocks, which may further impact household assets built up in the future. Also, consumption smoothing strategies and income loss due to shocks have feedback on household characteristics/assets in the medium to short term. With panel data showing household decisions over time, we can assess the recursive nature of these relationships. For instance, we study both the impact of previous shock exposure on output commercialization and the role played by investments in commercial inputs (seed and fertilizer) in reducing the negative effects of covariate shocks on subsequent output commercialization outcomes.

Hypothesis: Given the brief theoretical framework, we seek to test the following hypothesis:

H1: Long-term climate variability and seasonal shock exposure, such as increased heat stress, flood, and or drought shocks, reduce crop output commercialization. We expect crop output market participation and intensity to decrease with increasing climate variability and shock exposure as an *ex-post* coping measure to shocks.

H2: Using commercially purchased inputs reduces the negative effect of shocks on crop-marketed participation and intensity. We expect output market commercialization under shocks to be greater for farmers using commercially purchased input than their opposite counterparts. Using resilient crop inputs sourced from outside the farm is an essential adaptation strategy that can help the farmer increase output produced and surplus output sold on the market under shock exposure.

4. Research Issue

Smallholder agricultural commercialization as a development policy instrument has received its fair share of empirical attention (Jones Govereh & Nyoro, 1999; Strasberg et al., 1999; Gebre-ab, 2006; Leavy & Poulton, 2007; Jaleta et al., 2009; Gebremedhin & Tegegne, 2012; Poulton, 2017; Getahun, 2020; Minot et al., 2021). While its role in alleviating poverty is an issue of empirical consensus, little is known about how commercialization dynamics are evolving under a changing and variable climate. Scientific evidence shows that the global climate is changing and given the highly climate-sensitive nature of agriculture, this has obvious and important ramifications for commercialization. We build on earlier studies of smallholder agricultural commercialization in SSA (Jones Govereh & Nyoro, 1999; Strasberg et al., 1999; Gebre-ab, 2006; Leavy & Poulton, 2007; Jaleta et al., 2009; Gebremedhin & Tegegne, 2012; Poulton, 2017; Getahun, 2020; Minot et al., 2021), behavioral theoretical frameworks under risk (Binswanger & Rosenzweig, 1986; Chambers & Quiggin, 2000; Holden & Quiggin, 2017) and the general risk coping literature (e.g.,Dercon (2004, 2005); Dercon and Christiaensen (2011)) and use nationally representative household-level panel data complemented with historical climate data for Ethiopia to interrogate this issue. Our main contributions in this paper are as follows (i) We assess the impact of rainfall and temperature shocks (drought, flood, and heat stress) and long-term climate variability in the main cropping season on the *ex-post* decisions to sell part of crop production for cash on the market, (ii) further, we assess the possible role of *ex-ante* risk reduction strategies (investing in commercial inputs) in reducing the possible negative role of climate shocks on crop output sale decisions (probability and extent) in subsequent seasons. In addition, (iii) we rely on nationwide panel data covering several regions in Ethiopia and several cropping seasons, enabling us to get insights on both ex-ante and ex-post risk management strategies and their significance in smallholder commercialization. Further, (iv) we generate specific climate shocks using a longitudinal climate data source covering the historical monthly climate for 38 years (1980-2018), which gives us flexibility in defining shocks experienced at specific points in time (covered in the nationwide household panel data which we propose to use). Using such longitudinal and rich data allows the computation of shocks in specific crop growing seasons as normalized deviations from a reference point [2] (e.g., long-term (38-year) averages for rainfall and temperature in the growing season). By exploring the effects of specific shocks, e.g., drought (below normal rainfall conditions) or flood (above-normal rainfall conditions), and heat stress shock (above normal maximum temperature conditions), we can distinguish the effects of general climate variability [3] from the impact of specific shocks (drought or flood shocks). Also, by incorporating both rainfall and temperature shocks, we escape the highly probable omitted variable bias, given that rainfall and temperature variables and shocks jointly influence crop production and commercialization outcomes. In addition, we adopt appropriate panel data methods that help us explore important dynamics in smallholder commercialization decisions while addressing possible endogeneity of commercialization decisions probable from unobserved household heterogeneity. Overall, our approach gives us a complete picture of the dynamics in the relationships between climate risk factors and smallholder output commercialization decisions in Ethiopia, which adds value to the existing body of knowledge.

[2] By reference point here we mean the normal conditions as depicted by long-term averages for rainfall and temperature experienced during the main crop growing season.
[3] By general climate variability here we mean measures of the general uncertainty of climate which include both more than average and less than average climate conditions in one variable. This is different from specific shocks that distinguish for example: drought vs. flood shocks, or excessive cooling from heat stress.

5. Data & Methodology

5.1. Data Sources

5.1.1. Household survey data

The study uses a longitudinal panel data set for Ethiopia (Ethiopia Socioeconomic Surveys 2011/12, 2013/14, 2015/16, and 2018/19, which we call 2012, 2014, 2016, and 2019 throughout the paper for simplicity) available openly through the World Bank project- Livelihood Standards Measurement Surveys-Integrated Surveys on Agriculture (LSMS-ISA [4]). These four waves of Ethiopia Socioeconomic Survey (ESS), which we use, include a complete panel of households with three waves ESS 1 of 2012, ESS 2 of 2014, and ESS 3 of 2016. Waves 1, 2, and 3 of the Ethiopia Socioeconomic Survey (ESS) together represent a panel of households where we can trace the same households interviewed in all three rounds. The three waves (ESS1, ESS2, and ESS3) are therefore referred to as complete Panel I and subsequent rounds from ESS4 and rounds to come after that as Panel II. The 2019 ESS(ESS4) is a new panel, the first round of Panel II, which has no links to the first three waves (ESS1,2,3) that make a complete Panel I. Hence the application of some of the panel data methods we use is only feasible if we consider the first three rounds of ESS data, which makes a complete household panel. However, we start our analysis by applying methods that allow us to use pooled data, including all four rounds, test our hypotheses, and then move on to estimate specific panel data methods using a complete panel with the three waves (ESS 1-3). We provide more details on this process later in the paper (empirical methods).

The ESS survey data are collected by the LSM-ISA team of the World Bank in collaboration with the government of Ethiopia. The LSMS-ISA data collect comprehensive information on agricultural activities from input acquisition to post-harvest activities, various other information on households, their farming characteristics, community characteristics, and approximate locations of enumeration areas from which households were sampled. Useful to this study will be post-planting and post-harvest data captured under the Agricultural modules. The post-planting sub-modules ask farmers about input sourcing, input use, and particularly the quantities and values of complementary farming inputs commercially purchased, including fertilizer, agrochemicals, and seeds. In addition, the post-harvest modules capture harvesting activities and the use of harvested output, including the volumes and values of harvested crop output and sales. We use such information to define our proxy variables for agriculture commercialization. In addition, we use the household and community modules to define useful control variables for the study. We are guided by the Ethiopian context, theoretical framework, and related empirical literature (discussed earlier) in selecting household control variables, including farm, household, and regional control variables. Specific variables we include as controls include (i) endowments: - household labor, asset wealth endowments, farm size, (ii) access to institutional services (credit, safety-nets, extension), (iii) household characteristics (age, gender, education of household leader, and household size), and (iv) regional dummies (10 regions covered in Ethiopia LSMS). We report finer descriptions and descriptive statistics of all these variables in the attached supplementary material.

Also available with the LSMS-ISA data are approximate locations (longitude and latitude) of primary sampling units, also known as Enumeration Areas (EAs) used in data collection. These are villages from which households interviewed are sampled. We use these location data (longitude and latitude) to extract spatial information, such as climate variables. In the next sub-section, we describe how we use these data to extract and link historical weather data to our survey data.

[4] LSMS-ISA data are available publicly on the World Bank website(www.worldbank.org/lsms)

5.1.2. Weather data

We complement our survey data with climate data which we extract from available weather sites. Specifically, we extract historical monthly weather data for both rainfall and temperature for more than 30 years (1980-2018) from WorldClim (Fick & Hijmans, 2017) using georeferenced data (longitude and latitude) available with LSMS-ISA data at the Enumeration Area(EA) level. The WorldClim data are widely used in literature and proven to be reliable. They are available at a fine(high) spatial resolution of about 2.5 minutes (approximately ~21 km^2) and are also suitable for our study. These data are rationalized by the Climatic Research Unit, University of East Anglia, using WorldClim 2.1 for bias correction(Fick & Hijmans, 2017). We use the extracted rainfall and temperature data to build long-term climate and shock variables. Climate variables and shocks are defined for Ethiopia's main crop growing season, the Meher season, spanning from May to September. The Meher season is the most important season for crop production in Ethiopia, accounting for more than 90% of Ethiopia's food production(Taffesse, Dorosh, & Gemessa, 2012). We follow related studies (e.g.,(Ward & Shively, 2015; Michler, Baylis, Arends-Kuenning, & Mazvimavi, 2019; Bora, 2022; C. Makate, A. Angelsen, S.T. Holden, & O.T. Westengen, 2023; S Di Falco & Vieider, 2022)) and define climate shocks as normalized deviations in a growing season for climate variables (rainfall and temperature) from a reference point (long-term average). We process the rainfall and temperature data at the EA level. The processing involves computing climate variables of interest for the main crop growing season of Ethiopia (*Meher season*). We do this to ensure that our variables better reflect climate conditions and shock exposure during the main crop growing season. The ESS surveys collect about 8 to 15 households per EA the national sample has more than 400 EAs and the rural sample which we focus on has more than 280 EAs. This means when integrating our climate variables and shocks data back to household survey data about 8-15 households belonging to the same EA will have the same measures of climate and shocks which is a plausible thing to do since climate and shocks do not vary much over short distances, especially in the same village or enumeration area. In Figure 2, we plot the distribution of long-term mean rainfall and temperature for households in the final sample we analyze. Since 1980, the mean rainfall and mean temperature have been around 700 mm and 27 degrees Celsius during the Meher season, respectively. Figure 3 show the distribution of rainfall and temperature shock variables in the analysis (pooled) sample and for the main crop growing season (Meher season). For most of the seasons, the farmers experienced positive shocks for both rainfall and temperature.

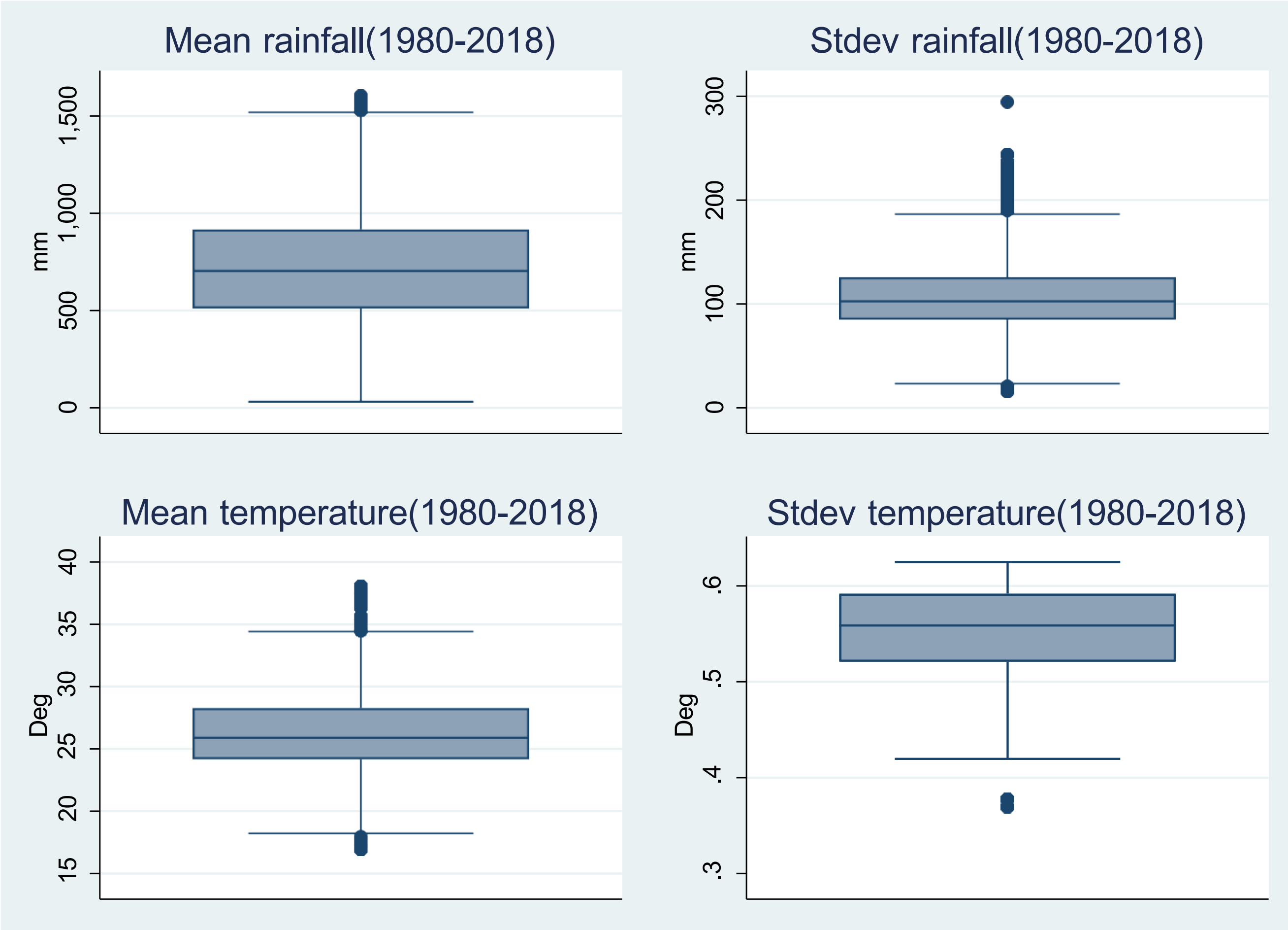

Figure 2:Distribution of historical mean rainfall, temperature and their standard deviations in the Meher season in Ethiopia based on the WorldClim monthly data and on the final sample of households we analyze in the manuscript.

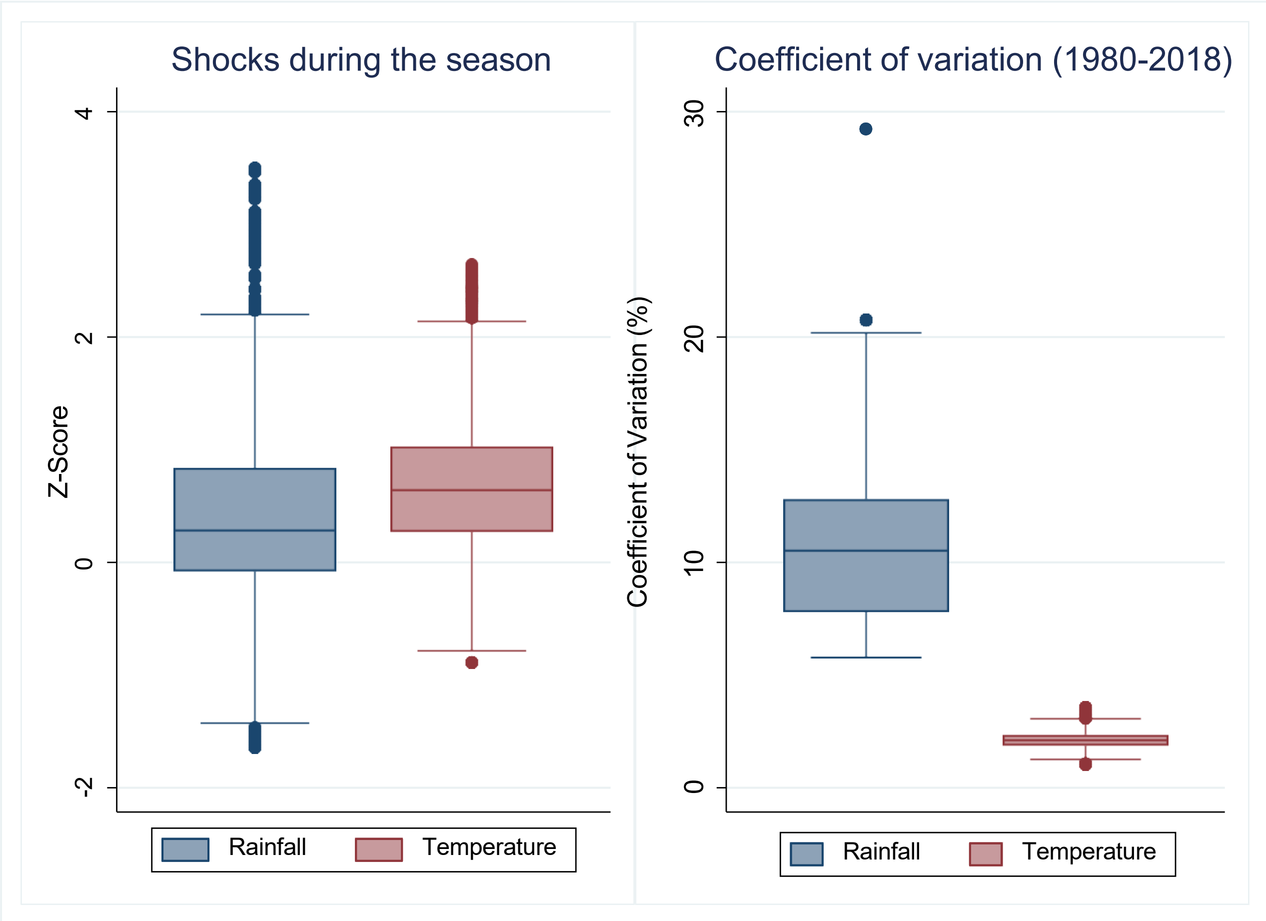

Figure 3:Distribution of rainfall and temperature shock variables in the analysis (pooled) sample and for the main crop growing season (Meher season). The left panel show rainfall and temperature shocks during the season for which crop production data are measured, and the right panel show long-term average coefficient of variation for temperature and rainfall based on the period (1980-2018).

5.2 Measuring the scale of commercialization.

To measure the scale of commercialization, we use the gross value of crop production sold per unit area. Unlike the commonly used Household Commercialization Index (HCI), this indicator is less demanding of data and is less susceptible to distress sales (Poulton, 2017). One might argue that using this variable as a proxy for output commercialization can potentially lead to misleading results in situations where households shift from one crop to another in response to market and institutional conditions. Important to note is that such a problem arises when the variables are defined to a single crop, yet in this study, we define household-level variables. Hence, we consider the household cropping portfolio, whether the household sold part of their crop production, and the extent of sale (value of crop output sold/ha in local currency and USD). However, as robustness checks to scale of commercialization and shows trends in commercialization levels for individual crops grown by the household, we also compute crop-specific shares of marketed output [5] (commercialization indices) and report descriptive statistics. We compute crop-specific commercialization indices as the share of crop output that is sold (Strasberg et al., 1999; Minot et al., 2021). We approximate this index for the specific crop(cc) grown and marketed by the household (jj) as a ratio of quantities sold(QQ_{ss}) to total quantities harvested(QQ_h) as follows: $W_{jjj} = \frac{QQ_{ss}}{QQ_h}$, and to get an approximate household level of crop

[5] The rationale for including marketed shares as proxy for commercialization is based on the notion that agricultural commercialization can also be defined as a gradual increase in the share of agricultural output that is sold, as opposed to being used for household consumption(Strasberg et al., 1999; Minot et al., 2021).

commercialization index, we get an average for all crops grown $\left(\sum_{j=1}^{n} V_{j}\right)/n$. We summarize the proportion of households selling part of their crop produce and extent (value sold in USD/ha and Birr/ha) by survey round in *Figure 4*. In addition, we show the average crop-specific shares of marketed crop output and the cumulative distribution of household average marketed shares by survey year in Figures 5 and 6. Trends from *Figure 4* show an increasing proportion of households selling part of their crop produce for cash by about 11% (38-49) from 2012 to 2014 and by about 7% from 2012 to 2016 in the household panel. Also, comparing the baseline of the first complete panel (2012-2016) to the 2019/20 refresher round, the proportions of participation in the crop output market increased sharply by about 25% (*Figure 4*). Likewise, the intensity of crop sales in the complete panel (2012-2016) ranges between 2000 and 2500 Ethiopian Birr (roughly 105 to 120 USD) and is slightly higher in the refresher round (2019/20) at an average of 6400 Ethiopian Birr(about 240 USD).

Figure 4:Crop output sales (aggregate for all crops) by survey year: Statistics are based on Ethiopia LSMS 2012-2019 for the rural sample; Intensity of input purchase and sales values are expressed in units/ha of land and are winsorized for outliers at 2%. Intensity value averages are shown for the conditional sample (conditional on the first decision). Values of output sold are converted to constant United States dollars to enable comparison across years.

Crop specific market shares show contrasting trends but a general increase in shares of marketed output from 2012 to 2019 (*Figure 5*). In *Figure 6*, we show the cumulative distribution of household crop commercialization index *(Average for individual crops grown with part of harvest sold)* by survey year, and it is evident that household average market shares have increased overtime (from 2012 to 2019.

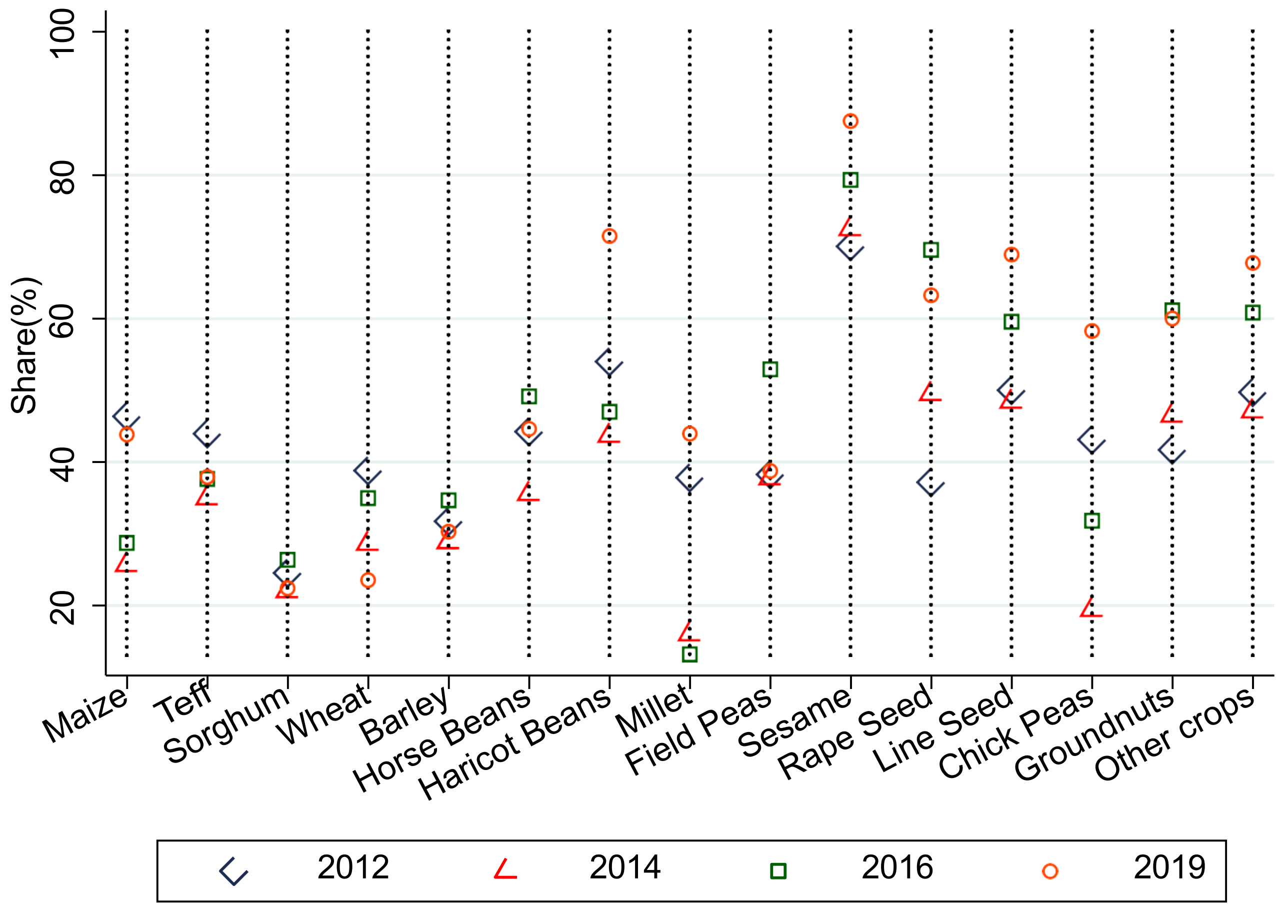

Figure 5: percent share (%) of crop output sold (crop commercialization) by survey year. Average shares of marketed output per crop are shown for the conditional sample (conditional on the first decision). A figure showing a detailed list of crops and average marketed shares is shown in the supplementary material.

In supplementary figures shown in the Appendix, we show the average intensities of crop output sales in the full sample (*including both participants and non-participants*) and a comparison of average proportions and intensities for farmers who invested in inputs at the beginning of the season (and those who didn't) and by survey year. It is clear from the descriptive statistics that the sub-groups of farmers who invested in input purchases earlier in the season have a comparably higher average for crop output sales at the end of the season. In addition, we also show descriptive statistics on key outcome and control variables used in the analysis in supplementary material.

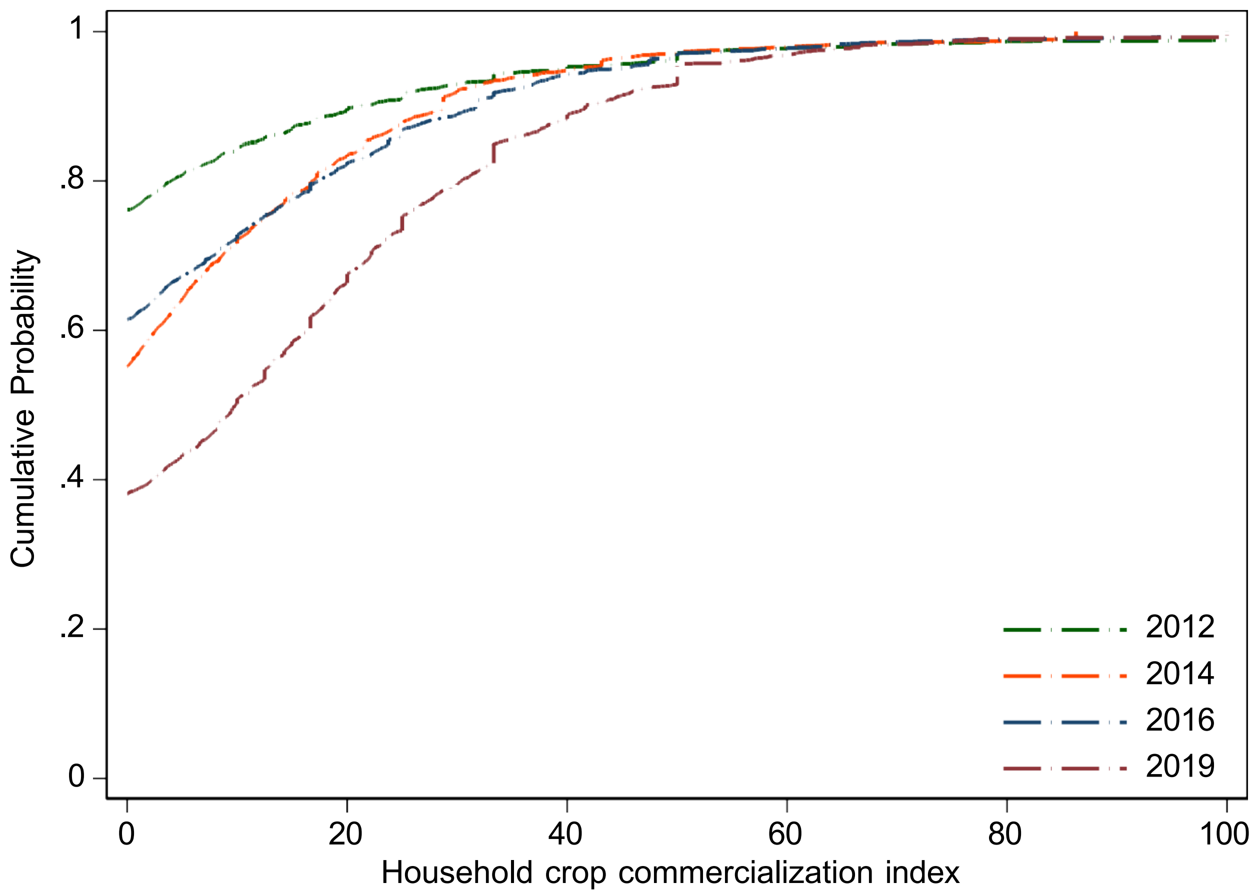

Figure 6: Cumulative distribution of household crop commercialization index (Average for individual crops grown with part of harvest sold) by survey year. Average shares of marketed output per household are shown for the conditional sample (conditional on the first decision).

5.3 Empirical methods:

5.3.1. Estimating the impact of climate shocks on agriculture output commercialization decisions.

To measure the effect of climate variability and shocks on agriculture output commercialization decisions we employ flexible Cragg (1971) Double Hurdle Models (CDHM) allow variables to have different effects on the probability and intensity of commercialization decisions(Cameron & Trivedi, 2005). An alternative will be to use the Tobit Models (Tobin, 1958) or Heckman sample selection models(Heckman, 1979). However, the Tobit model is restrictive as it assumes that both the probability and intensity of adoption decisions are explained by the same set of factors and have the same sign. Also, Heckman models are useful but for identification they require that the exclusion restriction is satisfied which relies on identification of valid instruments(Cameron & Trivedi, 2005). In the CDHM, the first hurdle involves estimating a probit model which determines the probability that the household adopt agricultural commercialization decisions (sell part of their output on the market). The second hurdle uses a sub-sample of households who engage in the first hurdle (i.e., the decision to engage in a particular commercialization decision) and estimates a truncated regression model that determines the intensity of participation. To assess the effects of climate variability [6] and shocks on output commercialization we estimate the following hurdles of participation and intensity of participation:

[6] According to the IPCC (IPCC (2012) climate variability refers to variations in the mean state and other statistics (such as standard deviations, the occurrence of extremes, etc.) of the climate at all spatial and temporal scales beyond that of individual weather events.

Hurdle 1(participation decision for output commercialization):

$$PPPP(\gamma\gamma_{iiii} = 1) = \beta\beta_0 + \beta\beta_1 ZZ_{iiii} + \beta\beta_2 DD_{iiii} + \beta\beta_3 DD^2_{iiii} + \beta\beta_4 FF_{iiii} + \beta\beta_5 FF^2_{iiii} + \beta\beta_6 VV + \beta\beta_7 VV^2 + \beta\beta_8 TT_{iiii} + \beta\beta_9 TT^2_{iiii} + \beta\beta_{10} WW + \beta\beta_{11} WW^2 + \beta\beta_{12} VVWW + \mu\mu_{ii} + \epsilon\epsilon_{iiii} \quad (1)$$

Hurdle 2 (intensity of participation for output commercialization):

$$yy_{iiii} = \emptyset_0 + \emptyset_1 ZZ_{iiii} + \emptyset_2 DD_{iiii} + \emptyset_3 DD^2_{iiii} + \emptyset_4 FF_{iiii} + \emptyset_5 FF^2_{iiii} + \emptyset_6 VV + \emptyset_7 VV^2 + \emptyset_8 TT_{iiii} + \emptyset_9 TT^2_{iiii} + \emptyset_{10} WW + \emptyset_{11} WW^2 + \emptyset_{12} VVWW + uu_{ii} + \varepsilon\varepsilon_{iiii} \;\; iiii\; \gamma\gamma > 0 \quad (2)$$

Where $\gamma\gamma_{iiii}$ and yy_{iiii} are respectively; the decision by household i to sell part of their output on the market at time t *and the* value of all crop sales (per unit area) by individual household ii at time tt. DD_{iiii} and FF_{iiii} are respectively normalized negative (drought) and positive (flood) rainfall deviations from a long-term reference point (38-year average) (in mm) at time tt, V is the historical rainfall coefficient of variation, TT_{iiii} is a measure of heat stress (positive normalized temperature deviations from a long-term average) at time tt, W is the historical temperature variation coefficient, VW is the rainfall and temperature interaction term, ZZ_{iiii} is the vector of other socioeconomic factors [7](elaborated below),$\beta\beta_{ii}$ and $\emptyset$ are the parameters to be estimated and $\epsilon\epsilon_{iiii}$ and $\varepsilon\varepsilon_{iiii}$ are error terms assumed to be independent and identically distributed. Lastly, $\mu\mu_{ii}$ and uu_{ii} are normally distributed random effects which are constant for each household over time. Given that rainfall and temperature are often correlated in determining production outcomes (Ochieng, Kirimi, & Mathenge, 2016; Makate et al., 2022), they are both included in this model to avoid omitted variable bias. Quadratic terms of rainfall and temperature shocks are also included to allow for non-linear relationships between these variables and the value of crop sales. From Equation (1 and 2), we will be able to test hypothesis 1(H1) separately for the probability and intensity of output commercialization decisions. In vector (ZZ_{iiii}) we are guided by available literature on agriculture technology adoption (e.g., Feder and Umali (1993); Takahashi, Muraoka, and Otsuka (2020)) and select household, and farm characteristics to use as controls in our specifications. We specifically include household characteristics (household labor units, household size, asset wealth endowments, access to credit, social safety nets, and extension services), characteristics of the household head (gender, age, education level completed (at least level 12), and farm characteristics (e.g., total farm size(ha).

5.3.2. The mediatory role of input usage on the impact of climate risk on output commercialization: Interaction Effects

Another important aspect the study aimed to uncover is the important role played by investments in commercial input use decisions in farmer adaptation to shocks. Accordingly, we explore the interaction effects of shocks and purchased input use decisions and how they affect output commercialization decisions. We follow specifications in Equations 1 and 2 and specify the equations with interaction effects as follows:

Hurdle 1 (participation decision for output commercialization):

$$PPPP(\gamma\gamma_{iiii} = 1) = \phi\phi_0 + \phi\phi_1 ZZ_{iiii} + \phi\phi_2(DD_{iiii} \times bbuuyyiinnbbuutt) + \phi\phi_3 DD^2_{iiii} + \beta\beta_4(FF_{iiii} \times bbuuyyiinnbbuutt) + \phi\phi_5 FF^2_{iiii} + \phi\phi_6 VV + \phi\phi_7 VV^2 + \phi\phi_8(TT_{iiii} \times bbuuyyiinnbbuutt) + \phi\phi_9 TT^2_{iiii} + \phi\phi_{10} WW + \phi\phi_{11} WW^2 + \phi\phi_{12} VVWW + \mu\mu_{ii} + \epsilon\epsilon_{iiii} \quad (3)$$

Hurdle 2 (intensity of participation for output commercialization):

[7] We were guided by the conceptual framework to choose control variables in our analysis. The control variables our analysis used include household assets (land and non-land assets), household characteristics, access to institutional services (extension, credit, safety nets), farm characteristics and characteristics of the household leader(s), and access to other sources of inputs (e.g., farmer saved seeds, organic manure).

$$yy_{iiii} = \varphi\varphi_0 + \varphi\varphi_1 ZZ_{iiii} + \varphi\varphi_2(DD_{iiii} \times bbuuyyiinnbbuutt) + \varphi\varphi_3 DD^2_{iiii} + \varphi\varphi_4(FF_{iiii} \times bbuuyyiinnbbuutt) + \varphi\varphi_5 FF^2_{iiii} + \varphi\varphi_6 VV + \varphi\varphi_7 VV^2 + \varphi\varphi_8(TT_{iiii} \times bbuuyyiinnbbuutt) + \varphi\varphi_9 TT^2_{iiii} + \varphi\varphi_{10} WW + \varphi\varphi_{11} WW^2 + \varphi\varphi_{12} VVWW + uu_{ii} + \varepsilon\varepsilon_{iiii} \quad iiii\ \gamma\gamma > 0 \quad (4)$$

Where $\gamma\gamma_{iiii}$ and yy_{iiii} are as described earlier and $(DD_{iiii} \times bbuuyyiinnbbuutt)$, $(FF_{iiii} \times bbuuyyiinnbbuutt)$, and $(TT_{iiii} \times bbuuyyiinnbbuutt)$ are respectively the negative (drought shock) , positive (flood shock) rainfall deviations from the long-term average, and a measure of heat stress (positive temperature deviations from a long-term average) interacted with a dummy variable showing whether household ii purchased both seed and fertilizer used earlier in the crop growing season and zero otherwise. The interaction effects analysis enables us to assess whether farmers using commercially purchased inputs and those without respond differently to climate shock exposure in their output commercialization decisions. Given that the use of purchased inputs can offer adaptation to climate shocks, farmers with access to such inputs may be more likely to have better yields hence more surplus to sell in the market compared to their counterparts. We show the definitions of some of our target climate risk variables in Table 1.

Table 1:Variable definitions of key climate variables and shocks

Variable	***definitions***
Negative rainfall deviation(D)	• *This variable is computed as the negative deviation of total rainfall received in a particular season of interest from the long-term average (38-year average) in mm. It range from 0 (those with zero and positive deviations) to +∞ in millimetres. We use this variable as a proxy for drought shock exposure (receiving less than average rainfall).*
Positive rainfall deviation(F)	• *This variable is computed as the positive deviation of total rainfall received in a particular season of interest from the long-term average (38-year average) in mm. It ranges from 0 (those with zero and negative deviations) to +∞ in millimetres. We use this variable to proxy a flood shock (receiving more than average rainfall).*
Historical rainfall coefficient of variation(V)	• *This variable is defined as the average long-term rainfall coefficient of variation (long-term Standard deviation/long-term mean) for the Meher season expressed as a percentage. The variable shows average level of rainfall variability(uncertainty) with values less(more) than 100% indicating than the standard deviation is less(more) than the average mean.*
Heat stress(T)	• *This variable measure positive temperature deviations from a long-term average (38-year average). The derived variable will range from 0 to +∞ in degrees Celsius (measuring heat stress).*
Historical temperature coefficient of variation(W)	• *This variable is defined as the average long-term maximum temperature coefficient of variation (long-term Standard deviation/long-term mean) for the Meher season expressed as a percentage. The higher(lower) the value of the variable the higher(higher) the variability (uncertainty) of temperature*

5.4. Estimation approaches

The estimation of Equations 1 and 2 is possibly complicated by household heterogeneity that influences commercialization decisions but is otherwise unobserved. Such unobserved heterogeneity may create selection bias as some farming households may be more likely to commercialize crop production outcomes than others hence complicating comparison. The standard panel data method to deal with that problem will be to include household fixed effects, which allow for arbitrary correlation between unobserved household heterogeneity and household level regressors. However, the censored nature of our dependent variables (commercialization indicators) means that data takes the form of a non-linear corner solution(Wooldridge, 2010, 2019). Therefore, our study adopts the Correlated Random Effects (CRE) approach in estimating the CDMH specified in equations (1-4) to avoid the incidental variables problem that fixed effects introduce in non-linear models(Wooldridge, 2010, 2019). The CRE approach was first suggested by Mundlak (1978) and Chamberlain (1982) and is equivalent to using household fixed effects models with continuous dependent variables. The CRE approach applies to many limited dependent variable models, including Probit/logit, Tobit, and Double hurdle models(Wooldridge, 2010, 2019). Given that we seek to understand both the probability of partaking in commercialization decisions (measured by dummy variables) and the extent of partaking in those decisions(censored variables for intensity of participation- Value/ha), we primarily apply CRE Craggit Double Hurdle models (Cragg, 1971) (Probit and truncated OLS regression models).

With the CRE approach, unobserved household heterogeneity is controlled by including the means of time-varying control variables (ZZ_{iiii}) across years as additional control variables to our specifications(Mundlak, 1978; Chamberlain, 1982). This means in our specifications vector ZZ_{iiii} include both observed variables in specific years and their average across years ($ZZ_{iiii} + ZZ_{iiii}$). However, the estimation of CRE models requires panel data (the same households repeatedly sampled over time)(Wooldridge, 2010, 2019). The data we use is from four waves of the Ethiopia Socioeconomic Survey (ESS), which include a complete panel with three waves ESS 1 of 2012, ESS 2 of 2014, ESS 3 of 2016, and ESS 4 of 2019. Waves 1, 2, and 3 of the Ethiopia Socioeconomic Survey (ESS) together represent a panel of households where we can trace the same households interviewed in all three rounds. The three waves (ESS1, ESS2, and ESS3) are referred to as complete Panel I, and subsequent rounds from ESS4 and rounds to come after that as Panel II. The 2019 ESS(ESS4) is a new panel, the first round of Panel II, which has no links to the first three waves (ESS1,2,3) that make a complete Panel I. Hence, applying the CRE approach is only feasible if we consider the first three rounds of ESS data, which makes household panel data. However, we start our analysis by specifying random effects Cragg double hurdle models where we pool all the data from the four rounds (ESS 1-4) and test our hypotheses, and then we move on to estimate CRE specifications using panel data of the first three waves (ESS 1-3). We report and discuss results from both specifications in the paper.

5.5. Robustness checks

Commercialization of crop production and response to climate shocks is a complex phenomenon that might involve some prioritization of cropping decisions, among other things. For instance, in response to recurring shocks, farmers could diversify crop production, with some crops earmarked to provide food to the family and some more targeted only to earn income for the household. This is another important aspect of commercialization dynamics under recurrent exposure that our analysis did not adequately cover due to data constraints. However, to highlight how shocks may drive crop-specific commercialization decisions (which could help us understand partly aspects of prioritization), we consider crop-specific marketed shares for some of the key crops covered in the data and test how their marketed shares respond to climate shocks such as drought, flood, and heat stress over time. In a supplementary analysis, we hence include crop marketed shares and the average for all crops (average of crop-specific shares grown by the household) and for crucial cereals (Teff, Maize, Sorghum, Wheat, Barley, and legumes (Haricot bean, Horse bean, Groundnut) and run truncated regressions with the exact specifications in equation (2). We show the trends in crop-specific marketed shares per survey round and the all-crop average in the Appendix. In addition, we summarize insights from the regression analysis in the paper and show the tables in the Appendix.

6. Main Findings

6.1 Impact of climate risk on Commercialization

We report results on the effects of climate shocks on output commercialization decisions in this section. We start reporting results from pooled Cragg double hurdle models, including four rounds of ESS data, and then afterward, we show CRE Cragg Double Hurdle models using the first three waves of panel data. Table 2 below presents the regression results for the effects of climate variability and shocks on the probability of participation in output markets and the intensity of participation. We included two outcomes on intensity, i.e., the value of traded output in log (Birr/ha) and the other one in log (USD/ha).

Table 2: Impact of climate risk on output commercialization decisions: Cragg Double Hurdle models using pooled data from four waves of ESS data 2012-2019

	Yes	BIRR	USD

	Coef	ME	Coef	ME	Coef	ME
Drought shock (ref season)	0.176	0.063	-0.970***	-0.970***	-0.878***	-0.878***
	(0.171)	(0.062)	(0.266)	(0.266)	(0.248)	(0.248)
Drought shock (ref season) squared	0.290*	0.104*	1.301***	1.301***	1.209***	1.209***
	(0.130)	(0.047)	(0.180)	(0.180)	(0.168)	(0.168)
Flood shock (ref season)	-0.004	-0.001	-0.354***	-0.354***	-0.334***	-0.334***
	(0.064)	(0.023)	(0.103)	(0.103)	(0.097)	(0.097)
Flood shock (ref season) squared	-0.018	-0.006	0.120**	0.120**	0.111**	0.111**
	(0.024)	(0.009)	(0.041)	(0.041)	(0.038)	(0.038)
Heat stress (ref season)	-0.037	-0.013	-0.324	-0.324	-0.322	-0.322
	(0.118)	(0.042)	(0.209)	(0.209)	(0.197)	(0.197)
Heat stress (ref season) squared	0.084	0.030	0.117	0.117	0.114	0.114
	(0.047)	(0.017)	(0.080)	(0.080)	(0.075)	(0.075)
Rainfall CV(long-term)	0.234***	0.084***	0.151	0.151	0.116	0.116
	(0.053)	(0.019)	(0.104)	(0.104)	(0.100)	(0.100)
Rainfall CV(long-term) squared	-0.006***	-0.002***	0.001	0.001	0.002	0.002
	(0.002)	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)
Temperature CV(long-term)	2.316***	0.833***	4.566***	4.566***	4.243***	4.243***
	(0.472)	(0.169)	(0.865)	(0.865)	(0.811)	(0.811)
Temperature CV(long-term) squared	-0.346***	-0.124***	-0.723***	-0.723***	-0.676***	-0.676***
	(0.081)	(0.029)	(0.141)	(0.141)	(0.129)	(0.129)
Rainfall * Temperature CV	-0.051**	-0.018**	-0.079*	-0.079*	-0.069*	-0.069*
	(0.016)	(0.006)	(0.032)	(0.032)	(0.031)	(0.031)
Constant	-4.887***		1.348		-0.961	
	(0.704)		(1.363)		(1.289)	
Sigma			1.402***		1.325***	
			(0.016)		(0.013)	
Household control variables	Yes	Yes	Yes	Yes	Yes	Yes
Region+year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10287	10287	4917	4917	4917	4917

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Coef and ME are shorthand for Coefficient and Marginal Effects; Yes=dummy variable identifying whether the farmer sold part of his output or not and BIRRand USD are measures of the extent of output sold in Ethiopia Birr/ha and USD/ha respectively. Refseason=reference season for agricultural data, CV=Coefficient ofvariation, long term meanaverage for the period 1980-2018.

Table 3: Impact of climate risk on output commercialization decisions: Correlated Random Effects (CRE) Cragg Double Hurdle models using household panel data from three waves of ESS data 2012-2016

	Yes		BIRR		USD	
	Coef	ME	Coef	ME	Coef	ME
Drought shock (ref season)	-0.277	-0.073	-0.743**	-0.743**	-0.689**	-0.689**
	(0.236)	(0.063)	(0.275)	(0.275)	(0.256)	(0.256)
Drought shock (ref season) squared	0.457**	0.121**	0.884***	0.884***	0.818***	0.818***
	(0.176)	(0.047)	(0.184)	(0.184)	(0.171)	(0.171)
Flood shock (ref season)	0.044	0.012	-0.012	-0.012	-0.018	-0.018
	(0.092)	(0.024)	(0.116)	(0.116)	(0.108)	(0.108)
Flood shock (ref season) squared	0.006	0.002	0.045	0.045	0.044	0.044
	(0.033)	(0.009)	(0.044)	(0.044)	(0.041)	(0.041)
Heat stress (ref season)	-0.212	-0.056	-0.466*	-0.466*	-0.444*	-0.444*
	(0.169)	(0.045)	(0.229)	(0.229)	(0.213)	(0.213)

Heat stress (ref season) squared	0.123	0.033	0.149	0.149	0.140	0.140
	(0.064)	(0.017)	(0.085)	(0.085)	(0.079)	(0.079)
Rainfall CV(long-term)	0.680***	0.181***	1.247***	1.247***	1.190***	1.190***
	(0.103)	(0.027)	(0.156)	(0.156)	(0.145)	(0.145)
Rainfall CV(long-term) squared	-0.016***	-0.004***	-0.021***	-0.021***	-0.020***	-0.020***
	(0.003)	(0.001)	(0.004)	(0.004)	(0.004)	(0.004)
Temperature CV(long-term)	2.973***	0.789***	7.642***	7.642***	7.338***	7.338***
	(0.830)	(0.219)	(1.105)	(1.105)	(1.027)	(1.027)
Temperature CV(long-term) squared	-0.268	-0.071	-0.839***	-0.839***	-0.801***	-0.801***
	(0.139)	(0.037)	(0.171)	(0.171)	(0.159)	(0.159)
Rainfall * Temperature CV	-0.166***	-0.044***	-0.343***	-0.343***	-0.331***	-0.331***
	(0.031)	(0.008)	(0.046)	(0.046)	(0.043)	(0.043)
Drought shock (ref season)	-8.026***		-7.207***		-9.440***	
	(1.285)		(1.841)		(1.712)	
lnsig2u	-0.328***					
	(0.085)					
Household control variables	Yes	Yes	Yes	Yes	Yes	Yes
Mundlak controls	Yes	Yes	Yes	Yes	Yes	Yes
Region+year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8254	8254	3631	3631	3631	3631

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Coef and ME are shorthand for Coefficient and Marginal Effects; Mundlak controls=means of time varying control variables (ZZ_{iiii}). Yes=dummy variable identifying whether the farmer sold part of his output, and BIRR and USD are measures of the extent of output sold in Ethiopia Birr/ha and USD/ha, respectively. Ref season=reference season for agricultural data, CV=Coefficient of variation, long term mean average for the period 1980-2018.

One of the main objectives of our study was to measure the effect of long-term climate variability and seasonal shock exposure to commercialization. Both Table 2 and Table 3 present the marginal effects of climate variables on their effects on both the probability and the extent of participation in crop output markets. In Table 2, the analysis used the pooled data from all surveys(2012-2019), but we can see that we got an almost similar pattern of results as those in Table 3, where we used a panel of the first three data waves. Focusing on Table 3, important to note here is that the decision and extent of participation are not affected by the same set of variables which justifies our choice of Craggit Double Hurdle Models as opposed to restrictive Tobit regression models. Consistent with our *apriori* expectations, drought, and heat stress negatively impact commercialization. While the effect of flood shock is negative, it is not statistically significant. Normal weather conditions encourage participation in output markets: when there are shocks within a given season, farmers are unable or unwilling to sell more on the market.

Shocks potentially have effects on yield and marketable output. This notion is in tandem with the general literature that confirms climate variability and hurting shocks like drought reduce agricultural production and, in extreme cases, lead to total crop failure (Deressa & Hassan, 2009; Salvatore Di Falco, Yesuf, Kohlin, & Ringler, 2012; Kurukulasuriya & Rosenthal, 2013). From the literature, the hurting effects of climate change and related shocks in crop production and related outcomes are felt through various channels. Some of the mechanisms through which climate change and shocks reduce agricultural output include through (i) the impact of temperature and rainfall changes in altering conditions and the distribution of agro-ecological zones and precisely crop suitability in those areas, (ii) altering the availability of run-off water and length of the growing season, (iii) loses of agricultural output from the increased frequency of extreme climate events such as floods, droughts and changes in temperature and rainfall variance (Hulme, 1996; Howden et al., 2007; Kurukulasuriya & Rosenthal, 2013). With reduced crop yields or total crop failure, farmers are known to implement various risk-coping measures to survive, ranging from distress renting out of the land, selling household assets, limiting or stopping the sale of key food crops, and keeping available food supplies for household consumption (Dercon, 2004; Gebregziabher & Holden, 2011). Hence, the reduced market participation extent we found in this paper can also be understood as an ex-post-risk coping strategy where households reduce shares of crop output sold for cash on the market after shock exposure.

Moreover, our findings reveal a convex relation between drought shock and output commercialization. This result possibly implies some level of threshold beyond which the marginal effect of drought on commercialization starts to increase. This probably indicates distress sales, where farmers are forced to make sales to meet pressing financial obligations despite the risk presented by the drought. Long-term rainfall and temperature variability positively affect the decision and extent of selling output. However, there is some level threshold beyond which the marginal effect of these two variables on commercialization starts to decline.

A major highlight from the robustness analysis results is that, in general, drought shock (less than normal rain in the growing season) reduces the average household share of crop output sold on the market, and more specifically for key cereals such as Teff, Sorghum, and Wheat. In addition, the results show non-linear relationships between crop-marketed shares and drought shocks, highlighting potential distress selling of crop output with increased drought shock exposure.

6.2 The mediatory role of input commercialization on the impact of climate risk on output commercialization: Interaction effects

In Table 4 and Table 5, we report results where we test for the potential mediatory role of investments in input commercialization decisions in mitigating the extent of the negative effects of climate risk factors on output commercialization. Simply put, here we aimed to see whether there is a noticeable advantage for farmers who had invested in modern inputs (in the form of both inorganic fertilizers and improved seeds) earlier in the season on their agricultural commercialization outcomes with shock exposure compared to their opposite counterparts (i.e., those using ordinary inputs local seeds and organic fertilizers). We start reporting results from pooled Cragg double hurdle models, including four rounds of ESS data (2012-2019), and then afterward, we show CRE Cragg Double Hurdle models using the first three waves of panel data (2012-2016). The focus is on interaction terms of shocks (drought, flood, and heat stress) interacted with a dummy variable with a value of 1 for farmers who purchased both inorganic fertilizers and improved seeds and zero otherwise.

*Table 4: **Mediatory role of input commercialization:** Impact of climate risk on output commercialization decisions: Cragg Double Hurdle models using pooled data from four waves of ESS data 2012-2019*

	Yes		BIRR		USD	
	Coef	ME	Coef	ME	Coef	ME
Drought shock * buy_input	0.399**	0.144**	-0.088	-0.088	-0.105	-0.105
	(0.141)	(0.051)	(0.231)	(0.231)	(0.218)	(0.218)
Flood shock * buy_input	0.053	0.019	-0.019	-0.019	-0.028	-0.028
	(0.038)	(0.014)	(0.056)	(0.056)	(0.054)	(0.054)
Heat stress * buy_input	0.087***	0.031***	0.055	0.055	0.052	0.052
	(0.025)	(0.009)	(0.037)	(0.037)	(0.035)	(0.035)
Rainfall CV	0.239***	0.086***	0.132	0.132	0.098	0.098
	(0.052)	(0.019)	(0.104)	(0.104)	(0.099)	(0.099)
Temperature CV	1.935***	0.698***	3.960***	3.960***	3.645***	3.645***
	(0.462)	(0.166)	(0.835)	(0.835)	(0.783)	(0.783)
Rainfall &temperature CV	-0.055***	-0.020***	-0.081**	-0.081**	-0.071*	-0.071*
	(0.016)	(0.006)	(0.031)	(0.031)	(0.030)	(0.030)
Rainfall CV squared	-0.006***	-0.002***	0.003	0.003	0.004	0.004
	(0.002)	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)

Temperature CV squared	-0.271***	-0.098***	-0.608***	-0.608***	-0.562***	-0.562***
	(0.079)	(0.028)	(0.136)	(0.136)	(0.124)	(0.124)
Constant	-4.388***		1.974		-0.335	
	(0.692)		(1.330)		(1.259)	
Sigma			1.418***		1.340***	
			(0.016)		(0.013)	
Household control variables	Yes	Yes	Yes	Yes	Yes	Yes
Region+year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10287	10287	4917	4917	4917	4917

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Coef and ME are shorthand for Coefficient and Marginal Effects; Yes=dummy variable identifying whether the farmer sold part of his output or not and BIRRand USD are measures of the extent of output sold in Ethiopia Birr/ha and USD/ha respectively.

Looking at the tables without interactions (Table 2 and Table 3) and those with interactions(Table 4 and Table 5) and focusing on the three shocks (drought, flood, and heat stress), we can notice two things: (i) we notice that the negative effect of shocks on commercialization intensity that was significant in both tables 3 and 4 are still negative but no longer significant(with input interactions) in the tables (5 and 6), and (ii) that drought shock and heat stress (with input commercialization) now have a significant positive effect on the probability of selling some output on the produce market. In Figure 7, we plot local polynomial regressions that summarize the basic relationships between output commercialization intensity and climate shocks (rainfall and temperature shocks) in the pooled sample and for sub-groups of farmers who had invested in purchased inputs(seed and fertilizer) and those without input purchases, The plots also support the negative impacts of flood, drought and heat stress on output commercialization and the gaps in the influence of those shocks on output commercialization between farmers with and without purchased inputs.

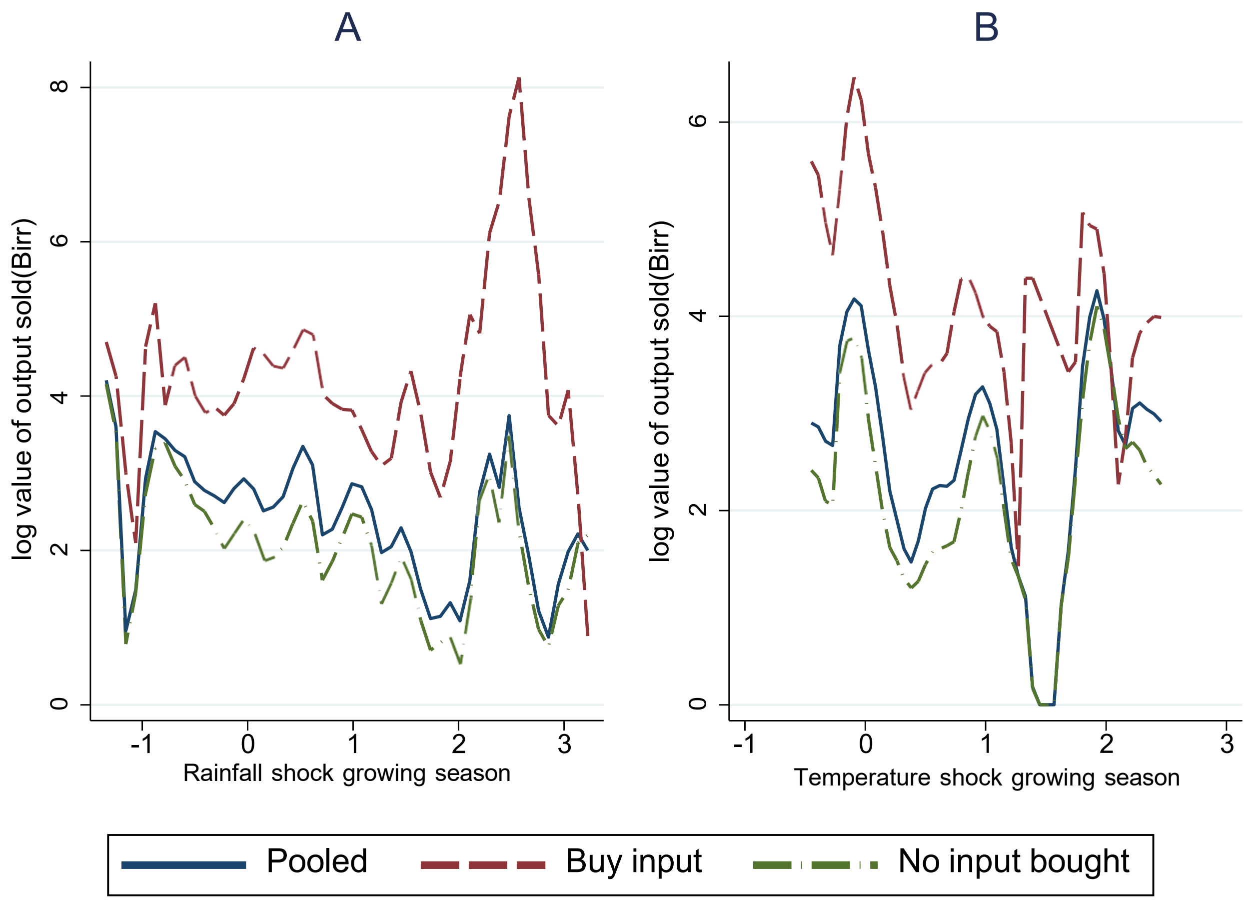

Figure 7: The *figure plots local polynomial regressions of the intensity of crop output commercialization on (A) rainfall shock, and (B) temperature shock in the pooled sample (Pooled), and in subgroups of farmers who had bought fertilizer and seed(Buy input), and those without input purchases(No input bought). The figure thus shows the basic relationship between the intensity of output commercialization and rainfall and temperature shocks for farmers with versus without commercial input purchases.*

Table 5: ***Mediatory role of input commercialization:*** *Correlated Random Effects (CRE) Cragg Double Hurdle models using household panel data from three waves of ESS data 2012-2016*

	Yes		BIRR		USD	
	Coef	ME	Coef	ME	Coef	ME
Drought shock * buy_input	0.168	0.044	-0.146	-0.146	-0.160	-0.160
	(0.190)	(0.050)	(0.186)	(0.186)	(0.173)	(0.173)
Flood shock *buy_input	0.119*	0.032*	0.092	0.092	0.085	0.085
	(0.055)	(0.014)	(0.066)	(0.066)	(0.062)	(0.062)
Heat stress * buy_input	0.099**	0.026**	0.008	0.008	0.006	0.006
	(0.034)	(0.009)	(0.038)	(0.038)	(0.036)	(0.036)
Rainfall CV	0.647***	0.171***	1.156***	1.156***	1.103***	1.103***
	(0.101)	(0.026)	(0.150)	(0.150)	(0.140)	(0.140)
Temperature CV	2.846***	0.753***	7.150***	7.150***	6.865***	6.865***
	(0.824)	(0.217)	(1.104)	(1.104)	(1.026)	(1.026)
Rainfall &temperature CV	-0.161***	-0.043***	-0.330***	-0.330***	-0.318***	-0.318***
	(0.031)	(0.008)	(0.046)	(0.046)	(0.043)	(0.043)
Rainfall CV squared	-0.014***	-0.004***	-0.018***	-0.018***	-0.017***	-0.017***
	(0.003)	(0.001)	(0.004)	(0.004)	(0.003)	(0.003)
Temperature CV squared	-0.257	-0.068	-0.771***	-0.771***	-0.736***	-0.736***
	(0.138)	(0.036)	(0.171)	(0.171)	(0.159)	(0.159)

Constant	-7.740***		-6.342***		-8.613***	
	(1.278)		(1.830)		(1.701)	
lnsig2u	-0.312***					
	(0.084)					
Household control variables	Yes	Yes	Yes	Yes	Yes	Yes
Mundlak controls	Yes	Yes	Yes	Yes	Yes	Yes
Region+year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8254	8254	3631	3631	3631	3631

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Coef and ME are shorthand for Coefficient and Marginal Effects; Mundlak controls=means of time varying control variables (ZZ_{iiii}). Yes=dummy variable identifying whether the farmer sold part of his output or not, and BIRR and USD are measures of the extent of output sold in Ethiopia Birr/ha and USD/ha, respectively.

These results highlight the mediatory role of decisions made by the farmer to invest in some commercial inputs such as fertilizers and improved seeds in adapting crop output to shocks which supports some level of crop output commercialization under stress. In fact, this also shows that access to purchased inputs helps farmers produce enough output for the family with extra output to trade on the market even when the weather conditions are not very favorable. These findings are in line with theory and empirical literature that reveal that altering the choice of inputs or investing in climate-resilient inputs is important in helping farmers adapt to climate risks(Howden et al., 2007; Nordhagen & Pascual, 2013; Holden & Quiggin, 2017; Acevedo et al., 2020; Makate et al., 2022; Makate & Makate, 2022). For instance, the use of purchased seeds is key for supporting seed diversification in ways that improve resilience (i.e., complementing own saved seeds with seeds sourced off-farm)(Nordhagen & Pascual, 2013; Clifton Makate, Arild Angelsen, Stein T Holden, & Ola T Westengen, 2023) and the purchase of inorganic fertilizers supports sustainable intensification and the application of climate-resilient micro-dosing fertilizer application techniques proven to give sufficient nutrition in highly degraded soils and to support effective adaptation to climate risks (Murendo & Wollni, 2015; Makate & Makate, 2022). Access to climate-resilient inputs such as fertilizers and seeds is hence important in supporting crop output commercialization in smallholder farming under a changing climate.

7. Conclusions and recommendations

This study explores how smallholder crop commercialization dynamics are shaped by climate risk using nationally representative household panel data (2012-2019) for Ethiopian smallholder farmers complemented with historical rainfall and temperature data (1980-2018). Results show that drought and flood shocks strongly and negatively affect output market participation and that investment in purchased inputs supports commercialization under a changing climate. Our findings imply that efforts to connect smallholder farmers to markets should not ignore the importance of protecting production from climate risk. Secondly, investments in inputs offer resilience to farmers and help sustain market participation under climate risk.

Appendices

A1: Descriptive statistics of key outcome variables targeted for the study

		(1) Pooled mean	sd	(2) 2012 mean	sd	(3) 2014 mean	sd	(4) 2016 mean	sd	(5) 2019 mean	sd
Investment on inputs(purchase)											
purch_fert_all	Purchased any chemical fertilizer(1=yes)	0.41	0.49	0.38	0.49	0.43	0.50	0.42	0.49	0.39	0.49
Wnpurch_fert_allKG	Quantity of chemical fertilizer purchased (kg/ha)	151.15	179.95	161.19	203.41	135.95	168.49	156.01	181.50	154.57	164.86
purch_fert_dap	Purchased any DAP fertilizer(1=yes)	0.31	0.46	0.38	0.49	0.41	0.49	0.31	0.46	0.13	0.34
Wnpurch_fert_dapKG	Quantity of DAP fertilizer purchased (kg/ha)	89.91	99.32	97.87	107.95	82.20	92.97	90.84	99.83	91.51	90.60
purch_fert_urea	Purchased any UREA fertilizer(1=yes)	0.32	0.47	0.30	0.46	0.34	0.47	0.33	0.47	0.31	0.46
Wnpurch_fert_ureaKG	Quantity of UREA fertilizer purchased (kg/ha)	76.14	82.96	75.91	87.88	68.11	77.69	79.86	86.79	82.09	78.48
seed_purchase	Purchased any Seed(1=yes)	0.52	0.50	0.52	0.50	0.54	0.50	0.50	0.50	0.50	0.50
Wnpurchase_qnt	Quantity of seeds purchased(kg/ha)	49.12	77.42	52.82	82.32	49.76	78.71	48.34	74.68	44.24	71.66
Wnseed_purchase_value	Value of seeds purchased (Birr/ha)	628.93	989.61	675.08	1103.02	539.76	922.38	633.36	975.93	691.92	932.22
Wnseed_purch_valueUSD	Value of seeds purchased (Usd/ha)	14.99	36.55	18.27	43.16	14.20	35.46	14.59	35.49	12.37	28.97
Selling output											
sold_output	Sold any part of the produce(1=yes)	0.48	0.50	0.38	0.49	0.49	0.50	0.45	0.50	0.63	0.48
Wnsold_outputquant_KG	Quantity of crop output sold (kg/ha)	308.09	486.20	251.79	446.06	254.64	407.12	254.77	396.72	457.70	617.34
Wnsold_outputValue_birr	Value of crop output sold (Birr/ha)	3423.51	5765.63	2151.34	4532.71	2455.33	4512.41	2368.41	3925.75	6424.92	7797.90
Wnsold_outputValue_usd	Value of crop output sold (Usd/ha)	145.59	236.22	111.27	210.07	119.06	202.03	106.73	170.19	236.27	306.32
CI	Household average "All crop" marketed share(%)	22.99	20.00	25.30	25.31	19.43	18.29	23.16	19.80	25.46	18.35
Observations		13149		3098		3549		3624		2878	

Notes: Statistics are based on Ethiopia LSMS 2012-2019 for the rural sample; Intensity of input purchase and sales values are expressed in units/ha of land and are trimmed for outliers at 2%. Intensity value averages are shown for the conditional sample (conditional on the first decision). Values of inputs purchased and output sold are converted to constant United States dollars to enable comparison across years.

A2: Descriptive statistics of control and other variables used in the analysis

		(1)		(2)		(3)		(4)		(5)	
		Pooled		2012		2014		2016		2019	
Variable	description	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
purch_fert_all	Purchased any fertilizer(1=yes)	0.41	0.49	0.38	0.49	0.43	0.50	0.42	0.49	0.39	0.49
Wnpurch_fert_allKG	Quantity of fertilizer purchased(kg)	151.15	179.95	161.19	203.41	135.95	168.49	156.01	181.50	154.57	164.86
purch_fert_dap	Purchased DAP fertilizer(1=yes)	0.31	0.46	0.38	0.49	0.41	0.49	0.31	0.46	0.13	0.34
Wnpurch_fert_dapKG	Quantity of DAP purchased(kg)	89.91	99.32	97.87	107.95	82.20	92.97	90.84	99.83	91.51	90.60
purch_fert_urea	Purchased any UREA(1=yes)	0.32	0.47	0.30	0.46	0.34	0.47	0.33	0.47	0.31	0.46
Wnpurch_fert_ureaKG	Quantity of UREA purchased(kg)	76.14	82.96	75.91	87.88	68.11	77.69	79.86	86.79	82.09	78.48
seed_purchase	Purchased any seed(1=yes)	0.52	0.50	0.52	0.50	0.54	0.50	0.50	0.50	0.50	0.50
Wnpurchase_qnt	Quantity of seed purchased(kg)	49.12	77.42	52.82	82.32	49.76	78.71	48.34	74.68	44.24	71.66
Wnseed_purchase_value	Value of seed purchased(Birr)	628.93	989.61	675.08	1103.02	539.76	922.38	633.36	975.93	691.92	932.22
Wnseed_purch_valueUSD	Value of seed purchased(USD)	29.48	46.90	35.69	54.95	27.04	45.25	29.31	45.81	24.94	37.13
sold_output	Sold any crop output(1=yes)	0.48	0.50	0.38	0.49	0.49	0.50	0.45	0.50	0.63	0.48
Wnsold_outputquant_KG	Average Quantity of output sold(kg)	308.09	486.20	251.79	446.06	254.64	407.12	254.77	396.72	457.70	617.34
Wnsold_outputValue_birr	Value of output sold (Birr)	3423.51	5765.63	2151.34	4532.71	2455.33	4512.41	2368.41	3925.75	6424.92	7797.90
Wnsold_outputValue_usd	Value of output sold (USD)	145.59	236.22	111.27	210.07	119.06	202.03	106.73	170.19	236.27	306.32
hh_laborunits	Household labour units(adult equiv)	3.64	1.67	3.75	1.57	3.45	1.59	3.71	1.81	.	.
wealth_index_1	Household wealth Index(PCA)	0.00	2.45	0.01	3.32	-0.00	2.23	-0.00	2.17	-0.00	1.82
farmsize_own_gps	Farm size(ha)	1.06	2.56	1.09	1.85	1.21	4.07	1.16	1.99	0.70	0.82
fd_ext_prog	Access to extension(1=yes)	0.30	0.46	0.27	0.44	0.30	0.46	0.31	0.46	0.34	0.47
credit_borrow	Borrowed credit(1=yes)	0.22	0.42	0.24	0.43	0.27	0.44	0.23	0.42	0.13	0.34
assistance_rec	Access tosocial safety nets(1=yes)	0.18	0.39	0.19	0.39	0.15	0.36	0.24	0.43	0.14	0.35
sex_hhh_female	Household head is female(1=yes)	0.24	0.43	0.21	0.41	0.24	0.43	0.26	0.44	0.24	0.43
age_hhh	Age of household head(years)	45.90	15.25	44.60	15.22	46.32	15.13	47.66	14.99	44.56	15.50
hh_size_count	Household size	5.55	2.48	5.16	2.25	5.70	2.46	6.16	2.64	4.97	2.32
edu_atleast12	Household head education	0.69	0.46	0.71	0.45	0.68	0.47	0.66	0.47	0.72	0.45
Zscore_WQ6lag0	Rainfall shocks current season	0.42	0.78	0.34	0.67	0.31	1.04	0.51	0.68	0.51	0.55
Zscore_WQ6lag1	Rainfall shock 1-year lag	0.29	0.68	-0.02	0.46	0.37	0.68	0.35	0.48	0.42	0.94
Zscoretemp_WQ6lag0	Temperature shock current season	0.82	0.82	0.56	0.33	0.76	0.32	1.75	0.89	0.03	0.29
COV_rain	CV of rainfall(1980-2018)	10.89	3.38	10.77	3.41	10.79	3.41	10.87	3.37	11.16	3.33
COV_temp	CV of temperature(1980-2018)	2.14	0.36	2.15	0.35	2.16	0.36	2.17	0.35	2.09	0.39
Zscoretemp_WQ6lag1	Temperature shocks 1-year lag	0.65	0.66	0.44	0.32	0.22	0.42	1.11	0.90	0.80	0.30
Observations		13149		3098		3549		3624		2878	

A3: Descriptive stats for proportion and intensities of purchasing Inputs

Figure A3: Investment decisions to purchase inputs and the extent of purchase in the pooled sample and by survey year: Statistics are based on Ethiopia LSMS 2012-2019 for the rural sample; Intensity of input purchase and sales values are expressed in units/ha of land and are trimmed for outliers at 2%. Intensity value averages are shown for the conditional sample (conditional on the first decision) Values of inputs purchased are converted to constant United States dollars to enable comparison across years.

A4: Proportion and intensity of crop output commercialization decisions

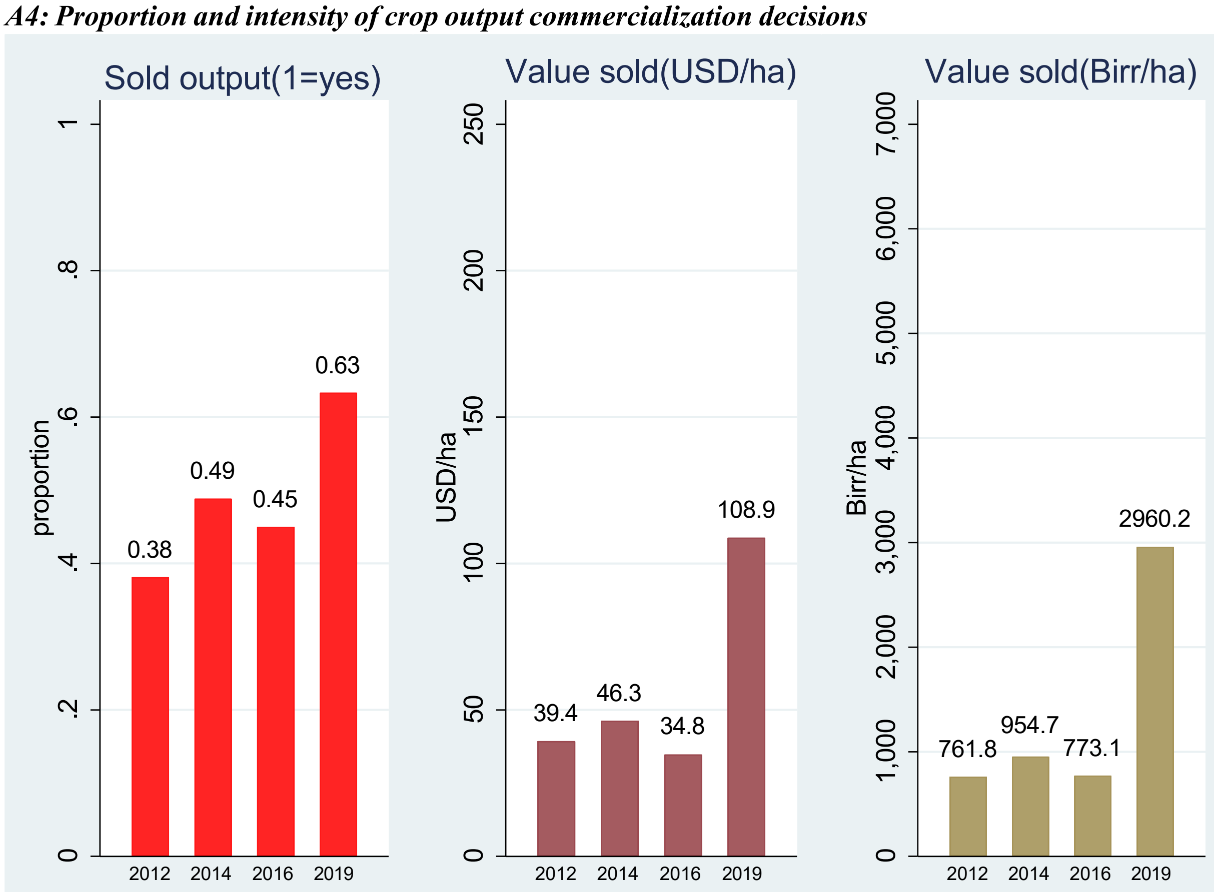

Figure A4: Crop output sales (aggregate for all crops) by survey year: Statistics are based on Ethiopia LSMS 2012-2019 for the rural sample; Intensity of input purchase and sales values are expressed in units/ha of land and are trimmed for outliers at 2%. Intensity value averages are shown for the full sample (participants + non-participants). Values of output sold are converted to constant United States dollars to enable comparison across years.

A5: Comparing household output commercialization decisions by input purchase

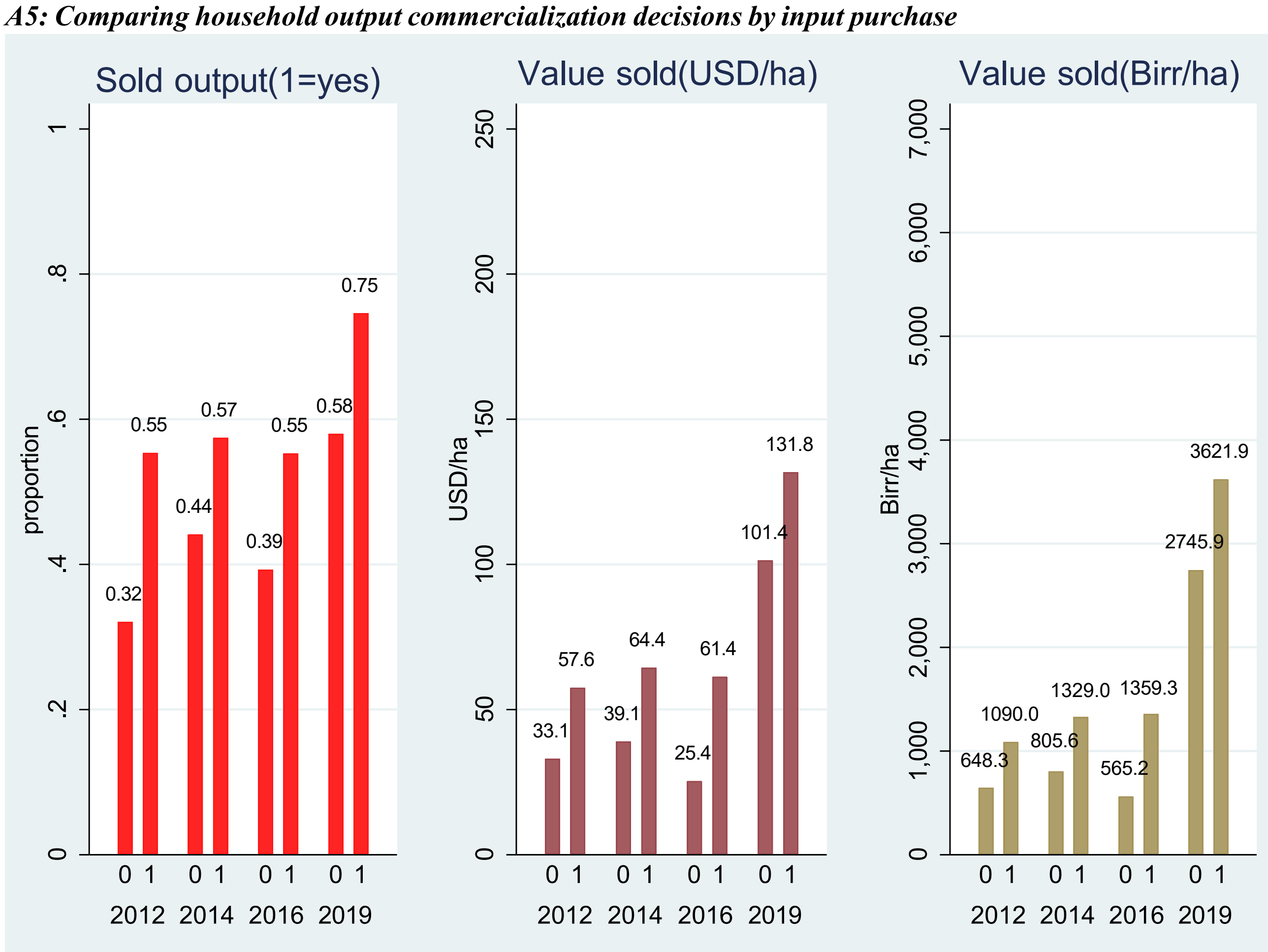

Figure A5: ***By Input purchase:*** *Crop output sales (aggregate for all crops) by input purchase(1=Buy inputs; 0=Did not buy inputs) and survey year: Statistics are based on Ethiopia LSMS 2012-2019 for the rural sample; Intensity of input purchase and sales values are expressed in units/ha of land and are trimmed for outliers at 2%. Intensity value averages are shown for the full sample (participants + non-participants). Values of output sold are converted to constant United States dollars to enable comparison across years.*

Robustness analysis: Using crop-specific marketed shares as measures of crop commercialization.

A6: Descriptive statistics of crop specific markets shares(%): Conditional on selling output

		(1)		(2)		(3)		(4)		(5)	
		Pooled		2012		2014		2016		2019	
	Description	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
crop_ciw	All crops	22.99	20.00	25.30	25.31	19.43	18.29	23.16	19.80	25.46	18.35
CI_Maize	Maize	32.18	29.73	46.45	38.55	25.86	23.14	28.86	26.58	43.94	35.06
CI_Teff	Teff	37.65	29.89	44.04	37.11	35.15	28.33	37.76	28.75	38.05	27.72
CI_Wheat	Wheat	31.69	26.34	38.91	34.73	28.75	24.50	35.10	25.23	23.70	19.31
CI_Haricotbn	Haricot bean	48.41	29.98	54.07	31.43	43.58	28.46	47.10	25.51	71.53	29.34
CI_Horsebn	Horse bean	42.27	28.28	44.33	33.99	35.78	25.18	49.24	28.50	44.72	27.36
CI_Gnut	Groundnuts	54.19	29.01	41.79	35.99	46.60	26.53	61.19	26.72	60.07	27.56
CI_Sorgum	Sorghum	23.96	22.52	24.67	25.79	22.18	21.42	26.52	21.80	22.58	23.55
CI_Barley	Barley	31.60	26.79	31.87	25.47	29.24	26.73	34.80	26.60	30.44	28.28
CI_Othercrops	Other crops	44.43	29.15	45.50	33.96	42.62	30.48	52.26	28.98	42.30	27.82
Observations		4513		643		1378		1182		1310	

A7: Crop output marketed shares by crop and survey year: Detailed crop list.

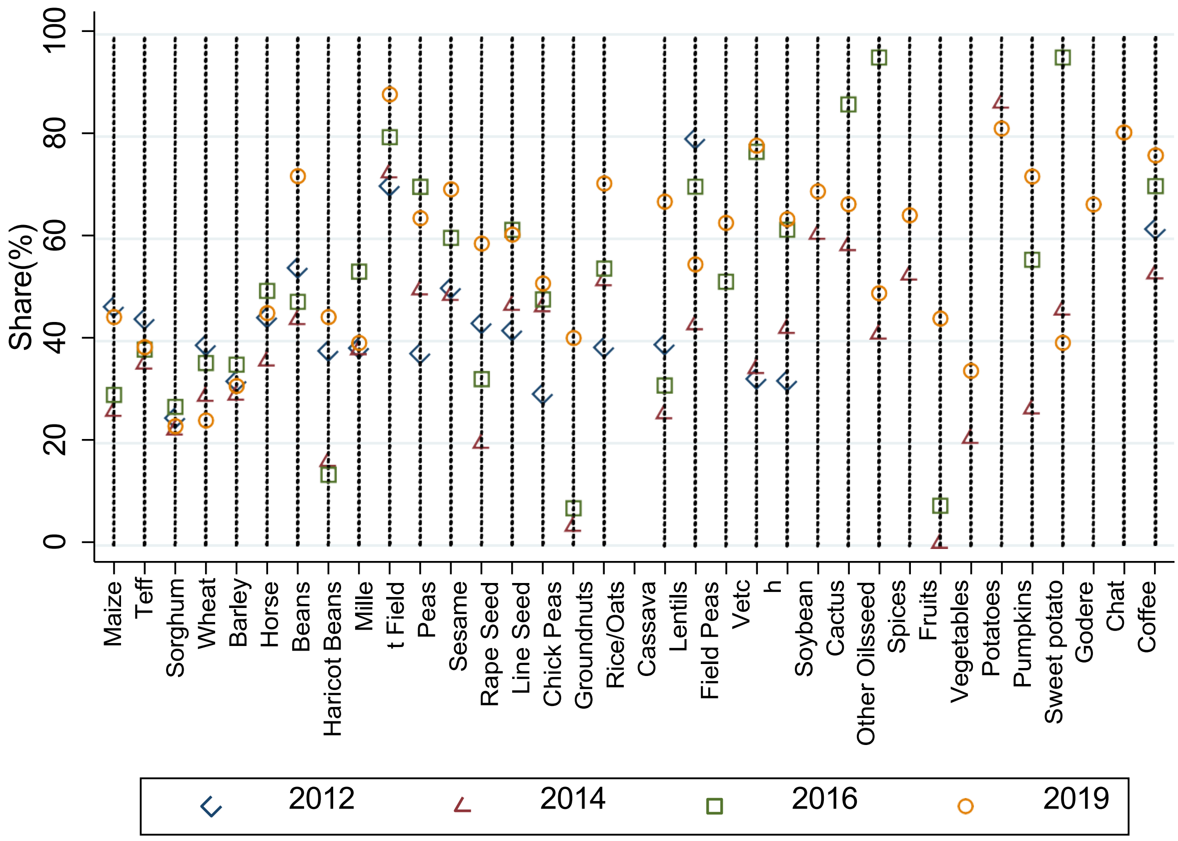

Figure A6: Detailed crop list: percent share (%) of crop output sold (crop commercialization) by survey year. Average shares of marketed output per crop are shown for the conditional sample (conditional on the first decision).

A8: Crop output marketed shares by crop and survey year: Unconditional on selling output (sellers plus non-sellers).

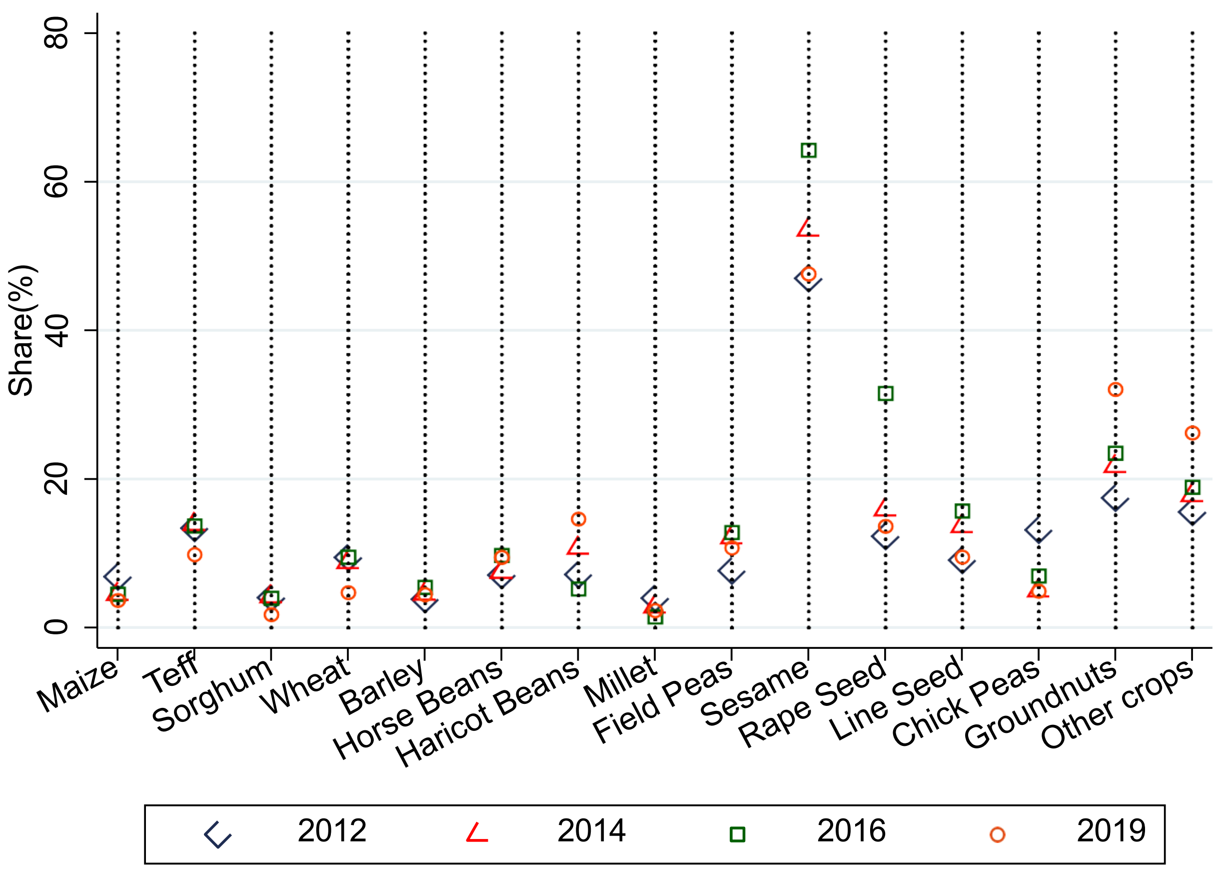

Fig A8: percent share (%) of crop output sold (crop commercialization) by survey year. Average shares of marketed output per crop are shown for the unconditional sample (participants+ non-participants).

A9: Regression results: Impact of climate risk on crop specific marketed shares truncated regression models using pooled data from four waves of ESS data 2012-2019.

	All crops	Maize	Teff	Sorghum	Wheat	Barley	Haricot bean	Horse bean	Groundnut	Other
Drought shock	-6.583	3.725	-33.915**	-41.611***	-21.572	29.475	27.118	21.225	131.089*	-9.280
	(4.057)	(13.134)	(13.023)	(11.714)	(25.419)	(32.825)	(105.220)	(29.195)	(65.756)	(13.165)
Drought shocks squared	7.949*	-9.922	27.631*	37.869***	29.141	-53.595	6.240	-47.365	-71.175	14.254
	(3.612)	(11.030)	(13.178)	(10.204)	(39.450)	(52.600)	(374.260)	(36.359)	(128.008)	(11.552)
Flood shock	-1.003	8.086	5.260	-7.136	-6.911	-13.096	22.841	-2.050	-15.172	-4.028
	(1.446)	(6.687)	(7.290)	(5.766)	(6.200)	(14.864)	(21.501)	(8.220)	(13.048)	(5.657)
Flood shock squared	0.227	-0.561	-3.671	3.560	1.473	19.268	-5.752	4.072	10.584*	1.290
	(0.521)	(2.761)	(5.383)	(2.109)	(2.452)	(11.562)	(7.222)	(3.987)	(4.468)	(3.247)
Heat stress	-2.896	5.365	1.291	-10.015	-22.343	-14.606	1.102	-5.022	-33.976	1.060
	(2.884)	(9.679)	(9.755)	(12.123)	(11.842)	(15.360)	(27.333)	(12.651)	(38.483)	(8.411)
Heat stress squared	0.761	-0.488	-2.152	3.116	9.498*	4.646	-6.343	1.573	5.682	-0.173
	(1.097)	(3.514)	(3.757)	(4.422)	(4.085)	(5.923)	(11.346)	(5.412)	(14.707)	(2.962)
COV_rain	-5.465**	2.791	-10.628	10.739	-6.329	-7.737	27.872	13.104	-35.633**	-8.493**
	(1.685)	(6.002)	(8.199)	(5.745)	(13.856)	(14.744)	(17.750)	(12.954)	(13.573)	(2.941)
sq_COV_rain	0.290***	-0.024	0.684**	0.112	0.977*	0.470	0.638	-0.386	1.363**	0.321***
	(0.048)	(0.143)	(0.225)	(0.142)	(0.425)	(0.539)	(0.587)	(0.532)	(0.500)	(0.094)
COV_temp	28.284	56.753	188.165**	137.159*	83.826	77.941	538.103	123.496	169.384	-52.300
	(14.553)	(68.155)	(61.305)	(55.333)	(63.723)	(57.097)	(333.313)	(71.367)	(291.228)	(28.412)
sq_COV_temp	-4.498*	-7.003	-35.583**	-12.610	-7.724	-13.433	-75.965	-19.352	-29.056	8.161
	(2.205)	(14.523)	(11.792)	(11.582)	(9.125)	(7.594)	(71.259)	(10.596)	(76.154)	(4.835)
cov_rain_temp	-0.914	-1.967	-2.656	-6.709***	-5.508*	-1.350	-20.342**	-3.315	-2.325	0.887
	(0.481)	(2.199)	(2.228)	(1.609)	(2.595)	(2.305)	(6.698)	(2.675)	(4.833)	(1.098)
_cons	43.635	1.921	-98.181	-165.969*	-6.500	-116.550	-669.651	-114.716	125.918	150.377***
	(23.581)	(86.376)	(96.597)	(83.515)	(133.594)	(124.664)	(423.620)	(131.105)	(323.246)	(43.158)
sigma	18.914***	26.292***	26.677***	19.945***	23.624***	22.514***	24.829***	25.755***	23.924***	27.303***
	(0.315)	(0.689)	(0.505)	(0.891)	(0.764)	(1.011)	(1.136)	(0.816)	(1.173)	(0.385)
HHcontrols	Yes	Yes	Yes	Yes	Yes	Yes	yes	Yes	Yes	Yes
Reg+year dum	Yes	Yes	Yes	Yes	Yes	Yes	yes	Yes	Yes	Yes
Observations	4441	731	1144	524	602	312	186	347	185	1713

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A10: Regression results: Impact of climate risk on crop-specific marketed shares-truncated OLS with Correlated Random Effects (CRE) model results using household panel data from three waves of ESS data 2012-2016

	All crops	Maize	Teff	Sorghum	Wheat	Barley	Haricot bean	Horse bean	Groundnut	Other
Drought shock	-7.318	0.837	-38.557**	-42.068***	-26.449	51.790	98.450	8.382	264.429	5.042
	(4.340)	(14.627)	(14.298)	(12.004)	(28.433)	(37.403)	(115.097)	(34.660)	(170.199)	(15.855)
Drought shock squared	6.678*	-9.457	31.678*	35.031***	34.535	-91.138	-290.739	-6.041	-311.418	5.371
	(3.256)	(11.985)	(14.936)	(8.451)	(49.587)	(59.502)	(394.331)	(52.719)	(216.710)	(12.414)
Flood shock	2.294	10.661	13.126	-13.287*	-2.975	-6.683	16.896	-3.683	26.852	14.804*
	(1.827)	(6.738)	(8.527)	(6.036)	(8.695)	(18.637)	(18.859)	(12.807)	(37.507)	(7.172)
Flood shock squared	-0.682	-0.215	-7.716	6.089**	-0.425	20.642	-5.936	4.097	-0.310	-7.498*
	(0.672)	(2.677)	(6.186)	(2.164)	(4.069)	(13.971)	(6.463)	(7.003)	(9.202)	(3.532)
Heat stress	4.593	-0.625	9.065	-11.297	-9.820	-37.821	-3.956	2.706	-24.405	12.320
	(3.701)	(9.990)	(10.619)	(12.124)	(16.304)	(20.619)	(24.189)	(17.421)	(59.796)	(12.132)
Heat stress squared	-2.059	1.314	-5.787	3.703	5.340	12.087	-3.492	-0.826	-11.729	-3.799
	(1.356)	(3.614)	(3.944)	(4.487)	(5.840)	(7.590)	(11.238)	(6.912)	(21.472)	(4.299)
COV_rain	2.173	14.598*	-16.615	4.126	-15.462	14.060	14.163	18.630	-22.530	-6.554
	(2.341)	(6.361)	(9.728)	(6.631)	(16.219)	(19.369)	(23.813)	(18.785)	(30.000)	(10.225)
sq_COV_rain	0.158**	-0.169	0.868**	0.202	1.384**	-0.466	0.486	-0.877	1.618	0.374
	(0.059)	(0.144)	(0.268)	(0.144)	(0.515)	(0.716)	(0.761)	(0.867)	(0.861)	(0.278)
COV_temp	62.309***	146.493*	142.643	106.655	76.127	41.104	597.169	127.219	352.619	54.406
	(16.861)	(67.299)	(89.383)	(69.123)	(75.559)	(70.918)	(402.135)	(87.179)	(771.336)	(80.545)
sq_COV_temp	-6.799**	-18.307	-28.290	-11.848	-6.281	-6.221	-106.118	-22.073	-47.451	-10.422
	(2.622)	(13.893)	(17.434)	(14.319)	(11.242)	(9.622)	(89.490)	(13.416)	(191.395)	(14.342)
cov_rain_temp	-3.157***	-6.372**	-1.661	-4.704*	-5.462	-1.655	-11.647	-2.142	-11.356	-1.201
	(0.677)	(2.304)	(2.712)	(2.113)	(3.057)	(3.219)	(9.363)	(3.512)	(8.548)	(2.760)
_cons	-36.800	-143.747	-29.663	-80.566	25.467	-73.075	-697.661	-164.112	-162.620	18.503
	(28.305)	(90.827)	(130.001)	(99.755)	(156.077)	(162.081)	(506.981)	(164.147)	(745.891)	(129.189)
HHcontrols	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Reg+year dum	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Mundlak cont	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	3172	648	984	472	523	256	168	282	122	710

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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