Rural Mobility and Climate Vulnerability: Evidence from the 2015 Drought in Ethiopia

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Ben Brunckhorst*

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Abstract

In 2015, Ethiopia experienced the worst meteorological drought in decades. This paper investigates vulnerability to drought by applying a difference-in-differences strategy to this event, in a natural experiment. I construct a Standardised Precipitation Index using 35 years of satellite rainfall data to exogenously measure local drought intensity, and combine with nationally representative household panel data. Results show that households experiencing at least a one in 20-year drought have, on average, 12 percent lower annual consumption and 38 percent lower agricultural production than they would otherwise have in a typical year. Results are robust to varying sets of counterfactuals, placebo treatments and identification using the change-in-changes method. Drought has a greater impact on poorer households, female-headed households and larger producers. Production is sensitive to drought severity. In a context of increasing drought frequency and intensity, these findings imply lower expected returns to investment in agriculture, hindering rural development. Results also suggest drought induces positive production spillover effects in nearby areas, which could support resilience. This mechanism may be facilitated by increased factor mobility and market interactions between villages during times of drought. Evidence from rural Ethiopia indicates that transport services, mobile phones and social networks are important for resilience, but the effect of road infrastructure alone is less clear. Public investment in these services may have untapped potential to reduce climate vulnerability.

Keywords: Drought, Ethiopia, Infrastructure, Rural Development

JEL Codes: Q54, 018, R58

*Graduate, MSc Economics for Development, University of Oxford. bbrunckh@gmail.com. This paper was adapted from my MSc dissertation. I am thankful for valuable comments and supervision from Ferdinand Rauch and Stefan Dercon.

"Natural disasters do not affect people equally" **- Neumayer and Plümper, (2007)**

1 Introduction

In 2015, Ethiopia experienced extremely dry conditions. The spring *belg* rains failed. The typically reliable *kiremt* summer rains were erratic and delayed. It was proclaimed the worst drought in 50 years in an already drought prone nation (Philip et al., 2018). As a country in which 80% of the population lives in rural areas and relies on rain-fed agriculture, Ethiopia is highly vulnerable to extreme climate conditions (UN DESA, 2019). The 2015 drought was marked by loss of crops, loss of livestock and widespread food insecurity. Famine Early Warning Systems Network estimate 15 million Ethiopians faced severe food insecurity by December 2015 (FEWS and WFO, 2015).

Despite the severity of the 2015 drought, its humanitarian impact pales in comparison to the famines of 1973 and 1984, which were exacerbated by civil conflict and market restrictions on the movement of goods (Webb and Von Braun, 1994). Since then, relative peace, stability and sustained economic growth have contributed much to resilience in Ethiopia. Public investment in rural road infrastructure, agricultural extension and the implementation of a national safety net program are particularly cited for reducing vulnerability in rural areas (Berhane et al., 2015; Gilligan et al., 2011; Stifel et al., 2016). The Universal Rural Road Access Program (URRAP) has constructed or upgraded 70,000 km of rural roads since 2010 (Nakamura et al., 2019). The share of farmers who received agricultural extension services increased from 25% to 75% since 2004 (Bachewe et al., 2018). Since 2005, the Productive Safety Net Program (PSNP) has pooled domestic and donor money to provide regular assistance to the poorest households, in exchange for labour on public works. Nonetheless, the government and international response to the 2015 drought included emergency food or cash assistance to 20% (or 18.2 million) of the population. More than $700 million was requested by the government of Ethiopia to deliver this relief (World Bank, 2017).

Reducing climate vulnerability is necessary for reducing dependence on humanitarian aid. How to build resilience is a pressing question. Climate change research predicts drought poses an increasing threat to the livelihood of rural populations in sub-Saharan Africa[1] (Dai, 2013). Design of policy to enhance drought resilience faces many challenges. There is scarce evidence *ex-ante*, since experimental evaluation under climate stress is mostly impossible. *Ex-post*, the damage is done and political impetus typically shifts to recovery. Given these challenges, costly relief persists as the status quo response to climate uncertainty, especially in low-income contexts with salient resource constraints. Many development policies might inadvertently contribute to drought resilience, but a convincing evidence base is needed to design them for this purpose. This paper adds to the body of evidence that informs a proactive agenda for building climate resilience.

Using nationally representative rural household data and an exogenous measure of local drought intensity, I estimate the causal effects of drought on consumption and agricultural production in Ethiopia. I then show how these effects change with access to road infrastructure and transport services to infer their contribution to resilience. I find that beyond road infrastructure, households with larger social networks, mobile phones and access to transport services are significantly less vulnerable to drought. Results also show the 2015 drought induced positive production spillovers outside affected areas, especially for more connected villages. Mobility can enhance resilience by permitting economic activity and food production to be temporarily dispersed.

A large number of economic studies show vulnerability to drought impedes rural development in sub-Saharan Africa. Improving the productivity of smallholder agriculture has long been considered an important development pathway for rural households (Binswanger and Townsend, 2000; Collier and Dercon, 2014). Despite progress in Ethiopia[2], rural households remain highly vulnerable to meteorological conditions. In Ethiopia, rainfall shocks are shown

[1]A recent study could not attribute the 2015 drought in question to anthropogenic climate change but concluded the strong 2015 El Niño increased its severity (Philip et al., 2018).

[2]Cereal production increased fourfold between 1994 and 2014, and use of fertiliser, improved seeds and advisory services also rose significantly(Bachewe et al., 2018).

to have a significant and persistent negative effect on consumption (Dercon, 2004; Gao and Mills, 2018). Other studies find negative impacts of drought on health and nutrition outcomes in Ethiopia (Dercon and C. Porter, 2014; Hirvonen et al., 2020). Households who experience severe or recurrent drought are also found to be more vulnerable to poverty (Carter et al., 2007; Davies, 2010). Policies that reduce exposure to repeated droughts are recommended to protect livelihoods and mitigate volatility to climate conditions. Climate change especially threatens continued rural development by increasing the frequency of extreme drought (jie Wang et al., 2014).

A related literature discusses investment in rural infrastructure as a source of resilience to shocks. Infrastructure promises to connect otherwise fragmented markets and provide new production possibilities. In particular, transport infrastructure is widely hailed as a ticket to rural development (Chamberlin and Schmidt, 2013; Damania et al., 2017). Despite mixed evidence from other countries (Asher and Novosad, 2020), road infrastructure is consistently found to contribute to rural welfare in Ethiopia (Dercon, Gilligan, et al., 2009; Mogues, 2011; Stifel et al., 2016; Wondemu and Weiss, 2012). Hine et al., (2019) suggests that high returns to road investment in Ethiopia may be explained by low initial levels of connectivity. Nakamura et al., (2019) recently show rural road development marginally increased household consumption and contributed to resilience using the same household surveys employed in this study. They estimate communities most affected by the 2015 drought, based on a vegetation index, were 14% less likely to fall into poverty. Hill and Fuje, (2018) attribute lower volatility in grain prices associated with drought in Ethiopia to better market access from road investment. A study on childhood nutrition outcomes found significant negative effects of the 2015 drought only in poorly connected villages (Hirvonen et al., 2020).

Transport services are less emphasised than roads despite being necessary for communities to benefit from infrastructure. A smaller collection of research emphasises that road building improves accessibility but is not sufficient to enhance mobility, especially in poor rural areas (Bryceson et al., 2008; Beuran et al., 2015). Many poor households lack transport assets and the ability to pay for services that take advantage of roads. Evidence from a randomised experiment in rural Malawi found willingness to pay for bus transport was too low for even a subsidised service to be financially viable, despite serving a large population on a good quality road (Raballand et al., 2011). For most rural households in Ethiopia, walking or pack-animals are the *modus operandi* and low ability to pay makes motorised transport unfeasible (G. Porter, 2014).

The contribution of mobile technology to market integration and improved mobility has been well established in literature (Abraham, 2007; Aker and Mbiti, 2010). Investment in mobile networks also has potential to facilitate information transfer and market transactions, which could reduce household vulnerability to drought in the same way as traditional infrastructure (Riley, 2018). Mobiles have been used to monitor water points and provide early warning of drought in Ethiopia (OXFAM, 2013). Tadesse and Bahiigwa, (2015) found very few farmers used mobile phones to search for information in Ethiopia, but empirical studies on the contribution of mobiles to drought resilience are lacking. This paper contributes by assessing vulnerability to drought across several indicators of mobility to inform effective policy for climate resilience.

Methodological issues threaten some existing empirical studies on vulnerability to drought. Firstly, drought intensity varies significantly and unpredictably over space. Aggregating spacial data at a level above variation in the intensity of treatment masks spatially heterogeneous effects (Heger and Neumayer, 2019; Burton and Hicks, 2005). Since meteorological drought can be highly localised, data with a sufficiently high spatial resolution is required to isolate its impact. Secondly, while meteorological drought intensity is plausibly independent of potential welfare outcomes, an exogenous (and local) measure is not always available. Researchers often compromise, opting for self-reported drought or crop loss proxies to measure local drought (Amare et al., 2018). This risks introducing endogeneity, or adopts a broader agenda than vulnerability to the climate per se. On the other hand, many objective measures based on rainfall or vegetation indices are spatially aggregated, prompting the local measurement issue above (Hill and C. Porter, 2017). Thirdly, causal identification methods are not prevalent in natural disaster studies. Large and relevant samples are usually required to estimate unbiased treatment effects but hard to come by. It is more common for researchers to investigate heterogeneous effects by exposure to drought, than conduct causal inference directly (Nakamura et al., 2019).

Section 2 describes household survey data and an exogenous drought index constructed from satellite data, which are employed in a difference-in-differences identification strategy to overcome these issues. Section 3 presents results on household vulnerability to drought, heterogeneous effects and potential channels of resilience. Section 4 examines the robustness of results and presents evidence of positive production spillovers. Section 5 concludes.

2 Drought as a natural experiment

The method to identify the impact of drought relies on comparing consumption and production between households that experienced severe drought (the treated) and those that did not (the control). The control group is used to estimate counterfactual outcomes in the treated group if no drought had occurred. Different levels of preparation for drought threaten this strategy. However, interviews show that many rural Ethiopians did not take adaptive measures for the 2015 drought, relied on traditional forecast methods and exhibit climate skepticism despite potential access to warnings (Singh et al., 2016). Furthermore, I use a measure of drought intensity that accounts for the probability of drought occurring, so there is no reason to believe past experience informs dissimilar coping strategies. In this section, I describe the data and provide more in depth justification for the assumptions required for causal inference.

2.1 Household survey data

I employ household survey data from the Ethiopian Socioeconomic Survey (ESS). The ESS is a panel survey conducted by the Central Statistical Agency (CSA) and World Bank Living Standards Measurement Study (LSMS) in 2012, 2014 and 2016 (CSA, 2017). The structure of the survey therefore provides household specific data one and three years before the drought, as well as immediately after[3]. The ESS is nationally representative of rural households and geocoded at village level. Including rural households in all three waves provides a sample of more than 2,800 households clustered in 287 villages with broad geographic coverage across Ethiopia (see figure 1)[4]. The ESS household and agriculture surveys cover demographics, consumption, income, employment and agricultural production. The community survey includes village level information on infrastructure and public services for each enumeration area (EA).

The primary outcomes of interest are household consumption per adult equivalent (paq) measured in 2016 Birr and agricultural production measured in kg per hectare. Consumption includes self produced and purchased food, and non-food expenditure. I adjust aggregate nominal consumption provided in the data to allow valid comparison by spatial price differences, using a regional price index from the Ministry of Finance and Economic Development, and inflation, using official consumer price indices at regional level at the time of surveys (CSA and MoFED, 2012; CSA, 2016). Agricultural production is reported in kg per crop in the post-harvest component of the ESS and divided by land area[5]. I aggregate production over major crop types and all crop types, presenting results for both.

[3] 2016 surveys were conducted between February and April.

[4] Attrition due to survey exit and data collection errors is low.

[5] Production here is strictly a measure of land productivity. Results are robust to other measures (appendix - table 18).

2.2 Measuring exogenous drought

To measure drought intensity, I construct a Standardised Precipitation Index (SPI) from satellite rainfall data for Ethiopia. The SPI is widely used to quantify meteorological drought (Wu et al., 2007). Raw precipitation is not normally distributed over time so standard z-values cannot be interpreted accordingly. To calculate the SPI, raw precipitation data is fitted to a gamma distribution, then transformed to a standard normal distribution with a mean value of zero, which allows comparability between different locations and climate zones (Agnew, 2000). An SPI value is easily interpreted as the number of standard deviations that precipitation varies from its normalized average. Negative SPI values indicate relatively dry periods and positive values point to wetter periods. Importantly, an equal SPI in two different locations represents equally likely precipitation conditions, not the same amount of precipitation. The relative nature of this scale reflects that rainfall shocks, rather than absolute precipitation, are found to affect rural production, welfare, and even conflict outcomes in developing countries (Amare et al., 2018; C. Porter, 2012; Sarsons, 2015). There is evidence that agriculture is adjusted to steady state climate conditions (Mendelsohn, 2008).

To construct the SPI, I use high spatial resolution (0.05°or 6x6 km grid above Ethiopia) monthly rainfall data for 1981 to 2015 from the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) data set (Funk et al., 2015). By accounting for the localised probability of drought, the SPI provides a measure of exogenous variation superior to rainfall anomaly measures often used in economic studies[6].

I calculate the SPI at each of the 287 villages in the sample using the average of the four closest grid cells. I define drought affected villages as those experiencing a 12 month SPI less than -1.645, corresponding with the 5þpercentile of the normal distribution. Therefore, all households in the treated group experience at least a one in 20-year drought event during 2015, based on localised historic rainfall data. This treatment threshold represents a drought intensity most likely unprecedented in living memory since the median age in the sample is

[6]Exceptions using SPI include Wenzel, (2018), who study drought and corruption across 122 countries.

21. No communities in the sample recorded an SPI below this threshold between 2011 and 2014, when the first two ESS survey rounds were conducted. Exposure to the 2015 drought varies significantly. I exclude households with an SPI between the 5þ and 10þ percentile for analysis so that the control group is more representative of a counterfactual in a typical year of precipitation[7]. Figure 1 shows the location and treatment status of surveyed villages, and 12 month SPI across Ethiopia in 2015. The SPI appears highly correlated with alternate drought measures in Famine Early Warning Systems Network 2015 analysis of the extent and severity of the drought[8] (FEWS, 2015).

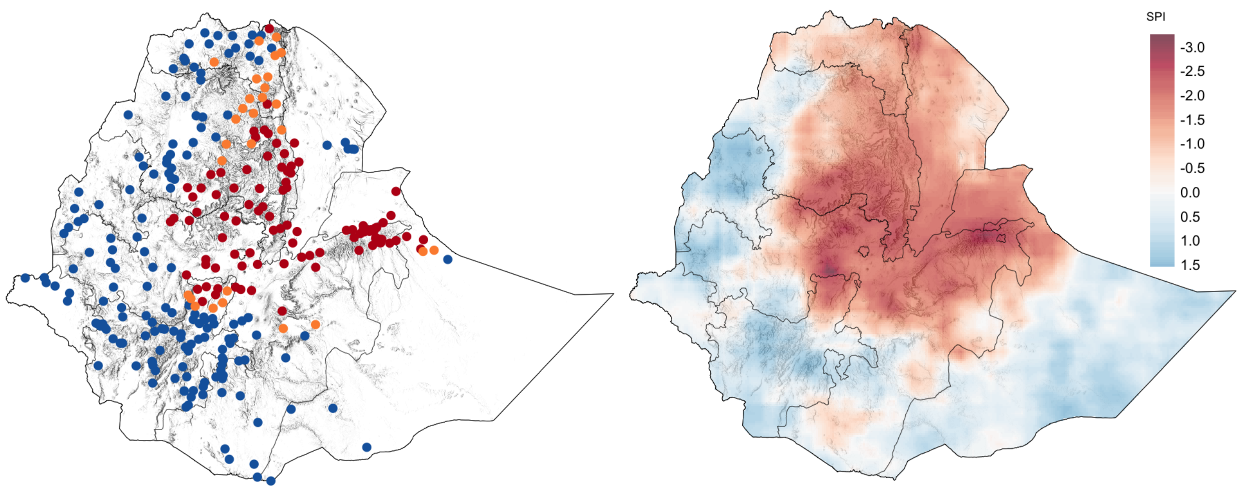

Figure 1: Left: Location and treatment status of surveyed villages. Red - treated; orange - excluded; blue - control. Right: 12 month SPI for January-December 2015.

2.3 Descriptive analysis

Table 1 summarises treatment assignment by region. The mean SPI in the control group closely corresponds with long term expected precipitation (zero). I also compare treatment based on meteorological drought with households that self-report drought and food insecurity in the ESS. At a national level, a similar share of households are represented in the treated group, self-report drought and self-report food insecurity. However, this masks large differences

[7]The group assignment is shown against the SPI distribution for 2015 in appendix - figure 8.

[8]Correlated measures include soil moisture anomaly, water availability per capita, Water Requirements Satisfaction Index (WRSI) for crops, vegetation anomaly and food security classifications.

between these categories at a regional level. Figure 2 plots the density function of households in each category against the SPI. A household experiencing severe meteorological drought in 2015 was no more likely to report food insecurity than a household in the control group[9]. This points to more complex determinants of food insecurity, and reiterates the importance of not conflating subjective and meteorological drought measures.

Table 1: Sample (share of households)

Region	Group assignment based on SPI			Self reported	
	Excluded	Control	Drought	Drought	Food insecurity
Tigray	36%	58%	7%	44%	25%
Afar	0%	53%	47%	59%	27%
Amhara	13%	34%	53%	27%	20%
Oromia	4%	49%	47%	22%	37%
Somalie	9%	40%	52%	81%	48%
Benshagul Gumuz	0%	100%	0%	0%	24%
SNNP	9%	82%	9%	19%	34%
Gambelia	0%	100%	0%	9%	27%
Harari	0%	0%	100%	73%	14%
Diredwa	0%	0%	100%	81%	41%
Total	10%	54%	36%	33%	30%
No. households	290	1549	1030	943	865
SPI (mean)	-1.48	-0.05	-2.15	-1.59	-0.85
SPI (std. dev.)	0.11	0.72	0.32	0.94	1.19

Table 2 compares the mean outcomes between the drought and control group before the drought (2012 and 2014 pooled). Mean consumption is approximately 40% higher on average for treated households[10]. Production outcomes are very similar between groups, with a normalised difference close to zero.

Table 3 compares community and household characteristics between groups in 2014. Groups appear very similar, with normalised differences of less than 0.1 standard deviations for most observable characteristics. Two observations stand out: the share of treated households participating in the PSNP labour program was double that of the control group before the drought, and the treated group is less remote on average, closer to both major roads and population centers. Agricultural production characteristics are similar with over

[9] 29% of households in the treated group report food insecurity and 30% of the control group.

[10] By chance, since exposure to drought is exogenous. The normalised difference is small.

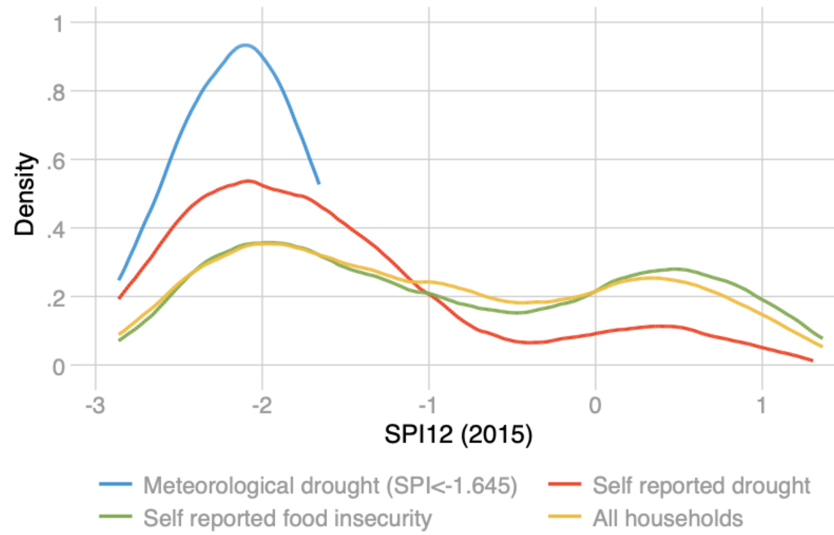

Figure 2: Meteorological drought vs. self reported drought and food insecurity.

Table 2: Outcomes before drought (2012 & 2014 pooled)

Variable	Control mean	Drought mean	Δ	Norm diff.	Obs.
Consumption paq (Birr)	5,949	8,359	2,410	0.202	5,140
Food consumption paq (Birr)	4,827	6,363	1,536	0.222	5,140
Non-food consumption paq (Birr)	1,055	1,720	6645	0.063	5,140
Production (kg/ha)	1,589	1,199	-390	-0.030	3,660
Total land area (ha)	1.33	1.34	0.01	0.002	4,721
Observations	3,080	2,060	5,140		

All prices in 2016 Birr, adjusted by a regional price index and CPI at regional level.

99% of households in each group participating in agriculture, 92-96% owning livestock and 39-42% selling crops. About two thirds of households in each group mostly produce the major cereal crops in Ethiopia, with sorghum the most prominent crop in the drought group compared to maize in the control group (appendix - table 11).

Figure 3 shows the distribution and trend of consumption for each group before and after the 2015 drought. Consumption is higher overall in the treated group before the drought, but distributions largely overlap[11]. There is very little change in the consumption distribution for the control group over time, with more obvious but heterogeneous effects visible in the

[11]No treated household has a higher consumption than any household in the control group.

Table 3: Community and household characteristics before drought (2014)

Variable	Control mean	Drought mean	Δ	Norm diff.	Obs.
Household size	5.159	4.915	-0.245	-0.075	2,570
Dependency ratio	1.350	1.224	-0.127	-0.059	2,387
Household head age (years)	45.5	47.6	2.10	0.097	2,570
Household head female	0.226	0.235	0.009	0.015	2,570
Household head attended school	0.355	0.280	-0.075	-0.114	2,570
Household engages in agriculture	0.993	0.996	0.002	0.021	2,266
Household sold crops	0.417	0.388	-0.029	-0.041	2,570
Household owns livestock	0.925	0.956	0.032	0.095	2,570
Number of cattle	4.144	3.602	-0.542	-0.087	2,271
Access to agricultural extension	0.951	0.921	-0.030	-0.087	2,520
Agricultural network outside village	0.492	0.489	-0.003	-0.004	2,501
Household member employed for wage	0.089	0.097	0.008	0.020	2,570
Non-farm enterprise	0.305	0.322	0.017	0.026	2,570
PSNP labour program in last 12 months	0.068	0.150	0.082	0.188	2,568
PSNP labour program income (Birr)	1,381	3,228	1,847	0.555	258
Household assistance (Birr)	1,697	1,782	85	0.029	385
Household credit (Birr)	2,623	3,475	852	0.171	710
Household owns mobile phone	0.341	0.417	0.076	0.110	2,570
Dwelling has electricity	0.064	0.222	0.158	0.327	2,569
Death of household member in last 12 months	0.042	0.026	-0.015	-0.060	2,570
Large weekly market in village	0.437	0.477	0.040	0.056	2,570
Sealed or graded gravel road	0.353	0.371	0.018	0.026	2,570
All-year road access	0.499	0.676	0.176	0.257	2,551
More than 20 km from a major road	0.319	0.157	-0.162	-0.273	2,570
Bus service (within 10 km)	0.464	0.579	0.115	0.163	2,511
Distance to city with pop>20,000 (km)	44.3	33.0	-11.3	-0.252	2,570
Distance to Zone capital (km)	185.9	143.0	-42.9	-0.240	2,570
12 month SPI for 2013	0.653	0.425	-0.228	-0.205	2,570
Observations	1,540	1,030	2,570		

consumption distribution for drought affected households.

Visual inspection suggests that pre-trends in consumption are not parallel, which threatens the validity of a counterfactual estimated from the control group. Crucially, the pre-trends differ in the opposite direction of the expected negative effect of drought. While consumption declines in both groups, households exposed to severe drought display a growth advantage in the pre-period. This suggests a naive difference-in-differences estimator would underestimate the treatment effect of drought (discussed further in section 2.4 and 4.2).

Figure 4 shows very similar distributions of production in treated and control groups before the drought. Changes over the drought period are only apparent for the treated group.

Trends in mean production are near parallel before the drought, followed by a pronounced decline in production for the treated group relative to the control group. Intuitively, there are few options to smooth agricultural production compared to consumption during severe drought.

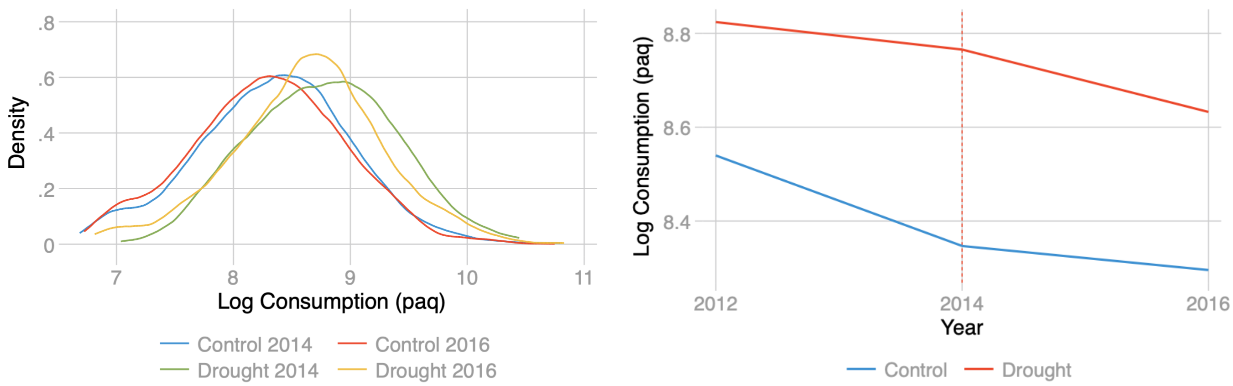

Figure 3: Left: Consumption distributions. Right: Consumption trends.

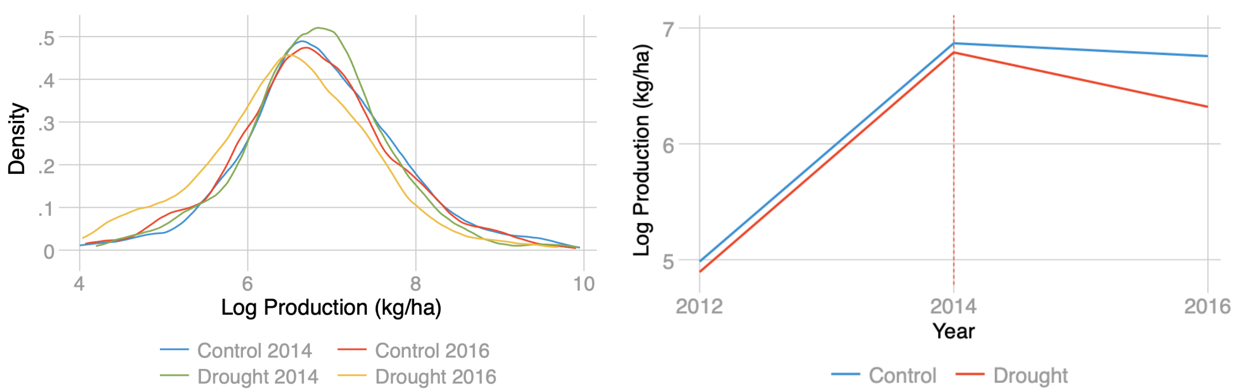

Figure 4: Left: Production distributions. Right: Production trends.

2.4 Causal identification strategy

I use a difference-in-differences (DiD) method to exploit the exogenous nature of drought for causal inference. I also employ the more general changes-in-changes model to check robustness to functional form and estimate distributional effects. Formally, households experiencing severe drought (SPI < -1.645) make up the treated group ($D = 1$) and households not in drought (SPI > -1.282) make up the control group ($D = 0$). There are two periods, the pre-treatment period (2014), denoted $T = 0$, and post-treatment (2016), denoted $T = 1$. Let $Y_{di}(t)$ be the potential outcome of household i with treatment status d in period t. The primary estimate of interest is the average treatment effect on the treated (ATET):

$$\alpha_{ATET} = E[Y_{1i}(1) - Y_{0i}(1)|D_i = 1] \tag{1}$$

The counterfactual, $Y_{0i}(1)$, is not observed but can be estimated from observed differences in outcomes between groups using DiD as follows:

$$\begin{aligned} \alpha_{ATET} = &\{E[Y|D = 1, T = 1] - E[Y|D = 0, T = 1]\} \\ &-\{E[Y|D = 1, T = 0] - E[Y|D = 0, T = 0]\} \end{aligned} \tag{2}$$

The key assumption for causal inference is that counterfactual outcomes for the treated without treatment follow the same time path as observed outcomes in the control group, or common trends (Imbens and Wooldridge, 2009). We have seen that drought, as measured, is plausibly independent of potential outcomes. Descriptive analysis has shown the groups are relatively similar, suggesting control households make a valid comparison. However, the average consumption level was higher and trend flatter in the treated group before the drought, casting some doubt on common trends.

To account for this concern, I control for lagged consumption. This specification assumes any difference in trends is largely explained by previous consumption levels (treatment is ignorable conditional on past outcomes)[12]. The 2015 drought was not forecast at the time 2014 surveys were conducted, so consumption measured in the pre-period is independent of future treatment (Singh et al., 2016). Previous consumption also provides a proxy for savings, which households identify as the main coping method for shocks. Hence, controlling

[12]For more discussion see Ding and Li, (2019), who describe the bracketing relationship between DiD and lagged dependent variable adjustment.

for lagged consumption is expected to reduce differences in consumption trends between groups caused by contemporaneous shocks. This holds true in the pre-period; conditioning on 2012 consumption closely aligns consumption pre-trends and levels in 2014 (appendix - figure 9). For production, no similar controls are necessary. Parallel pre-trends, overlapping distributions and similar production characteristics together provide strong evidence for common trends, suggesting DiD will compute an unbiased estimate of the ATET (Kahn-Lang and Lang, 2019).

Alternative approaches might address these concerns. Matching or synthetic control methods are commonly applied to DiD where confounding is present, but arbitrary selection of variables and choice of functional form can introduce other issues[13]. Simply conditioning on lagged consumption is clean, consistent with data, theoretically underpinned and sufficient for inference in our context, but these methods could be considered in future research.

The Stable Unit Treatment Value Assumption (SUTVA) for causal inference is less assured. Using panel data ensures the composition of groups is stable over time, but spillover effects violate SUTVA. Drought could increase competition for resources, lifting equilibrium prices in the economy and suppressing consumption in the control group. In a series of studies International Food Policy Research Institute found no evidence of widespread adverse price effects from the drought in labour or cereal markets (Bachewe et al., 2018). Migration also poses little concern since attrition in the sample is low. To investigate further, I formally test for statistically significant spillover effects in section 4.4.

Practically, I use log transformed outcomes and a single pre-treatment period to avoid inconsistent standard errors caused by multiple pre-periods (Bertrand et al., 2004). The resulting regression framework can be represented as:

$$Y_{igt} = \alpha + \beta_1 Y_{igt-1} + \beta_2 T + \beta_3 (D_g \times T) + \delta_g + \epsilon_{igt} \tag{3}$$

Y_{igt} is the outcome for household i in village g at time t. Y_{igt-1} controls for the lagged

[13] Such as regression to the mean, see Daw and Hatfield, (2018) for discussion.

outcome, included only for consumption. D_g is a dummy with $D = 1$ if village g is in the treated (drought) group. T is a dummy with $T = 1$ in the post-treatment period (equivalent to a time fixed effects term). δ_g denotes village fixed effects, to account for time invariant characteristics. β_3 captures the ATET of the 2015 drought on the outcome, assuming that the counterfactual is valid. For valid inference, standard errors are clustered at village (treatment) level to account for auto-correlation, given there is a large number of clusters (Imbens and Wooldridge, 2009).

If the same regression is applied to data for 2012 and 2014, β_3 captures the difference in trends in the pre-period. If the coefficient is insignificant, we cannot reject that pre-trends are parallel. This may point to common trends in the treatment period, but is neither necessary nor sufficient for DiD (Kahn-Lang and Lang, 2019). It is straightforward to estimate how sensitive outcomes are to drought intensity (the dose-response) by replacing D_g in equation 3 with a continuous measure of drought (the SPI) for the treated group.

The regression framework is easily extended to identify heterogeneous effects, and quantify whether villages with certain characteristics are more or less vulnerable to drought:

$$\begin{aligned} Y_{igt} = \alpha + \beta_1 Y_{igt-1} + \beta_2 T + \beta_3 (D_g \times T) + \beta_4 (X_g \times D_g) \\ + \beta_5 (X_g \times T) + \beta_6 (X_g \times D_g \times T) + \delta_g + \epsilon_{igt} \end{aligned} \tag{4}$$

X is a dummy variable identifying units with a particular characteristic (e.g. road access). β_6 is the difference in treatment effect between treated households with X=1 and those with X=0. Additional interactions account for differences in outcomes for households with and without X in the control group, to estimate the relevant counterfactual[14].

To estimate the distributional effects of drought on consumption and production, and to check robustness to functional form I use Athey and Imbens, (2006) changes-in-changes model (CiC). CiC is a generalisation of difference-in-differences that recovers the whole distribution of the counterfactual outcome. This makes it well suited for estimating treatment effects

[14] Treated households with a road are compared to control households with a road.

at different quantiles of the outcome distribution. Specifically, the CiC estimator relaxes additivity, single index and identity transformation assumptions implicit in the difference-in-differences set up (Imbens and Wooldridge, 2009). By relaxing functional form, potential outcomes in the absence of treatment can be written as:

$$Y_i(0) = h_0(U_i, T_i) \tag{5}$$

U_i represents all unobservables. CiC allows for the distribution of unobservables to vary across groups within time periods but not across time within groups (similar to a group coefficient in DiD). The key assumption is that changes in the distribution of outcomes for each group (without treatment) only occur because $h_0(u_i, 1)$ differs from $h_0(u_i, 0)$; the relationship between u and Y change over time. Recent extensions use semi-parametric methods to add covariates without imposing additivity, meaning CiC can be used to estimate conditional counterfactual distributions (Kranker, 2016). This allows me to control for lagged consumption and compare CiC estimates to DiD as specified above[15]. I conduct inference using bootstrapped standard errors clustered at village level, as recommended in Athey and Imbens, (2006) and Chernozhukov et al., (2013).

3 Results

3.1 Drought, consumption and production

Table 4 presents estimates of the effect of drought on consumption and production. Column one confirms the graphical observation that consumption trends are significantly different between groups before the drought (without controlling for lagged consumption)[16]. The second column estimates the treatment effect using the full specification given in equation 3. Controlling for lagged consumption, households in the treated group suffer 12% lower annual

[15]The Stata program *cic* is available from the Statistical Software Components archive (Kranker, 2019).
[16]Further discussion is included in section 4.2.

consumption, on average, than if the drought did not occur. For production, coefficients testing for differences in pre-trends are shown in columns three and five. They are close to zero and insignificant, so we cannot reject that pre-trends are parallel. Together with the observation of overlapping distributions and similar production characteristics, this suggests the DiD yields a valid counterfactual for production. The impact of drought on production (columns four and six) is highly significant. Drought decreased average production in kg/ha of all crops by 38% and major crops by 27% compared to a year without drought.

Table 4: Consumption and production

	Log Consumption (paq)		Log Production (kg/ha)			
			All crops		Major crops	
	(1)	(2)	(3)	(4)	(5)	(6)
droughtXpre	0.134***		0.0246		0.0470	
	(2.94)		(0.14)		(0.27)	
droughtXpost		-0.116**		-0.382***		-0.266**
		(-2.21)		(-3.30)		(-2.21)
L.Log Cons.		0.253***				
		(12.43)				
Observations	5140	5140	3342	4410	2328	3098
R^2	0.472	0.486	0.503	0.385	0.399	0.371

Includes EA (village) and time fixed effects. Standard errors clustered at EA (village) level. t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Similar research finds commensurate effects of drought, but differences in drought measures makes comparison difficult (Dercon, 2004; Hill and C. Porter, 2017; Amare et al., 2018). It is clear from the results that households employ coping methods to smooth consumption during drought. Many households in the sample are quasi-subsistence producing around 60-80% of consumption. This implies that without consumption smoothing, the estimated fall in production would cause a 20-30% decrease in consumption (ceteris paribus), compared to the 12% detected. In surveys, households list their own savings, selling livestock, unconditional assistance and transfers from relatives as the most important coping methods for drought shocks, though 8% of respondents "do nothing" to cope with drought. On the surface, these observations of consumption smoothing are consistent with the predictions of a dynamic stochastic macroeconomic model, where there are credit constraints and frictions in savings.

This paper does not delve further from a theoretical lens of consumption smoothing, instead focusing on empirical analysis, though such discussion is an obvious avenue for future research.

Figure 5 shows the distributional effects of drought on consumption and production using the changes-in-changes method. The ATET estimated using CiC (-0.117 and -0.381 respectively) closely match those above, implying the DiD specification is not sensitive to functional form. The quantile graph shows that the average treatment effect is driven by the effect of drought on the bottom quintile of the consumption distribution. The 2015 drought most heavily impacts poorer households, consistent with other drought vulnerability literature (Gray and Mueller, 2012). Intuitively, these households have less savings, assets and other coping methods at hand. Results for production demonstrate the most significant and negative impact of drought falls on the upper half of the production distribution. The fact that more productive producers suffer proportionally greater losses implies that the threat of drought reduces expected returns to agricultural investment. This adds weight to evidence that uncertainty undermines incentives for technology adoption among smallholder farmers (Dercon and Christiaensen, 2011; Mwangi and Kariuki, 2015).

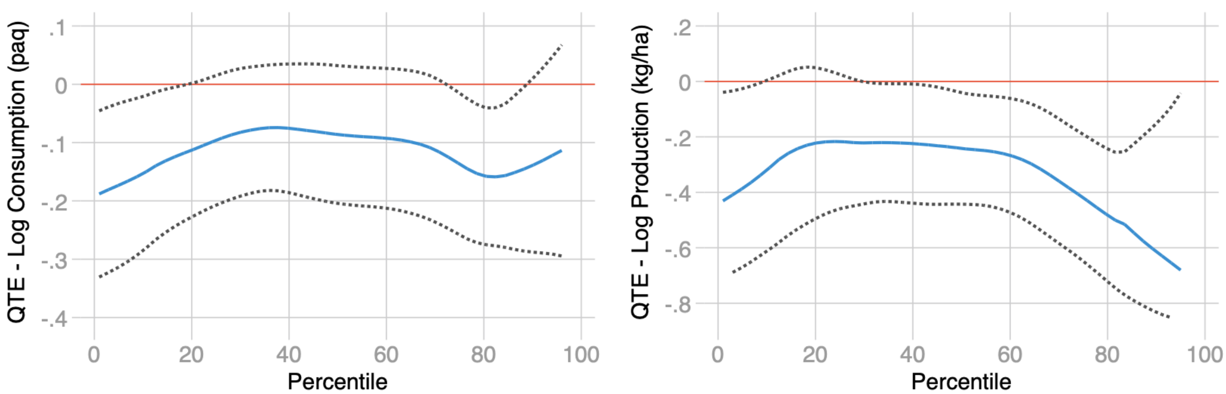

Figure 5: Quantile Treatment Effects estimated by CiC. Left: Consumption. Right: Production

3.2 Drought intensity

Table 5 presents results showing the sensitivity of consumption and production to drought intensity in the treated group. Drought intensity clearly matters more for production, decreasing yield per hectare by 13-19% per unit decrease in the in SPI below -1.645.

Table 5: Drought intensity

	Log Consumption (paq) All crops	Log Production (kg/ha) Major crops	
	(1)	(2)	(3)
intensityXpost	-0.0504**	-0.189***	-0.129**
	(-2.05)	(-3.35)	(-2.34)
Observations	5140	4410	3098
R^2	0.486	0.386	0.372

Lagged consumption not shown. Includes EA (village) and time fixed effects. Standard errors clustered at EA (village) level. t-statistics in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

To further illustrate the effect of drought intensity, I simulate the estimated treatment effect when varying the SPI threshold that defines treatment from -0.5 (dry) to -2 (very severe drought). The control group is fixed, comprising of households with SPI > -0.5 (compared to > -1.282 in the main specification) to allow analysis over a wider range of drought intensity[17]. Results are shown in figure 6 for consumption and production. We observe that consumption is relatively insensitive to drought intensity and production results are driven by households experiencing the most severe drought. There is weak evidence of a U shape for consumption, which could reflect that households receive more assistance when drought is very severe or engage in new activities. Taken together, results point to a progressive decoupling of household consumption and production when drought becomes more intense[18]. With drought expected to become more frequent and severe due to climate change, these findings imply lower returns to investment in agriculture in the future, casting doubt on the prospect of household led transformation within the agricultural sector. Movement out of agriculture becomes more attractive. Without access to technology that improves resilience,

[17]This further restriction to the control group has little impact on the ATET estimated at the original treatment threshold.

[18]A similar relationship is observed when restricting production to major crops only.

expanding agricultural production will become an even riskier business for rural households.

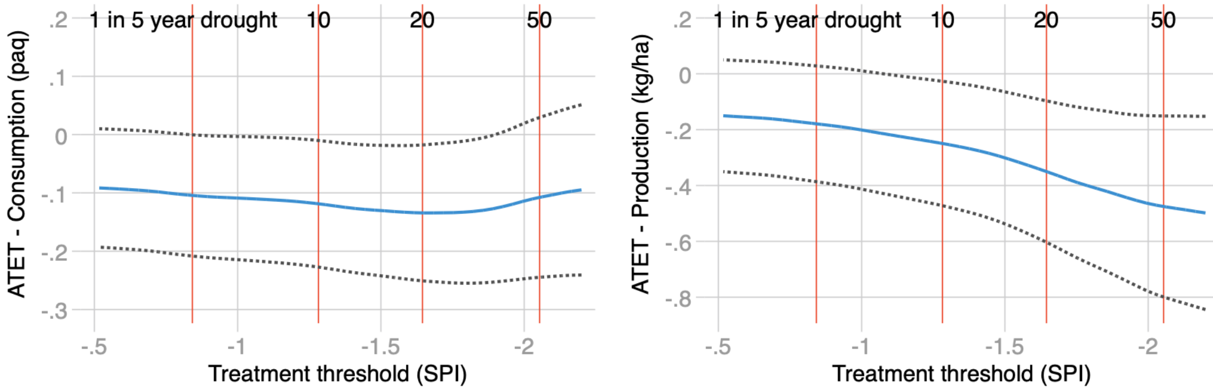

Figure 6: Varying treatment threshold. Left: Consumption. Right: Production.

Since consumption seems unresponsive to drought intensity, I look for evidence of short term structural transformation caused by the 2015 drought. Did the drought lead households to engage in more profitable activities outside agriculture? Or was external assistance responsible for the consumption smoothing we observe? I estimate the effect of drought on several economic outcomes using DiD. Overall there is no convincing evidence of short run transformation, and lack of post-treatment data prevents detection of lasting effects in any case.

Full results are reported in appendix - table 12 for succinctness. They suggest that external assistance played a limited role in reducing vulnerability to drought. Drought significantly increased participation in the PSNP labour program and the share of households receiving any assistance in the treated group, but this accounts for only 13% of affected households receiving assistance they would not have otherwise received. Moreover, drought had no effect on the average level of PSNP income or assistance for 20% of treated households who were already receiving some amount before the drought. It follows that external assistance was not a coping method specific to meteorological drought for the vast majority experiencing severe drought. Other estimates show no significant effect of drought on the number of households participating in agriculture, hours of wage work, or the rate of urban migration[19]. Results

[19]Samples are smaller for these outcomes, so statistical power is limited.

do indicate a significant decrease in credit held by treated households, but this was already substantially higher than in the control group before 2015. Nonetheless, borrowing does not seem a coping strategy available to households, on the contrary, debts were collected where drought was severe.

3.3 Heterogeneous treatment effects and mobility

Understanding the heterogeneous effects of drought can shed light on sources of resilience. In this section, I use interaction terms to differentiate the effect of drought on subsets of the treated group using equation 4. Firstly, I estimate heterogeneous effects along household characteristics (results in appendix - table 14). I find households with female heads had significantly lower consumption during drought relative to their counterparts. They experienced, on average, 23% lower annual consumption compared to 8% (insignificant) for male headed households[20]. This further substantiates the gendered nature of vulnerability to natural disasters established in other studies (Neumayer and Plümper, 2007). Households with educated heads and those participating in the PSNP labour program were not significantly better off during the drought. Remote households (23% of treated) did not experience significantly different impacts with respect to consumption or production, though point estimates suggest they were less vulnerable on average[21]. The effect of drought on production was not significantly different for male or female headed households, educated or uneducated. Treated households participating in the PSNP labour program produced virtually nothing, suggesting the PSNP program acts as a substitute, not complement, for agricultural production during drought.

Next, I compare the effect of drought on households differentiated by indicators of mobility. I refer to mobility broadly, including access to road infrastructure, transport services, mobile phones and social networks. All these factors potentially play a role in coping with drought shocks by facilitating the movement of goods, labour, capital and information. Using equation

[20]Households with female heads account for 25% of the treated group.

[21]Remote is defined as more than 50km away from a population center of at least 20,000 people.

4 we can identify significant dimensions of heterogeneity but, crucially, should not interpret these results as causal. The placement of roads is unlikely to be random. Correlated factors such as wealth, for example, could be contribute to the heterogeneity we observe. Nonetheless, identification of heterogeneous effects remains valuable to guide policy and pinpoint vulnerabilities.

3.3.1 Transport infrastructure

Table 6 shows results for consumption and production where drought interacts with indicators of road quality and access. For consumption, all coefficients on the interaction terms are positive, but only the estimate for year-round access to public transport is (weakly) significant. Road access appears more important for consumption resilience than road quality. Villages with public transport access (one third of treated) had 25% higher consumption than those without it during the drought. Communities with a sealed road (one out of five) were no better off in terms of consumption but had 17% higher production than they would have in a typical year without drought[22]. This counter-intuitive result could arise because communities on sealed roads have access to better quality soils or inputs including seeds, fertiliser and labour during drought. Higher production may also be driven by demand because sealed roads provide access to new markets during drought. One caveat to this result is that the treated group is less remote on average than the control group. Therefore, the benefit of a sealed road could be underestimated in the counterfactual, which should be considered before extrapolating these results.

3.3.2 Transport services and networks

Lastly, I analyse heterogeneity by differentiating households based on access to transport services, mobile phone ownership and whether households list contacts beyond their own community in an agriculture network roster (completed as part of the ESS surveys). Results

[22]Very similar results are found when production is restricted to major crops only (appendix - table 15)

Table 6: Transport infrastructure

	Log Consumption (paq)			Log Production (kg/ha)		
	(1)	(2)	(3)	(4)	(5)	(6)
droughtXpost	-0.136**	-0.206**	-0.301**	-0.501***	-0.366*	-0.213
	(-2.20)	(-2.22)	(-2.31)	(-3.73)	(-1.75)	(-0.82)
Interactions:						
Sealed road	0.0945			0.668**		
	(0.78)			(2.02)		
Sealed or maintained gravel road		0.148			-0.0217	
		(1.29)			(-0.07)	
All year access (public transport)			0.262*			-0.280
			(1.83)			(-0.91)
Observations	5140	5140	5140	4410	4410	4410
R^2	0.488	0.487	0.488	0.387	0.387	0.387

Lagged consumption not shown. Time and group interactions with dummy variable not shown. Includes EA (village) and time fixed effects. Standard errors clustered at EA (village) level. t-statistics in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

Table 7: Transport services and networks

	Log Consumption (paq)				Log Production (kg/ha)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
droughtXpost	-0.202**	-0.125**	-0.145**	-0.168***	-0.805***	-0.375***	-0.460***	-0.640***
	(-2.20)	(-2.37)	(-2.36)	(-2.79)	(-3.74)	(-3.23)	(-3.56)	(-4.01)
Interactions:								
Bus service	0.178				0.774***			
	(1.48)				(2.77)			
Crop sold by motor vehicle		0.447*				-0.121		
		(1.90)				(-0.22)		
Mobile phone			0.0501				0.174	
			(0.85)				(1.56)	
Network outside community				0.114				0.486***
				(1.50)				(2.88)
Observations	5081	5140	5140	5041	4355	4410	4410	4410
R^2	0.486	0.487	0.490	0.492	0.396	0.385	0.386	0.396

Lagged consumption not shown. Time and group interactions with dummy variable not shown. Includes EA (village) and time fixed effects. Standard errors clustered at EA (village) level. t-statistics in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

are shown in table 7. Households who sell crops by motorised transport have significantly higher consumption, outweighing even the negative impact of drought, but this result is driven by few units in the sample. Crops sold by motorised transport may reach distant markets, fetching higher prices or allowing the sale of more diverse crops. Bus services and having contacts outside the community are statistically insignificant in consumption results, but potentially important for resilience given large point estimates for these variables[23].

Production is significantly less vulnerable to drought where there is a bus service (49% of treated) and for households with agricultural networks outside their community (47% of treated). Having a mobile phone (46% of treated) is also significant when restricting production to major crops (appendix - table 16). The presence of a bus service effectively eliminates the negative impact of drought on production based on our sample. Similar to sealed roads, a bus service may permit access to better or more inputs and labour, allow crop diversification or give access to plots of land further away that are less affected by drought. Households without either a mobile phone or a network outside their community were much more vulnerable to drought. Social networks and mobile phones could provide a valuable source of information advising more resilient agricultural practices during drought, a promising avenue for future research.

4 Robustness

4.1 Outcome measurement

Treatment effects estimated using DiD can be sensitive to functional form (Wing et al., 2018). Using the changes-in-changes method, I show that results were consistent when additivity is not imposed in section 3.1. I also estimate treatment effects using different measures of consumption and production to confirm that a single outcome measure is not driving results. Results confirm that drought has a significant negative effect on consumption and production whether outcomes are measured in level or logarithmic form (appendix - table 17 and 18). Crop income is also significantly lower due to drought. I also estimate production results by specific crop type for the six major crops (appendix - table 19). Sorghum production is most impacted by drought, and the most common crop among the treated (grown by 28%). Coefficients are negative but insignificant for all other crops except barley.

[23] I define bus services as having a bus stop within 10km with at least weekly service frequency.

4.2 Persistent pre-trends

It is highly recommended to confirm that the main conclusions from DiD studies are not sensitive to pre-trend differences, even if we cannot reject parallel pre-trends (Bilinski and Hatfield, 2019; Kahn-Lang and Lang, 2019). In the case of consumption, pre-trends were significantly different but in the opposite direction of the treatment effect. They do not diminish the estimated treatment effect or significance level, even at the lower bound. Figure 7 shows the consequences of allowing the significant difference detected in pre-trends to persist in the treatment period. This approach is suggested by Roth and Rambachan, (2019), though implemented directly compared to their nested optimisation method. The estimate on the far left of the graph is obtained assuming trends between groups are parallel in the treatment period (without accounting for pre-trend differences). The estimate on the far right is obtained if the full extent of pre-trend differences persist, but unfortunately, no further historical data is available to test this assumption. Controlling for lagged consumption is equivalent to accepting that 25% of the difference in pre-trends would persist in the counterfactual. The analysis therefore shows that the main specification is appropriately conservative and results are relatively robust to deviations from parallel trends.

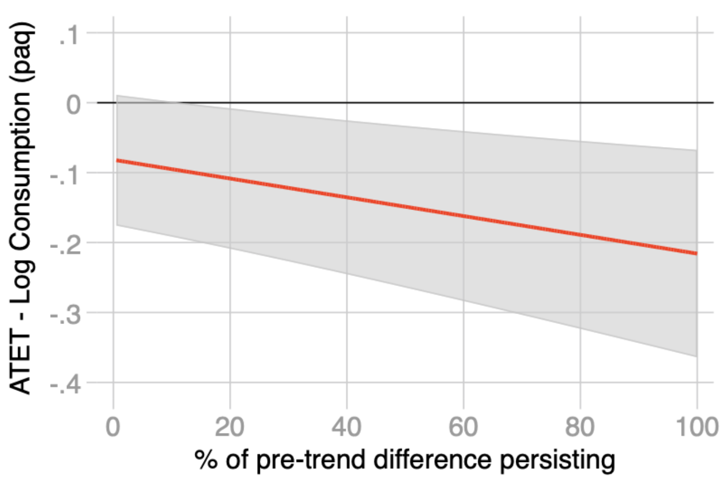

Figure 7: Persistent pre-trends - Consumption.

In results for production, there was no statistically significant difference in pre-trends between the treated and control group. I also check whether the confidence interval on this test could eliminate the estimated treatment effect of drought on production. The lower bound of the 95% confidence interval is substantial (-0.32) but does not rule out a causal effect of drought on agricultural production, so the main production result also holds up to this scrutiny.

Bilinski and Hatfield, (2019) offer an alternative "Non-Inferiority Approach to Difference-in-Differences" to investigate the validity of parallel trends. The method involves comparing estimates from a DiD model with a more complex trend difference than assumed with a simpler model (assuming parallel trends). Unfortunately, fitting different pre-trends is rather uninformative in this study because there are only two pre-periods. However, even without additional statistical evidence for stable pre-trends from this test, I suggest there remains strong evidence for identification of treatment effects from DiD. The contextual discussion and descriptive analysis (section 2), statistical results (section 3.1) and sensitivity analysis here together provide evidence to dismiss reasonable concerns about time-varying confounding.

4.3 Varying groups

Difference-in-differences can be sensitive to the subset of households included in each group due to confounding from time varying factors, such as a new region specific policy. Table 8 shows results when modifying groups based on geographical proximity and administrative region. All specifications estimate a significant causal effect of drought. The first column for each outcome includes only neighbouring villages within 100 km of treated in the control group. The second column excludes regions where no households were treated, the third excludes regions where all households were treated, and the fourth excludes regions that are not represented in both treated and control group. Consumption results are very robust to varying group membership, with no significant differences compared to using the full sample (see appendix - figure 10.

Production results are more variable. The ATET estimated for production is -45% when

Table 8: Varying groups

	Log Consumption (paq)				Log Production (kg/ha)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
droughtXpost	-0.118*	-0.116**	-0.131**	-0.132**	-0.474***	-0.375***	-0.224**	-0.217**
	(-1.72)	(-2.18)	(-2.37)	(-2.33)	(-3.30)	(-3.20)	(-2.13)	(-2.03)
Observations	2934	4758	4688	4306	2504	4067	4003	3660
R^2	0.456	0.495	0.442	0.449	0.357	0.392	0.371	0.378

(1) & (5) neighbouring villages only, (2) & (6) only regions represented in treatment group, (3) & (7) only regions represented in control group, (4) & (8) only regions represented in both groups. Control for lagged consumption not shown. Includes EA (village) and time fixed effects. Standard errors clustered at EA (village) level. t-statistics in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

comparing drought affected households to neighbouring control villages only. On the other hand, excluding regions where all units were treated, estimates an ATET of -22%. This may suggest that production is particularly vulnerable in regions where severe drought is widespread. Further analysis shows the region of Diredwa, with all villages treated, experienced particularly severe drought. Since production is sensitive to drought intensity, outcomes from this region drive the result. Results are also robust to excluding one region at a time (appendix - figure 11).

4.4 Placebo and spillover effects

Finally, I test that results are not significant when households in the control group are assigned to a placebo treatment group. Villages within 135 km of the treated (the median distance) are assigned to a placebo group and the remainder of untreated units to a new control group[24] Group assignment by proximity means this regression also tests for evidence of spatial spillover effects.

Table 9 shows results from DiD regression on these groups. The coefficient in column one is close to zero and insignificant, indicating consumption results are robust to placebo treatment (drought has no significant effect on nearby consumption). There is no significant effect on production of all crops for the placebo group, but production of major crops is significantly higher by 30% in placebo villages. I rule out more favourable weather conditions

[24]Similar estimates are obtained using a distance of 100 km (appendix - table 20).

Table 9: Placebo (135 km)

	Log Consumption (paq)	Log Production (kg/ha)	
		All crops	Major crops
	(1)	(2)	(3)
placeboXpost	-0.00594	0.116	0.297**
	(-0.09)	(0.98)	(2.16)
Observations	3080	2684	1728
R^2	0.434	0.389	0.401

Control for lagged consumption not shown. Includes EA (village) and time fixed effects. Standard errors clustered at EA (village) level. t-statistics in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

as a possible explanation; the SPI indicates much drier than average conditions in the placebo group than the control group[25]. The result implies meteorological drought had positive spillover effects on production in nearby villages. Evidence of a production spillover suggests that the impact of local crop losses where drought was severe is mitigated by increased production elsewhere. Given we detect no effect of drought on consumption in the placebo group, this increase in agricultural production is presumably consumed elsewhere, which could explain the consumption smoothing we observe among the treated. Another implication is that the estimated impact of drought on production would be much more modest if larger spatial units were used in our analysis, since they would internalise the spillover.

4.5 Production spillovers and mobility

In this section, I investigate the role that transport infrastructure and services could play to facilitate production spillovers and resilience. Table 10 presents DiD estimates for production of major crops, interacting the placebo group defined above with indicators of mobility[26]. Estimates show that villages with a bus service have 33% higher production during the treatment period than in a year without nearby drought, based on the control group[27]. Households in the placebo group with agricultural networks beyond their own community

[25] The median SPI is -0.66 for the placebo group and 0.29 in the new control group.

[26] Similar heterogeneous effects are found for production of all crop types (appendix - table 21), even though the average spillover effect in table 9 is not statistically significant

[27] 57% of households in the placebo group and 37% of the control group have a local bus service.

(64% of placebo) also produced significantly more in the treatment period. However, having all year road access (62% of placebo) or high quality road infrastructure (21% of placebo) alone does not correspond with significantly higher production for nearby communities.

Table 10: Production spillovers and mobility - Major crops

	Log Production (kg/ha) - major crops				
	(1)	(2)	(3)	(4)	(5)
placeboXpost	-0.0941	0.0122	-0.244	-0.0290	-0.194
	(-0.49)	(0.07)	(-1.25)	(-0.21)	(-1.17)
Interactions:					
Sealed or maintained gravel road	0.261				
	(0.91)				
All year road access		-0.0277			
		(-0.10)			
Bus service			0.572**		
			(2.14)		
Mobile phone				0.156	
				(1.22)	
Network outside community					0.391**
					(2.16)
Observations	3098	3081	3063	3098	3098
R^2	0.370	0.374	0.374	0.369	0.371

Time and group interactions with dummy variable not shown. Includes EA (village) and time fixed effects. Standard errors clustered at EA (village) level. t-statistics in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

Public transport services could be especially important for resilience to drought. They may allow inputs, labour and agricultural output to be diffused, bolstering production in areas less affected by drought and supplying consumption where crops are lost. Transport services may also provide access to markets that emerge in times of drought, but are normally served by local or subsistence agriculture. Together with results on mobility for the treated group, these spillover findings draw attention to public transport and social networks as potentially very important for climate resilience. Public investment to improve connectivity in rural Ethiopia, beyond infrastructure projects, could prove an effective policy for reducing vulnerability to drought.

5 Conclusion

Does rural mobility matter for climate resilience? This study on the impact of the 2015 drought in Ethiopia provides evidence, but not just with regard to infrastructure. An exogenous measure of local drought intensity and household panel data were used to overcome methodological issues and estimate the causal effect of drought. Households experiencing at least a one in 20-year drought suffered 12 percent lower annual consumption and 38 percent lower agricultural production, on average, than they would have in a typical year.

Compared to consumption, production is highly sensitive to drought intensity and more productive households experienced proportionally greater crop losses. These findings predict lower expected returns to agricultural investment under the threat of drought. In a future of more frequent and severe droughts, as predicted by climate change, household led agricultural transformation is less likely. If improving the productivity of smallholder agriculture remains a development objective, policy to reduce rural exposure to climate risk is indispensable.

Moreover, some groups are more vulnerable to drought than others. In terms of consumption, female headed households are significantly worse off during drought. This points to a gender-bias in vulnerability to climate threats, availability of coping methods or access to relief, which policy targeting should seek to address. Existing literature points to road infrastructure as a source of resilience. Evidence from this study also shows that households with access to bus services, mobile phones and wider social networks were substantially less vulnerable to drought, especially in terms of agricultural production. Results indicate that the 2015 drought induced positive production spillovers to nearby areas. Specifically, production of major cereal crops in nearby villages with transport services was 33% higher than if no drought had occurred, but no similar spillover was present for places with good road infrastructure alone. Greater mobility between villages during drought can contribute to resilience by permitting food production to be spatially redistributed. Public investment to connect villages with transport services and agricultural networks may have untapped potential to reduce climate vulnerability in rural areas.

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Appendix

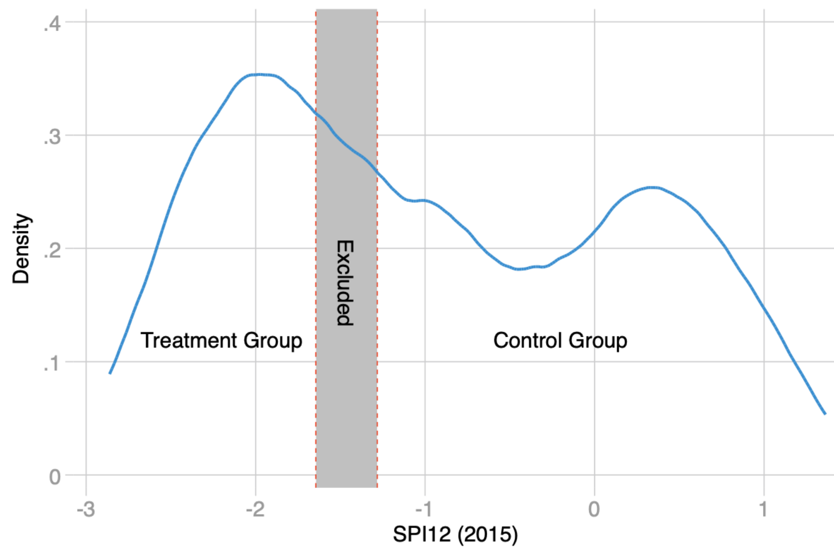

Figure 8: SPI distribution for January-December 2015 over rural households included in the ESS sample, and group assignment.

Table 11: Major crop production (share of households)

Crop	Control		Drought	
	2014	2016	2014	2016
Barley	2%	3%	5%	5%
Maize	24%	23%	15%	12%
Sorghum	11%	9%	28%	27%
Teff	7%	6%	10%	9%
Wheat	5%	5%	7%	11%
Enset	9%	8%	3%	1%
Total	58%	54%	68%	65%

Share of households in group that mostly produce a major crop. Barley, Maize, Sorghum Teff Wheat are cereal crops. Enset is a major root crop.

Table 12: Effect of drought on economic outcomes - Discrete variables

	PSNP (1)	Assistance (2)	Non-farm (3)	Livestock (4)	Cropping (5)	Migration (6)
droughtXpost	0.0476**	0.132***	-0.00493	0.0159	0.0417**	-0.141**
	(2.06)	(3.26)	(-0.24)	(1.33)	(2.11)	(-2.34)
Observations	5138	5140	5140	4543	4543	5140
R^2	0.361	0.497	0.339	0.151	0.235	0.704

Linear Probability Model. Includes EA (village) and time fixed effects. Standard errors clustered at EA (village) level. t-statistics in parentheses.
* p < 0.10, ** p < 0.05, *** p < 0.01

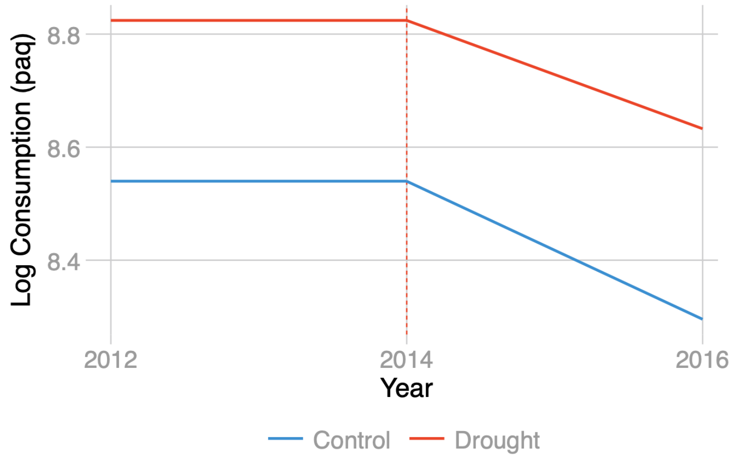

Figure 9: Consumption trends - controlling for lagged consumption (2012) in the pre-period.

Table 13: Effect of drought on economic outcomes - Continuous variables

	PSNP income (1)	PSNP assistance (2)	Assistance (3)	Credit (4)	Wage hrs (5)	Migration (6)
droughtXpost	-0.235 (-0.65)	-0.0656 (-0.15)	0.264 (0.88)	-0.390** (-2.29)	0.120 (0.51)	-0.0420 (-0.65)
Observations	506	259	963	1331	210	5140
R^2	0.527	0.525	0.607	0.388	0.568	0.640

(1) Log PSNP labour program income (2016 Birr), (2) Log PSNP assistance (2016 Birr), (3) Log total assistance (2016 Birr), (4) Log credit (2016 Birr), (5) Log wage hours, (6) Migration to urban areas (% households). Includes EA (village) and time fixed effects. Standard errors clustered at EA (village) level. t-statistics in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

Table 14: Household heterogeneity

	Log Consumption (paq)				Log Production (kg/ha)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
droughtXpost	-0.158*** (-2.64)	-0.0811 (-1.46)	-0.0718 (-1.22)	-0.0883 (-1.58)	-0.457*** (-3.48)	-0.386*** (-3.17)	-0.390*** (-3.11)	-0.249** (-2.32)
Interactions:								
Remote	0.174 (1.46)				0.321 (1.22)			
Head female		-0.148** (-2.36)				0.0297 (0.21)		
Head school			-0.124* (-1.93)				0.0259 (0.17)	
PSNP labour program				-0.105 (-1.12)				-0.743*** (-3.45)
Observations	5140	5140	5140	5138	4410	4410	4410	4409
R^2	0.487	0.489	0.490	0.488	0.387	0.387	0.385	0.394

Lagged consumption not shown. Time and group interactions with dummy variable not shown. Includes EA (village) and time fixed effects. Standard errors clustered at EA (village) level. t-statistics in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

Table 15: Production and transport infrastructure - Major crops

	Log Production (kg/ha) - major crops			
	(1)	(2)	(3)	(4)
droughtXpost	-0.426***	-0.312	-0.201	-0.0795
	(-3.04)	(-1.62)	(-0.75)	(-0.35)
Interactions:				
Sealed road	0.847***			
	(3.26)			
Sealed or maintained gravel road		0.0763		
		(0.28)		
All year access (public transport)			-0.152	
			(-0.48)	
Observations	3098	3098	3098	3098
R^2	0.376	0.373	0.374	0.375

Time and group interactions with dummy variable not shown. Includes EA (village) and time fixed effects. Standard errors clustered at EA (village) level. t-statistics in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

Table 16: Production, transport services and networks - Major crops

	Log Production (kg/ha) - major crops				
	(1)	(2)	(3)	(4)	(5)
droughtXpost	-0.422**	-0.264**	-0.325**	-0.408***	-0.395**
	(-2.03)	(-2.16)	(-2.26)	(-2.96)	(-2.43)
Interactions:					
Bus service	0.304				
	(1.08)				
Crop sold by motorised transport		-0.186			
		(-0.28)			
Mobile phone				0.343***	
				(2.84)	
Network outside community					0.247
					(1.40)
Observations	3063	3098	3098	3098	3098
R^2	0.376	0.371	0.372	0.373	0.374

Time and group interactions with dummy variable not shown. Includes EA (village) and time fixed effects. Standard errors clustered at EA (village) level. t-statistics in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

Table 17: Effect of drought on various measures of consumption

	Consumption (paq) - various measures					
	(1)	(2)	(3)	(4)	(5)	(6)
droughtXpost	-0.116**	-0.0660	-638.3*	-0.0658	-0.0396	-0.145
	(-2.21)	(-1.25)	(-1.79)	(-1.13)	(-0.50)	(-1.33)
Observations	5140	5140	5140	5140	5088	2755
R^2	0.486	0.412	0.338	0.375	0.431	0.442

(1) Log real, (2) Log nominal, (3) Level (Birr), (4) Log food only, (5) log non-food only, (6) Log education only. Units are (log) 2016 Birr adjusted for regional price differences. Control for lagged consumption not shown. Includes EA (village) and time fixed effects. Standard errors clustered at EA (village) level. t-statistics in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

Table 18: Effect of drought on various measures of production

	Production - various measures				
	(1)	(2)	(3)	(4)	(5)
droughtXpost	-0.382***	-1501.6	-0.316***	0.0541	-0.268*
	(-3.30)	(-1.49)	(-2.70)	(0.86)	(-1.74)
Observations	4410	4531	4423	3773	1902
R^2	0.385	0.083	0.315	0.190	0.464

(1) Log (kg/ha), (2) Level (kg/ha), (3) Level (kg), (4) Log (kg/hr), (5) Log income from sale (2016 Birr). Includes EA (village) and time fixed effects. Standard errors clustered at EA (village) level. t-statistics in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

Table 19: Effect of drought on production by crop type

	Log Production (kg/ha) - by crop type						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
droughtXpost	0.588**	-0.0722	-0.564***	-0.409	-0.103	-0.138	-0.266**
	(2.78)	(-0.32)	(-2.95)	(-1.32)	(-0.37)	(-0.42)	(-2.21)
Observations	167	970	871	371	316	281	3098
R^2	0.483	0.361	0.392	0.473	0.350	0.518	0.371

(1) Barley, (2) Maize, (3) Sorghum, (4) Teff, (5) Wheat, (6) Enset, (7) All major crops. Includes EA (village) fixed effects. Standard errors clustered at EA (village) level. t-statistics in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

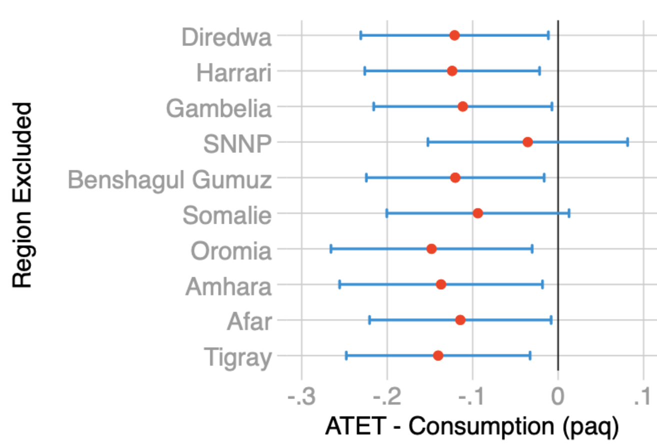

Figure 10: Excluding regions - Consumption.

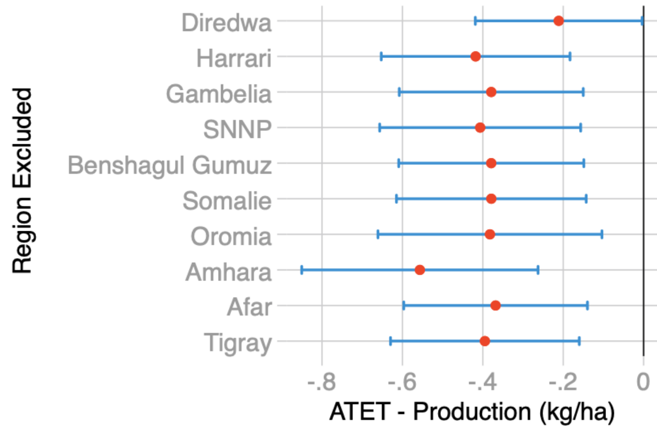

Figure 11: Excluding regions - Production.

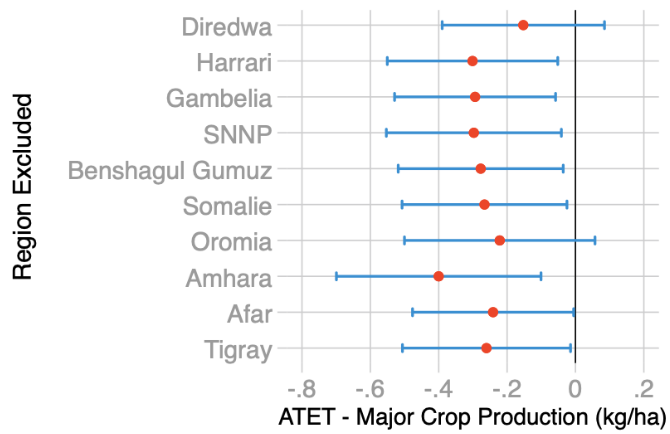

Figure 12: Excluding regions - Production major crops.

Table 20: Placebo (100km)

	Log Consumption (paq)	Log Production (kg/ha)	
		All crops	Major crops
	(1)	(2)	(3)
placeboXpost	0.00280	0.129	0.238*
	(0.04)	(1.04)	(1.69)
Observations	3080	2684	1728
R^2	0.434	0.389	0.399

Control for lagged consumption not shown. Includes EA (village) and time fixed effects. Standard errors clustered at EA (village) level. t-statistics in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

Table 21: Production spillovers and mobility - All crops

	Log Production (kg/ha)				
	(1)	(2)	(3)	(4)	(5)
placeboXpost	-0.188	-0.104	-0.553***	-0.172	-0.422***
	(-1.07)	(-0.62)	(-3.10)	(-1.50)	(-2.86)
Interactions:					
Sealed or maintained gravel road	0.0671				
	(0.26)				
All year road access		-0.112			
		(-0.48)			
Bus service			0.770***		
			(3.18)		
Mobile phone				0.0480	
				(0.45)	
Network outside community					0.437***
					(2.74)
Observations	4410	4393	4355	4410	4410
R^2	0.382	0.383	0.391	0.380	0.390

Time and group interactions with dummy variable not shown. Includes EA (village) and time fixed effects. Standard errors clustered at EA (village) level. t-statistics in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01