Land Fragmentation and Food Insecurity in Ethiopia[*]

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July 2017

Working Paper

[*]The authors would like to thank Chris Barrett and Mark Constas, as-well as seminar participants at Cornell University and the World Bank for their valuable feedback. The authors are grateful to the UK Department for International Development Ethiopia and Tim Conway for generous funding assistance.

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Abstract

We revisit the economic consequences of land fragmentation, taking seriously concerns regarding the exogeneity of fragmentation, its measurement and the importance of considering impacts in terms of welfare metrics. Using Ethiopian data well suited for addressing these issues, we find that land fragmentation reduces food insecurity. This result is robust to how we measure fragmentation and to how we address exogeneity concerns. Further, we find that land fragmentation mitigates the adverse effects of low rainfall on food security. This is because households with diverse parcel characteristics can grow a greater variety of crop types.

Introduction

Assessments of the economic consequences of land fragmentation - the division of holdings into discrete parcels that are dispersed over a wide area but operated by a single farmer and his or her household - have a long history in agricultural economics and related disciplines. Shaw (1963), referring to his study sites near Dubrovnick in the former Yugoslavia, laments that the fragmentation of land holdings led to lost labor time as farmers spent many hours walking from their homes to their dispersed plots. He writes:

"A serious effect is that the farmer tends to neglect strips farthest from his village...which leads to a reduction in output. ... Any form of mechanization is thwarted by the extreme degree of land fragmentation, and the application of improved techniques is severely inhibited. The net effect of excessive fragmentation of land is that farming is made unnecessarily difficult, expense is increased by the duplication of fixed equipment (field boundaries, water supply, store huts, threshing floors, and the like), and a larger labor force is required. The minute subdivision of the land, and the construction of a maze of field boundaries and ways of access, result in the wastage of land, which is already too little (Shaw, 1963, pp. 50-51).

Echoes of these concerns are found in more contemporary work. Studies find that land fragmentation is associated with lower agricultural output and reduced productivity in settings as diverse as rural China (Tan et al. 2010; Nguyen, Cheng, and Findlay 1996; Wan and Cheng 2001), India (Rahman and Rahman 2009; Jha, Nagarajan, Prasanna, et al. 2005; Monchuk, Deininger, and Nagarajan 2010), Vietnam (Van Hung, MacAulay, and Marsh 2007) and Rwanda (Ali, Deininger, and Ronchi 2018), while others find no significant effect on yields (Tan et al. 2008). Land fragmentation is associated with higher production costs, particularly in terms of labor, because of the lost time spent getting to spatially separated parcels (Van Hung, MacAulay, and Marsh 2007; Tan et al. 2008). Finally smaller, more fragmented parcels hinder mechanization, increase fixed costs like fencing and increased likelihood of land disputes (Foster and Rosenzweig 2011; Demetriou, Stillwell, and See 2013).

Shaw also noted that fragmentation had benefits – the risk of natural disasters was spread out spatially and diversification often meant that farmers had access to a greater variety of soils. This observation is also echoed in the literature. Using panel data from Rwanda, Blarel et al. (1992) show that increased fragmentation decreases the variance of total farm income per hectare over time. Veljanoska (2016) uses panel data from Uganda to show that land fragmentation mitigates the adverse impact of deviations in rainfall on yield.

While the basic economic issues of surrounding land fragmentation have been clear for decades, by the early 2010s empirical work on this topic had largely run its course without resolving three fundamental issues. First, land fragmentation reflects exogenous factors – such as legal and social norms regarding the acquisition and division of holdings – but also conscious decisions by farmers to buy, sell, rent in or rent out, plots of land. Where these decisions reflect unobservable characteristics such as farmer skill, the level of fragmentation becomes correlated with the disturbance term in regression analyses, rendering the coefficient on the land fragmentation term biased. Second, most papers measure fragmentation as the number of plots (or an index number based on count and area of plots), but fail to account for the geo-spatial dispersion of the land, which is likely the more relevant attribute for capturing benefits from fragmentation. Third, fragmentation remains pervasive throughout the developing world. While it reflects in part incomplete land markets or a lack of access to credit needed for land consolidation Binswanger, Deininger, and Fe (1995), the widespread existence of fragmentation despite its perceived drawbacks suggests that on balance, farming households perceive that in utility or welfare metrics, its advantages outweigh its drawbacks. Yet to our knowledge, this has received little attention in the literature.

In this paper, we contribute to the literature on the economic consequences of land fragmentation, taking these three fundamental issues seriously. Building on insights found in Ali, Deininger, and Ronchi (2018) and Veljanoska (2016), we address issues of endogeneity by exploiting a unique natural experiment, Ethiopia's history of land reform and allocation which we argue represents an exogenous source of household-level land fragmentation. Like Ali, Deininger, and Ronchi (2018), we are able to construct multiple complementary fragmentation measures, reflecting number of parcels, size and geographical dispersion. Unlike most studies, however, our data source - Ethiopia's Living Standards and Measurement Study-Integrated Survey on Agriculture (LSMS-ISA) – contains information on household food security outcomes allowing us to assess the impact of land fragmentation on welfare metrics in terms of food security.

We find that in Ethiopia, land fragmentation reduces food insecurity. To understand why, the paper unpacks the risk diversification mechanism. Consistent with Shaw's (1963) conjecture, land fragmentation mitigates the adverse effects of low rainfall on food security. Households with diverse parcel characteristics in terms of slope, elevation and wetness can grow a diverse set of crops. By allowing farmers to create a diverse crop portfolio, land fragmentation helps mitigate weather risks, improving food security outcomes.

The evolution of access to land in Ethiopia

Our identification strategy hinges on our assertion that land access and fragmentation are exogenous to farmer ability. Justifying this claim first requires understanding the evolution of access to land in the diverse regions of Ethiopia.

Under imperial rule prior to 1974, Ethiopia was characterized by three regional-specific systems of land tenure (Ofcansky and Berry 1991; Deininger et al. 2008). In the northern highlands, the principal form of land tenure was rist, a form of communal ownership within family lineages, entitling every male and female descendant to a share of land in the form of usufruct rights. Since the land belonged to the family rather than the individual, it could not be sold, mortgaged or bequeathed outside the family, but was passed on to descendants (Kebede 2002). In southern regions, land access operated through gult, a land right bequeathed by the monarch or regional governors. Holders of gult rights were entitled to a share of the harvest and to labor services from the peasantry (Ofcansky and Berry 1991). After conquering the south at the end of the 19th century, Emperor Menelik II distributed gult rights to northern nobles and loyal southern landlords. This meant that, unlike the northern highlands where tenancy was rare, sharecropping predominated in the south, constituting 65-80% of holdings (Kebede 2002). In the pastoral regions of Afar and Somali, land access was governed by clans. In Afar, clan leaders allocated primary land rights, waamo, to clan members. Waamo rights conveyed both use rights to rangeland as well as the right to transfer these rights to heirs but not others (Hundie and Padmanabhan 2008).

In 1975, following the overthrow of Emperor Haile Selassie, the Marxist Derg regime announced a land reform program under which all land was nationalized and tenancy abolished (Ofcansky and Berry 1991). Land sales, rentals or the use of hired labor were prohibited. Large landowners, including the nobility, church and those who operate large commercial estates, had their land seized. The government encouraged peasant cooperatives to form in each kebele (community) and proceed in redistributing land. Peasants were to receive 'possession rights' to a plot of land not exceeding 10 hectares, though in practice they often received much less. Families received land in proportion to household size, each adult eligible for one timad of land, or about 1/4 of a hectare (Holden and Yohannes 2002). In an attempt to ensure equitable quality, land was classified into 4 categories according to soil depth: deep, medium, shallow and very shallow. The cooperatives then sought to ensure each family had access to a parcel of land in each of these four categories (Kosec et al. 2016). Land fragmentation increased as a result. A study found that in Gojjam, a region in northern Ethiopia, the proportion of farmers with three or four parcels of land more than doubled (Ofcansky and Berry 1991). Land redistribution was particularly prevalent in the highlands, where rist had been the dominant form of land tenancy. In the south and particularly in the modern day Southern Nations, Nationalities, and Peoples' (SNNP) region, reforms focused on abolishing sharecropper payments to their landlords. These reforms did not affect Afar or Somali where clan leaderships continued to determine access to land.

The Derg fell to the EPDRF in 1991, but the new government did not reverse these reforms or redistributions; in fact re-distribution continued up to 1997 (Deininger et al. 2008). Under Article 40 of the 1995 Federal Constitution of Ethiopia, ownership of land was vested in the State (FDRE 1995). Land administration was devolved to the regional level through the Rural Land Administration and Use Proclamation No. 89 in 1997, revised subsequently in 2005. These proclamations reaffirmed that the State owned all land while conferring indefinite tenure rights to smallholders, i.e. rights to property produced on land and to land succession (Abza 2011). However, parcels cannot be smaller than 0.5 timad, restricting households' ability to sub-divide land among their children (Kosec et al. 2016). While in principle any child can inherit land, customary norms and practices tend to favor men, either the eldest or youngest, especially as marriage is predominantly patrilocal and sons are expected to care for their parents (Fafchamps and Quisumbing 2005). Further, Kosec et al. (2016) note that these allocations through inheritance reflected birth order, with older brothers typically obtaining larger and more productive plots. The 2005 proclamation also allowed for land rental but land sales and mortgaging remained prohibited (Abza 2011; Deininger et al. 2008; Kosec et al. 2016). However, land use rights remained contingent on physical residence (Dessalegn 2003) and all regions apart from Amhara had legal provisions that limited the amount of land that could be rented out to (usually) 50 percent of holding size (Deininger et al. 2001). Concerns that uncertainty regarding tenure status was limiting investments in land led to efforts to provide farmers with land certificates (Deininger, Ali, and Alemu 2011). In Afar and Somali, these proclamations re-affirmed that land was owned by the state but land access remained communal based on clan and sub-clan membership (Abza 2011; Hundie and Padmanabhan 2008).

The continuation of the Derg's land redistribution, the ban on land sales and mortgaging, limitations on land rentals and customary land inheritance practices mean that land access and fragmentation in Ethiopia are conditioned by history, location and demography. We argue that land fragmentation due to government allocation or inheritance is therefore orthogonal to farmer ability.

Data and Measurement

We use data from the Living Standards and Measurement Study-Integrated Survey on Agriculture (LSMS-ISA). [1] These surveys collect socio-economic panel data at the household level, with a special focus on agricultural statistics and

1. LSMS-ISA is part of an initiative to collect high quality, standardized data in developing countries in order to inform policy making. It was implemented by the Central Statistics Agency of Ethiopia with technical assistance from the World Bank's Development Data Group and funding from the Bill and Melinda Gates Foundation.

the link between agriculture and other household income activities. Ethiopia's LSMS-ISA data-set is a panel with three rounds collected in 2011-2012, 2013-2014, and 2015-2016. The first round collected data on 3,776 rural households, before expanding to 5,262 in the 2nd round to include households living in urban areas.[2] The attrition rate across rounds is 5.54%. The survey is representative at the national and regional levels with population weights to adjust for sample design.

Ethiopia's LSMS-ISA data is characterized by its combination of detailed agricultural data with household characteristics. It contains both household and parcel level indicators, including detailed data on the following:

- Parcel-level data detailing the origin of land tenure for each parcel of land.
- Parcel-level measures of area, crop, geophysical characteristics and location, allowing for the calculation of land fragmentation measures.[3]
- Household-level data on welfare outcomes specific to food security.
- Household-level data on demographic characteristics and assets held by the household.
- Household-level data on shocks experienced, such as drought.

Land Access

Our review of the history of land reform and redistribution indicated that land access is governed principally by land allocations made by government officials and through inheritance. We see this in Table 1. In the Highland and Lowland

2. A number of these households living in peri-urban areas has access to land parcels, and we include them in our analysis.

3. Land data in the LSMS-ISA is collected at three levels of aggregation: parcels; fields; and plots. Plots are the smallest unit of analysis. Multiple plots can make up a field. Multiple fields make up a parcel; parcels are the highest unit of land aggregation. For our main analysis we chose to aggregate all these measures up to parcels, weighed by area. See appendix for details.

regions, between 69 and 87 percent of parcels were obtained from local officials or through inheritance. In the Highlands, consistent with the redistributions that occurred under the Derg and the EPDRF, land received from local leaders is the primary means of acquiring land. Because the lowlands were dominated by sharecropping, there was less redistribution, as is particularly evident in SNNP where only 20% report receiving land from local leaders and where access through inheritance dominates.

In pastoral areas (Afar and Somali) most plots are acquired from local leaders or via inheritance but a considerable fraction (38 and 27 percent respectively) are acquired "without permission". Where this has occurred, land acquisition and therefore fragmentation becomes partly endogenous. Given this feature, along with the fact that pastoralism not sedentary agriculture is the principal livelihood strategy in Afar and Somali, we exclude these two regions from our subsequent work.

Excluding Afar and Somali, just over 70 percent of parcels are acquired either from local leaders or through inheritance. Because land purchases were illegal, these were not asked about in rounds 1 and 2 but the relatively large number of 'other' acquisitions prompted follow-up work which revealed that some households were taking advantage of a loophole allowing land transactions if they include a built structure. The survey therefore added an explicit question regarding land purchases in round 3. A significant fraction of parcels, however, are rented in through cash or sharecropping or rented out. Households with fewer working age adults, often headed by widows and the elderly, lease out their land to those with the manpower and capital to farm it. Households renting in land are younger on average, have smaller families and a lower dependency ratio. Households renting out land are more likely to be female headed, older and with a higher dependency ratio.

Land fragmentation and characteristics

We use the LSMS-ISA data to calculate four measures of land fragmentation, summarized in Table 2a. The simplest measure is the number of parcels K held by a household. All else being equal, more parcels suggest greater fragmentation.[4]

$$\text{Number of Parcels} = K \tag{1}$$

However this does not take into account the different size of parcels in hectares, which we denote α_k. One measure incorporating both parcel count and size is the Simpson land fragmentation index (FI):

$$FI = 1 - \frac{\sum_k^K \alpha_k^2}{(\sum_k^K \alpha_k)^2} \tag{2}$$

Where K is the number of parcels, and α_k their size in square meters. A score of 0 would indicate no land fragmentation, while as $K \to \infty FI \to 1$. This index has three properties (Demetriou, Stillwell, and See 2013):

1. Fragmentation increases proportional to n
2. Fragmentation increases when the range of parcel sizes α is small
3. Fragmentation decreases as the area of large parcels increases and that of the small parcels decreases.

We also consider a measure of fragmentation which captures the variability of fragment size, as proposed by Monchuk, Deininger, and Nagarajan (2010). They point out that the Simpson index conflates the effect of increased number of parcels $\frac{\delta FI}{\delta n} > 0$ with the effect of increased variability in fragment areas

4. The Januszewski index is similar to the Simpson index in scale and composition. We also calculated it but the results were so similar to those derived from the Simpson index that we do not report them.

$\frac{\delta FI}{\delta\sigma^2} < 0$. Since both of these can be thought to increase' fragmentation, they propose to isolate the effect of variability in fragment area through the following measure:

$$S_k = \frac{\sqrt{(\alpha_k - \bar{\alpha})^2}}{\bar{\alpha}} \tag{3}$$

A shortcoming of the above is that it registers a value of 0 for a single parcel as-well as for a number of parcels with the same size. It should therefore be considered as complementary to other measures, such as the *number of parcels*, rather than a perfect substitute. For a household we take the weighted average of S_k.

The above measures consider the size and number of parcels, but not their physical dispersion. If the correlation between fragmentation and labor costs is driven by travel time, this is an important measure. With the georeferenced coordinates of each parcel, we calculate D_t, the minimum round trip distance to reach all parcels and return home (Igozurike 1974).

$$D_t = \min_{x_{kj}} \sum_{k}^{K} \sum_{j \neq k}^{K} c_{kj} x_{kj} \tag{4}$$

$$\text{where } x_{kj} = \begin{cases} 1 & \text{use path between parcel } k \text{ and } j \\ 0 & \text{otherwise} \end{cases}$$

and c_{kj} is the distance from parcel k to parcel j. We calculate D_t using a travelling salesman algorithm, finding the shortest route connecting multiple parcel locations as defined by their longitude and latitude.[5]

Calculating the Simpson Fragmentation Index and deviations in parcel size

5. The parcel coordinates are first flattened to cartesian space. A distance matrix is calculated for each household's parcels, and fed into a travelling salesman minimization algorithm, specifying the home as the start and end point.

both require an accurate measures of parcel area α. Most measures in the data were calculated using GPS coordinates. When GPS observations were missing, enumerators measured area using a rope-and-compass method. They also inquired as to the farmer's own estimate of the field size. Across three rounds 10.4% of parcels were missing area measurements taken by GPS, the bulk of them in the first round. Where GPS measures were missing but rope-and-compass measures were available, we used the rope-and-compass measures of α. This allowed us to recover half of the missing observations. In order to validate this substitution, we regressed GPS measured area on rope-and-compass area for those parcels with overlapping measures, and found them to be strongly correlated, with a $\hat{\beta} = 1.04$ and $R^2 = .44$.[6]

We attempted to incorporate the self-reported measures, but many of these were expressed using traditional Ethiopian measures of area, such as the timad. Our attempts to convert these measures to standard hectares found them to be poorly correlated with GPS measures of area.[7] Furthermore, it is well documented that self-reported measures of parcel area suffer from non-random measurement error (Carletto, Gourlay, and Winters 2015).

Fragmentation measures and parcel characteristics across regions are reported in Table 2b, including average parcel size $\bar{\alpha}$ and the total area farmed by a household $\sum \alpha_k$. We find evidence that the pattern of land tenure due to land redistribution persists. In the highland regions most affected by the reforms, the number of parcels are in the range of $\approx (3.5, 4.5)$, which corresponds neatly with the four categories of land discussed earlier. In other parts of the country, the number of parcels is closer to 2. In these regions land tenancy is character-

6. See appendix for details.

7. The LSMS Ethiopia documented district specific units of conversion from 'Timad' to hectare. We therefore attempted to convert these self-reported measures but produced a large number of outliers. As an alternative, we tried using a standard conversion for the 'Timad', treating it as 1/4 of an acre in line with the FAO standard. However, comparisons between self-reported area and GPS measurements when the two overlapped showed the former to be inconsistent. See appendix for further details.

ized by homesteads. The size of parcels varies, but tends towards a quarter or half hectare. Recall that the distribution was done in 'timads', approximately a quarter hectare. Finally, the total number of hectares held by households is between .9 and 1.5 hectare, reflecting strict limits on large land tenure and further evidence of the legacy of land redistribution efforts.

In addition to area α, the data-set contains geovariables matched at the plot level using non-scrambled GPS coordinates. These include: Distance from plot to household (in km); slope of the plot (in percentages); plot elevation (in metres), plot potential wetness index.[8] These plot level characteristics were averaged at the parcel level, weighted by plot area. They are also reported in Table 2b.

Welfare measures: Food Insecurity

LSMS-ISA contains two measures of welfare, $Y_{i,t}$, well suited for our purposes. Both relate to food insecurity: the number of months a household experiences hunger, and the Coping Strategy Index (CSI).

Months Hungry, also referred to as the food gap, measures the temporal extent of hunger. It is the sum of months in the past year a household experienced hunger for five or more days. This welfare measured is used widely in Ethiopia, including in the evaluation of its flagship social protection program, the Productive Safety Net Programme (Berhane et al. 2014; Knippenberg and Hoddinott 2017). Households were asked whether, in the last 12 months, they faced a situation when they did not have enough food to feed the household for five of more days. Those who did were prompted to list in which months they lacked sufficient food. The measure of Months Hungry is the sum of those

8. Local up-slope contributing area and slope are combined to determine the potential wetness index: $WI = ln(A^s/tan(b))$ where A^s is flow accumulation or effective drainage area and b is slope gradient. Data matched from the Africa Soil Information Service by the World Bank.

months.

$$\text{Months Hungry} = \sum_{m}^{12} \mathbb{1}(\text{days hungry}_m \geq 5) \tag{5}$$

The CSI measures the intensity of hunger in the past week. It is a composite weighted score of various strategies households engage in when faced with short-term food shortages s (Maxwell 1996). It is a measure of the intensity of hunger. Coping strategies c are a set of 8 questions which reflect undesirable activities households are forced to engage in due to food insecurity, a set of strategies c.[9] As these strategies are unpleasant, unhealthy and socially stigmatizing, resorting to them is an indicator of short term food stress (Maxwell et al. 2003). The survey asks the number of days in the past week a household engaged in each of these activities, then multiplies those days by a weight w_c indicating its severity. The scores are then compiled into the following index:

$$\text{Coping Strategy Index} = \sum_{c}^{8} days_c * weight_c \tag{6}$$

Where $days_c$ is the number of days a household had engaged in a given strategy c over the past week, and w_c is the assigned severity weighting based on existing literature.

The CSI is highly correlated with more complex and time intensive measures of food insecurity (Maxwell, Caldwell, and Langworthy 2008). A higher CSI score indicates greater levels of food insecurity and therefore lower well-being.

9. Coping strategies and corresponding weights:

"In the past 7 days, how many days have you or someone in your household had to...	Number of Days	Weight
Rely on less preferred foods?		1
Limit the variety of foods eaten?		1
Limit portion size at mealtimes?		1
Reduce number of meals eaten in a day?		2
Restrict consumption by adults for small children to eat?		2
Borrow food, or rely on help from a friend or relative?		2
Have no food of any kind in your household?		3
Go a whole day and night without eating anything?"		4

For example, a household with a CSI of 10 may eat less preferred foods or limit portion size a few days a week. A household with a CSI of 30 may do this every day, while also skipping meals and occasionally borrowing food. A household with a CSI of 70 is engaging in all these coping mechanisms daily, but also occasionally spends a day and night without eating.

Figure 1 illustrates the percentage of households in each round and region which experience non-zero CSI and non-zero Months Hungry. In general there is a trend towards improved food security outcomes, with fewer households reporting food insecurity in later rounds. Yet in some regions up to 40% of the population continues to experience chronic food insecurity in the latest round.

Household Controls

To control for other household characteristics that would affect food security, the specification includes demographic characteristics such as whether the household head is female, the size of the household, and its composition in terms of the dependency ratio.[10] We also use a roster of 40 reported assets to create an asset index using Principal Component Analysis (PCA). The index plots all households along the first axis of a PCA vector, maximizing variance, offering an ordinal ranking of households' wealth in terms of their asset holding. Descriptive statistics for these are given in Table 3.

Shock Statistics

The LSMS dataset also matches household level GPS coordinates with geospatial characteristics, most notably the level of rainfall.[11] By comparing it to

10. The dependency ratio is calculated as $\frac{\text{HH Members aged 0-14 \& 65 and older}}{\text{HH Members aged 15-64}}$.

11. In addition to plot level geovariable characteristics mentioned earlier, the dataset includes measures of distance, climatology, soil and terrain, and other environmental factors matched using household geo-referenced coordinates. Rainfall data is drawn from NOAA CPC Rainfall Estimates.

long term trends we can construct the standardized deviation (Z score) $Z_{i,t}$ of total rainfall in the wettest quarter, which farmers rely on most for their crops. These deviations allow us to objectively quantify weather shocks a household has experienced in a given year, and infer whether land fragmentation mitigates or exacerbates the effect of these shocks on food security.

Results

We model the relationship between our measures of food security ($Y_{i,t}$) and land fragmentation fragmentation (F_i) in the following manner:

$$Y_{i,t} = \beta_0 + \beta_1 F_i + \beta_2 A_{i,t} + X_{i,t} + \delta_t + k_i + \epsilon_{i,t} \tag{7}$$

where $\epsilon_{i,t}$ is a time variant error term.[12] δ_t controls for time fixed effects.Our measure of land fragmentation is based on the data provided in the first round of the LSMS-ISA.[13] For this reason, we control locality (kebele) fixed effects (k_i), kebeles being the smallest administrative unit in which our households reside, the total amount of farm land (ha) operated by the household as ($A_{i,t}$) as well as saturating the model with household level controls $X_{i,t}$. These include whether the household head is female, her age, the size of the household, its dependency ratio and an asset index. We estimate equation (7) separately for our longer term measure of food security, Months Hungry, and our short term measure, the Coping Strategy Index. To assess whether our results our robust to the way in which land fragmentation is measured, we use each measure in a separate regression.

12. We use population level weights in all our estimation, and cluster errors at the household level.

13. Fixed effects would absorb the exogenous variation due to our natural experiment, while inter-temporal variations are largely driven by decisions to rent-in or rent-out land. We therefore fix fragmentation to the first round and run a pooled regression.

OLS results

Table 4 gives the basic results of estimating equation (7). Table 4a looks at the association between land fragmentation and the Food Gap measured in Months Hungry. We find a negative and statistically significant association across all four measures of fragmentation. Recall that as our measure of food security rises in value, households become more food insecure and so a negative coefficient means that food security is improving with increased fragmentation, *ceteris paribus.* As an illustration of the magnitudes in these associations, from Table 4a column (1) farming an additional parcel of land, holding area constant, reduces the number of months hungry on a scale equivalent to farming an additional 2.2 hectares.[14] From column (2), a household at the 25th percentile of the Simpson Index ($FI \to 0$) moving to the 75th percentile of land fragmentation ($FI = .656$), while holding area constant, would decrease the Food Gap by a third of a month.[15]

Table 4b finds a negative correlation between land fragmentation and the intensity of hunger measured using the Coping Strategy Index. Again we see that across all four measures, there is a negative and statistically significant association between fragmentation and food security, here implying that as fragmentation increases, the use of the coping strategies (both in terms of their frequency and severity) falls.[16] To illustrate using results from Table 4b column (2), moving from the 25th to 75th percentile of land fragmentation decreases CSI by -2.22, the equivalent of going hungry so one's children can eat for a day. This negative correlation retains its significance across the various measures of fragmentation, suggesting it is a combination of the number of parcels, deviation

14. $\frac{\hat{\beta}_{Parcels}}{\hat{\beta}_{Area}} = \frac{-0.060}{-.027} \approx 2.22$

15. $\hat{\beta}_{Simpson} * (.656 - 0) \approx -.354$

16. i.e. eating less preferred foods is less severe (Weight=1) than going a whole day and night without eating (Weight=4).

in parcel size and distance travelled that is driving the narrative.

Instrumental Variable Estimation

Our core results are premised on the assumption that given the history of land reforms in Ethiopia, together with norms regarding inheritance, land fragmentation is uncorrelated with components of the disturbance terms – such as unobserved farmer ability – that might have a direct effect on food security. We also noted that most, but not all, land obtained, by our sample came from either government officials or through inheritance. But because some holdings were acquired in other ways, there may be a lingering concern that our measures of fragmentation are correlated with the disturbance term. In tables 5 and 6 we therefore use the number of parcels inherited or received from the government as an instrumental variable for land fragmentation, similar to the identification strategy used by Veljanoska (2016) and Ali, Deininger, and Ronchi (2018).

The exclusion restriction is satisfied under the assumption that land redistribution was orthogonal to farmer ability and that this arbitrary allocation was perpetuated by legal and cultural constraints. The first stage regression in tables 5a and 6a confirms the instrument's relevance. The second stage regressions in tables 5b and 6b finds results similar to Table 4 in sign and significance, allaying our concerns of bias. In columns (1) and (2) these coefficients are of similar magnitude, while in columns (3) and (4) they are almost an order of magnitude larger.

Robustness (1): Data Subsets

For succinctness, we have summarized the following robustness checks in Table 7, where each coefficient represents a separate regression. We restrict our specification to the highlands, where the historical evidence leads us to believe that land redistribution exacerbated land fragmentation. This sub-sample, which includes the highlands of Amhara, Tigray and Oromia, includes about half of the original observations. The coefficients are reported in Table 7 column (1). The coefficient on deviations in parcel size loses significance (Table 7a column (1)), but is otherwise consistent with the coefficient in Table 4a col (3). The rest of the coefficients are consistent in sign, significant and magnitude for both Months Hungry and CSI.

The existence of some households who are buying or renting in land may mean that at least some of our fragmentation is being driven either by the actions of entrepreneurial farmer, or alternatively, risk averse farmers concerned about their food security. In Table 7 col (2) we therefore restrict our sample to farmers for whom all parcels are either inherited or received from the government.[17] When we compare these estimates for both Months Hungry and CSI across all measures of fragmentation, we find similar effects in sign, significance and magnitude to those reported in Table 6, suggesting that such farmers are not biasing our results.

Robustness (2): Non-Linear Estimation

A separate concern lies with mis-specification due to non-linearity of the data generating process. Both the CSI and Months Hungry have a mass point at 0. Furthermore, Months Hungry is a discrete count variable, taking on integer values from 0 to 12. Hence there is a concern that using a linear regression does not properly reflect the underlying data-generating process. As a robustness check we estimate our principle specification across fragmentation measures using two alternative Maximum Likelihood Estimators (MLE). Table 7 col (3) estimates a Poisson MLE, and Table 7 col (4) estimates a negative binomial MLE. Be-

17. Though many of these households do live in the highlands, there is only a 48% overlap between this sub-sample and the previous one.

cause we use a non-linear estimator, to compare the average marginal effects we multiply the coefficients by the sample average of the outcome variable. The results are consistent with the results reported in Table 4 in sign, magnitude and significance.

Mechanism

What drives this relationship between land fragmentation and reduced food insecurity? If we allow that land fragmentation decreases yields and profits as the literature suggests, the effect on food security must be through risk mitigation. Building on Blarel et al. (1992) we argue that land fragmentation allows households to better manage the downside risk of shocks such as drought. With incomplete access to credit and markets, households with multiple parcels are endowed with an inherently more diverse portfolio. This diversity is reflected in the difference in parcel level characteristics, which is correlated with decreased food insecurity. Households can take advantage of this diversified portfolio by tailoring the crop grown to the parcel characteristics. Households with more land fragmentation also grow a greater diversity of crops, which is correlated with decreased food insecurity. We explore these ideas here.

Land Fragmentation and Rainfall Shocks

Under the risk mitigation hypothesis, land fragmentation is particularly useful in the context of severe shocks. To illustrate this, we estimate:

$$Y_{i,t} = \beta_0 + \beta_1 F_{i,t} + \beta_2 Z_{i,t} + \beta_3 F_{i,t} * Z_{i,t} + A_{i,t} + X_{i,t} + \delta_t + k_i + \eta_{i,t} \tag{8}$$

where $Z_{i,t}$ is the standardized deviation (Z score) of total rainfall in *Meher*, the rainy season (June-September). Trivially we expect $\hat{\beta}_2 < 0$, a good year of rainfall decreases food insecurity and vice versa. Our interest is in testing whether land fragmentation exacerbates this sensitivity to rainfall $\hat{\beta}_3 < 0$ or mitigates it $\hat{\beta}_3 > 0$. Tables 8 and 9 show that rainfall indeed correlates with decreased food insecurity as measured by Months Hungry and CSI, respectively. Since $\hat{\beta}_3 > 0$, land fragmentation mitigates the sensitivity of food security to rainfall. Figure 2 illustrates this visually. Figure 2a illustrates the difference in distribution of CSI between households with a low level of land fragmentation (FI=0) and households with perfect fragmentation (FI=1), in a normal year, where the Z-score for rainfall is 0. We find that households with diversified plots have lower levels of CSI, *ceteris paribus*. Figure 2b illustrates the difference in distribution of CSI outcomes for the same two households in a year of drought, where the Z-score for rainfall is -2. We find that though both types of households see increases in the CSI levels, the difference between the two increases. The household with no land fragmentation experiences more severe food insecurity in times of drought.

Reduced Risk through Diversification

This drought buffering effect is linked to a diversified portfolio. Land fragmentation means a greater diversity in parcel level characteristics. We therefore expect households with a more diverse portfolio of land to have better food security outcomes. Tables 10 and 11 regress the household level average characteristics and standard deviation against Months Hungry and CSI, respectively. These characteristics include distance from the home, slope, elevation and wetness. Tables 10a and 11a show a null result, suggesting that the level is not significantly correlated with food security. There is no optimal slope, elevation or wetness. However, having a diverse set of plots does improve food security. Table 10b shows a negative and significant correlation between Months Hungry and the standard deviation in distance, slope and elevation. Table 11b suggests that households with a diverse set of plots in terms of slope and wetness experience lower levels of CSI. Together, these results suggest that agroecological heterogeneity plays an important role in helping households diversify their portfolio. Though no particular slope, elevation or wetness is ideal, a heterogeneous mix offers a good buffer against shocks, leading to better food security outcomes.

Endowed with this portfolio of land characteristics, farmers can choose the crops grown accordingly in order to minimize risk. Dercon (1996) models how households with fewer assets mitigate their risk by cultivating low yield, low variance crops, such as sweet potato, while households with more assets are likelier to cultivate high yield, high variance cash crops such as cotton. In the case of Ethiopian farmers, this portfolio of land is an endowment under our assumption of exogeneity, which households can take advantage of by tailoring their crops to the land's characteristics.

Table 12 unpacks this dynamic. . Having identified the seven most prevalent crops grown by households in our Ethiopian sample, Table 12a calculates the conditional probability of a household growing a crop A conditional on it also growing crop B.[18] Certain crop combinations, such as maize and Teff or wheat and barley, are particularly prevalent. Table 12b estimates the probability of growing each crop on a given parcel given the parcel's physical characteristics. These characteristics shift the probability of planting given crops. For example, farmers are more likely to plant teff and less likely to plant maize in soils with a high wetness index. Farmers with multiple parcels whose characteristics vary

18. $P(CropA|B) = \frac{P(CropA \cap B)}{P(CropB)}$

can therefore plant a variety crops, creating a diverse portfolio.

Agro-ecological variation may effect food security via crop diversity or by directly reducing production risk within a given crop. Mediation analysis using a controlled direct effects regression can help disentangle these two mechanisms (Baron and Kenny 1986). Given the variation in geovariables $GV_{i,t}^{sd}$, food security $Y_{i,t}$ and crop diversity as the mediator $CD_{i,t}$, CDE estimates:

$$CD_{i,t} = \gamma_0 + \gamma_1 GV_{i,t}^{sd} + \gamma_2 X_{i,t} + \epsilon_{i,t} \tag{9}$$

$$Y_{i,t} = \beta_0 + \beta_1 GV_{i,t}^{sd} + \beta_2 CD_{i,t} + \beta_3 X_{i,t} + \eta_{i,t} \tag{10}$$

Where $\hat{\beta_1}$ is the direct effect and $\hat{\gamma_1} * \hat{\beta_2}$ is the indirect effect. Table 13 explores the relationship between land fragmentation, crop diversity and food insecurity.'Number of Distinct Crops' counts the number of different crop types a household grows across its parcels. From Table 13a, increased diversity in agro-ecological characteristics increases the diversity of crops grown. Table 13b suggests that the increased diversity of crops contributes to improvements in household food security, evidence of the indirect effect of agroecological heterogeneity via crop diversification. In the case of CSI, variation in slope and wetness also directly affect food security, likely by reducing production risk within a given crop. Both mechanisms operate in tandem.

Conclusion

We revisit the economic consequences of land fragmentation. We take seriously concerns regarding the exogeneity of fragmentation, its measurement and the importance of considering impacts in terms of welfare metrics. We argue that our Ethiopian are well-suited to address these concerns. The continuation of the Derg's land redistribution, the ban on land sales and mortgaging, limitations on land rentals and customary land inheritance practices mean that land access and fragmentation in Ethiopia are conditioned by history, location and demography. Our data allow us to construct multiple complementary fragmentation measures, reflecting number of parcels, size and geographical dispersion. Unlike most studies, we have information on household food security outcomes allowing us to assess the impact of land fragmentation on welfare metrics in terms of food security.

We find that in Ethiopia, land fragmentation reduces food insecurity. This result is robust to how we measure fragmentation and to how we address exogeneity concerns. Consistent with Shaw's (1963) conjecture, land fragmentation mitigates the adverse effects of low rainfall on food security. Increased land fragmentation means households are endowed with a more diverse set of parcels in terms of walking distance, slope, elevation and wetness. The level of these characteristics has no effect on food security, but a higher standard deviation translates to improved food security outcomes. In part, this is because a farmer with multiple parcels can cater the crop she grows to her parcel's characteristics. Farmers who grow more crop types are more food secure. This suggests that consideration of efforts to consolidate holdings should account for the possibility that fragmentation enhances farmers' ability to cope with adverse climatic shocks.

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Tables

Table 1: **Land Tenure By Region**

		Highlands		Pastoral*	
Tenure Type	Tigray	Oromia	Amhara	Afar	Somalie
Granted by Local Leaders	64%	33%	48%	14%	15%
Inherited	13%	44%	33%	31%	52%
Rent	11%	4%	5%	9%	1%
Borrowed for Free	3%	4%	3%	3%	1%
Moved in Without Permission	1%	7%	0%	38%	27%
Shared Crop	0%	0%	0%	0%	0%
Purchased	1%	2%	2%	1%	1%
Rented out	5%	2%	4%	1%	2%
Other	2%	4%	3%	4%	0%
Total	100%	100%	100%	100%	100%

		Lowlands		
Tenure Type	Benshagul Gumuz	SNNP	Gambelia	Total
Granted by Local Leaders	64 %	20%	48%	36%
Inherited	8%	67%	21%	43%
Rent	6%	2%	2%	5%
Borrowed for Free	3%	2%	4%	3%
Moved in Without Permission	8%	0%	4%	5%
Shared Crop	1%	0%	0%	0%
Purchased	4%	2%	7%	2%
Rented out	1%	3%	2%	3%
Other	4%	4%	13%	4%
Total	100%	100%	100 %	100%

Source: LSMS Ethiopia parcel dataset

* Subsequently excluded from analysis

Table 2: **LSMS Key Statistics**

(a) **Proposed Fragmentation measures**

Measure	Equation	Interpretation	Data required
Number of Parcels	Np	• n number of parcels	• Parcel count
Simpson	$FI = 1 - \frac{\sum_k^K \alpha_k^2}{(\sum_k^K \alpha_k)^2}$	• n number of parcels • α size in square meters • A total size of the land holdings • $K \to \infty FI \to 1$	• Parcel count • Parcel area
Monchuk et al	$S_k = \frac{\sqrt{(\alpha_k - \bar{\alpha})^2}}{\bar{\alpha}}$	• Captures deviation from the average size • Independent of number of parcels	• Parcel area
Igozurike	D	• Round trip distance to reach all fields • Measured with travelling salesman algorithm	• Parcel Geocodes

Source: Authors

(b) **LSMS Land Statistics, Regional Mean**

		Highlands			Lowlands		
	Tigray	Amhara	Oromia	Benshagul Gumuz	SNNP	Gambelia	Total
Fragmentation Measures							
Number of Parcels	3.15	4.48	3.83	3.36	2.47	2.03	3.39
Simpson Fragmentation Index	0.40	0.51	0.43	0.38	0.33	0.25	0.41
Deviation in Plot Size	0.44	0.56	0.54	0.59	0.37	0.41	0.48
Round Trip Distance Travelled (km)	4.33	4.92	4.04	6.14	3.96	5.09	4.38
Parcel Characteristics							
Average Parcel Area (HA)	0.43	0.27	0.51	0.48	0.40	0.21	0.39
Total Area Farmed (Ha)	1.29	1.23	1.69	1.46	0.93	0.47	1.23
Distance from House to Parcel (km)	1.20	0.99	0.80	1.64	1.37	1.40	1.13
Slope (%)	11.88	14.72	10.33	6.17	15.42	3.69	12.81
Elevation (m)	1859.73	2122.35	2007.55	1294.88	1894.25	754.68	1908.63
Wetness	12.92	12.69	12.71	12.97	12.61	14.53	12.77

Table 3: **Household Level Statistics**

Variable	Mean	Standard Deviation	Min	Max
Food Insecurity				
Coping Strategy Index	4	8.3	0	84
Months Hungry	.9	1.7	0	11
Fragmentation				
Number of Parcels	3.4	2.7	1	26
Simpson Fragmentation Index	.38	.31	0	.95
Deviation in Plot Size	.46	.48	0	7
Round Trip Distance Travelled (Travelling Salesman)	4.2	6.6	0	60
Household Controls				
Total Area Farmed (Ha)	1.2	2	0	69
Household Head is Female	.28	.45	0	1
Household Size	4.7	2.4	1	16
Dependency Ratio $(\frac{\text{\# under 15 or over 64}}{\text{\# between 15 and 64}})$	1.2	1.1	0	11
Age of Household Head	44	16	3	100
Asset Index	.29	3	-1.2	42

Table 4: **Food Insecurity and Land Fragmentation, Pooled OLS**

(a) **Months Hungry and Land Fragmentation**

	Months Hungry			
	(1)	(2)	(3)	(4)
Number of Parcels	-0.063***			
	(0.010)			
Simpson Fragmentation Index		-0.539***		
		(0.103)		
Deviation in Parcel Size			-0.115**	
			(0.054)	
Distance Travelled				-0.009***
				(0.003)
Total Household Area Farmed	-0.037***	-0.043***	-0.050***	-0.050***
	(0.012)	(0.012)	(0.013)	(0.013)
N	8698	8698	8698	8445

(b) **CSI and Land Fragmentation**

	Coping Strategy Index			
	(1)	(2)	(3)	(4)
Number of Parcels	-0.240***			
	(0.055)			
Simpson Fragmentation Index		-3.390***		
		(0.670)		
Deviation in Parcel Size			-0.825***	
			(0.293)	
Distance Travelled				-0.064***
				(0.019)
Total Household Area Farmed	-0.173***	-0.170***	-0.211***	-0.215***
	(0.048)	(0.046)	(0.052)	(0.051)
N	8698	8698	8698	8445

Fragmentation measures fixed to first round. Excludes cities, pastoral areas (Afar, Somalie)
Not reported: controls for gender of household head, dependency ratio, size of household, asset index, Kebele, round. Household clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: **Months Hungry and Land Fragmentation, Instrumental Variable**

(a) **First Stage**

	Number of Parcels (1)	Simpson Fragmentation (2)	Deviation in Parcel Size (3)	Distance Travelled (4)
Number of Parcels inherited or received from local authorities	0.730***	0.065***	0.052***	0.476***
	(0.025)	(0.003)	(0.004)	(0.057)
N	8853	8853	8853	8763
R^2	0.630	0.447	0.168	0.108

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) **Second Stage, Regressing on Months Hungry**

	Months Hungry (1)	(2)	(3)	(4)
Number of Parcels	-0.064***			
	(0.012)			
Simpson Fragmentation Index		-0.718***		
		(0.131)		
Deviation in Parcel Size			-0.894***	
			(0.170)	
Distance Travelled				-0.102***
				(0.020)
Total Household Area Farmed	-0.055***	-0.052***	-0.033**	-0.026
	(0.012)	(0.012)	(0.013)	(0.016)
N	8602	8602	8602	8513

Not reported: controls for total area farmed, gender of household head, dependency ratio, size of household, asset index, Kebele and time fixed effects. Household clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: **CSI and Land Fragmentation, Instrumental Variable**

(a) **First Stage**

	Number of Parcels (1)	Simpson Fragmentation (2)	Deviation in Parcel Size (3)	Distance Travelled (4)
Number of Parcels inherited or received from local authorities	0.730***	0.065***	0.052***	0.476***
	(0.025)	(0.003)	(0.004)	(0.057)
N	8853	8853	8853	8763
R^2	0.630	0.447	0.168	0.108

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) **Second Stage, Regressing on CSI**

	Coping Strategy Index			
	(1)	(2)	(3)	(4)
Number of Parcels	-0.361***			
	(0.057)			
Simpson Fragmentation Index		-4.068***		
		(0.593)		
Deviation in Parcel Size			-5.194***	
			(0.793)	
Distance Travelled (km)				-0.555***
				(0.097)
Total Household Area Farmed	-0.166***	-0.151***	-0.038	-0.007
	(0.047)	(0.044)	(0.052)	(0.068)
N	8602	8602	8602	8513

Not reported: controls for total area farmed, gender of household head, dependency ratio, size of household, asset index, Kebele and time fixed effects. Household clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: **Robustness Checks, Coefficient Estimates**

(a) **Dependent Variable: Months Hungry**

	Data Subsets		MLE Specification	
	Highlands Only	Inherited or Granted Parcels Only	Poisson MLE	Negative Binomial MLE
	(1)	(2)	(3)	(4)
Number of Parcels	-0.060***	-0.086***	-0.075***	-0.089***
	(0.011)	(0.016)	(0.008)	(0.013)
Simpson Fragmentation Index	-0.562***	-0.630***	-0.389***	-0.520***
	(0.119)	(0.14)	(0.053)	(0.098)
Deviation in Parcel Size	-0.091	-0.223***	-0.122***	-0.169***
	(0.062)	(0.082)	(0.032)	(0.057)
Distance Travelled	-0.010**	-0.015***	-0.012***	-0.016***
	(0.004)	(0.005)	(0.003)	(0.005)
N	4768	4843	8698	8698

(b) **Dependent Variable: Coping Strategy Index**

	Data Subsets		MLE Specification	
	Highlands Only	Inherited or Granted Parcels Only	Poisson MLE	Negative Binomial MLE
	(1)	(2)	(3)	(4)
Number of Parcels	-0.163***	-0.291***	-0.106***	-0.143***
	(0.043)	(0.095)	(0.004)	(0.020)
Simpson Fragmentation Index	-2.502***	-3.628***	-0.687***	-1.089***
	(0.548)	(0.936)	(0.027)	(0.145)
Deviation in Parcel Size	-0.626**	-1.186***	-0.172***	-0.247***
	(0.255)	(0.448)	(0.016)	(0.082)
Distance Travelled	-0.076***	-0.070**	-0.017***	-0.024***
	(0.022)	(0.030)	(0.001)	(0.006)
N	4768	4843	8698	8698

Each coefficient is from a separate regression estimating equation eqn. (7) for each measure of land fragmentation, as in Table 5.

Table 8: **Months Hungry and Land Fragmentation interacted with Rainfall, Pooled OLS**

	Months Hungry			
	(1)	(2)	(3)	(4)
Total rainfall in wettest quarter (mm)	-0.128***	-0.184***	-0.032	-0.117***
	(0.045)	(0.055)	(0.044)	(0.039)
Number of Parcels	-0.053***			
	(0.011)			
Number of Parcels* Total rainfall in wettest quarter (mm)	0.011 (0.007)			
Simpson Fragmentation Index		-0.434***		
		(0.109)		
Simpson Fragmentation Index * Total rainfall in wettest quarter (mm)		0.219** (0.091)		
Deviation in Plot Size			-0.105*	
			(0.056)	
Deviation in Plot Size Total rainfall in wettest quarter (mm)			-0.094 (0.060)	
Distance Travelled				-0.006
				(0.004)
Distance Travelled * Total rainfall in wettest quarter (mm)				0.006* (0.004)
N	5861	5861	5861	5817

Fragmentation measures fixed to first round. Excludes cities, pastoral areas (Afar & Somalie).
Not reported: controls for farmed area, gender of household head, dependency ratio, size of household, asset index, Kebele and time fixed effects.
Household clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: **CSI and Land Fragmentation interacted with Rainfall, Pooled OLS**

	Coping Strategy Index			
	(1)	(2)	(3)	(4)
Total rainfall in wettest quarter (mm)	-1.223***	-1.129***	-0.987***	-0.881***
	(0.209)	(0.259)	(0.194)	(0.171)
Number of Parcels	-0.153***			
	(0.056)			
Number of Parcels * Total rainfall in wettest quarter (mm)	0.138***			
	(0.036)			
Simpson Fragmentation Index		-2.446***		
		(0.548)		
Simpson Fragmentation Index * Total rainfall in wettest quarter (mm)		0.949**		
		(0.436)		
Deviation in Plot Size			-0.681**	
			(0.273)	
Deviation in Plot Size * Total rainfall in wettest quarter (mm)			0.517**	
			(0.242)	
Distance Travelled				-0.057**
				(0.023)
Distance Travelled * Total rainfall in wettest quarter (mm)				0.036**
				(0.018)
N	5838	5838	5838	5794

Fragmentation measures fixed to first round. Excludes cities, pastoral areas (Afar & Somalie).
Not reported: controls for farmed area, gender of household head, dependency ratio, size of household, asset index, Kebele and time fixed effects.
Household clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: **Months Hungry and Geo-Variables**

(a) **Household Mean of Characterisitics**

	Months Hungry			
	(1)	(2)	(3)	(4)
$\bar{Distance}$	-0.007			
	(0.008)			
$\bar{Slope}$		-0.002		
		(0.005)		
$\bar{Elevation}$			0.000	
			(0.000)	
$\bar{Wetness}$				0.007
				(0.016)
N	8551	8573	8573	8573

Not reported: controls for total area farmed, gender of household head, dependency ratio, size of household, asset index, Kebele and time time fixed effects.
Household clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) **Household Standard Deviation of Characteristics**

	Months Hungry			
	(1)	(2)	(3)	(4)
$Distance^{sd}$	-0.080***			
	(0.021)			
$Slope^{sd}$		-0.022***		
		(0.006)		
$Elevation^{sd}$			-0.001***	
			(0.000)	
$Wetness^{sd}$				-0.028
				(0.026)
N	8552	8574	8574	8574

Not reported: controls for total area farmed, gender of household head, dependency ratio, size of household, asset index, Kebele and time fixed effects.
Household clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: **CSI and Geo-Variables**

(a) **Household Mean of Characterisitics**

	Coping Strategy Index			
	(1)	(2)	(3)	(4)
$\bar{Distance}$	0.033			
	(0.043)			
$\bar{Slope}$		-0.012		
		(0.021)		
$\bar{Elevation}$			-0.000	
			(0.001)	
$\bar{Wetness}$				0.137
				(0.103)
N	8348	8348	8348	8348

Not reported: controls for total area farmed, gender of household head, dependency ratio, size of household, asset index, Kebele and time time fixed effects.
Household clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) **Household Standard Deviation of Characteristics**

	Coping Strategy Index			
	(1)	(2)	(3)	(4)
$Distance^{sd}$	-0.057			
	(0.112)			
$Slope^{sd}$		-0.113***		
		(0.029)		
$Elevation^{sd}$			-0.003	
			(0.002)	
$Wetness^{sd}$				-0.349***
				(0.093)
N	8327	8349	8349	8349

Not reported: controls for total area farmed, gender of household head, dependency ratio, size of household, asset index, Kebele and time fixed effects.
Household clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: **Evidence of Complementary Crops**

(a) **Probability of Growing Crop A conditional on Crop B**

	Crop B						
Crop A	Barley	Maize	Sorghum	Teff	Wheat	Coffee	Ensette
Barley		20%	15%	29%	53%	15%	26%
Maize	42%		56%	61%	46%	47%	36%
Sorghum	23%	39%		37%	23%	38%	24%
Teff	46%	45%	39%		53%	42%	36%
Wheat	58%	24%	17%	37%		17%	26%
Coffee	14%	20%	24%	25%	14%		51%
Ensette	23%	15%	14%	20%	21%	48%	

(b) **Parcel Characteristics and Crop Grown, Probit**

	Barley (1)	Maize (2)	Sorghum (3)	Teff (4)	Wheat (5)	Coffee (6)	Ensette (7)
Distance	0.002	-0.006***	-0.001*	-0.000	0.002*	-0.004**	0.003***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Slope	0.007***	-0.009***	0.008***	-0.002**	0.001	0.002***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Elevation	0.001***	-0.001***	-0.001***	-0.000	0.001***	-0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Wetness	-0.005	-0.007*	-0.007	0.031***	0.023***	-0.027***	-0.051***
	(0.007)	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)	(0.008)
Observations	47729	48468	48468	45208	47729	48468	41507

Not reported: controls for round and region.

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: **Land Fragmentation, Crop Diversity and Food Insecurity**

(a) **Number of Crops and Land Fragmentation**

	Number of Distinct Crops			
	(1)	(2)	(3)	(4)
$Distance^{sd}$	0.090***			
	(0.025)			
$Slope^{sd}$		0.023***		
		(0.008)		
$Elevation^{sd}$			0.003***	
			(0.001)	
$Wetness^{sd}$				0.129***
				(0.024)
N	5904	5918	5918	5918

Not reported: land area, controls for gender of household head, dependency ratio, size of household, asset index, Kebele and time fixed effects.
Household clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) **CSI and Number of Crops**

	Months Hungry	CSI
	(1)	(2)
Number of Distinct Crops	-0.030*	-0.353***
	(0.016)	(0.071)
$Distance^{sd}$	-0.008	-0.154
	(0.023)	(0.106)
$Slope^{sd}$	-0.011	-0.126***
	(0.007)	(0.028)
$Elevation^{sd}$	0.000	0.001
	(0.001)	(0.002)
$Wetness^{sd}$	0.014	-0.352***
	(0.025)	(0.110)
N	5904	5753

Not reported: land area, controls for gender of household head, dependency ratio, size of household, asset index, Kebele and time fixed effects.
Household clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figures

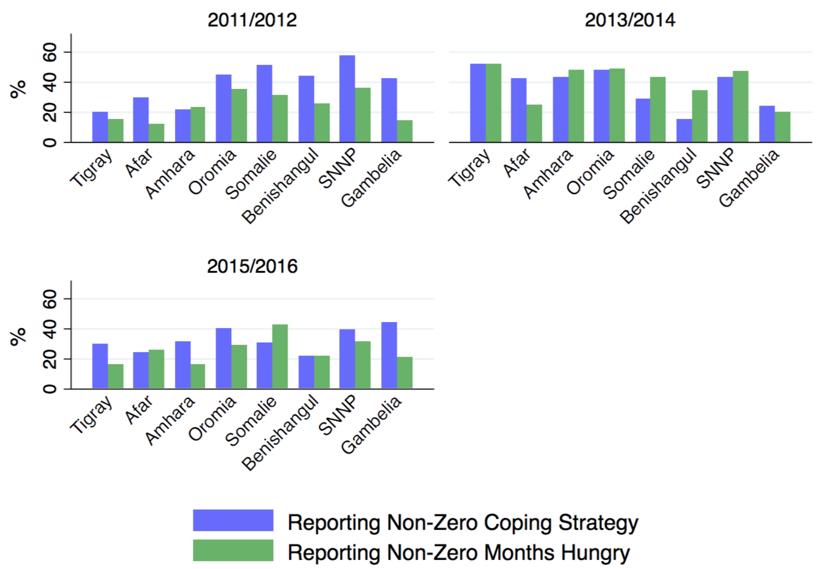
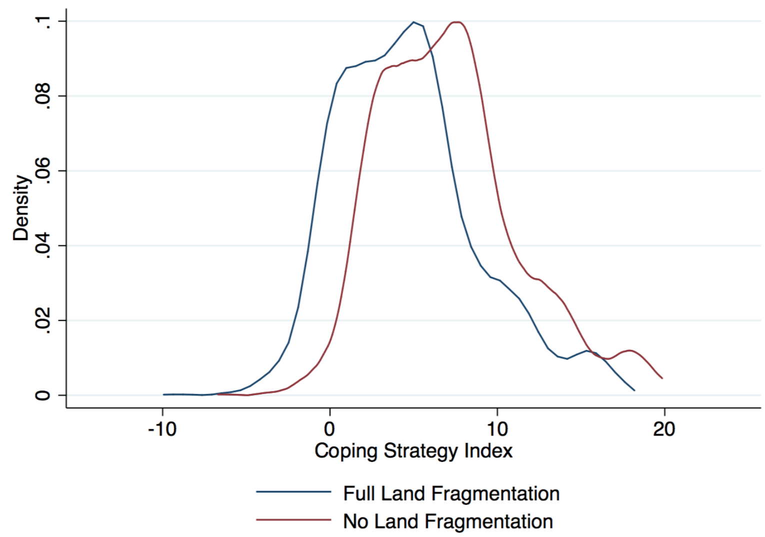
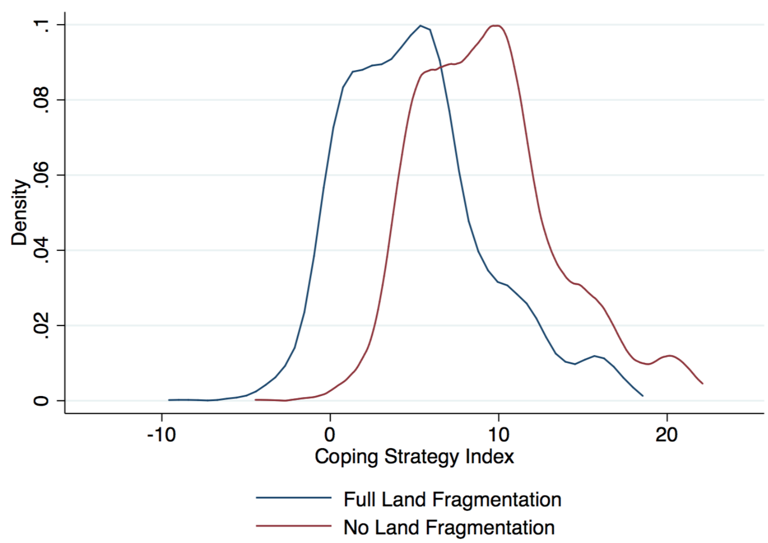


Figure 1: Prevalence of food insecurity across regions



(a) Non-Drought Year (Z-score= 0)



(b) Drought Year (Z-score= -2)

Figure 2: Distribution of Food Insecurity