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Do Safety Nets Promote Technology Adoption? Panel Data Evidence from Rural Ethiopia[*]

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Abstract

We use panel data from rural Ethiopia to investigate if participation in a safety net program enhances fertilizer adoption. Using a difference-in-difference estimator and inverse propensity score weighting we find that participation in Ethiopia's food-for-work program increased fertilizer adoption. Results also indicate that the likelihood of adopting and the intensity of fertilizer usage increased with livestock holdings for food-for-work-participant households providing some evidence that the intervention helped asset-rich farm households more than asset-poor households. We find no significant effects of free distribution on fertilizer adoption or intensification. Our results are consistent with the hypothesis that safety nets can be viewed as mechanisms that allow households to take on more risk to pursue higher profits. The paper highlights important policy implications related to the inter-related dynamics of safety nets and extension services that aim at promoting productivity enhancing modern agricultural technologies.

Keywords: Safety Net, Fertilizer Use, Inverse Propensity Score Weighting,

JEL: O12, O33, Q12, Q16

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1 Introduction

There is a rich literature investigating why poor households are unlikely to adopt risky technology (Feder et al., 1985). The availability of inputs, uncertainty about profitability, and credit constraints are a few of the explanations that have received the most attention in academic research and in government resources. However, few studies have (empirically) looked at the role of insurance (the ability to smooth consumption) in explaining technology usage.[1] The adoption of income-improving technologies is hindered by farmers ability and willingness to access credit. On the supply side, asymmetric information and imperfect enforcement lead to credit rationing. On the demand side, imperfections in the insurance market, the inability of households to protect against downside shocks, lead to risk rationing where farmers are less willing to take on risk and voluntarily withdraw from the credit market (Binswanger and Sillers, 1983; Boucher et al., 2008; Dercon and Christiaensen, 2011). In short, poor households that are ill-equipped to handle negative shocks may engage in less risky, less profitable activities.[2] In this paper we add to the literature on technology adoption by investigating the role safety nets play in the likelihood of a household taking on more risk. Identifying mechanisms which allow households to overcome the initial uncertainty of adopting a potentially profitable technology has important policy implications for poverty alleviation.

Dercon and Christiaensen (2011) investigate the ability of households to take on risky production technologies in the presence of credit and insurance constraints. A key prediction of their model is that households will adopt fewer risky inputs when they face higher ex-post downside consumption risk. Using data from rural Ethiopia, we investigate this further and explore the role that food aid can play in the adoption and usage of fertilizer (a risky production technology). Food aid programs are implemented to protect against ex-post downside consumption risk and in essence can mitigate the adverse effects of shocks allowing households to engage in higher return, higher risk activities.[3]

At the same time, food aid may provide a disincentive to households to invest in productive assets and may lead households to become dependent upon aid. Previous studies investigated the impact of safety nets on household behavior and outcome. Andersson et al. (2011) investigate the impact of the Ethiopian Productive Safety Net Program on rural households livestock wealth and tree

[1] Gine and Yang (2009) is one of the few studies which empirically explores the relationship between insurance and technology adoption. The authors implement a randomized field experiment where they offer credit to purchase a new crop technology. The treatment group was also required to purchase a weather insurance policy. The authors found that take-up was lower among farmers offered insurance with the loan.

[2] These environments can lead to risk-induced poverty traps where households which are able to insure their consumption against income shocks engage in more profitable activities and escape poverty, while others are stuck with low-return, low risk activities trapping themselves into poverty.

[3] Other papers have explored the demand for formal insurance among farmers (Gine and Yang, 2009; Gine et al., 2008). Unlike these papers we explore an insurance mechanism, in the form of food aid, which does not require a direct cost to purchase.

planting. They find a positive impact of the program on the number of trees planted by households but no impact in livestock holdings. Gilligan and Hoddinott (2007) on the other hand study the impact of the emergency food aid programs after the 2002 drought in rural Ethiopia which we consider in the current paper. These authors find that participation in food-for-work increased growth in total consumption and food consumption for participating households while free food distribution helped to raise growth in food consumption but impacted negatively on food security. In this paper, we add to the literature on the effects that food aid has on household behavior by exploring how it affects fertilizer usage, a critical productivity-enhancing modern agricultural input. Understanding how the intervention affected technology adoption is important to have a full picture of its impact on the different aspects of household outcomes.

Identifying the effect of food aid on household behavior is hindered due to selection into the program; assignment of treatment is not random. We address the non-random assignment of aid allocations by using inverse-propensity score weighting and a difference-in-difference estimator by exploiting the expansion in Ethiopia's food aid program during the 2002 drought. We find that participation in Ethiopia's food-for-work program increased fertilizer adoption. We also find that the likelihood of adopting and the intensity of fertilizer usage increased with livestock holdings for food-for-work-participant households providing some evidence that the intervention helped asset-rich farm households more than asset-poor households. We find no significant effects of free distribution on fertilizer adoption or intensification. Our results are consistent with the hypothesis that safety nets can be viewed as mechanisms that allow households to take on more risk to pursue higher profits. The paper highlights important policy implications related to the inter-related dynamics of safety nets and extension services that aim at promoting productivity enhancing modern agricultural technologies.

The rest of the paper is structured as follows. Section 2 presents a theoretical discussion of the role food aid can play in technology adoption. Section 3 discusses the data. Section 4 presents the identification strategy and the econometric model. Section 5 presents mean treatment effects and section 6 concludes.

2 Theory

The decision to adopt productivity-improving technologies depends on households' willingness and ability to access credit. Credit market imperfections make it difficult for farmers in developing countries to access credit in order to adopt profit-maximizing production technologies. The combination of information asymmetries and limited liability make providing credit riskier for the lender than the innate cause of uncertainty. Adverse selection, moral hazard, and imperfect enforcement are examples of factors which restrict poor households access to credit.

At the same time, imperfections in the insurance markets may affect farmers' willingness to demand credit (Binswanger and Sillers, 1983; Boucher et al., 2008; Dercon and Christiaensen, 2011). Dercon and Christiaensen (2011) provide a model that links imperfections in insurance markets to inefficiencies in production choices. The authors show that imperfections in credit markets and uninsured consumption risk results in less than optimal usage of modern inputs.

Boucher et al. (2008) show that households may voluntarily withdraw from the credit market due to high-collateral contracts that provide lower expected utility than engaging in a risk-free, subsistence activity. In other words, households will choose to adopt less risky technologies to avoid permanent damage to their welfare. Their model also suggests that conditional on having access to credit markets, households will under-utilize modern inputs.[4]

The theoretical literature suggests that mechanisms that protect against downside shocks should encourage risk-averse farmers to demand more credit to adopt more profit-maximizing production technologies. Evidence on the effects of insurance on the adoption of improved technologies have produced conflicting results. Dercon and Christiaensen (2011) found that downside consumption risk leads to lower fertilizer usage in rural Ethiopia, while Gine and Yang (2009) found that farmers which were offered an insured loan to purchase high-yielding hybrid maize and groundnut seeds for planting in Malawi had lower take-up rates than farmers that were offered an uninsured loan.

Food aid is a form of insurance that protects against downside risk and in principle could encourage adoption among risk-averse farmers. There are no direct financial costs incurred by the farmer which in turn do not drive up the costs of an insured loan as in the case of Gine and Yang (2009) and its purpose is to protect against downside consumption shocks. While the theoretical literature suggests the potential for food aid to increase the adoption of improved techniques, there may exist disincentive effects from the availability of food aid that would discourage farmers from investing in more profitable technologies.[5] At the same time, labour requirements with the food-for-work program may crowd out labour input in other productive activities.

Below we empirically test the effects that food aid has on the adoption of fertilizer. The Ethiopian Government has demonstrated its commitment to agricultural development by introducing policies

[4]Boucher et al. (2008)'s model can be modified so that the risk to the lender is not determined by the effort allocated by the borrower but by the knowledge the farmers possess about the new technology. Extension services remove some of this risk so that lenders offer lower collateralized loans.

[5]Little (2008) fail to find evidence that households become dependent on food aid and Andersson et al.(2011) find that food aid actually encourages investment in tree planting.

that promote the use of modern inputs in order to intensify crop yields. The relatively large number of smallholder farms that have adopted chemical fertilizer gives us a large enough sample to investigate the adoption of a particular modern input. At the same time, examining the adoption of a single technology allows us to avoid the difficulty in controlling for differences across technologies in potential profitability and risk.[6]

3 Context and Data

To investigate the role of the Ethiopian Government's food aid safety net program on fertilizer usage, we exploit the Government's response to the 2002 drought. The 2002 drought decreased cereal production by over 25 percent and left over 12.3 million Ethiopians in need of food aid assistance. The government responded to the drought by expanding its food aid program which primarily consists of food-for-work and free distribution.[7] Using longitudinal data from the Ethiopian Rural Household Survey (ERHS), we are able to observe household behavior before and after the drought which will allow us to identify the effect of food aid on fertilizer adoption and intensification. In essence, we are able to identify the effect of the Ethiopian Government's response to the 2002 drought.[8]

The ERHS was conducted in 15 Peasant Associations across rural Ethiopia.[9] The survey was administered by the International Food Policy Research Institute (IFPRI) in collaboration with the department of economics at Addis Ababa University (AAU) and the Center for the Study of African Economies (CSAE) at Oxford University. The ERHS interviewed 1,477 households seven times between 1994 and 2009. We make use of the 1999 and the 2004 rounds of the ERHS. We restrict our analysis to 6 of the 15 Peasant Associations as these are the only Peasant Associations where a nontrivial share of households report using fertilizer and receiving food aid. This leaves us with a sample size of 456 households.

Our measure of aid comes from self-reported measures of aid received from the government or a non-Government Organization. The 2004 round of the ERHS asked specific questions about the 2002 drought, the impact the drought had on crop output, and how responsive the government was

[6] Holden et al. (2001); Pender and Gebremedhin (2008); Freeman and Omiti (2003); Adesina (1996); Waithaka et al. (2007); Alem et al. (2010); Doss (1999); Dercon and Christiaensen (2011) discuss the determinants for fertilizer adoption.

[7] Refer to Gilligan and Hoddinott (2007) for a more detailed description of the 2002 drought and farmers' perception concerning the severity of the drought and the efficacy of the food aid program.

[8] This is important, as we are not investigating changes in food aid receipt over time. The treatment we are exploiting is the one time response to the 2002 drought.

[9] The Peasant Associations are the lowest administrative unit in Ethiopia and consists of several villages. Throughout the paper we will refer to a village and a Peasant Association interchangeably.

to the drought. The treatment is a dummy variable equal to 1 if the household reports receiving aid between September 2002 and March 2004 and 0 otherwise.[10]

The expansion in the food aid program primarily resulted in covering more areas as opposed to covering more households within historically aid recipient villages. Table 1 reports the share of households receiving aid for the 15 Peasant Associations sampled in the ERHS by survey year. Between 1995 and 1999, no more than 7 of the 15 villages had received some form of assistance in the form of food aid in a given year. In 2004, 9 of the 15 villages had received some form of food aid. This is the same number of villages which received aid during the 1994 drought. While there exists variation in the share of households receiving food aid within a village over time, the table does not suggests that the expansion resulted in more coverage within villages.[11]

There may exist concern that aid recipient households are fundamentally different from non-recipient households. Prior research on food aid targeting in Ethiopia has shown that there exists substantial errors of inclusion and exclusion in household targeting (Sharp, 1997; Clay et al., 1999; Jayne et al., 2002; Broussard et al., 2012). Table 1 depicts the variation in the share of households covered within a village over time. Of the villages used in the analysis only 16 percent of households never received food aid between 1994 and 2004 and only 5 percent of households received food aid in every round their village received aid. Most households cycle on and off food aid (conditional on the village receiving aid) and between free distribution and food-for-work.[12]

The survey also asked detailed questions about inputs used for crop agriculture. Households were asked about the type and amount of fertilizer used during the previous main season. Households that report using chemical fertilizer make up our sample of fertilizer adopting households. Table 2 provides a summary of the share of households using fertilizer and the intensity of fertilizer usage for the 15 Peasant Associations by survey year. In 2004, 45 percent of the households surveyed in the ERHS used fertilizer, an increase from the 43 percent of households which used fertilizer in 1994. Many households switched in and out of using fertilizer over the 10 year period. Intensity rates in 2004 were approximately 94 kilograms of fertilizer per hectare, a decrease from its 1994 level. Most households in the survey reported that the main constraint to using modern inputs, including fertilizer, were due to costs, with few households reporting availability of modern inputs as a constraint (Dercon and Christiaensen, 2011). The table shows that between 1999 and 2004 for many of the villages used in the analysis the share of households using fertilizer and the quantity

[10] We use the same measure of aid receipts used by Gilligan and Hoddinott (2007).

[11] The existing literature does not suggest that within village targeting improved following the 2002 drought relative to other years. Broussard et al. (2012) use the first 6 rounds of the ERHS to investigate food aid targeting, they found no evidence that the (household) targeting strategy used in 2004 differed from the earlier rounds.

[12] The cycling between free distribution and food-for-work is primarily due to the fact that villages rarely received both programs in a given period.

of fertilizer used per hectare declined.

The six Peasant Associations used in the analysis are Haresaw, Dinki, Adele Keke, Korodegaga, Aze Deboa, and Gara Godo. Between 12 and 86 percent of the households in these villages reported using fertilizer in 2004 and between 36 and 94 percent of the households reported receiving food aid in response to the 2002 drought.

4 Identification Strategy and Econometric Model

To identify the effect of the Ethiopian Government's response to the drought on fertilizer adoption we adopt a methodology similar to Gilligan and Hoddinott (2007). We compare adoption behavior of aid recipient households to non-aid receiving households. The ERHS contains a rich set of variables used by village representatives to select aid recipient households and due to the errors of inclusion and exclusion of aid recipients reported by earlier studies (Sharp, 1997; Clay et al., 1999; Jayne et al., 2002; Broussard et al., 2012) we believe that households which did not receive aid are suitable controls for aid recipient households. By comparing fertilizer usage of treatment and control groups before and after the 2002 drought, we are able to capture the effect of the Ethiopian Government's food aid safety net program. The naive difference-in-differences estimator is estimated from the following regression:

$$\Delta Y_i = \beta_0 + \beta_1 D_i + \epsilon_i \tag{1}$$

where D is an indicator variable equal to 1 if the household received food aid and 0 otherwise.

Comparing simple differences between recipient and non-recipient households could lead to biased estimates of the true impact of food aid due to the fact that food aid was not randomly assigned and pretreatment characteristics determined selection into each food aid program.[13] To account for the non-randomness of food aid allocations we employ inverse-propensity score weighting (Hirano et al., 2003; DiNardo, 2002).

Let X be a vector of observable control variables which determine selection into the food aid program. Regressing ΔY on D and X would allow us to identify the effect of treatment on the outcome variable. This is the unconfoundedness assumption or the selection-on-observables as-

[13]The difference-in-differences estimator controls for selection bias due to unobservable time-invariant characteristics.

sumption, which states that treatment is independent of potential outcomes conditional on the observed covariates. This means that, conditional on covariates, treated and non-treated households would, on average, be expected to experience the same changes in outcomes following the drought in the absence of treatment.

Rosenbaum and Rubin (1983) show that conditioning on the propensity score, where the propensity score is $Pr(D = 1|x)$, also achieves identification. Instead, we employ inverse-propensity score weighting which Hirano et al. (2003) has shown to produce an efficient estimate of the average treatment effect. Inverse-propensity score weighting constructs two counterfactual means and takes their difference to obtain the average treatment effect (DiNardo, 2002). The treatment mean and the control mean for the population is obtained by a weighted mean of outcomes in the treated and control group, respectively. This approach reweights the data to balance the distribution of covariates across treated and untreated households.[14]

Denoting the estimated propensity score for person i as $\hat{p_i}$, the estimated inverse-propensity score weight for person i is:

$$\hat{w}_i = \frac{D_i}{\hat{p_i}} + \frac{1 - D_i}{1 - \hat{p_i}} \tag{2}$$

and the estimated average treatment effect is:

$$A\hat{T}E = \frac{1}{N_T} \sum_{i \in T} \hat{w}_i y_i - \frac{1}{N_C} \sum_{i \in C} \hat{w}_i y_i \tag{3}$$

where N_T is the number of treated observations and N_C is the number of control observations.

The decision to adopt fertilizer depends on a households ability to access credit. Livestock holdings are an important source of collateral in rural Ethiopia given the the many restrictions in the land market. We allow the impact of receiving aid to vary with the household's value of livestock holdings. The difference-in-difference reweighting estimator is obtained via the following regression:

$$\Delta Y_i = \beta_0 + \beta_1 D_i + \beta_2 x_i + \beta_3 D_i(x_i - \bar{x}) + \epsilon_i \tag{4}$$

where ΔY_i is the outcome of interest for individual i, D is the indicator for treatment, x_i is the household's value of livestock holdings in 1999, and $\bar{x}$ is the mean value of livestock holdings for the sample so that $(x_i - \bar{x})$ is the demeaned value of livestock holdings. We weight the regression

[14] This approach has been used recently in the economics literature to estimate the average treatment effects of economic development programs (Busso and Kline, 2008) and welfare reforms (Bitler et al., 2006), just to name a few. Refer to DiNardo (2002) and Hirano et al. (2003) for a discussion of the use of propensity score reweighting to estimate the average treatment effect.

by the inverse propensity score described above. β_1 identifies the average treatment effect, while $\beta_1 + \beta_3$ identifies how the treatment effect varies with different values of livestock holdings. If β_3 is significantly different from zero, there is evidence of heterogeneity of treatment effects by asset holdings. We estimate standard errors for the impact estimates by a bootstrap using 1000 replications of the sample.

Due to the different selection criteria and work requirements across the two forms of food aid programs, we estimate separate treatment effects for participation in FFW and in FD. The controls we include for the participation regressions include 1999 household characteristics, variables which capture the households social networks, political connections, and death and illness shocks.[15]

5 Results

We use a logit model in order to estimate the propensity scores for both the FFW and FD programs. We adopted many of the same set of control variables which are believed to be associated with the probability of participating in each food aid program as used by Gilligan and Hoddinott (2007).[16] The control variables selected are believed to be associated with the probability of participating in each food aid program.

For the FD program, the control variables used to estimate the propensity scores include changes in monthly log real consumption per adult equivalent between previous rounds of the ERHS survey; pre-drought (1999) land area owned and its square; pre-drought household demographics variables (number of male household members between the ages of 15 and 64, the number of female household members between the ages of 15 and 64, the number household members younger than 15 years of age, the number of household members older than 64 years of age, the household's dependency ratio, whether the household is headed by a female, and the log age of the household head); whether the household head's primary job was farming; whether the household head had any formal education; the household head's highest grade completed in school; whether the household reported experiencing a drought between 1999-2002; whether the household experienced a death or serious illness shock between 1999-2002; whether all household members were too weak, sick, young or old to work; measures of the household's political and social connections in the village (whether the parents of the household head were important in the village, whether a parent of

[15] Refer to Gilligan and Hoddinott (2007) for a more detailed description of the variables used.

[16] The differences in the variables used to estimate the propensity score are due to ensuring that the "balancing property" is met. Because we use only a subset of the villages used in Gilligan and Hoddinott (2007) we had to exclude some of the conditioning variables used in their paper in order to insure that the treatment sample and the sample of comparison observations had similar mean propensity scores and observables at various levels of the propensity scores.

the respondent holds a local official position (interacted with regional dummies), number of iddirs the household belonged to prior to the drought, and the number of people that would help the household in time of need); and an indicator for whether the household met any targeting criteria for FD in its village.

The control variables used to estimate the propensity scores for the FFW sample include many of the same variables used for the FD sample. Additional variables include whether the households social network has grown since five years prior to 1999, and an indicator variable for if the household head was born in the village. We also include an indicator variable for whether the household met any targeting criteria for FFW in its village. We exclude the variables for if the household head's primary job is farming and the household head's highest completed grade. The logits also include village fixed effects.

Table 3 provides means of the variables used to identify the selection into the two food aid programs. Column 1 provides the means for the full sample of households in the 6 villages used in the analysis (509 households). Because propensities near zero or one violate the condition required for reweighting that the probability of treatment be bounded away from zero and one, the remaining columns provide the means and difference in means for the samples used in the analysis in which the estimated propensities are never near zero or one. The FFW sample consists of 172 control households and 284 treated households. The FD sample consists of 178 control households and 264 treated households. Columns 2 and 3 provides the means for the treated and control samples for the FD sample. Column 4 provides the differences in means between the treated and control samples. FD recipient households tend to have more land, have fewer male household members, the household head is slightly more educated and they had more household members that were too sick to work relative to the non-FD recipient households.

Columns 6 and 7 provide the means for the treated and control samples for the FFW sample. Column 8 provides the differences in means between the treated and control samples for the FFW samples. FFW recipient households also tend to have more land, have a lower dependency ratio, the household head tends to be younger and slightly more educated, they had more household members that were too sick to work, their parents tend to be important in the village, they are more likely to have had a household member died, and they are less likely to have been born in the village relative to the non-FFW recipient households.

Columns 5 and 9 of table 3 reports estimated differences between the treated and control samples after adjusting using inverse propensity score weighting. The differences in means between the aid recipient households and non-aid recipient households are no longer statistically different.

Table 4 presents the results from the naive difference-in-difference analysis without covariate adjustment. The outcome variables are the change in fertilizer usage and the change in the quantity of fertilizer used in kilograms per hectare. The change in the outcome variables are between 1999 and 2004 (two years before and after the drought). Bootstrapped standard errors are presented in parentheses. Panel A presents the results for food-for-work and panel B presents the results for free distribution. The naive estimator shows that food aid recipient households had lower adoption rates and use less fertilizer per hectare than non-aid recipient households, however these results are not significantly different from zero.

Table 5 presents the average treatment effect from the reweighted difference-in-difference analysis. Row 1 provides the mean outcome for participants, row 2 provides the mean outcome for non-participants, and row 3 provides the average treatment effect. Bootstrapped standard errors are presented in parentheses. Columns 1 and 2 presents the results for fertilizer usage to see if food aid encouraged households to take on more risk. Reweighting the difference-in-difference estimator for covariate imbalance changes the sign of the point estimates for the food-for-work sample but does not change the sign or the magnitude of the point estimates for the free distribution sample.

For the FFW sample, the estimated mean effect on fertilizer intensity is positive but insignificant while the estimated mean effect on fertilizer adoption is statistically significant at the 10 percent level. Because fertilizer usage decreased between 1999 and 2004, the results show that FFW participant households decreased their fertilizer usage by 11.4 percentage points less than non-participant households. Column 3 of the table investigates if the positive effect on fertilizer usage translates into increases in the change in the real value of crop output per adult equivalent. Our results show a positive average effect of aid on the change in the value of crop output but the point estimate is not statistically significant from zero.

The differences between the naive and the reweighted difference-in-difference estimates demonstrate the selection bias associated with the targeting of the food aid programs. The differences suggests that food-for-work was targeted towards households that were less likely to adopt fertilizer and to those households that use less fertilizer per hectare in the absence of treatment. The similarities between the naive and reweighted difference-in-difference estimates for the free distribution sample support results from earlier papers which suggest insufficient targeting of free distribution (Clay et al., 1999; Jayne et al., 2002; Dercon and Krishnan, 2003; Broussard et al., 2012). The negative effects we find from the FD regressions suggests that the disincentive effects may exceed the positive effects. However, we do not obtain significant effects on any of the negative coefficients.

To investigate whether the increase in fertilizer adoption is attributable to the protection against downside consumption risk, column 4 and 5 present the average treatment effect on the change in monthly log real total consumption per adult equivalent (column 4) and the change in monthly log real food consumption per adult equivalent (column 5). Although we find a positive effect of FFW on total consumption and food consumption, the results are not significantly different from zero. However, we do find that FD increased food consumption. This casts doubts on the hypothesis that households are taking on more risk due to the insurance that food aid provides against downside consumption shocks.

Finally, column 6 of table 5 investigates if food aid protects households from selling their assets, measured by the change in the real value of livestock in thousands of Ethiopian Birr. The results show that food aid had no effect on livestock holdings. The results for consumption and livestock in columns 4-6 allow us to compare our findings from inverse propensity score weighting with results from Gilligan and Hoddinott (2007) who use propensity score matching. For FFW, our point estimates for the average treatment effect on consumption and livestock are very similar to the point estimates obtained in table 3 of their paper, although our villages are a subset of villages used by them. In fact, Our findings are consistent with the findings from Gilligan and Hoddinott (2007) when they exclude Shumsha village, which is also excluded from our sample. For free distribution, our results are virtually identical in magnitude and significance to the results obtained in table 4 reported by the authors.

5.1 Heterogeneous Impacts of Food Aid Participation by Livestock Holdings

Households with more assets will have easier access to credit and therefore will have the ability to invest in income-improving technologies such as fertilizer. The results presented so far provided the average treatment effect of receiving food aid, however, the effect of receiving food aid on fertilizer adoption and intensification may vary with the household's holdings of assets that can be use for collateral. In Ethiopia, land can not be used as collateral so livestock plays an important role for many rural Ethiopians. We investigate if the effect of aid on fertilizer use varies with livestock holdings.

The final row of table 5 presents the coefficient on the interaction term of aid participation with demeaned livestock holdings in 1999. For FFW, the interaction term is positive and significant at the ten percent level for both fertilizer adoption and fertilizer intensification; FFW increases the likelihood of adopting fertilizer and increases the amount of fertilizer used per hectare the higher the household's livestock holdings. These findings suggests that the government's response to the 2002 drought helped asset-rich farm households more than asset-poor households. We still fail to find any evidence that the increases in fertilizer translate into increases in the value of crop output.

We do not find heterogenous effects of participation in free distribution on fertilizer usage or on the value of crop output.

5.2 Falsification Test

There may still be concerns that the significant differences reported in table 5 for FFW households are driven by unobservable characteristics. If unobservable characteristics determine selection into the food aid program and these characteristics are correlated with future fertilizer usage behavior, then the reported estimates will be biased. To test this concern we preform the following falsification test. We test the effect that the government's response to the 2002 drought had on fertilizer behavior in 1999, before food aid was administered (in response to the 2002 drought). If unobserved characteristics are driving our results, we would observe differences between the treated and control groups in years prior to the actual treatment.

Table 6 presents results from this falsification test. The dependent variable is the change in fertilizer usage between 1997 and 1999. The treatment is whether the household received food aid in 2002. The coefficients are negative and not significantly different from zero suggesting that our results are not driven by unobserved characteristics of the households.

6 Conclusion

The paper investigated the role safety nets, in the form of food aid, play in fertilizer adoption. Using a difference-in-difference estimator along with inverse propensity score weighting we were able to identify the average treatment effect of food aid on fertilizer usage. We find that households that participated in the food-for-work program following the 2002 drought were more likely to adopt fertilizer 18 months later. We also found that the likelihood of adopting fertilizer and the intensity of fertilizer usage increased with livestock holdings for food-for-work participant households. We found no significant effects of free distribution on fertilizer usage.

While we did find positive effects of food-for-work on consumption, we were unable to reject the hypothesis that the coefficients were equal to zero. This casts doubts on the hypothesis that households are taking on more risk due to the insurance that food aid provides against downside consumption shocks. However, our results are consistent with the hypothesis that safety nets can be viewed as a mechanism that allows households to take on more risk to pursue higher profits. The fact that food-for-work had statistically significant effects on fertilizer usage while free distribution did not, suggests that the work requirement from the food-for-work program discourages disincentives to engage in productive activities.

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Table 1: Share of Households Receiving Aid by Survey Year

	Survey Year					
Village	1994a	1994b	1995	1997	1999	2004
Haresaw	0.64	0.00	0.50	0.15	0.65	0.64
Geblen	0.77	0.88	0.00	0.67	0.64	0.72
Dinki	0.00	0.83	0.00	0.00	0.27	0.67
Yetemen	0.00	0.00	0.00	0.00	0.00	0.00
Shumsha	0.96	0.90	0.60	0.56	0.55	0.70
Sirbana Godeti	0.00	0.00	0.00	0.00	0.00	0.00
Adele Keke	0.25	0.00	0.00	0.57	0.00	0.47
Korodegaga	0.17	1.00	0.17	0.00	0.00	0.94
Trirufe Ketchema	0.00	0.00	0.14	0.00	0.00	0.00
Imdibir	0.00	0.64	0.63	0.17	0.00	0.00
Aze Deboa	0.00	0.00	0.00	0.00	0.00	0.76
Adado	0.00	0.00	0.00	0.00	0.00	0.00
Gara Godo	0.00	0.87	0.11	0.00	0.00	0.36
Doma	0.00	0.97	0.73	0.00	0.48	0.22
D.B. -Milki	0.00	0.00	0.00	0.00	0.39	0.00
Total	0.20	0.39	0.18	0.14	0.21	0.36

Notes:

Table 2: Fertilizer Usage By Village By Round

	Share of Households Using Fertilizer						Application Rate Per Hectare (KG)					
Village	1994a	1994b	1995	1997	1999	2004	1994a	1994b	1995	1997	1999	2004
Haresaw	0.00	0.07	0.01	0.15	0.30	0.12	0.00	47.50	25.00	36.83	28.87	29.50
Geblen	0.03	0.03	0.02	0.19	0.08	0.02	37.50	27.50	5.00	23.33	35.90	14.00
Dinki	0.02	0.07	0.04	0.14	0.25	0.18	10.13	30.83	33.42	32.79	46.21	39.21
Yetemen	0.69	0.74	0.73	0.61	0.73	0.66	160.43	180.64	190.74	186.88	157.45	138.46
Shumsha	0.00	0.01	0.00	0.09	0.13	0.10	0.00	1.00	0.00	44.00	35.56	9.50
Sirbana Godeti	0.77	0.81	0.85	0.82	0.84	0.79	241.80	294.68	271.28	250.48	100.56	203.79
Adele Keke	0.37	0.49	0.08	0.43	0.46	0.44	101.42	96.36	57.50	86.63	34.72	67.25
Korodegaga	0.28	0.46	0.63	0.84	0.61	0.52	53.00	49.96	58.16	82.67	53.21	51.00
Trirufe Ketchema	0.77	0.86	0.81	0.91	0.84	0.89	90.62	107.29	93.16	151.87	91.61	79.99
Imdibir	0.00	0.00	0.00	0.02	0.00	0.05	0.00	0.00	0.00	4.00	0.00	25.00
Aze Deboa	0.91	0.95	0.83	0.78	0.87	0.57	39.81	47.00	32.53	39.10	32.77	52.71
Adado	0.00	0.00	0.00	0.02	0.02	0.04	0.00	0.00	0.00	37.00	37.50	18.67
Gara Godo	0.75	0.92	0.63	0.96	0.89	0.86	38.19	33.93	22.59	58.70	74.59	44.41
Doma	0.00	0.08	0.06	0.10	0.38	0.00	0.00	12.00	21.25	90.00	43.84	0.00
D.B. -Milki	0.77	0.75	0.60	0.79	0.74	0.86	130.85	122.68	115.88	95.89	91.71	122.82
Total	0.37	0.43	0.36	0.48	0.49	0.45	112.02	114.50	111.81	109.08	74.61	93.84

Notes: Application rates per hectare are for households which report using fertilizer.

Table 3: Characteristics of Sampled Households

		Free Distribution Sample				Food-For-Work Sample			
	Full Sample	Levels		Differences		Levels		Differences	
Selection Variables	(ERHS)	Treated	Control	Unadjusted	Adjusted	Treated	Control	Unadjusted	Adjusted
Difference in ln real consumption, 1997-1999	-0.120	-0.099	-0.127	0.028	-0.027	-0.073	-0.203	0.130	0.025
Difference in ln real consumption, 1995-1997	0.393	0.392	0.344	0.048	0.017	0.416	0.357	0.059	-0.027
Difference in ln real consumption, 1994-1995	-0.196	-0.184	-0.175	-0.010	-0.025	-0.211	-0.184	-0.027	0.042
Land area owned (hectares)	1.269	1.417	1.089	0.328***	-0.053	1.562	0.855	0.707***	0.121
Land area owned squared	3.115	3.764	2.316	1.448	-0.287	4.513	1.089	3.424**	0.811
Number of Adult Men	1.503	1.496	1.522	-0.026**	0.046	1.609	1.390	0.220	0.024
Number of Children	2.717	2.591	3.051	-0.460	-0.064	2.810	2.663	0.147	0.024
Number of Elderly Adults	0.230	0.197	0.225	-0.028	0.010	0.222	0.233	-0.011	-0.005
Number of Adult Female	1.597	1.614	1.607	0.007	-0.080	1.683	1.535	0.148	0.017
Dependency ratio	1.243	1.179	1.309	-0.130	-0.032	1.198	1.262	-0.064*	-0.013
Ln of household head age	3.824	3.823	3.806	0.017	-0.008	3.806	3.857	-0.051**	-0.023
Household head has any formal education	0.189	0.212	0.180	0.032**	0.001	0.225	0.140	0.086***	0.024
Household head is female	0.287	0.269	0.303	-0.034	0.005	0.254	0.302	-0.049	0.027
Households experienced drought	0.833	0.845	0.820	0.024	-0.004	0.852	0.797	0.056	0.000
Male household member had serious illness	0.092	0.080	0.096	-0.016	0.003	0.088	0.105	-0.017	-0.011
Female household member had serious illness	0.086	0.091	0.090	0.001	0.007	0.088	0.105	-0.017	0.002
Household members weak/sick/young/old	0.061	0.080	0.039	0.040*	0.007	0.025	0.087	-0.063***	0.009
Parent important in PA social life	0.676	0.678	0.685	-0.007	0.007	0.729	0.634	0.095**	0.003
Number of iddir household belonged to	0.874	0.871	0.798	0.073	-0.054	0.915	0.837	0.078	0.003
Number of people that will help in time of need	7.189	6.977	7.152	-0.174	0.097	7.701	6.826	0.875	-0.143
Network size has grown in last 5 years						0.285	0.349	-0.064	0.017
If household head primary job is farmer	0.768	0.792	0.764	0.028	0.003				
Household member died	0.222	0.227	0.208	0.019	-0.011	0.500	0.413	0.087*	0.002
Household head born in this PA						0.697	0.802	-0.105***	-0.015
Household heads highest completed grade	1.048	1.087	0.933	0.155	0.035				
Household met at least one targeting criterion	0.448	0.405	0.455	-0.050	0.003	0.859	0.750	0.109***	0.012
Parent holds official position in Kebele									
Tigray region	0.018	0.011	0.022	-0.011	-0.001				
Amhara region	0.016	0.015	0.022	-0.007	0.001				
Oromia region	0.055	0.061	0.039	0.021	0.006				
SNNPR region	0.069	0.080	0.039	0.040*	-0.013				

Notes:

Table 4: Naive Estimates of the Impact of Food Aid

Panel A: Food For Work		
	Outcome Variables	
	Adoption	Intensity
Difference in average outcomes, ATE	-0.011	-0.154
	(0.052)	(0.211)
Panel B: Free Distribution		
	Outcome Variables	
	Adoption	Intensity
Difference in average outcomes, ATE	-0.043	-0.240
	(0.053)	(0.225)

Significance levels : $*$: 10% $**$: 5% $***$: 1%

Notes: The FFW sample consists of 172 control households and 284 treated households. The FD sample consists of 178 control households and 264 treated households. Bootstrapped standard errors in parentheses using 1000 replications of the sample. Fertilizer adoption is an indicator for if the household used fertilizer in 2004 relative to 1999, where -1 = stop using fertilizer, 0 = no change in usage, 1 = started using fertilizer. Fertilizer intensification is the change in the quantity of fertilizer used in kilograms per hectare, 1999-2004. The crop income variable is the change in the real value of crop output per adult equivalent, 1999-2004.

Table 5: Estimates of the Impact of Food Aid

Panel A: Food For Work

	Outcome Variables					
	Fertilizer			Consumption		
	Adoption	Intensity	Crop Income	Total	Food	Livestock
Average outcome, FFW participants	-0.123	-0.548	0.469	0.179	0.339	0.739
Average outcome, non-participants	-0.243	-0.774	0.359	0.062	0.209	0.741
Difference in average outcomes, ATE	0.114*	0.208	0.107	0.117	0.129	-0.002
	(0.069)	(0.233)	(0.200)	(0.129)	(0.157)	(0.197)
Impact by Livestock Holdings, 1999:						
Interaction Term	0.110*	0.297*	-0.057			
	(0.0651)	(0.177)	(0.165)			

Panel B: Free Distribution

	Outcome Variables					
	Fertilizer			Consumption		
	Adoption	Intensity	Crop Income	Total	Food	Livestock
Average outcome, FD participants	-0.129	-0.584	0.612	0.161	0.363	0.744
Average outcome, non-participants	-0.076	-0.369	0.437	0.033	0.095	0.558
Difference in average outcomes, ATE	-0.056	-0.216	0.177	0.128	0.268**	0.186
	(0.060)	(0.223)	(0.199)	(0.101)	(0.120)	(0.229)
Impact by Livestock Holdings, 1999:						
Interaction Term	0.016	-0.041	-0.114			
	(0.056)	(0.189)	(0.104)			

Significance levels : $*$: 10% $**$: 5% $***$: 1%

Notes: The FFW sample consists of 172 control households and 284 treated households. The FD sample consists of 178 control households and 264 treated households. Bootstrapped standard errors in parentheses using 1000 replications of the sample. Fertilizer adoption is an indicator for if the household used fertilizer in 2004 relative to 1999, where -1 = stop using fertilizer, 0 = no change in usage, 1 = started using fertilizer. Fertilizer intensification is the change in the quantity of fertilizer used in kilograms per hectare, 1999-2004. The crop income variable is the change in the real value of crop output per adult equivalent, 1999-2004. Outcome variables for consumption are change in monthly log real total (food) consumption per adult equivalent, 1999-2004. The livestock variable is the change in the real value of livestock in thousands of Ethiopian Birr, 1999-2004.

Table 6: Falsification Test

Panel A: Food For Work			
	Outcome Variables		
	Fertilizer		
	Adoption	Intensity	Crop Income
Difference in average outcomes, ATE	-0.074	-0.230	-0.193
	(0.048)	(0.212)	(0.169)
Panel B: Free Distribution			
	Outcome Variables		
	Fertilizer		
	Adoption	Intensity	Crop Income
Difference in average outcomes, ATE	0.055	0.286	0.026
	(0.053)	(0.208)	(0.183)

Notes: The FFW sample consists of 172 control households and 284 treated households. The FD sample consists of 178 control households and 264 treated households. Bootstrapped standard errors in parentheses using 1000 replications of the sample. Fertilizer adoption is an indicator for if the household used fertilizer in 1999 relative to 1997, where -1 = stop using fertilizer, 0 = no change in usage, 1 = started using fertilizer. Fertilizer intensification is the change in the quantity of fertilizer used in kilograms per hectare, 1997-1999. The crop income variable is the change in the real value of crop output per adult equivalent, 1997-1999.