TARGETING OF FOOD AID IN RURAL ETHIOPIA: CHRONIC NEED OR INERTIA?

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ABSTRACT

This paper quantifies the factors underlying the allocations of food aid by the Ethiopian government, together with local and international non-governmental organizations (NGOs), both across rural regions and to households within regions. We focus on "reduced form" specifications in which as little structure as possible is put on the decision rules, because so little is known about these rules and their implementation. Nationally representative, rural household data from Ethiopia, collected in 1996, are used. The paper determines the extent to which food aid (both free distribution and food for work) is targeted to poor households and communities. We also demonstrate that food aid allocations display a large degree of spatial continuity over time, and are concentrated in areas that, at least during the time of the survey, are not the poorest. The paper attempts to disentangle two competing explanations for the apparent spatial rigidity of food aid allocations: that the recipient areas are chronically needy, or that needs shift geographically from one year to the next, but that fixed costs in setting up operations and in the process of identifying needs lead to a degree of inertia in the location of food aid programs over time. We conclude that the evidence best fits the inertia explanation.

1. INTRODUCTION

Governments and donor agencies have been grappling for decades with how to design and implement food aid programs in developing countries. The main recurrent issues of food aid programs, as with other transfer programs, is how to target aid to intended beneficiaries and how to avoid disincentive effects (see Barrett, 1998, for a recent review). The lion's share of past literature on food aid has concerned itself with the disincentives issue – the effect of food aid distribution on local food prices and labor allocation. These issues are arguably still unresolved. Yet despite the enormity of cross-country food aid transfers, which were running as high as 15 million tons annually during the early 1990s, very little empirical work has shed light on the issue of targeting; even though interest in poverty alleviation and targeting of anti-poverty programs has greatly heightened during the 1990s.[1] Furthermore, as the availability of world food aid declines, as it has in the 1990s,[2] the importance of effective targeting is likely to increase.

This paper quantifies the factors underlying the allocations of food aid both across and within rural regions by the Ethiopian government, together with local and international non-governmental organizations (NGOs). We focus on "reduced form" specifications in which as little structure is put on the decision rules as possible, because so little is known about these decision rules and their implementation at the village level. The paper examines the degree to which food aid is targeted according to pre-aid percapita household income, child health status, as well as other factors. Data are drawn from three linked rural household surveys in 1995/6, to which we merge information on local rainfall as well as the Ethiopian government's assessment of historical and current food aid needs.

Ethiopia is one of the poorest countries in the world and has suffered two major famines in the past twenty-five years, in 1973 and 1984/5. It has also received enormous amounts of food aid over the past several decades, almost 10 million metric tons from 1984 to 1998, an average of almost 10 percent of national cereal production over this period. In bad production years food aid has been as high as 1/5 of domestic production. In the late 1980s, Ethiopia was receiving roughly 25 percent of all food aid deliveries to Africa, and as late as 1996 was still receiving 20 percent.[3]

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[1]See van de Walle, 1998, for a recent review. Very few studies have tried to infer targeting rules from micro data for safety net or other social programs in developing countries. Recent studies have quantified how subsidies such as for health facilities, school attendance, or food are distributed across income groups (see for example the papers in van de Walle and Nead, 1995; or Pinstrup-Andersen, 1988). Yet most of these studies just show cross-tabulations against income deciles and do not consider other potential factors statistically. Nor, in general, do they examine how safety net programs are targeted across geographical areas (see Datt and Ravallion, 1993, for an exception). Recently, there has been a burgeoning interest in empirical political economy, in measuring how underlying demographic and other factors affect government expenditure and tax behavior (for instance Besley and Case, 1995), or the placement of school or health facilities (Pitt, Rosenzweig and Gibbons, 1993). Few of these examine a specific social safety net program, and certainly not food aid in a developing country.

[2]By the late 1990s food aid quantities had dropped almost in half, to 7 million tons per year, in part because of changes in General Agreement on Tariff and Trade regulations and domestic policies that have reduced agricultural subsidies in some major donor countries, which has in turn reduced surplus production. This and other aggregate food aid statistics come from the World Food Program's (WFP) website at http://www.wfp.org.

[3]During the 1990s, Sub-Saharan Africa has been receiving as much as 1/3 of all food aid delivered in the world (WFP, website statistics).

Given the large amount of food aid coming in to Ethiopia, it is interesting to know whether and how it is being targeted. Developing a measure of need is difficult and controversial and there is no consensus on how to do so. Income is agreed by many analysts to be a very imperfect measure of need, nevertheless is readily available from many household surveys and so it is of interest to examine whether food aid receipt is related to income, or income percapita. Figure 1 demonstrates that both the percent of the value of total food aid of total rural household income (including aid), and the probability that households receive some form of food aid are negatively related to the log of percapita pre-aid income.[4] The share of food aid in total income ranges from 2% to 8%, while the probability of receiving aid varies from near 30% (for relatively low-income households) to roughly 10% (for households at the high end of the income distribution). Since the 1995 cropping year was a good one, it is perhaps surprising that households in the high end of the income distribution nevertheless have a non-trivial chance of receiving some form of food aid.[5]

In addition to targeting by income, there is important targeting by region. Table 1 indicates that the Tigray Region and the north Wello area of Amhara Region received relatively large amounts of food aid in 1995/6 -- five times the national per capita average -- yet do not have abnormally low household incomes or an abnormally large fraction of population in the poorest quartile. In fact, many of the areas of Ethiopia containing the greatest proportion of households in the bottom national income quartile (e.g., parts of the Southern and Oromiya Killils, and the combined "other" Killils) received relatively little food aid in 1995/6. Indicators of severe stunting (very low height for age), an indication of very poor cumulative health of children, and wasting (low levels of weight given height), a more current measure, show that children in Tigray have levels at about the national average (Table 1, columns c and d), although children in North Wello do have much higher levels.[6] We also observe that the current spatial allocation of food aid in Ethiopia is highly correlated with the spatial pattern of vulnerability as determined by the Government during the 1984/5 famine (column e, Table 1), as well as the government's assessment in 1995 (column f, Table 1).

There are several possible explanations for these observations. First, the spatial incidence of poverty and food insecurity in 1995/6 may still be very correlated with that of 1984/5, which would justify a high degree of spatial continuity in food aid operations year after year. We refer to this as the "chronic needs" hypothesis. A second possible explanation, however, is that inertia may exist in program operations, leading to rigidities in the spatial pattern of food aid allocations in spite of potential

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[4]Figure 1 and the other figures in this paper are created using locally weighted smoothed scatter plots (LOWESS, Cleveland, 1979) with window length set at .6 or .7 of the neighboring observations.

[5]The average poverty line in rural Ethiopia for 1995 has been estimated to be approximately 600 birr percapita, a log income of 6.4 (Dercon and Krishnan, 1998).

[6]Child stunting is usually defined to be having height that is less than 2 standard deviations below some reference mark that is adjusted for age and gender. Because the proportion less than 2 standard deviations is so large in these data, we use the proportion less than 3 standard deviations of the reference median (which is also very large). Stunting is widely considered to be a very good marker for cumulative health (Falkner and Tanner, 1986).

differences in the spatial pattern of vulnerability and poverty from one year to the next. This inertia hypothesis was first identified by Clay, Molla and Debebe (1999). There exist several explanations for the potential spatial inertia in food aid distribution. First, fixed costs in program operation may arise in the development of supply channels, organizational structures, and field level infrastructure for identifying vulnerable groups and delivering food to them. In such cases, governmental or non-governmental organizations (NGOs) may rationally prefer not to move their operations, if for example they are interested in minimizing their costs associated with distributing a given volume of food aid to recipients. Governments and donors may find that local food aid authorities differ in their organization and capacity to manage the distribution of food aid, which can lead to spatial inertia in distribution patterns. Moreover, the use of food aid for development purposes creates the need for sustained food aid programs in particular areas, as food is used as the method of payment for multi-year labor-intensive public works projects. A second possible class of explanations involve political economy issues, at both the central and regional government levels. For example, the central government may have regional income transfer objectives which it seeks to promote through food aid allocations.

A high degree of "inertia", i.e. inflexibility in the location and amount of food aid distributed from one year to the next will affect how much targeting is optimal. If, for example, fixed costs is the reason, then presumably the degree of optimal targeting would be lower if needs change frequently.[7] The theoretical literature on optimal targeting rules (Besley and Kanbur, 1988, 1993; Besley and Coate, 1992, 1995; Besley, Coate and Guinnane, 1993; Besley, 1997) explores how optimal targeting rules would vary according to the information authorities have regarding household or individual needs. Papers to date have considered issues of moral hazard.[8] These models are mostly static however, and hence do not consider the implications of having high fixed costs of program establishment. Nor does this point seem to have been raised to date in the small empirical literature.[9]

With respect to food aid, very little multivariate household-level analysis related to targeting has been conducted. Few papers have examined how unconditional food transfers, so-called "relief aid," are allocated, in part because household data on the receipt of such food transfers is usually unavailable.[10] In the case of food for work there have been studies that have examined determinants of household

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[7]Jalan and Ravallion (1998) make the same point regarding targeting poverty alleviation programs when there is a large transitory component to income, as they find in China. They don't consider the possibility of high fixed set-up costs, however.

[8]For instance if one is close to a means cutoff then it may be in one's interest to misinform, or to act, so as to make one eligible. The targeting literature has considered ways to induce self-selection to avoid such behavior, including, for instance, imposing work or other unpleasant requirements, such as mandating that recipients live in a poorhouse, as done in 19th century England.

[9]See Clay, Molla, and Debebe (1999) for an exception.

[10]Reardon and Matlon (1988) discuss regional targeting of food aid in Burkina Faso in the early 1980s. However, their sample has only 3 regions and so they are not able to analyze the factors that underlie the allocations.

participation in such programs (eg. Ravallion, Datt and Chaudhuri, 1993; Datt and Ravallion, 1994; 1995), as we also do, but only a few studies, such as Datt and Ravallion (1993), have analyzed why such programs are distributed across areas in the way in which they are. Furthermore, because of the nature of the data that we use, we are able to examine conditions underlying not only current (i.e. survey year) receipt of food aid, but also chronic use over the past five years. Finally, we are able to measure the importance of past allocation patterns in explaining current period allocations as well as the influence of past assessed needs.

The paper is organized as follows: Section 2 describes institutional aspects of food aid programs in Ethiopia that are especially germane to understanding our specifications and results. Section 3 presents the data sources and sample characteristics for the analysis. The models and variable construction are explained in Section 4. Section 5 presents and interprets the main results of the models. Section 6 examines the determinants of chronic recipients of food aid and Section 7 assesses the degree to which the very strong continuity of food aid operations in particular areas reflects chronic needs versus inertia. Section 8 synthesizes the study's conclusions and policy implications.

2. Food Aid in Ethiopia

Figure 2 plots national production of cereals and of food aid (with different scales).[11] Notice that there is not a close medium-run or even short-run correspondence between the two series. While there is a negative relationship in some years between production and aid, in 1986/7 for instance, in other years, 1987/8, there is not. In the medium-run, cereals production has trended upwards over the 1985-96 period, but food aid did not trend downward until after 1994.[12] This may at first seem strange, in that famine relief needs arguably declined over this period as domestic production rose. However, the rationale for food assistance was gradually expanded in the late 1980s from famine relief to "rehabilitation", or the use of food aid as a wage pool to recruit labor to build perceived useful local infrastructure (Webb, von Braun, and Yohannes, 1992). By the early 1990s, such efforts to "link relief to development" became popularized and integrated into the food aid programs of both donors and the government.

In 1974 the Ethiopian government established the Relief and Rehabilitation Commission (RRC) to monitor the incidence of food insecurity across the country and coordinate food aid activities, including those of international NGOs. In 1985, 48 international NGOs were operating relief projects in the country. In the mid-1990s, 50 were active (Webb and von Braun, 1994). Local church and other organizations have also been quite active historically (Webb, von Braun, Yohannes, 1992).

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[11]The major food aid commodities distributed in Ethiopia are cereals (93%). Wheat in particular constitutes the largest share and accounts for about 84% of the total volume of food aid supplied between 1992-1995. Sorghum and maize account for about 8% and 3% respectively, while oils and fats make up another 3% of the total.

[12]A trend regression of cereal food aid from 1984/5 through 1993/4 results in a coefficient of .017 with a standard error of .054. Clearly there is no trend over this period.

Food aid in Ethiopia has historically taken two major forms: free distribution (FD), which is sometimes referred to as "emergency" or "relief" distribution, and food for work (FFW), sometimes referred to as "development" food aid.[13] We briefly describe the policy objectives and implementation of these two food aid types.

Free Distribution

FD programs in Ethiopia distribute cereals and cooking oil directly to households.[14] Food aid allocations are made in two stages: from federal authorities to *weredas* (which are roughly akin to a county) and then from wereda authorities to households. The administrative mechanisms used at each level are distinct (Sharp, 1997). In the first stage, the wereda administration determines the number of households "in need" within each wereda.[15] These assessments are forwarded to the zonal, then regional, and subsequently federal-level Disaster Prevention and Preparedness Commission (DPPC). Based on the supply of food aid pledged by donors, and its own field-level assessments, the DPPC then modifies (usually downward) the number of households to be allocated food in each region.

The second stage of selecting beneficiary households occurs after wereda-level allocations have been determined. According to the Government's National Policy for Disaster Prevention and Management (TGE, 1993), local-level responsibility for selecting food aid beneficiaries lies with the wereda administration, but implementation is actually carried out by elders and community representatives at the Peasant Association (PA) level. Individual Peasant Associations take on the task of preparing lists of beneficiary households for approval by the wereda council. PAs are urged to use a set of selection criteria to determine which households are eligible, including livestock ownership, grain production, assets, income, and housheold size (Sharp, 1997), but the control is theirs'; neither the DPPC nor NGOs have control over selection of beneficiaries.[16]

Food For Work

Ethiopia's official food aid policy states that no able-bodied person should receive food aid (food for work) without working on a community development project in return. This is complemented by

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[13]A third form, cash for work, has been used only sparingly in Ethiopia and is not addressed here. Also, so-called program food aid, which is food that is sold on local markets (not directly given to households) for local currency which is then used for general budget support, has not been much used in Ethiopia.

[14]During the 1984/5 famine camps were set up at which food aid was distributed. Now food aid goes directly to permanent villages.

[16] The exact criteria used to determine "needs" could not be clearly established through liaison with DPPC, and interviews with local officials indicated that the process is to some degree vulnerable to differences across weredas in the determination of neediness.

[16]There is little attempt to self-target relief food aid, i.e., provide foods that will be eaten predominantly by the poor, as was the case, for instance, in Mozambique in the early 1990s when food aid consisted largely of yellow maize, a staple of the poor (Tschirley, Donovan and Weber, 1996). Wheat, the predominent grain distributed as food aid in Ethiopia, is considered a normal good in both rural and urban areas (Kebede, Jayne, and Tadesse, 1998).

targeted free food aid for those who cannot work. The official goal, as described above, is to expand work-based food aid to the point where it accounts for 80% of all distributions (WFP 1995).[17] Food for work programs are used to build community assets such as roads, bunds, and dams, although in principle, they are also targeted to the most vulnerable areas to alleviate hunger.

FFW programs have operated under widely differing rules (Sharp, 1997). In some cases self-targeting has been used, by which households decide whether to send members to work at the offered food wage. Typically a given project pays a constant daily food wage, not differentiating by the human capital of workers (Sharp, 1997). In the past, offered wages have typically been higher than local market wages (Webb, von Braun and Yohannes, 1992; Sharp 1997), which should result in much less income targeting than in a low wage regime. The justification for providing in-kind wages that are higher than local wage rates for manual labor is that poverty is endemic in many rural areas, so that targeting is implicitly not needed, plus a concern that a "livable" wage be paid. However, programs in other areas have targeted FFW opportunities more narrowly to specific types of households. In these schemes, a local community group chooses households who will be eligible for participation based on some underlying criteria, such as land size, livestock, and other asset ownership (Sharp 1997). In some cases there is *de jure* rationing of either spaces (restricting the number of eligible participants per household) or time allowed per person.

Flexibility versus inertia in spatial allocation of food aid

Emergency or relief food aid is programmed annually, and is designed to respond to changes in the spatial incidence of vulnerability from one year to the next. Both Canada and the US make pledges of their emergency food either through WFP or directly to DPPC. By contrast, all development food aid (i.e., FFW) essentially is programmed on a multi-year basis in selected areas designated for development projects. Such development-oriented food aid is typically programmed with a five-year time frame, in which the amount of food targeted for recipient weredas is based on the amount of work-days needed to accomplish the task. Ostensibly, in light of greater efforts to use food aid to simultaneously meet both relief and development objectives, the selection of recipient weredas is also based on vulnerability and need. The nature of the activities of the sponsoring NGO influences how flexible they are in moving from one area to the next according to need. For example, Lutheran World Federation specializes in using FFW for soil and water conservation investments, which means that they are able to relocate their operations relatively more easily and within a shorter time span than most other NGOs that tend to be involved in “integrated area development” activities in specific weredas. In general, however, we hypothesize that there is considerably less flexibility in targeting vulnerable weredas and households

[17] However, household-level data show that, of the total kilocalories of food aid received nationally over a full twelve-month period in 1995/96, only 35% involved work on development programs (Clay, Molla, and Debebe, 1999). During the period January-May, 1996, the Disaster Prevention and Preparedness Commission (FDRE 1996) reports that 63% of the relief food was distributed through employment-generating schemes.

through FFW operations than FD programs, i.e., a greater degree of inertia in response to changes in spatial incidence of vulnerability.

3. Data Sources and Samples

The data come from three sources: the 1995/6 Annual Agricultural Sample Survey (ASS), fielded by the Ethiopian Central Statistical Authority (CSA); the Food Security Survey (FSS), fielded on a subset of ASS households in 1996 by the CSA and the Grain Marketing Research Project; and the 1995/6 Household Welfare Monitoring Survey (WMS), fielded on a sub-sample of the ASS households by the CSA, with World Bank support. In addition, monthly rainfall data are taken from 40 rainfall stations distributed throughout Ethiopia and matched to the locations of the household samples. We also use annual wereda-level estimates of the population in need of food aid assistance in each wereda as derived from the administrative procedure described in Section 2. The 1995/6 Agricultural Sample Survey uses the same frame of enumeration areas (EAs) as used to conduct the 1994 Population Census. Some 612 rural EAs are sampled out of roughly 60,000, with probability proportional to population size.[18] In each of the EAs, 25 households are randomly selected, for a total of 15,374 households. Out of these, 7 are randomly sampled to be in the Food Security Survey, some 4,112 households total.[19] The Food Security Survey collected detailed information regarding amounts of food aid received by each household, plus other information. The Welfare Monitoring Survey collected data on a 50% sub-sample of the ASS households, and overlapped with the FSS survey as well, forming the basis of our ability to link the three surveys. Among other information, weights and heights of children under 5 years old were collected, information which we will use. Of the households in the three surveys, we drop 86 because they are in one region, Afar, for which rainfall data was unavailable (Afar households are mostly pastoral households), another 71 which are in a similar pastoral region, Somali, and another 8 because of gross outliers in income.[20] Further, out of the roughly 25 ASS households per EA, 15 are selected for the collection of detailed field-crop information, including actual measurement of fields and cutting and weighing of crops from the Meher (main) season.[21] Since the income variable that we use is constructed from field cutting data, for reasons detailed below, our analysis sample is constrained to the field cutting sample. Of the 3,823 cropping households in the Food Security sample, 3,244 have field cutting data for

[18]Some 8 EAs were dropped because of security and accessibility inadequacies. In Ethiopia, each EA normally contains from 100-200 households.

[19]Actually, out of the FSS households, 126 are *not* in the ASS sample, for reasons that are not documented. They are more likely to be female headed, with half the land owned and a much greater likelihood of receiving food aid compared to the 3,823 households in both FSS and ASS.

[20]We dropped households with gross incomes per capita less than 3 or greater than 20,000 birr.

[21]The cuttings are taken from a randomly selected 16 meter^2 area within each chosen field. The yield estimate is blown up to a field production estimate using the actual field size measurement.

their Meher crops. A further 377 households have missing crop cut information on at least some of their fields, resulting in a final sample size of 2,796 households.

Receipt of food aid is measured for each household in the Food Security Survey. For the past year the respondent is asked whether at least one member of the household participated in the food aid program. If yes, the type of program as reported by the household is recorded, separating free distribution from food for work, and by type of commodity received.[22] If aid was received, for each month from June 1995 through May 1996 the quantities received were recorded. These were then turned into values using local market purchase prices. Thus all the food aid variables are at the household level.

Free food was distributed in roughly 27.5 percent of weredas, and FFW programs operated in 21.5 percent of weredas over the recall period. However, only 13 percent of households report receiving free food and only 10 percent took food under a FFW arrangement. On average, about 40 percent of households receive FD or FFW in weredas that receive food aid. However, as shown in Table 1, both the proportion of households receiving aid, and the amounts received, vary substantially across zones.

4. Empirical Models and Variable Construction

Empirical Models

Evidence cited in Section 2 is consistent with a two-stage process in allocating food aid: first, aid is allocated across regions and weredas by the Ethiopian government at its various levels, and second, based on amounts to be allocated to each area, beneficiaries are selected by local village committees. Furthermore, in the case of FFW, households must decide whether or not to work in exchange for the food ration depending on their other labor opportunities. For FD, only stigma would prevent a household from accepting food, which seems unlikely in the context of areas in which food aid is endemic. These considerations suggest that estimation should be stratified by FD and for FFW, and that further, a two-stage estimation strategy be used in which first we explain allocations across local areas, corresponding to government decisions, and then within these local areas, corresponding to village leaders' decisions. The level of local area aggregation that we use is the wereda, a local political unit akin to a district with population sizes that vary from under 20,000 to 200,000 (for further detail, see Clay et al., 1999, and Sharp, 1997). Furthermore, since the bivariate descriptive figures presented in the first section suggest that the impacts of conditioning variables differ between whether households or villages get aid and how much they get, we use a hurdle model which distinguishes any receipt from how much. We use probits to model whether communities or households receive aid and a two-part model to examine how much food aid weredas receive, conditional upon receiving.[23] Thus, for both FD and FFW, we use probits to

[22]Households tend to report more free food, relative to food for work, than is supposed to be the case according to government plans (Clay et al, 1998). However, anecdotal field reports indicate that food that was supposed to be distributed in return for work was in many cases actually distributed freely, with no work obligation imposed. Consequently it seems reasonable to use the household's assessment of whether they explicitly worked for the food received.

[23]We don't feel that we have plausible identifying information, so we don't attempt any selection corrections.

analyze which weredas receive such food aid and OLS to examine the average value per household. We do the same at the household level.

For each of the probit and two-part model regressions at the wereda level, we use a specification in which observable wereda variables are used together with dummy variables at a more aggregate region level, the killil. For the household-level regressions we use a specification with household level covariates together with wereda dummy variables. Thus in these regressions, only households living in weredas in which the food aid distribution among our sample households is incomplete (between 0 and 100 percent) get used.[24]

In the case of food for work, participation by a household requires that a FFW project is present in the community and the household must send an individual(s) to work. If there are no binding hours constraints, then a simple income maximization model can be considered in which a household will send one or more members to work for food, at an implicit wage of w, if the person's shadow wage in home work, w^*, is less than w. Thus observables used as covariates should be ones that help explain the potential market wage or the shadow wage. Unfortunately the survey did not record which household members worked for food aid, so that the analysis has to be done at the household, not individual, level.

Covariates

Since we have little ex-ante insight into the nature of allocation decisions, we use a variety of covariates at the community and household levels that are likely to be exogenous to these decisions and that may be known to government and NGO officials. We divide these into variables that attempt to measure household resources, child health, household demographics, community accessibility, community long-run agro-climatic potential, and short-run weather shocks, in both the wereda-level and household-level models.

Household Resources

The household resource variables we use are whether the head of household has any schooling, the amount of land owned, and the log of household gross income percapita.[25] For the wereda analyses, wereda means are included for each of these covariates. Gross income is the sum of production value for food crops in the 1995 Meher growing season (harvest typically being from September through December) taken from crop cuttings;[26] plus self-reported production value in 1995 for non-food crops such as coffee (no field cuttings were taken for these crops); plus 20 percent of the value of livestock as

[24]Finally, we also run upper-censored tobits on the percentage of households within each wereda that receive food aid, including weredas in which all sample households are recipients. We do not report those results as they are quite similar to the household-level probits that use kill-zone, not wereda, dummy variables.

[25]Schooling information is only available for the household head in both the Agricultural Sample Survey and the Food Security Survey. Unfortunately no health outcome information is available in these two surveys.

[26]Self-reports are also available, however CSA considered the crop cut data to be more reliable. This is because self-reports of production are reported in many different local units, and to convert into a common unit such as kilograms, one has to use CSA gathered conversion factors of uncertain reliability.

an approximation to livestock gross income; plus an estimate of off-farm cash income contributed by each household member over the past year prior to the survey.[27] Free food receipts and food for work payments are not included in this measure, since we will be attempting to explain them.

It is arguable that income may be endogenous, if food aid has health effects which help to make workers more productive. Further, the impacts of several of our other covariates may well work through income. For this reason we run alternate models excluding income to check the robustness of the other covariates.

The top two panel graphs of Figure 3 show how the probability of receiving food aid vary with the log of percapita income, while the bottom two panels show how percapita amounts received (conditional on positive receipt) vary with the log of percapita income. The left-hand panels graph the relationships at the wereda-level and the right-hand panels for households. The household-level graphs are conditioned on living in weredas that have some sample households that receive aid (unlike Figure 1, which is unconditional). One can see that wereda participation rates are declining in mean log percapita income for both FD and FFW, with the free distribution receipt probabilities being higher than those for food for work by just over 5 percent, across the distribution of mean incomes. Percapita amounts received are also inversely related to mean log percapita income for free distribution, but are constant for food for work. At the household-level, the FD and FFW participation curves are almost identical. They display a gentle negative slope until a log-percapita income of around 6, corresponding to just under the 60th percentile, but then participation drops off much more steeply for households with higher log percapita incomes. The amounts received percapita by households fall off with log percapita income for free distribution, but not for food for work. Figure 3 strongly suggests that the probability of receiving food aid is linearly related to our log income measure at the wereda level. We use this fact to justify our linear specification used in the regressions. However, these bivariate figures indicate, especially for food for work at the household level, that non-linearities may be important. We explore these possibilities in the empirical work as well.

Child Health

We standardize the child height and weight measures for children between 6 months and 5 years, using WHO standards and calculate z-scores for height given age and sex and for weight given height.[28]

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[27]We cannot calculate net incomes since we do not have information about the quantity (and value) of family labor. Cash expenses are negligible; only 10 percent of households hire labor for their Meher crops (and much less for the Belg season) and we do not have expenditure data for hired labor in any case. Some 30 percent of households use fertilizer, however the average value used is only 61 birr per household, compared to 2326 birr of household gross income. Netting out fertilizer costs makes no difference in our results; the correlation between the log of percapita incomes, netting out chemical fertilizer and not, is over .99. Netting out fertilizer costs only changes the income coefficients in most cases to the third decimal place, ie. from -.102 to -.103 in Table 2, column 1.

30 Z-scores are often used in making anthropometric calculations; they measure the number of standard deviations (in the reference population) that the height is from the median height (again in the reference population) for a given age in months and gender of child. A similar calculation is made for weight standardizing on height and gender.

At the household level we calculate whether any children have a height for age z-score under 3 standard deviations below reference standards, a measure of severe stunting, which reflects very poor cumulative health of the child. For weight for height we use a 2 standard deviation cutoff, which is the normal cutoff used internationally to measure wasting, a more current health measure.[29]

At the wereda-level, we calculate the proportion of children measured that have height for age z-scores less than -3 and separately the proportion of children with weight for height z-scores under -2. Since the sample sizes of children in some weredas is quite small, we aggregate and use zone (there are 52) as the level at which we calculate these sample fractions.

The degree of severe stunting reported in the WMS is extremely high (Table 1), however the levels are not out of line with other surveys in Ethiopia.[30] The fraction of children with low weight for height, wasting, is high, but not so extreme.

Household Demographics

We control for household size and the proportion under 9 years and over 55. We also allow for dummy variables if the self-reported head of household is a currently unmarried woman, or a married woman. We also allow for dummy variables if the head is moslem or protestant (the omitted category being Ethiopian Orthodox, the major religion in the country). These are included to explore the possibility of religiously-based discrimination in food aid allocation that is sometimes anecdotally reported in some areas.

Community Access and Agro-climatic Covariates

Community access should be related to the cost of providing food aid. Ethiopia has notoriously poor infrastructure. We have GIS data at the wereda level as to whether certain types of roads are present, from paved roads to dirt paths. Consequently we use five dummy variables, road type 1 being the best conditioned road, followed by type 2, 3 and so forth. We also know wereda-level mean elevation (in meters), which will be related to agro-climatic conditions and possibly to accessibility. Elevation readings were taken using the Global Positioning System, a satellite-based system to take such readings.

Rainfall is a critical factor related to cereals production in Ethiopia because farming is almost entirely rainfed. Drought-induced production shortfalls and consequent large cereals price spikes were major causes of the 1984/5 famine in Ethiopia (Webb, von Braun and Yohannes, 1992). We have available median Meher season planting rainfall (in millimeters) from 1988 through 1995.[31] These were

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31 In the regressions, we also use dummy variables set to one if the household have no children covered in the Welfare Monitoring Survey and another set to one if the household has children but their measurements were unusable.

32 For instance, longitudinal data from a rural household survey collected by Oxford University, Addis Ababa and the International Food Policy Research Institute show similarly high levels (World Bank, 1998). Remember that Ethiopia is among the very poorest countries in the world, ranked 210 in income percapita by the 2000/2001 World Bank World Development Report (World Bank, 2000).

[31]These years were chosen because earlier years had many missing observations for many stations.

derived by summing April through August rainfalls for these years from data collected by 40 rainfall stations of the Ethiopian National Meteorological Services Agency. Each sample zone (an area whose size is in between a wereda and a killil) was matched up to the closest rainfall station, provided there was at least one in the area. In rural Ethiopia long-run cropping season rainfall is related to wereda mean log percapita income levels (see Jayne, Strauss, Yamano and Molla, 2000).

Weather and Other Shocks

We use two types of weather shock covariates. First we use our rainfall data and compute the differences between Meher rainfall in 1994 and 1995 and the longer run median. We use both 1994 and 1995 because our food aid receipt variables cover the period from June 1995 through May 1996. Crop income from 1994 would be relevant needs criteria for food aid allocations up to at least the middle of 1995, while income from the 1995 crop year would be relevant in considering food aid allocations in late 1995 and 1996.

We also have available plot-level information from the Agricultural Sample Survey regarding whether a plot suffered damage from too little rain, too much rain, or from pests and diseases. We construct three variables that measure the percent of household or wereda field area so affected. These plot-level "shocks" are only available for the 1995 Meher season, so we can't infer changes from them. We can tell how a particular household fares relative to the wereda average in 1995, but some part of the "shock" may in fact be predictable. Controlling for the wider area rainfall shocks (that are deviations), one should interpret the plot variables as being roughly the impact of variation within zones, because only a small part of the variation in the plot-level drought variable is related to the community long-run and deviation rainfalls.[32] Hence there is much independent variation of these plot-level shock variables.

Food Aid History

As emphasized in the introduction, one of the central concerns of this paper is the extent to which current allocations depend on past allocations, and if so, why. While the data are cross-sectional, we have two sources of information on past food aid allocations: one direct and one indirect. In the Food Security Survey questionnaire, respondents were asked whether they had received free food or food for work in the past year, as well as the number of years they have received either of these types of food aid in the four years prior to 1995/6. We create a series of dummy variables if the household was a recipient during one, two, three or four of the prior four years and use these to represent recent historical patterns of food aid allocation in some of our specifications. At the wereda level we take the maximum number of years out of the prior four that some sample household received food aid and create a similar dummy variable, separately for free distribution and food for work.

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[32]A regression of percent of area affected by too little rainfall on the these other rainfall variables, plus elevation, road type dummies and killil dummies has an R^2 of only .25. The coefficients on long-run rainfall and on deviations in 1994 and 1995 are -.0108 (t=5.4), -.0079 (t=3.1) and -.0136 (t=5.8) respectively. Regressions of the percent of area affected by too much rainfall or by diseases or pests on these same covariates have much lower R^2s, .047 and .014 respectively.

Insights on near-historical distribution patterns can also be obtained by calculating which weredas and households have received food aid for three or more years out of the five years prior to the survey (including the 1995/6 survey year). We refer to these households and weredas as "chronic recipients," and form binary dependent variables from them, which are analyzed in Section 6. Some 13.5 percent of weredas are chronic recipients of free food over the period 1991/2 to 1995/6 and 9 percent are chronic recipients of food for work. Among households in these chronic recipient weredas, 31.5 and 19.8 percent are chronic recipients of free food and food for work respectively.

5. Results

Regional and Community Allocations

Probability of Receiving Food Aid

We begin with a discussion of the characteristics of weredas that received the different types of food aid in 1995/6. Table 2 provides the basic results.[33] We start, in columns 1 and 4, by reporting the simple probits using only the killil region dummies. One can immediately see that Tigray Killil has a much higher probability of receiving food aid than any other region, and significantly so, the differential being especially high for free distribution.

In columns 2 and 5 we add the observable wereda mean characteristics, plot shocks, and agro-climatic covariates. The mean log of percapita income has significantly negative effects on participation, both for free food and for food for work. Increasing wereda mean log percapita income from the 25th (5.5) to the 75th (6.2) percentile would decrease the probability of receiving free distribution from 29.5 percent to 24.3 percent.[34] For food for work the predicted reception probabilities decline from 24.7 to 16.7 percent. And yet the predicted probabilities of receiving free food or accepting food for work when mean log percapita income is 6.6 (the 90th percentile), are still substantially above zero, 21.9 and 13.5 percent respectively. Thus, although there is definite income targeting with respect to the weredas that are allocated food aid by the federal government, targeting is very incomplete, i.e., there is only a moderate difference in the probability of being a recipient across fairly large differences in income. No targeting is apparent with respect to education of household heads or to mean land owned.

One reason why predicted wereda participation probabilities may not decline more as mean log incomes increase is that there are still numerous households within the weredas with low incomes. That is a given wereda may have a lot of poor households. To test this more explicitly, we replace the mean log percapita income with a variable measuring the fraction of wereda households falling under the 20th percentile of percapita income nationally. While we could use a more standard poverty line such as $1

[33]We report the marginal probabilities, and asymptotic normal statistics. For dummy variables, the "marginal" probabilities are calculated from discrete changes in the dummy variable, holding other variables constant at their sample means.

[34]These probabilities are calculated as the mean over all sample points after changing the log of each wereda's mean log percapita income to the appropriate amount (ie. 5.5 for the 25th percentile). We use the same method to calculate expected probabilities for other covariates.

per day, that would result in a large fraction of households being below it and so would not be very discriminating. The results, not shown, are almost the same as in Table 2 on non-income coefficients. The marginal probability of this poverty measure is .20, with a t-statistic of 1.47.

Separately from income, the proportion of children with severe stunting or wasting have independent impacts on the receipt of free distribution, but not on food for work. For height for age, increasing the fraction of children in the zone with z-scores under -3 from the 25th to the 75th percentiles raises the predicted probabilities of receipt of free distribution from 23.0 to 32.1 percent.[35] Moving from the 25th to the 75th percentiles of zones ranked by the weight for height variable raises predicted receipt probabilities from 23.1 to 30.5 percent. The absence of a measurable impact of either height for age or weight for height on the allocation pattern of food for work may reflect distribution criteria being based on "economic development" criteria, although these would be development criteria that don't include healthiness of population or the long-term economic development effects of poor child health.

Median Meher season rainfall from 1988-95 is negatively (significant at the .05 level) related to the chance of weredas receiving food aid, even controlling for other observables. The mean of median Meher rainfall across weredas is 843mm, a fairly high amount. There is a great deal of dispersion, however, for instance the 25th percentile is 672mm and the 75th percentile, 1047mm. Changing median long-run rainfall from the 25th to the 75th percentiles lowers the average probability of a wereda receiving free distribution by 9.3 percentage points, to 21.7 percent. For food for work average probabilities are lowered from 25.3 to 15.2 percent. So there is some targeting of food aid by long-run regional rainfall levels.[36]

The zone-level rainfall deviation variables (for 1994 and 1995) are not jointly significant in either the free food or food for work case, although rainfall shocks in 1995 has a negative marginal probability almost identical to that on long-run rainfall for free food, and it is significant at the 10 percent level.[37]

Of the plot-level shock variables, farmer reports of having too little rain is positively related to both free distribution and participation in food for work at the wereda level and reports of too much rain are positively related to receiving food for work, each significant at 5%. Moving from the 25th to the 75th percentiles of the plot drought variable raises the probability that a wereda would receive free

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35The 25th and 75th percentiles of the fraction of children 6 months to 5 years with height for age z-scores under -3 are .44 and .54 respectively. For weight for height z-scores under -2 the 25th and 75th percentiles are at .072 and .097.

[36]Quadratic terms, when tried, were only significant when history variables are added. They are not reported here.

[37]We experimented with quadratic terms in both rainfall shocks, thinking that larger shocks might elicit a larger response. In the case of free distribution that turned out to be the case for the 1995 shock, but the opposite held true for the 1994 shock. The marginal effects are 5.73e-5 (z-statistic of 0.28) and -6.07e-7 (z-statistic of 1.86) for 1995 and -3.5e-4 (z-statistic of 1.10) and 1.21e-6 (z-statistic of 1.71) for the 1994 shock. The joint chi-square statistic is 10.32, which is significant at the .05 level. For food for work, the rainfall shock variables remain not jointly significant at standard levels, a chi-square statistic of 5.65 with 4 degrees of freedom.

distribution from 24.4 to 26.7 percent The disease and pest shock variables do not significantly affect food aid receipt. Food for work probabilities increase from 18.0 to 20.5 percent across the interquartile range for the drought shock variable and from 17.4 to 20.4 percent for the flood shock variable. The fact that these are small changes in the odds of wereda participation stems in part from the fact that the interquartile range for drought problems is small, from 0 to 7.5 percent of area.

Specifications were tried that included interactions between long-term rainfall and the two rainfall shock variables and separately, between long-run rainfall and plot-level shocks. None of these proved jointly significant. In addition, we interacted mean wereda percapita income with each set of shock variables, separately. Neither was close to significant in the case of rainfall shocks,[38] while plot-shock-income interactions were jointly significant at the .05 level for free distribution.[39] The major effect is that the impact of flooding on receiving aid is greater for higher income weredas.

Among other covariates, elevation is positively (and significantly at the .10 level for free distribution, at the .05 level for food for work) related to receipt of food aid, but the road dummy variables tend not to be significant. The interpretation of the elevation variable is not straighforward, but may be related to the fact that highland areas tend to suffer from greater land degradation and population pressure compared to lowland areas and, as a result, tend to be more intensively targeted in food assistance programs.

The Tigray marginal probability is almost unchanged for free distribution when covariates are added, and actually increases for food for work. One can conclude that these observable covariates do not help explain why weredas in Tigray (and the small “other regions” category) are so likely to receive food aid. As shown in Table 1, per capita incomes in Tigray during the survey year were actually 12 percent higher than the national average, only 15 percent Tigrean households fell into the bottom national income quartile, and the incidence of child stunting and wasting are comparable to the national averages.

Once we control for the wereda's recent history of receiving food aid, which we do in columns 3 and 6 of Table 2, the regional effects lose their explanatory power in the case of free distribution. The Tigray "marginal" probability falls from .5 to .1 and loses statistical significance. In contrast, the Tigray effect on food for work shrinks only a little and remains significant at the .10 level. Marginal impacts of being in other regions also shrink towards zero for free food, except for Amhara, which becomes more negative.

The history dummy variables have extremely large "marginal" effects that swamp all else. The single most important factor determining current year probability of receiving aid is how commonly it was received in the past. Interestingly, the "cross-program" effect (e.g., the change in marginal probability of receiving free food resulting from receiving food for work in the past) is positive and

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[38]Chi-square statistics testing the two interaction terms jointly are 2.05 and 0.97 for free distribution and food for work respectively.

[39]The chi-square statistic for those three interactions is 9.55.

significant at the .01 level.[40] The pattern of allocation by government indicates that it does not view the two programs as substitutes.

The interpretation of these "own" and "cross" program effects is tricky because these history variables are effectively lagged endogenous variables. One can usefully think of the problem as one of separating the impacts of unobserved heterogeneity from history, or state dependence (see, for instance, Heckman, 1981). Equation 1 is a prototype example in which the regression includes a lagged dependent variable, $Y_{i,t-1}$ while the unobserved error term includes a part, μ_i, which is time-invariant, but differs by

$$Y_{i,t} = Y_{i,t-1}\alpha + X\beta + \mu_i + \varepsilon_{i,t} \qquad [1]$$

weredas or households and a part, ε, that is independent over time and across weredas.[41] The problem is that $Y_{i,t-1}$ is correlated with μ_i, though it is independent of $\varepsilon_{i,t}$, so that OLS (or simple probit) estimates of α are inconsistent as estimates of the true history effects, so long as μ exists. Another way of looking at the problem is that our usual estimates of α can't distinguish between whether the impact of $Y_{i,t-1}$ represents a true history effect or the effect of the omitted unobserved heterogeneity term, μ_i. The error component μ_i can usefully be thought of as arising from time-invariant unobserved variables at the wereda (or household) level, such as may be related to long-run neediness. Real effects of $Y_{i,t-1}$, can be usefully thought of as representing inertia. From these probit results we unfortunately can't distinguish between the two, although later we will use what we consider to be good proxies for μ_i in an attempt to do so.

Note that the income and average rainfall variables that had significant impacts in our earlier specification are no longer significant and have marginal effects that shrink to practically zero, particularly in the free distribution equation. However, the child health variables in the free distribution equation and the plot-level shocks in both FD and FFW probits maintain the magnitude of their marginal impacts (or shrink slightly) and their significance levels. This finding is important because it implies that even controlling for past receipt of aid, having extremely poor child health and plot-level water shocks will increase the chance of an area remaining an aid recipient. This implies that despite history, some flexibility exists in the case of free distribution. But the magnitude of these impacts are small compared to the effects of historical receipt on current food aid allocation.

Values of Food Aid Received by Weredas

In addition to exploring whether weredas received food aid, it is of interest to explore the determinants of how much food aid was received per household. The decision rules applied may be quite

[40]We have tried disaggregating the food for work history dummy variable in the same way as we do the free distribution variables, when estimating the free distribution receipt probits (and visa versa), but it does not make much difference.

[41]When we analyze households with wereda fixed effects, the fixed effects will capture any wereda-level unobserved effect. However, there may be unobserved household-level effects that remain.

different than the ones used to determine whether a wereda should receive any aid. For example, if the fixed costs of moving aid programs across weredas is very high, one wouldn't expect programs to move rapidly as new information, such as on new rainfall shocks, became known. However, it is plausible that fixed costs related to changing throughput may be less, especially for reducing throughput. Consequently it is possible that the impact of shocks, even conditional on past history may be larger for the amount of aid per household than it is on the probability that weredas are dropped or added to the programs.

In this analysis, we exclude weredas that received no food aid because we want to concentrate on the decisions made regarding amounts, which as discussed in Section 2 seem to differ from those having to do with who gets any. Table 3 contains the truncated OLS results for free distribution and food for work respectively. The table is organized similarly to Table 2. The sample sizes are small, and hence nothing is estimated with precision. Indeed F-tests of all coefficients jointly passes at just under and just over the .10 level for free distribution and food for work respectively. Among the individual coefficients that are significant at the .10 level, mean wereda percapita income negative affects the value of free distribution received percapita, while a higher proportion of elderly positively affects the value of FF received. Having more area affected by diseases also raises the amounts percapita that are received. In the case of mean income, a large change, from the 25th to the 75th percentiles, would lower the mean percapita value received by approximately 15.4 birr, just over 60 percent of the 24.9 mean percapita value of free distribution received in the 96 weredas that receive FD. A shift equivalent to the interquartile range in the percent of area affected by disease would increase mean value of free food aid received by 13.5 birr, also a substantial amount. For food for work, increases in rainfall in 1995 above the 88-95 median actually raises the value coming in. Interestingly, differences in child health and historical allocation patterns among weredas receiving aid have no relationship to how much free food or food for work is received now.

Household Allocations Within Weredas

We now turn to the allocation of food aid to households within weredas. We condition these samples on weredas that have some food aid of the same type available in the same year. This is done to identify the inferred criteria driving allocations within weredas, which, as discussed in Section 2, are made by local committees, not by the central government. Of the households in these weredas, only 40 percent received free distribution and 40 percent food for work. As before, we model receipt of food aid separately from the value received.

We report two specifications. Both contain wereda level dummy variables or fixed effects. One does not contain *household*-level history variables and one does. Because we include wereda fixed effects, in the probit regressions this means that only weredas in which household participation is incomplete are used in the estimation Of course, this is not true for the 2-part OLS regressions for the value of aid received.

Probability of Receiving Food Aid

Table 4 contains the probit results for the probability of a household's receiving food by free distribution and for work. Higher household percapita income reduces the chance of receiving free distribution but has little impact on receiving and accepting food for work. Households at the 25th percentile of national log percapita income have an average probability of 37.5 percent of receiving free food and this falls to 28.9 percent at the 75th percentile. It remains relatively high, at 25.1 percent at the 90th percentile.

The negative income effect for free food remains significant and its magnitude unchanged when history variables are added. The results generally indicate that income targeting does play an important, but incomplete role in allocating free food to households. In the case of food for work, income does not affect households' decisions to participate in food for work programs should they be operating in the area.

Education of the household head also has a negative impact on households receiving free distribution, independent of income. Education of the household head has a much smaller, and not significant, independent effect on receiving FFW. Households with a higher proportion of children are more likely to obtain free food, as are protestant households. However, household size and having an unmarried female head are only weakly (negatively and positively, respectively) related to the probability of getting free food and child health is not related at all. Households with more elderly members are less likely to engage in food for work.

None of the shock variables are related to the distribution of free food and only having disease or pest problems is related to food for work participation. With wereda fixed effects included, we have a good test of whether free food aid is being used to insure against idiosyncratic plot-level shocks. The fact that we don't observe significant plot shock impacts suggests that this form of aid is not being used for insurance purposes. On the other hand, these results are holding current income constant. However, when income is removed from these regression (Table A.1), still the plot level shock variables are not significant.

Instead of insuring against negative weather or pest shocks, the results indicate that food aid, particularly food for work, is going to households that received it chronically, for all 4 years in the prior 4 years to 1995, possibly reflecting long-run need. On the other hand, households that received aid only once or twice in the past 4 years are *less* likely to receive it now (remember that this is in weredas in which some, but not all, households receive aid). This suggests cycling over time of households getting aid, but that is cycling unrelated to the covariates that we are controlling for. This, in turn, suggests that there is some flexibility of inter-year distribution within weredas.

Values of Food Aid Received By Households

Table 5 contains the 2-part OLS results for households living in weredas participating in food aid programs. The major result, for both free distribution and food for work value received is the very strong negative relationship with household size. Within weredas, adding one person (in the age proportions as

currently exist) lowers the value of free distribution by 11.8 birr percapita. Remembering that the average value of free food consumed among those that receive it is 18 birr, this is a substantial impact. For food for work, the magnitude of the effect is smaller, 4.8 birr less for every additional household member, but is still highly significant.[42]

The negative impact of household size on food aid within weredas is intriguing. The Sharp Report (1997) suggests that for food for work, there sometimes may be constraints in the *dejure* rules whereby only one member per household is allowed to work. To test for this we re-run the food for work 2-part regressions, but using total value of household food for work as the dependent variable instead of percapita value. This turns the household size coefficient positive, still significant at the .05 level when wereda dummy variables are used.[43] Hence larger households receive more food for work aid, but less percapita.

The plot-shock covariates are never significant in these regressions; the F-statistics are 0.6 for free distribution and 0.5 for food for work. Hence there is no evidence that local authorities use food aid as local insurance to help households who have suffered transitory losses.

The coefficients on the history variables differ from the wereda results. The group coefficients are jointly significant only in the case of food for work, although the coefficient for receiving in all of the last four years is significant in the free distribution equation. The magnitude is only large if the household has been a chronic receiver of food aid (in three or four of the past four years), in which case food for work increases by between 23 and 35 birr per year.

Robustness Checks

As mentioned, there is an issue of the potential endogeneity of current income. Several of our measured covariates may work through income, and thus have their impacts be understated when income is included. As a check we run the regressions without income, for both the basic wereda and household probit specifications. We add the value of animal assets owned at the time of the survey (including (including cattle, sheep, goats, poultry, pigs, donkeys, and horses) to measure resource availability. The results are reported in Table A.1. As one can see, coefficient estimates are remarkably similar to those of the base specifications, so it would appear that endogeneity of current income is not such a problem in this case.

6. Chronic Participation

The results so far infer factors associated with *current* participation in food aid programs. We can actually do somewhat more. While we don't have panel data, we do know whether households received free food or food for work in the four-year period before June 1995, and how many years out of

[42]A quadratic term in household size is significant in the food for work truncated regressions. The shape of the relationship is negative and convex.

[43]Then log of percapita income coefficient becomes more negative and is significant at the .10 level.

that period. We can therefore analyze factors associated with past participation and whether the household (or wereda) is a chronic participant. Chronic recipients of food aid may be at risk of becoming dependent on aid, changing their behavior significantly.

For this analysis we define chronic use as a wereda or household that has received aid for 3 or more of the past five years. Table 6 contains the probit results for both weredas and households. At the wereda level, we see that there is a strong Tigray effect on chronic receipt of free food. Of the 47 sampled weredas that were chronic recipients of free food, 30 of them are in Tigray. The probability of a wereda being a chronic recipient of free food is increased by 60 percentage points for weredas in Tigray. Smaller but significant regional effects are observed for Amhara and other non-South killils. These findings are consistent with either the inertia hypothesis or the chronic needs hypothesis, or both. However, no such regional effects are observed for food for work. Remember that there is a significant Tigray effect on current year food for work, which suggests food for work is becoming more concentrated in Tigray within the five year recall period (1991/2-1995/6).

Higher mean log percapita income lowers the probability of a wereda receiving chronic food aid, with a larger and more precisely estimated impact on food for work. An increase from the 25^{th} to the 75^{th} income percentile lowers the predicted probability that a wereda is a chronic recipient of food for work from 12.0 to 6.7 percent, the mean rate being 9.0 percent. Relative to the mean, this is a large impact. The income effect is smaller for free food. Being in an area with higher long-run rainfall also significantly lowers the chances of being a chronic recipient, particularly for free distribution. In that case, predicted probabilities of receiving FD at the interquartile range of long-run rainfall are 16.9 and 6.7 percent. Having a higher proportion of children with height for age z-scores under -3 raises the probability of being a chronic recipient of food for work, but interestingly, not of free food.

For chronic recipient households, the analysis is confined to households that live in weredas containing chronic recipients. We control for wereda fixed effects with the inclusion of wereda dummy variables. We find that households with low current percapita income, a head without formal education, a high proportion of elderly members, and a female head without a living spouse are all more likely to be chronic free food aid recipients. Chronic participation in food for work is negatively related to current income, but to little else. Predicted conditional household participation probabilities range from 34.8 to 22.4 percent at the interquartile range of percapita income for free food and from 21.9 to 14.1 for food for work. As mentioned, it is likely that attenuation bias affects the current income variable as a measure of long-run income, so that the true income effects may be larger in magnitude. However, it is also possible that past food aid may raise productivity among household workers which might raise current income, imparting a positive bias.

7. Does Past Receipt of Food Aid Reflect Chronic Needs or Inertia?

A major question raised by these results is whether current and chronic allocations reflect chronic need or perhaps high fixed costs of changing the area of program operations, or both. As discussed above, this is a very difficult question to answer because of the problem of unobserved

heterogeneity across weredas. While we won't be able to claim to have answered this question conclusively, we can shed some light on it by including two additional variables: one showing food aid needs during the 1980s, as assessed by the Ethiopian Relief and Rehabilitation Commission (RRC), the precursor to the current Disaster Prevention and Preparedness Commission, and the other showing food aid needs in 1995 as assessed by the DPPC.

Records from the RRC at the old Administrative District level (there are 93), indicate that agency's estimate of the severity of the food situation in each year, measured as the proportion of the district population that "need" food aid.[44] We match the 1995/6 wereda boundaries to those of the old Administrative Districts and then construct a variable that averages by Administrative District the RRC estimates of "needs" over the five year period 1984-88.[45] By doing so, we create a variable that measures the food aid needs during the major 1984/5 famine and the first four recuperative years after it. We use this variable as a proxy for unobserved time-invariant heterogeneity, μ_i in equation [1], to try to explain current year and chronic food aid receipt at the wereda level, adding this variable to our base specifications in Tables 2 and 6.

We also add the assessed needs variable from 1995. Since the DPPC makes their needs assessment *before* making their allocations, this "needs" variable is not another form of our dependent variable, although in principle it should be highly correlated with it. Adding it to the base results obviously changes the interpretation of our other included variables to be net of this factor, but we include it to help control for current period unobserved (by us, the analysts) needs.

We then add the wereda lagged receipt variables to see if they are still significant. To the extent that the RRC assessed 1980s needs variable, together with the DPPC 1995 needs variable, plus the other measured variables such as current mean log percapita income, child health, and region and plot-level shocks, adequately control for μ_i, this should greatly reduce, though possibly not eliminate, the bias when using the history variables.[46]

Before discussing the main results it is useful to examine how much of the variation in RRC needs assessments represents time-invariant versus time series variation. If needs assessments have a strong time-invariant component then we can use that variable, or its average over time, as a measure (albeit imperfect) of unobserved time-invariant need. In that case, if we continue to find strong history effects when also controlling for the RRC needs assessment, that would be evidence in favor of inertia in food aid program operations, since we would be controlling for needs that are time-invariant. If on the

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[44]The data cover the period from 1979 through 1988. How "needs" are established by the RRC is unclear, but according to Patrick Webb, a nutrition scientist who spent much time conducting field work in Ethiopia during the mid- and late-1980s, they are an assessment of perceived food aid needs (personal communication).

[45]The program MapInfo was used to rescale the current wereda boundaries to the same scale as the hardcopy Administrative District maps that we have. We were then able to do the matching.

[46]We also considered using the RRC variable as an instrument for the history variables, but since there are four of those, we need additional instruments for identification. Lagged rainfall deviations were tried, but did not explain the history variables very well.

other hand, perceived needs do change over time, then one would have to worry more about controlling for current year needs when interpreting the history variables. Using the 1995 DPPC needs assessment variable should go some way towards meeting that goal.

To explore the question of the time-invariance of needs, we take the raw RRC assessments of the percent of the Administrative District population that needs food aid, for each year of data available, and regress this on a set of Administrative District dummy variables. This is equivalent to an analysis of variance, and it turns out that 52 percent of the needs variation is across ADs (that is the R^2 is .52), the other 48 percent being over time, within districts.[47] Thus the RRC needs assessment variable does have a strong time-invariant component to it, but it does vary over time as well. To remove the time-varying part, we average the variable over the period 1984 to 1988.

For the DPPC 1995 needs assessment, an obvious question is how related it is to our observed covariates, including the 1984-88 RRC assessed needs. We answer this question using tobit regressions in Table 7. Column 1 findings indicate that DPPC determined that the fraction of households in need of food aid was 27% higher in Tigray and 19% lower in the other smaller regions than in the South (the omitted regional category). And after controlling for all other wereda mean household characteristics, plot shocks, and agro-ecological variables (column 2), the Tigray effect remains. After accounting for all other observed effects (including income levels and child health), weredas in Tigray are assessed to contain 33% more people in need (as determined by the DPPC) than weredas in other regions with similar characteristics. In results not shown, we disaggregate the region dummies into smaller geographic units (domains) and find that there are also significant but smaller impacts of being in a few other domains, not just Tigray. In column 3, the Tigray effect becomes insignificant when we add the RRC variable, in column 3. This indicates that any Tigray bias has existed since the1980s famine period.

It is interesting that the variables that help explain current year allocations are also important in explaining the DPPC needs variable: this includes mean log percapita income, both low child heights and weight for heights, mean log-run rainfall and current period rainfall shortages. Thus a mixture of longer run and current variables seem to be taken into account when the DPPC is making its needs assessments. Adding the RRC variable reduces the magnitudes of several of the coefficients of these variables, such as long-run rainfall, child health and mean household size, and to a lesser extent current income. Hence it would appear that there is both a responsiveness to current conditions as well as a strong time-invariant component to food aid needs as assessed by the current Ethiopian government.

In Table 8 we update the wereda probit results from Tables 2 and 6. We model chronic receipt of aid adding only the RRC variable (columns 1 and 4) and then current year receipt adding both RRC and DPPC assessments (columns 2, 3, 5, and 6). We first see that both chronic receipt of food for free and food for work are positively and significantly related to the average RRC needs assessment from

[47]Using region dummies instead we find a very strong effects for Tigray and Wello, the two most affected areas in 1984; coefficients of .39 for Tigray and .33 for Wello, with t-statistics of 8.6 and 8.2 respectively. The only other region with a coefficient significant at the .05 level is Harrage and its coefficient is only .09 with a t-statistic of 2.3.

1984 through 1988. An increase in the percent affected from 0 to 17 percent (the interquartile range) doubles the mean probability of chronic free food receipt, from 4.3 to 10.0 percent. An increase of the percent of population assessed in need to 44 (the 90th percentile) raises the predicted wereda chronic probability to 27 percent (remember that only 13.7 percent of weredas are chronic receivers, so that these are very large impacts). For food for work, the historical needs impact is a little smaller; a rise in predicted probability of chronic receipt from 4.8 to 8.6 percent at the 25th and 75th percentiles (only 9 percent of weredas are chronic receivers of food for work). Notice in the free distribution probit that the Tigray coefficient drops in half from roughly .60 to .20, being just significant at the .10 level.[48] These results indicate that a large part of the Tigray Region's chronic receipt of free food during the early- and mid-1990s stems from perceptions of its neediness during the 1980s. We conclude that assessed post-famine food aid needs during the 1984-88 period does influence which weredas have remained chronic recipients of food aid in the mid-1990s.

For chronic receipt of free food, it turns out that needs assessment during one year only, 1984, does as well as the average from 1984 to 1988 in explaining distribution across weredas in the 1991/2-1995/6 period.[49] 1984 was the first year of the mid-80s major famine in Ethiopia, so that evidently, free food distribution programs initiated after the famine operated recurrently in those areas for at least a decade. Food for work programs became more prominent later in the 1980s, which is why the 1984-88 average and not the 1984 variable explains chronic placement in that case.

Not only does the 1980s needs assessment variable explain chronic wereda food aid receipt, it also explains current year receipt as well (in results not shown). However, when we add the 1995 needs assessment, in columns 2 and 5, the 1980s needs variable is not significant in explaining current year allocations for free distribution. However, even controlling for the 1995 assessments, those from a decade earlier do affect food for work allocations. Conversely, the impacts of the current needs variable is large in the free food case, but effectively zero for food for work. This pattern makes some sense since food for work allocation decisions are made several years in advance, while free distribution decisions are made more concurrently.

Note, too that the Tigray coefficients greatly shrink towards 0: it halves in the food for free equation and shrinks almost to 0 in the case of food for work.[50] Thus the 1980s and 1995 needs assessment variables are having a very similar impact to the 1990s lagged receipt variables. This is exactly what we would expect if unobserved, time-invariant heterogeneity is important; that is $Y_{i,t-1}$ and μ_i have similar impacts when entered separately into the probits.

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[48]For food for work, the Tigray coefficient is near zero before the RRC variable is added so that this argument is not relevant.

[49]The marginal probability for free food is .517 with a t-statistic of 3.15. For food for work the coefficient is .097 with a t-statistic of only 0.69.

52 Interestingly, the coefficient on other killils does not shrink for free distribution and does so only a little for food for work.

To distinguish the separate influences of lagged receipt and time-invariant needs, we add the lagged receipt variables to the current year wereda receipt probit. As one can see in columns 3 and 6, the coefficient on current year needs variable drops by 25 percent in the free food probit and gets even closer to zero in the food for work probit. The 1980s needs variable continues to have zero impact on free distribution and it magnitude on food for work drops in half. On the other hand, comparing the magnitudes of the history coefficients to their values in Table 2, one can see that the two are very close and that the history coefficients are still jointly highly significant when the two needs variables are introduced. We conclude from this exercise that the very large wereda-level impacts of lagged receipt of food aid is not driven by persistent need from the 1984-88 period or of assessed current needs in 1995. These results provide support in favor of the inertia hypothesis.

One potential reason that some observers believe is related to the large allocations to Tigray is an implicit income transfer by the central government to the Tigray region after the ending of the civil war in 1991. If this story is driving the strong history effects, then we wouldn't expect these influences to persist when we drop Tigray from the analysis. However, as can be seen in Table A2, the impact of the history variables, alone and with the RRC and DPPC needs assessment variables, are quite close to the results in Table 8. Hence the key findings hold outside of Tigray as well as within it.

Hence while not absolutely conclusive, the evidence is consistent with a story that inertia in the spatial allocation of food aid operations is an important part of the story explaining current year allocations. The results cannot be explained away by the possibility that current food aid allocations represent an underlying political pro-Tigray objective, since the key findings hold even when Tigray observations are dropped from the analysis.

This finding of inertia has been discussed with and corroborated by selected representatives of food aid agencies in Ethiopia, who have indicated that there are certain fixed costs in setting up supply channels, relationships and standard operating procedures with local authorities. Perhaps, most importantly, there are differences across local authorities in their accountability and organizational ability to manage food aid (such as being able to properly keep accounts of the aid), creating incentives for food aid donors and NGOs to continue doing business with established local groups.

8. Conclusions

Efficient targeting of food assistance is important because if food aid resources are scarce, some targeting is likely to be required in order to maximize it's contribution to improved health. Great efforts have been made in both high-income and low-income countries to effectively target food assistance resources to the poor. Despite these efforts, there is a paucity of evidence to determine the degree of targeting that is actually achieved in food assistance programs in developing countries, and thus a very limited empirical foundation on which to assess their cost-effectiveness in achieving objectives or to provide feedback to improve the design of food assistance programs in the future. Consequently, and because neither central governments nor food aid donors typically have control or knowledge over the

ultimate recipients of food aid at local levels, policy discussions of food aid often take place within an empirical vacuum.

This paper starts to shed light on the targeting issue by using nationally representative, rural household data from Ethiopia, collected in 1996, to infer criteria used in the allocation of food aid, both among areas and to households in areas in which food aid is received. The paper determines the extent to which food aid (both free distribution and food for work) is targeted to poor households and communities and to communities with large fractions of children at health risk. We also demonstrate that food aid allocations display a large degree of spatial continuity over time, and are concentrated in areas that, at least during the time of the survey, are not the poorest. Nor does excessively bad health of children (relative to the rest of the country) fully explain the regional distribution. The paper attempts to disentangle two competing explanations for the apparent spatial rigidity of food aid allocations: that the recipient areas are chronically needy, or that needs shift geographically from one year to the next, but that the distribution process is vulnerable to a degree of inertia in the location of food aid programs over time.

The analysis in this paper highlight five key findings: First, there are significant inverse associations between mean percapita income and the probabilities of receiving free food and food-for-work, both for weredas and households within weredas. However, the targeting that this implies is quite incomplete. For example, the wereda results indicate that the probability that a particular wereda (local administrative unit) would receive free food varies from 30.4 percent for the 25^{th} percentile of wereda mean log percapita income, to 24.1 percent for the 75^{th} income percentile, to 21.1 percent for the 90^{th} income percentile. The estimated amounts received also decline significantly as incomes increased, but again incompletely. Assets such as land owned are not related to food aid allocations. Long-run rainfall, is negatively related to aid receipt, but weakly.

Second, independently from low incomes, food aid is targeted to regions having children with extremely low heights and weights given heights.

Third, food aid receipt is responsive to shocks in local rainfall, but also only weakly. Amounts received, on the other hand, are not responsive to weather shocks. Within local areas it does not appear that field-level rainfall shocks affect local allocations to households, so that a potential insurance role of food aid is not being used.

Fourth, there are significant differences in the amounts of food aid allocated regionally, which cannot be explained by observable household and wereda level characteristics.

Fifth, the study's findings indicate that the single most important determinant of whether a wereda receives free food or food for work is whether that wereda has been a recipient in previous years. On its face, it is unclear whether historical use should be interpreted as indicating that inertia is determining allocations; or whether it is unobserved, time-invariant or slowly changing unobservables, such as ones related to chronic need; that are important. In an attempt to differentiate, albeit imperfectly, we find that historical receipt during the early 1990s is highly correlated with an average of assessments of food aid needs from 1984 through 1988, which we use as a proxy for unobserved time-invariant needs.

The 1984/5 famine was a defining event that influenced the subsequent location of investments of food aid operations in Ethiopia. The available survey data indicate that the poorest areas of the country in 1995/6 were generally not the ones hardest hit by the this famine. However, conditional on historical 1980s needs, and on assessed needs in 1995, it is the recent 1990s pattern of food aid allocation that is most important in determining receipt in the 1995/6 survey year.

From these results, and the fact that current weather shocks have only a small impact on allocations, we tentatively conclude that there is a degree of inertia, or time-invariant rigidity in food aid distribution over time, particularly for food-for-work. This rigidity in food aid distribution does not seem to be accounted for by time-invariant or time-varying unobserved needs, as best as we can measure them. This may arise from high fixed program costs, successful political lobbying by recipient groups, or possibly other reasons. This spatial inertia, whatever the exact cause(s), is a factor that has so far been ignored in both the theoretical targeting and the policy-related food aid literatures.

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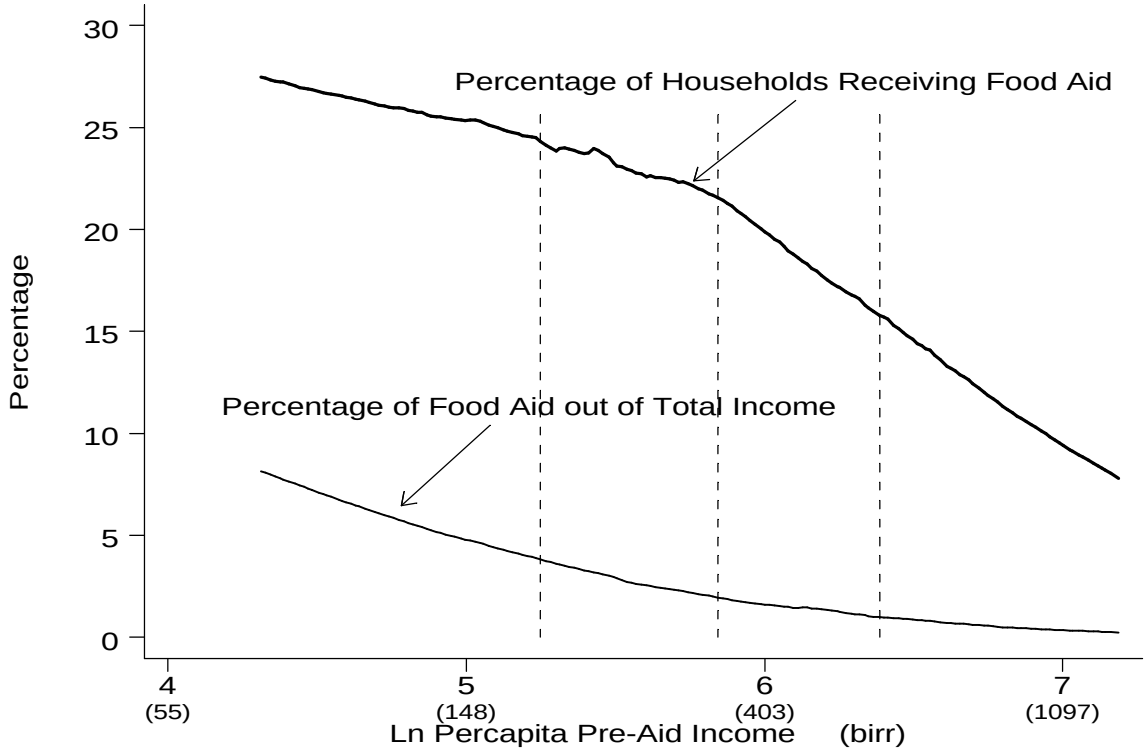
Figure 1. Household Food Aid Allocation by Ln Percapita Pre-Aid Income



Note: Dotted lines are drawn at the 25th, 50th, and 75th percentiles of ln percapita pre-aid income, corresponding to 190, 345, and 595 birr.

Figure 2. Annual Grain Production and Food Aid in Ethiopia, 1974-1997

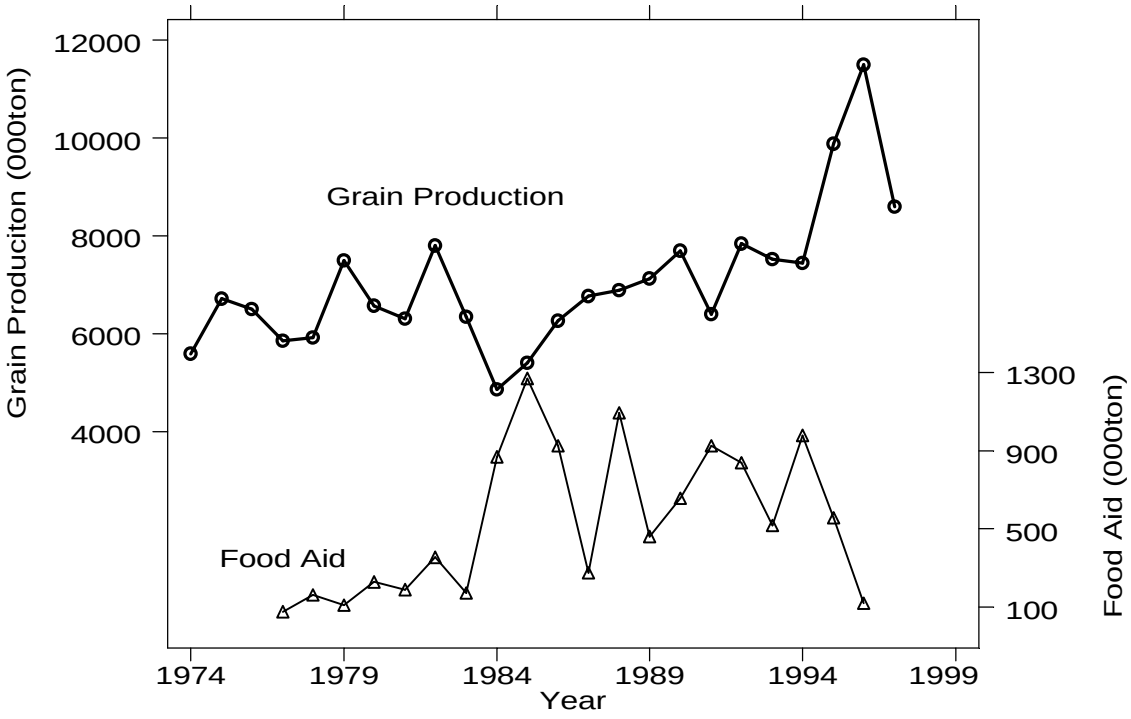
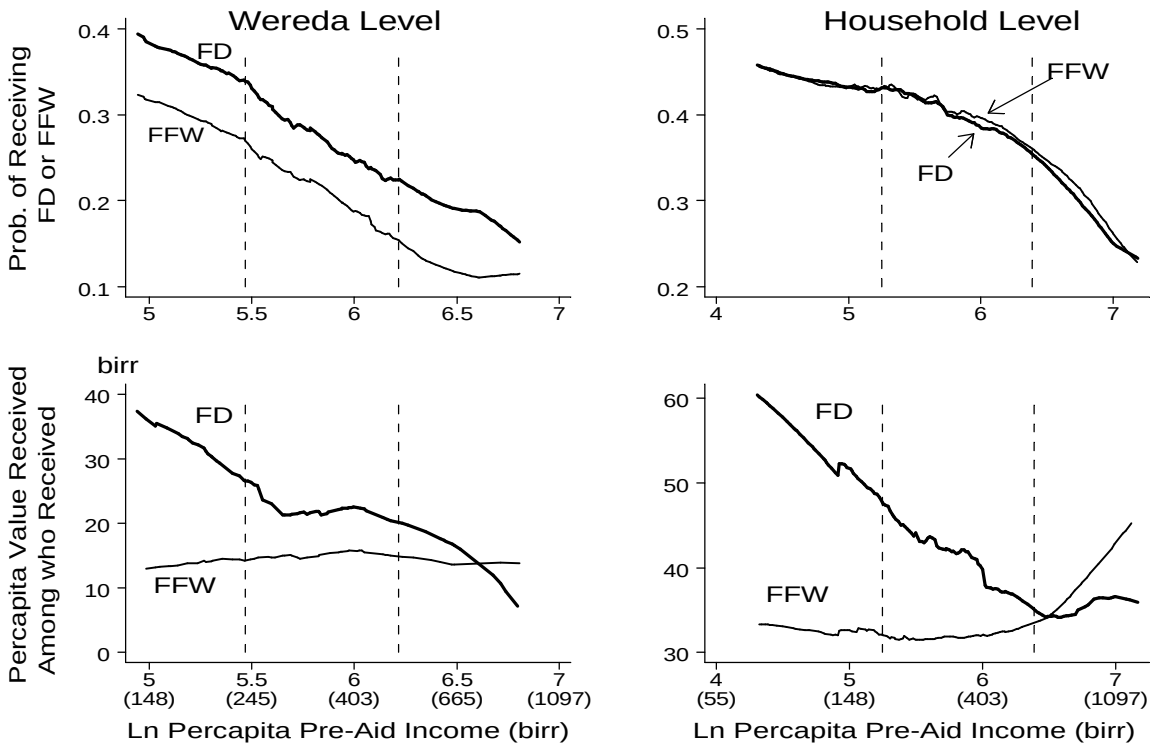


Figure 3. Free Distribution and Food For Work by Ln Percapita Income



Note: Dotted lines are drawn at the 25th and 75th percentiles of ln percapita pre-aid income, corresponding to 237 and 500 birr for weredas, and 190 and 595 birr for households.