DOES PARTICIPATION IN PUBLIC WORKS ENCOURAGE FERTILIZER USE IN RURAL ETHIOPIA?

by

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ABSTRACT

A sixth of the world's population receives inadequate nutrition.[1] The problem is especially severe in Africa where agricultural sectors are dominated by subsistence farmers. African smallholder farmers could double yields by doubling their fertilizer use.[2] Yet, in many countries, subsistence farmers do not utilize technologically advanced agricultural technologies that are apparently available to them at subsidized prices. Extreme poverty and the lack of effective access to disposable income in the aftermath of shocks are likely to be a partial determinant of the low rates of technology adoption among smallholder farmers in Africa. One strategy to address this situation is the provision of economic assistance through food aid programs.

This thesis evaluates the indirect impact of food aid programs on agricultural productivity via changes in participants' input decisions. This project also identifies the main determinants of participation in public works programs and fertilizer use and examines whether these decisions affect one another. Our contribution to the literature is twofold. First, we apply novel econometric techniques to correctly compute the marginal effects of a system of two simultaneous models with binary and censored latent dependent variables. Second, we use a unique cross-sectional sample of households from rural Ethiopia that permits us to examine the relation between fertilizer use and participation in a recently established safety net program.

Our results show no evidence that participation in public works programs and other income support programs adversely affect the adoption of technology. In fact, the results suggest that the programs, to some extent, encourage adoption. We also show that previous choices of both fertilizer use and participation in public works, educational attainment, household characteristics, income-related variables, and some regional agro-ecological factors are among the main determinants of the participation and usage decisions. Although the empirical results support the argument that participation in safety net programs may help reduce poverty and the risks of food insecurity via changes in the participants' production habits, the results also indicate that there is room for improvement in the distribution of food aid.

[1] FAO Hunger Report, 2009.
[2] International Fund of Agricultural Development, 2011.

INTRODUCTION

> Most of the people in the world are poor, so if we knew the economics of being poor, we would know much of the economics that really matter. Most of the world's poor people earn their living from agriculture, so if we knew the economics of agriculture we would know much of the economics of being poor.
>
> ~T.W. Schultz, 1980

For many developing countries, growth in agriculture has a disproportionate effect in poverty and food insecurity.[3] Technological change is seen by many agricultural experts as a prerequisite to expand agricultural productivity. Thus, understanding the factors that drive innovation and technological change in subsistence agricultural societies is important to contemporary economics research that addresses poverty in the developing world.

Relatively recently, several economists have argued that aid based or aid subsidized income safety net programs for smallholder farm households are likely to have positive effects on technology adoption and farm productivity.[4] Identifying both the qualitative and quantitative relationships between assistance delivered through donor-backed social protection programs and the diffusion of agricultural technologies

[3] For most developing countries, growth in agriculture has a disproportionate effect in poverty because more than half of the people in developing countries reside in rural areas. Some 57 percent of the world's rural population lives in lower-middle-income countries, and 15 percent lives in the least-developed countries. Most of rural households in poor countries are dependent on agriculture. Rural households in Ethiopia, Malawi, and Vietnam, for example, derive about three-quarters of their income from agricultural activities, mainly subsistence farming (The World Bank, 2005).

[4] See for example the work of Barrett et al. (2010), Barret and McPeak (2006), Bezuneh et al. (1988), Reardon et al. (1994), Bezu and Holden (2008), Ravallion (1991, 1999), Ravallion et al. (1993), Besley and Coate (1992), and von Braun (1995).

is therefore critical to any assessment of the impact of such aid policies on agricultural productivity, rural poverty, and longer run economic growth.

The issue examined in this study concerns food-for-work or public works programs, which provide a partial safety net for smallholder farmers and are often funded through foreign aid programs.[5] Do food-for-work programs mitigate food insecurity risks in developing countries by encouraging the adoption of yield-improving technologies? To address the issue, we evaluate the effects of one type of decentralized participatory food-based community development program in Ethiopia, the Productive Safety Net Program (PSNP). In particular, we examine the impact of food wages on fertilizer use at the household level.

Four hypotheses are considered: (1) a variety of farmer-specific traits, farm-specific factors and regional characteristics systematically determine whether or not subsistence farmers in Ethiopia participate in food-for-work programs and whether or not they choose to adopt or intensify their use of chemical fertilizer; (2) participation in food-for-work programs affects farmers' use of chemical fertilizer; (3) the use of

[5] Food-for-work programs (FFW), also known as public works programs (PW) or employment generating schemes (EGS), function as welfare safety nets for poor communities in food insecure areas and distribute the bulk of food assistance in many developing countries. Rather than distributing free assistance, the concept of food-for-work prescribes that able-bodied beneficiaries work in labor-intensive public works in exchange of a food-wage. (FFW programs typically revolve around either labor-intensive public works such as road construction or afforestation, or income generating activities like the setup of home gardening businesses.) In general, FFW programs are intended to guarantee short-term food security and immediate assistance for farmers who have been affected by natural disasters or severe food shortages; prevent the selling of productive assets; provide direct benefits from improved physical infrastructure; and indirectly enhance productivity growth in the long run by increasing the likelihood that the recipient invests in productive technologies. For detailed descriptions of the theory and evidence on EGS see Ravallion (1991, 1999), Ravallion et al. (1993), Besley and Coate (1992) and von Braun (1995).

fertilizer affects farmers' participation in food for work programs; and (4) both of these decisions are determined simultaneously.

To evaluate these hypotheses, we first develop a theoretical model of agricultural household behavior that examines the interaction between participation in public works (PW) programs and the adoption of chemical fertilizer by Ethiopian farmers. Using the results of the theoretical analysis, we then develop an empirical model and use sophisticated econometric techniques to test it.[6] To estimate the model we use cross-sectional data from a survey of Ethiopian rural households collected by the University of Addis Ababa and the Centre for the Study of African Economies (CSAE) in collaboration with the International Food Policy Research Institute (IFPRI) in 2009.

The public works participation and input adoption decisions are regressed on a vector of variables that includes measures of farmer demographic characteristics, variables specific to farm productive capacity and household wealth, and regional characteristics. The results of the empirical analysis indicate that participation in public works and chemical fertilizer use are, in general, positively but weakly related. Furthermore, they are found to be endogenous to one another.

Our empirical findings provide some statistical support in favor of the institutionalization of safety net programs. The results indicate that aid-backed safety net programs significantly encourage fertilizer use and therefore agricultural production

[6] Our econometric framework uses instrumental variables to estimate a system of simultaneous equations with limited and binary dependent variables. Reduced form estimates, standard errors, and p-values are calculated using standard jack-knife bootstrapping method of 1000 draws with replacement. Latent correlations and marginal effects are obtained using estimation procedures proposed by Atwood and Bittinger (2011). We provide a detailed discussion of our empirical methodology in Chapter 6.

in some low income regions with limited productive capacity and high levels of poverty in Ethiopia. Our findings are consistent with recent trends of growth in Ethiopia's economic productivity.

Our estimates also suggest that community-based projects may be misallocating resources in some rural communities as equivalent increases in fertilizer use could be attained for a fraction of the amount currently spent on the studied safety net program. However, given the available analytical and measurement tools, whether or not the establishment of comprehensive social protection programs is an economically viable approach to encourage agricultural production and therefore alleviate the risks of food insecurity and chronic poverty in Ethiopia is a question we may not be ready to answer.

This thesis is organized as follows. Background information on the agricultural sector in Ethiopia, the country's geographical context and institutional history, the state of food security in the country, and the specifics of the Productive Safety Net Program are described in the next chapter. Chapter 3 provides a detailed review of the existing literature on the causes of poverty, the impacts of social safety nets in developing countries, and the determinants of technology adoption and diffusion in agricultural societies. A theoretical model of farm household behavior is presented in Chapter 4. Chapter 5 describes the data used to test the hypotheses developed in Chapter 4. Empirical modeling and econometric estimation issues are discussed in Chapter 6 and empirical results are presented in Chapter 7. Economic and policy implications are discussed in Chapter 8 and conclusions presented in Chapter 9.

ETHIOPIA'S AGRICULTURAL SECTOR

Agriculture is the most important sector of Ethiopia's economy, accounting for over 46 percent of GDP, 84 percent of exports and 80 percent of employment. (Figure 1 shows value added of Ethiopia's agricultural sector as a percentage of GDP from 1997 to 2011, according to FAO statistics.) In the country, farming is dominated by small-scale enterprises that rely on traditional technologies and family labor for farm production and produce primarily for household consumption. Most of these farmers live in the Central and Eastern mountainous regions. (However, the number of large-scale commercial farms, particularly in the Gambella region in the country's South West, has increased dramatically since 1996 largely due to recent government efforts to attract foreign investment for commercial agriculture.) Land is owned by the state and it is distributed based on household size and average land holdings in Ethiopia are below one hectare per household.

Grains are the traditional principal field crops and constitute the dietary base of the majority of smallholder households. Teff, barely, wheat, maize, sorghum and millet account for more than 95 percent of cereal acreage and cereal output in the country. (Ethiopia is Africa's second largest producer of maize.) Figure 2 shows production of barely, maize sorghum and wheat between 1993 and 2010. Table 1 presents data on cereal production by crop between 2004 and 2008, including number of producers, annual levels and growth rates of production, area cultivated, and yields per hectare.

Pulses are the second most important component in the national diet and the principal source of protein. Plantain, yam and sweet potatoes are also important staple foods; they are commonly grown in the southern and southwestern highland regions. Oilseed cultivation is too an important agricultural activity and vegetable oils are widely used for household consumption at the national level.

Coffee is the main export commodity and the main source of cash income (25 percent of Ethiopia's population works in coffee production which accounts for 55 percent of the country's exports). Oilseeds, cut flowers, cotton, khat, and livestock are also important export commodities.

Ethiopia's livestock population is said to be the largest in Africa and the majority of the rural population is somehow involved in animal husbandry. Livestock provide draft power, food, cash, transportation, fuel, and in some cases they serve as wealth repositories. The majority of the sheep in the country are raised by small farmers who use them as a major source of meat and cash income. Alternatively, goat herds are generally maintained by pastoralist societies in low-altitude regions. Horses, mules and donkeys are used mostly for by farmers in higher elevations for draft power and organic fertilizer. Camels play a similar role among pastoralist societies. Poultry farming is also widely practiced for consumption and cash sale.

In recent years, Ethiopia's agricultural production increased rapidly, with yields of barely, teff, maize and sorghum expanding by more than 40 percent. (Figure 3 shows Ethiopia's production of principal staples between 1997 and 2007.) Extensive areas of

arable land, diverse ecological zones, generally adequate rainfall, and a large labor pool positively influence the agricultural sector's potential. However, in spite of a promising agricultural potential, Ethiopian agriculture remains highly undercapitalized and the country remains one of the world's least developed countries. (Ethiopia ranked 174 out of 187 in the 2011 UNDP Human Development Index).

Only 1.5 percent of the country's total land area is irrigated (export crops such as coffee, oilseed and pulses are mostly rain-fed, and by some estimates, about 10 percent of the total cereal cropland is irrigated); average road density in rural Ethiopia is well under the African average of 50 km of road per 1000 square kilometers of land area (national average road density is 35 km per 1000 square km); and diffusion rates of technologically advanced inputs are low even by African standards. (Figures 4 and 5 show imports and consumption of chemical fertilizer between 2004 and 2008.)

With a rain-fed agriculture as the foundation of its economy, household food security is highly vulnerable to changes in multiple factors. Soil degradation and recurrent droughts, imbalanced population growth, the widespread use of obsolete technologies, a history of skewed agricultural policies and a precarious geo-political status are some of the factors associated with growing pressures of food insecurity and chronic poverty in Ethiopia. [7] In the remainder of this chapter we consider important

[7] Ethiopia's land area is 426,400 sq miles; 14 percent of the land area is arable. Demeke (1997) estimates that half of Ethiopia's arable land has been affected by soil degradation and erosion. In Ethiopia, population growth has averaged 3.2 percent between 2008 and 2012 (World Bank, 2012). The population density in the Central and most Eastern mountainous regions, where 85 percent of Ethiopia's population live, is 255 persons per sq mile; the corresponding national figure is 48 persons per square mile (UN Population Division, 2012). Average land holdings in Ethiopia are below one hectare per household. This

aspects of Ethiopia's bio-physical context, and institutional history that continue to impact and shape the country's agricultural outlook.

Ethiopia's Agro-Ecology

Located in Horn of Africa, Ethiopia's landscape varies from deep river valleys to high alpine plateaus and its tropical climate varies with elevation and rainfall. The Ethiopian Lowlands, areas below the arbitrary mark of 1,500 meters (or 4,921 feet) are hot and arid zones mostly covered by desert soils that are poor in nutrients. Populations inhabiting these low elevation regions are predominantly nomadic pastoralist communities whose main economic activity is animal husbandry.[8]

The Ethiopian Highlands, regions at or above 1,500 meters, are cooler, wetter, and have more productive soils. Moderate temperatures and reliable annual rainfall make the Highlands a favorable zone for agricultural activities. About 85 percent of Ethiopia's 84 million people live in the mountainous Central and Eastern regions. About 60 million of them rely on small-scale agriculture for their survival.

Average annual rainfall in Ethiopia is also highly variable. Annual precipitation ranges from 78 to 315 inches in the Lowlands and from 315 to 866 inches in the Highlands. Rainfall patterns in Ethiopia can be unimodal or bimodal, and given the type

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distribution is mostly a remnant of the 1974 the Marxist-Leninist land redistribution policy. Although land redistribution has ceased in principle, there is currently a ban on land sale and rental against fixed payment. Finally, Ethiopia is landlocked and has unstable relations with Eritrea. Substantial freight costs limit the extent Ethiopia can engage with the international markets, thus, food shortfalls are hardly filled with imports.

[8] Not all the soils in the Lowlands are barren and unsuitable for agriculture. Some soils, like those of the Great Rift Valley and the Awash River Basin in the Central region, support large-scale commercial farms.

of rainfall regime, a climatic region in Ethiopia may have two, three, or four rainy seasons a year. In general, moving north and east from a high rainfall pocket area in the southwest Highlands, annual average annual rainfall declines.

Given the diversity of Ethiopia's climates, the agricultural calendar varies among regions. However, some patterns are observed nationwide. The critical seasons in the Ethiopian agricultural calendar are the Kiremt, Belg, and Bega. The K*iremt* rains are long and heavy rains from mid-June to mid-September; they account for 60 to 90 percent of the country's rainfall in most regions. The Kiremt are of major importance in Ethiopia's agricultural calendar because they prepare the land for the main growing season, the *Meher*, in which 90 to 95 percent of the country's annual food output is produced.

The *Bega* or a dry and hot season occurs between October and January. During this time, farmers harvest their M*eher* crops—thus, these months are referred to as the Meher harvest. By some estimates, as much as 80 percent of annual grains sales occur during and soon after the Meher harvest, between January and March.

Lastly, the B*elg* rains are short and moderate rains that occur between February and May (they correspond to the secondary harvest season in the northern Highland areas). These rains are crucial for planting short-cycle crops such as wheat, barley, teff, and pulses, which are harvested in June or July, and for planting long-cycle cereal crops such as corn, sorghum, and millet, which are harvested during the Meher harvest.

Although the B*elg* harvest accounts for only 5 to 10 percent of the total annual grain production of the country, it provides up to 50 percent of the yearly food supply in

some Highland areas. For instance, in the agro-pastoral areas of Ethiopia, the B*elg* rains are the main annual rains and are critical in assuring pasture and water for livestock.

History of Agricultural Policies

Historically, Ethiopian governments have been heavily involved in agricultural markets. Inhospitable terrain and no obvious exportable economic resources allowed Ethiopia to keep a feudal system and its independence from European colonial powers until conquered by Italy in 1935. In 1942, the British restored Emperor Haile Selassie to power. In 1952, seeking to change the country's landlocked status, the Emperor claimed the former Italian colony of Eritrea. Decades of endemic violent conflict between Ethiopian military and Eritrean separationists followed this geopolitical takeover.

Between 1957 and 1974 the government attempted to address the country's slow economic growth through a series of national development plans. The overall approach was based on development ideas of the 1950s when economic growth was thought to be linked primarily to capital accumulation and industrialization. The majority of these strategies emphasized investments in infrastructure, manufacturing and technology and large-scale farms that would feed a growing urban labor force and generate export earnings. These plans neglected the importance of the small-farm sector and therefore limited progress was made in transforming Ethiopia's peasant agriculture.

A military coup in 1974 deposed the old Imperial order and under President Mengistu Haile Mariam Ethiopia endured nearly two decades of Marxist-Leninist rule backed by Soviet military sponsorship. By 1980 the power of the Ethiopian state had expanded into virtually all spheres of agricultural commerce, from domestic input and output markets to international trade.

The military junta, or Derg, created the Agricultural Marketing Corporation (AMC) and the Agricultural Input Supply Corporation (AISCO), both state-owned enterprises that monopolized formal grain and input trade, distribution and marketing in the country. Heavy interventions by the state resulted in market distortions that had far reaching effects on the welfare of market participants and undermined the performance of the economy as a whole.

In 1984-1985m Ethiopia experienced a severe famine. About eight million Ethiopians were affected, and one million people were estimated to have died. Famine vulnerability continued through the mid-1990s owing to high grain prices and asset depletion that followed the shock. (Violent conflict in the North and recurrent droughts also explain the persistence of food insecurity during this time.)

In 1991, when the Ethiopian People's Revolutionary Democratic Front (EPRDF) came into power, a radical set of market reforms was enacted to replace the centrally planned economy with a market-oriented economic system. Restrictions on private interregional trade, officially fixed prices, compulsory delivery quotas, and grain rationing were abolished. The AMC, renamed the Ethiopian Grain Trade Enterprise

(EGTE), was transformed into a buffer stock scheme and the government moved towards liberalizing output and input markets.[9]

In 1993, Eritrea invoked its right of self-determination and after nearly 30 years of war it seceded from Ethiopia. Between 1993 and 1995 the government of Ethiopia in conjunction with different partners launched various comprehensive agricultural-development programs aimed at familiarizing smallholder households with modern technological inputs and farming techniques. The use of demonstrations plots and extension service programs together with the withdrawal of state control from output markets in the 1990's and the provision of credit for subsidized inputs purchase improved the efficiency of grain production, helped increase the number of participants in private grain trading and advance grain marketing as a whole.

Notwithstanding concerted efforts by the Ethiopian government to promote agricultural productivity, Ethiopian grain markets remained poorly integrated and rates of technology adoption much lower than expected.[10] The country's endemic structural deficit became evident when in 2003 Ethiopia experienced another famine despite two consecutive years of good harvests.

During the bountiful harvest seasons of 2001 and 2002, farmers in surplus producing areas were unable to take advantage of high prices in other regions because

[9] The National Fertilizer Policy of 1994 called for the gradual removal of subsidized fertilizer prices. Retail prices were completely deregulated as of February 1997, and wholesale prices followed in 1998.
[10] Efforts by the Ministry of Agriculture's Department of Extension and Cooperatives, such as the Participatory Demonstration and Training Extension System (PADETES), were found successful at influencing farmers' production habits in the short-run. However, the programs did not appear to provide the necessary incentives to sustain changes in farmers' behavior (Bittinger, 2010).

they lacked access to reliable price information, roads and other communication networks. The lack of storing and financial institutions further exacerbated the problem as producers were forced to sell their surplus soon after the harvest in order to avoid crop losses and fulfill other short-term financial obligations. Thus, in early 2002, grain prices fell below the historic average in these producing regions (sometimes by almost 80 percent) creating a disincentive for production.

Largely due to reduced profitability of production, input utilization and production fell significantly during that year. It is estimated that in 2003 seed and fertilizer use declined 27 percent, agricultural production decreased 21 percent and grain prices increased by 85 percent (Gabre-Madhin, 2003). Yields were not sufficient to combat the extreme risk of food insecurity affecting the majority of poor households and about six million people were in need of urgent food aid; other 15 million faced high risk of starvation.

Paradoxically, after two years of bumper crops, Ethiopia's government had to reach out to the international community for assistance because domestic production was unable to provide adequate quantities of food to keep people alive. These dynamics are not uncommon in Ethiopia. Excessive supplies often characterize fertile areas where food prices are low and food availability levels are sometimes low in regions with high food prices. Small agricultural ventures often experience a high degree of price volatility, food shortages sometimes follow years of good harvest in surplus producing regions and chronic food insecurity persists to afflict millions in rural Ethiopia.

In 2011, the Horn of Africa experienced its most recent drought. According to UN relief programs, the lives of 10.5 million people were compromised. It is estimated that between four and five million people became dependent on emergency food assistance for their survival.

Food Aid Programs in Ethiopia

After the 1983-1984 Ethiopian famine, the Emergency Food Security Reserve Administration was created to manage the distribution of donations to relief and development projects throughout the country. Since then, the typical policy response to food insecurity has been a series of ad hoc emergency appeals for food aid and other forms of hunger-relief programs. Figure 6 shows the quantity of food donations to Ethiopia between 1991 and 2007. Figure 7 shows the population in need of emergency food aid between 1991 and 2009.

Following the change in political regime in 1991 and the adoption of structural reforms in 1992/1993, Ethiopia has seen a substantial and growing inflow of international aid. (According to OECD-DAC statistics, the World Bank has committed a total of $3.1 billion to Ethiopia since 1993.) Over the last two decades, Ethiopia has been the largest recipient of food aid in Africa and one of the largest recipients in the world,

receiving around 24 percent of World Food Program's and 27 percent total global food aid deliveries to sub-Saharan Africa.[11]

While emergency food aid has saved millions of lives, the unpredictable nature of these efforts has meant they have largely failed to protect livelihoods, prevent asset depletion, and induce behavioral changes. Furthermore, variations in the intensity of emergency responses have meant that the provision of food assistance has not been integrated into ongoing long-term economic development activities.[12] Recently, comprehensive policy measures and social security programs have been designed to incorporate food aid into existing development projects.

The Productive Safety Net Program

Since the issuance of the Sustainable Poverty Reduction Program in 2001, the Ethiopian government and various international donors have offered hunger-relief programs to both mitigate the risks and impacts of natural disasters and induce

[11] Between 1996 and 2005, food donations to Ethiopia deviated between 0.2 and 1.2 million metric tons and had large fluctuations from year to year, making apparent the unstable nature of emergency relief initiatives (WFP, 2012). Annual average of food aid inflows over the same period was 700,000 metric tons.

In 2007, Ethiopia received about $1.24 billion in aid (which amounts to over 30 percent of the nation's budget), making the country the fifth largest recipient among 169 aid receiving developing countries and the largest borrower from the International Development Association (OECD-DAC, 2007). The biggest donor country to Ethiopia between 2001 and 2007 was the USA. During this period, it gave Ethiopia US$2.5 billion. The next biggest donors to Ethiopia were United Kingdom (US$813 million), Germany (US$443 million), Italy (US$389 million), Netherlands (US$353 million), and Canada (US$335 million) and Sweden (US$276 million).

[12] According to World Bank data, the number of individuals in need of emergency food assistance has risen from approximately 2.1 million people in 1996 to 10.5 million in 2011, reaching a peak of 13.2 million in 2003. The lowest numbers of individuals in need of emergency food assistance were 700,000 and 1 million in 1999 and 2007, respectively. Despite of well-intended development policies, officially, about 80 percent of Ethiopians live on less than $2 a day. It is sometimes substantially less than that. One foreign charity, Action Contra la Faim, recently found that the average cash income for households in one area was six cents a day. It is estimated that 13 percent of children in nearby villages in the high hills are severely malnourished (The World Bank, 2009; The Economist, 2007).

beneficiaries to improve the productivity of their land. One of these initiatives is the Productive Safety Net Program (PSNP).[13]

The PSNP was launched by the government of Ethiopia in 2005 and it has grown to be the backbone of safety net activities in Ethiopia. (In 2012, the PSNP was the largest social protection program operating in sub-Saharan Africa outside of South Africa with a budget exceeding $1200 million.) The PSNP is administered by the Food Security Coordination Bureau (FSCB), part of Ethiopia's Ministry of Agriculture and Rural Development, and is financed by nine donor countries and organizations, including Ireland, Sweden, the United Kingdom, the United States, Canada, the European Union, the World Bank and the World Food Program.

The PSNP operates as a safety net, primarily targeting transfers to chronically food insecure households in two ways: through Public Works (PW) and Direct Support (DS).[14] With its focus on shifting from food to cash transfers, the program seeks to accomplish two objectives. First, it aims at smoothing consumption and preventing asset depletion among chronically food insecure households by providing them with predictable and adequate transfers of cash and/or food.[15] Second, the program aims at

[13] Other initiatives include the National Relief Program, Targeted Supplementary Feeding, the HIV/AIDS Program, the Purchase for Progress Program (P4P), Food for Education, MERET (Managing Environmental Resources to Enable Transition) and Food Assistance to Refugees.

[14] In Ethiopia, DS programs distribute cereals (primarily wheat and maize), cooking oil (primarily vegetable oil) and limited cash directly to households.

[15] The transfers for the program as a whole are split 50 percent cash and 50 percent food. The PSNP design allows for variability in the balance between cash and food provided to beneficiaries. In 2008, increased food prices reduced the value of cash transfers, so the program increased the volume of food transfers (WFP, 2010).

building community assets and to indirectly enhance productivity growth in the long run.

The initial phase of the project, also referred to as Adaptable Program Loan 1 (APL1), had an approved budget of $370 million. APL1 was approved on January 1st of 2005 and closed on December 31st of 2006. In 2005, the program covered 7 out of Ethiopia's 10 regions and targeted 318 out of 500 *woredas* or districts.[16] Within these districts, the PSNP had a target caseload of 7.75 million people (9 percent of Ethiopia's population). 85 percent of the program's resources were distributed through the PW component and the remaining 15 percent via direct support handouts (The World Bank, 2012).

Two subsequent Adaptable Program Loans followed as the government met safeguard conditions identified in APL1. APL2 covered January, 2007 to June, 2010 with a budget of $1030 million. APL3 was approved on October, 2009 and will end in June 30, 2015; it has an approved budget of $1227 million.

Distribution Mechanisms

The assignment and the distribution of food aid and food wages are determined through a complex procedure. Using local records, the government conducts the annual needs assessment and develops a food-aid appeal to the international community. Food

[16] In Ethiopia, rural districts are called woredas; the equivalent of a county in the US. They are further divided into villages or Peasant Associations (PAs) that are also referred to as *Kebeles.* PAs are the smallest administrative unit equivalent to a ward. Each woreda consists of up to several villages. A cluster of 100 villages is called a *Tabia*.

aid is then allocated according to two distinct mechanisms, one pertaining to DS programs and the other applicable to PW projects.

The aid assigned to DS programs is distributed to specific *woredas* according to their needs assessments and the overall quantities of food aid already received in the current period. The *woreda* council subsequently allocates quotas to *tabia* (cluster of villages) and households.[17] Households eligible for DS transfers are those who, in addition to being chronically food insecure, have no labor and no other sources of support. (They may include labor-scarce households whose primary income earners are elderly or disabled, orphans, people who are sick, pregnant or lactating.) These households receive 30 birr ($3.5) or 15 kg of grain per person, per month, for six months each year.

In contrast, food donations delivered through public works (PW) are provided as an investment in agricultural production and conservation. Under Ethiopian law, Public Works (PW) must be the largest component of the PSNP.[18] Rather than distributing free food aid to those in need, the PW concept requires able-bodied beneficiaries to work for food or a cash wage. The general idea of the program is to employ food-insecure farm workers during the slack season (when little work needs to be done on the farm) and pay them with food or cash to build public infrastructure like roads or irrigation canals,

[17] Each *tabia* council has three to five people who prepare the list of beneficiaries.
[18] In 1993, the TGE brought a policy stating that no able-bodied person should receive gratuitous relief. As a result, at least 80 percent of food aid resources in Ethiopia are committed to Public Works (PW) programs (Bezu and Holden, 2008).

participate in afforestation activities, or work on building soil and water conservation structures.

Geographic and household-level targeting is used to select PW beneficiaries. Drought-prone geographic areas are selected first. In these areas, the amount of food targeted for recipient *woredas* is based on the number of workdays needed to complete the projects proposed and designed by local administrative agencies. (The types of public works are determined at the local level and therefore differ from village to village.) Then, participants are selected by local community leaders are either given three kilograms of cereals (usually maize) or a cash payment of 6 birr ($0.7) per day of work.[19] Beneficiaries are paid for up to five days of work per month per household member, for six months each year.

Numerous reviews and evaluations have concluded that the PSNP is having a positive impact on food security. However, impact evaluations vary in their assessment of the extent of the program's contribution.[20] In the following chapter we present a thorough review of works in the areas of development and agricultural economics comprising key results regarding the impacts of social safety nets and food aid on innovation decisions among subsistence farmers.

[19] The payment rate is fixed by the PW guidelines, but some evidence indicates that the rate varies from village to village (Barret et al., 2002). According to recent 2011 UN data, the average monthly income per capita in Ethiopia is equivalent to $23—which roughly translates into $0.77 per day per person.
[20] For thorough evaluations of the project see 2009 report by the International Food Policy Research Institute (IFPRI) "An impact evaluation of PSNP", and the 2008 report by the Institute of Development Studies (IDS): "Ethiopia's PSNP, assessment report".

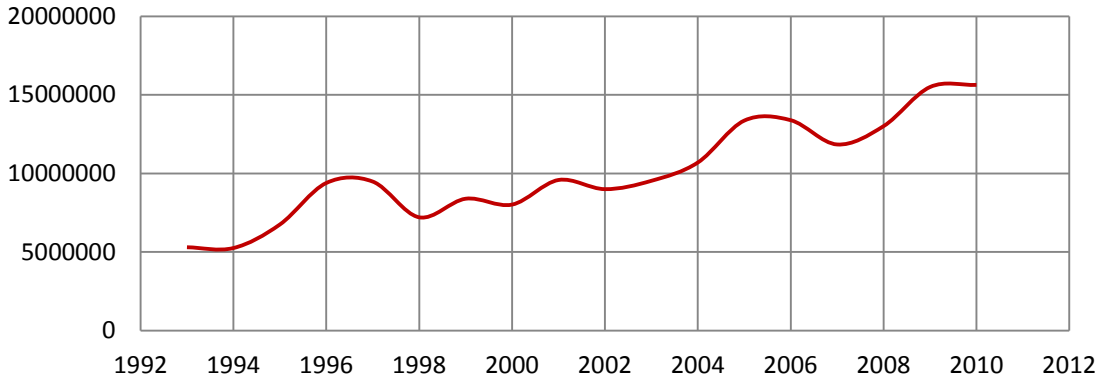


Figure 1. Ethiopia's Agriculture: Value Added as Percentage of GDP.
(Source: The World Bank, 2012)

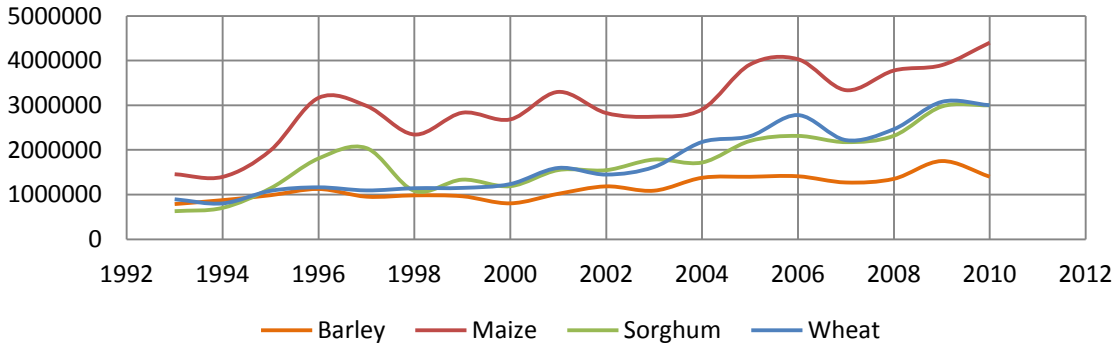


Figure 2. Ethiopia's Agriculture: Production of Cereals in Hg/Ha.
(Source: FAO Statistics, 2012)

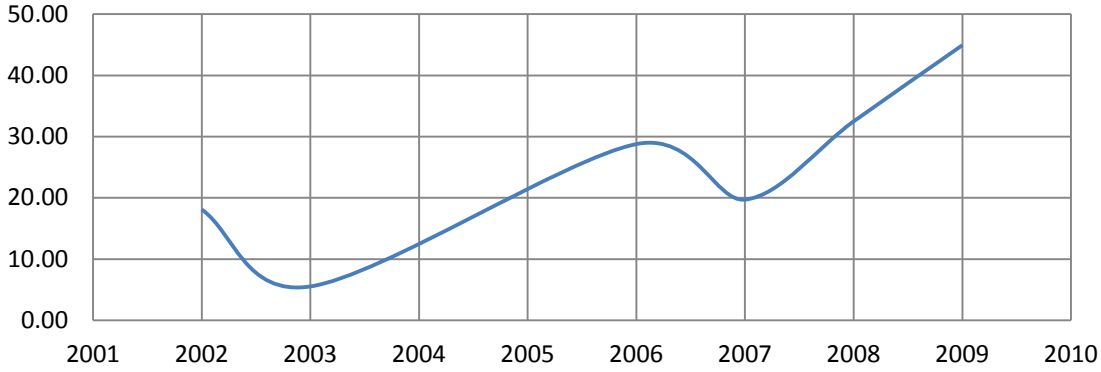


Figure 3. Production of Principal Staples in Ethiopia (tons).

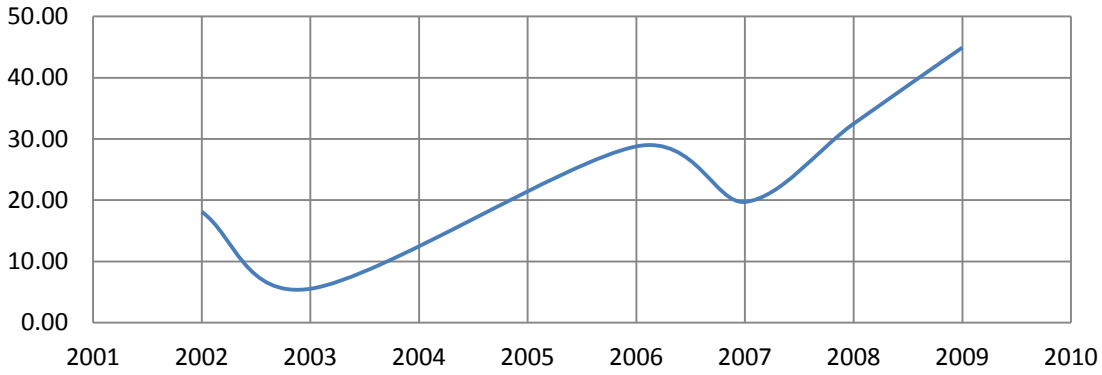


Figure 4. Input Use in Ethiopia: Imported Quantity of Chemical Fertilizer (tons per 100 Ha of arable land).

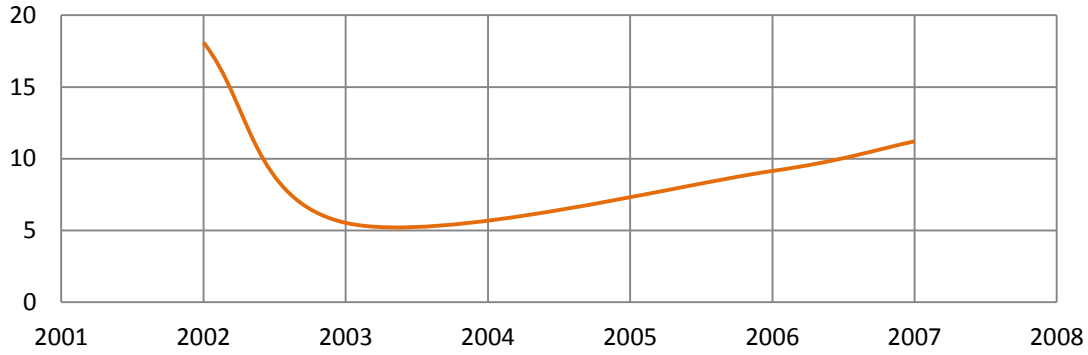


Figure 5. Input Use in Ethiopia: Consumption of Fertilizer (tones per 100 hectares of arable land)

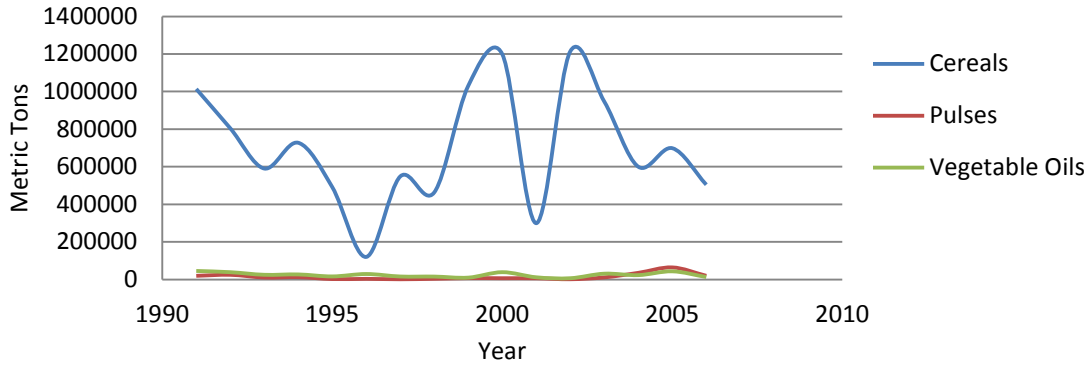


Figure 6. Total Food Donations to Ethiopia

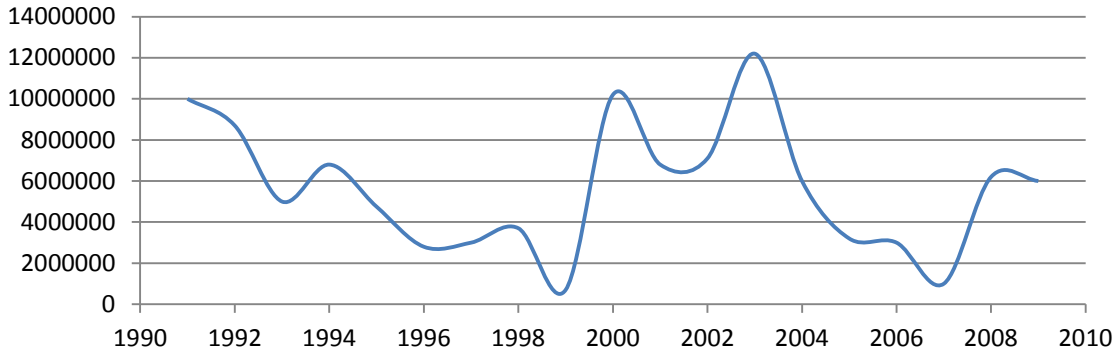


Figure 7. Population in Need of Food Aid.
(*Source:* The World Bank, 2011)

Table 1. Cereal Production by crop—2004/2005-2007/2008

	Average 2004/2005-2007/2008						
		Production (100 kg)		**Area Cultivated (hectares)**		**Yield (100 kg per hectare)**	
Crop	**Number of holders**	**Level**	**Annual Growth rate (%)**	**Level**	**Annual Growth rate (%)**	**Level**	**Annual Growth rate (%)**
Cereals	11,156,837	120,629,724	12.2	8,230,211	4.8	14.0	6.2
Teff	5,462,782	24,079,480	15.9	2,337,850	6.7	10.2	7.7
Barley	3,842,462	13,264,217	0.7	1,024,390	-3.4	13.0	4.5
Wheat	4,118,164	22,933,077	2.1	1,439,098	0.6	15.9	1.5
Maize	7,287,931	33,142,865	18.9	1,595,238	9.0	20.6	7.8
Sorghum	4,253,534	22,161,808	18.3	1,429,886	7.4	15.4	8.9

Source: Seyoum Taffasse (2009) based on computations using CSA data (July 2006, July 2007, and June 2008). *Note:* Cereal yield is calculated as acreage-share weighted average of the yields of the five major cereals listed in the table.

Table 2. Modern Input Use 1997/1998-2007/2008 on Cereals

Modern Input	**1997/1998**	**2001/2002**	**2007/2008**
Fertilizer Applied area (share in total area cultivated as percent)	39	42.8	32.3
Fertilizer application (total 100kg/total hectares)	0.45	0.3	0.37
Fertilizer application (100 kg per hectare of fertilizer applied area)	1.16	1	1.15
Improved seed applied crop area (percent of crop area)	4.7	3.5	2.4
Pesticide applied crop area (percent of crop area)	20.8	10.8	12
Irrigated crop area (percent of crop area)	1.1	1.3	0.6
Extension package covered crop area (percentof crop area)	14.5		

Source: Calculation from Seyoum Taffasse (2008) using CSA data (1998-2008) for all cereals.

LITERATURE REVIEW

The issue of technology adoption as a mechanism for agricultural development and overall economic growth has received extensive attention in the form of theoretical and econometric studies. Similarly, the literature on the role of food aid as a tool of rural development has been the focus of a rich debate. This chapter is organized in four sections. Section 1 examines evidence on the causes of, and challenges to economic growth and agricultural development. Section 2 reviews the existing literature on the impacts of social safety nets in developing countries. Section 3 examines models of farm households' decision-making and presents theoretical and empirical findings about the factors that determine input and output decisions. Section four provides a summary of key insights and their implication for the research reported in this thesis.

Economic Growth: Technological Change and Poverty Traps

Technology is central to economic growth. In 1957, Robert Solow developed an economic model in which long-term growth depended primarily on exogenous technological change. However, more recently, numerous cross-country studies, using different time periods, country samples and statistical techniques indicate that economic growth to be a more complex process than originally thought by economic theorists (Kenny, 2011).

There is a rich derivative literature from Solow's work. Some economics researchers have used his model to predict at least a degree of global income convergence. According to them, relatively poor countries would see greater returns to investments than rich countries until they were relatively rich as well. However, in fact, income divergence has been observed among countries and across sectors since 1960 (although income inequality in the world economy has not necessarily increased among individuals or countries with similar observable characteristics).[21]

To account for the observed increase in welfare and income gaps between developing and more advanced economies, economists have extended Solow's model to treat technological change as an endogenous factor that depends on country-specific features ranging from climate and natural endowments to trade, history and institutions. One insight obtained from a variant of these endogenous growth models is the household poverty trap hypothesis: that self-reinforcing mechanisms exist which cause poverty to persist.

Technology traps occur when, for whatever reason, individuals consistently choose productive technologies that involve low production risks but also result in low returns. Poverty traps may be related to low agricultural productivity and, therefore, food insecurity. Many factors can contribute to a poverty trap, including inadequate investment in agricultural technologies, limited access to credit and capital markets, extreme environmental degradation, corruption, dysfunctional institutions, capital

[21] Acemoglu, Daron (2009). Introduction to Modern Economic Growth. Princeton, New Jersey: Princeton University Press: 3-23.

flight, war and endemic violence, or decreasing returns from investments in health, education, or physical capital (Mansuri and Rao, 2012).

Evidence with respect to the existence of technology traps is limited and the conclusions of the few studies that have examined the issue are mixed at best. While some evidence suggests that technology traps largely account for poverty in sub-Saharan Africa (Fofack, 2008), other studies find little or no evidence of the existence of such traps at low levels of development (Kraay and Raddatz, 2007).[22]

Communities can also become trapped in chronic poverty because of the absence of economic institutions (there is considerable debate about what institutions are essential for growth; there is a broad consensus, however, that central obstacles to growth in many poor countries are institutions that make property rights review of the theories identifying factors and mechanisms that potentially create poverty traps). Lack of access to insurance or finance drives farmers to adopt risk-mitigating production practices that often leave them exposed to market volatility and climate-related shocks (Barrett et al., 2010). Evidence shows that farmers in some disadvantaged settings sell their productive assets to circumvent the problem of missing insurance and credit markets, worsening the productive capacity of their farms and possibly starting another iteration of the vicious cycle.[23]

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[22] Fofack (2008) shows that if African countries were operating on the global technology frontier enjoyed by OECD countries, their income level would be over four times the current estimates, ceteris paribus.

[23] Dercon and Christiansen (2011) find that the lack of insurance or alternative means of keeping consumption smooth leaves some farmers trapped in low return, lower risk agriculture—one of the mechanisms through which poverty perpetuates itself in agrarian settings. Additional evidence and

Alternatively, to cope with shocks and guarantee basic levels of consumption, subsistence farmers sometimes form farmer-associations and other types of social groups that can serve as safety networks in adverse economic conditions. This practice is widely used across regions. However, such mechanisms can also invite free riding behavior and attenuate incentives for self-protection against shocks, contributing to the perpetuation of poverty traps (Fafchamps and Gubert, 2006).

Nevertheless, individuals in developing countries may not have to rely solely on production-related or community-based risk-spreading tools to circumvent market failures and dampen consumption fluctuations. Some point to evidence of migration for this purpose (Rosenweig and Stark, 1987); others to evidence of income diversification for consumption smoothening (Reardon et al., 2007).

Drawing upon evidence on entrepreneurial activity and dynamics of labor markets, some analysts argue that social programs encouraging improvements in rural labor markets can empower individuals to break out of poverty (Barrett and McPeak, 2006). Some also maintain that insurance programs encourage capital accumulation, new technology adoption and market participation (Barrett et al., 2010). The hypothesis is that these systems ease cash-flow constraints and raise the prospect of future growth for impoverished farmers by protecting them from adverse shocks or providing reliable sources of income. In the following section we present evidence for and against social protection programs in developing countries.

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discussion on the topic can be found in the work of Barrett et al. (2010), Barret and McPeak, 2006, Rosenzweig and Binsenwanger (1993) and Enfors and Gordon (2008).

Aid-Based Social Safety Net Programs

In many sub-Saharan African countries, international aid provides the primary resources to sustain social protection or safety net programs (Barrett and McPeak, 2006).[24] Thus, assessing the effectiveness of aid-based safety net programs has been a concern for governments, donors and interest groups.

Several studies of agrarian societies have attempted to identify the effects of food assistance programs on rural and economy-wide economic development. On one hand, the argument that food aid programs are beneficial to African agriculture emphasize food aid's role in increasing poor household's access to, and consumption of, food in the face of shocks, improving nutritional status, health, labor productivity, and income earning capacity of the beneficiaries (Abdulai et al., 2005).

On the other hand, critics of food aid programs note that food aid deliveries depress food prices and discourage food production. One argument is that they create disincentives for work (either on the farm or in the off-farm labor market) as a result of increased in income. In the case of food for work programs (FFW), labor may be attracted away from agricultural and other productive activities (Bezu and Holden, 2008). Overall, the literature on international aid programs has provided only limited empirical evidence about their impacts on labor allocation and labor market

[24] Over the past fifty years, the world's largest donors have spent $2.3 trillion on poverty reduction. Nevertheless, the world's wealthiest nations dedicate on average less than one percent of their income for this purpose (Mansouri and Rao, 2012; Karlan and Appel, 2012).

participation decisions. Sometimes aid appears to encourage increased work and sometimes it does not; the results appear to be highly context-specific.

Disincentive Effects

The logic behind the disincentive effect in food production argument is that food aid deliveries increase food supplies more rapidly than they stimulate food demand (through an income effect), depressing food prices received by recipient country producers and traders. Lower crop prices then discourage producers from investing in improved technologies or in storage and transport capacity (Abdulai et al., 2005). Concerns about the food price effects of food aid deliveries have been corroborated empirically in several cases in sub-Saharan Africa.[25] Also, some evidence indicates that farmers who cease to rely on agricultural production for their livelihood lose their incentives to work and to protect or improve their farms' productive capacity (Holden et al., 2004; Gebremedhin et al., 2002).[26]

Some studies report that food aid programs have overall negative impacts on economic growth (and may have a role in perpetuating poverty among recipient countries) as they induce governments to reduce expenditure on the provision of relief (Agenor and Aizenman, 2010). Others provide evidence that food aid's characteristic volatility and poor timing have adverse impacts on household welfare and long-term

[25] See Gelan (2006), Barrett and Maxwell (2005), Donovan et al. (1999) and Demeke et al. (1996).
[26] In their study of the Ethiopian highlands, Holden et al. (2004) find that access to non-farm income reduces farm households' incentives to invest in soil conservation activities. Similarly, Gebremedhin et al. (2002) show that farm beneficiaries of public soil conservation programs in Ethiopia were less likely to invest privately in either stone terraces or soil bunds.

development as future income uncertainty increases current consumption at the expense of investment (Desai and Kharas, 2010). However, much of the evidence provided in these studies about food aid's disincentive effects is highly anecdotal and not statistically robust (Lentz, 2003).

Several studies have reported that when careful controls for other potential effects are included in the anlayses, food aid flows do not appear to have created disincentives for local agricultural production, labor supply, asset investment, or mutual support (Abdulai et al., 2005; Letz, 2003; Dorosh et el., 1995; Bezuneh et al., 1988).

In Ethiopia, most studies do not find evidence to support the existence of disincentive or dependency effects.[27] On the contrary, recent research reports that social transfer programs facilitate savings and investments, encourage innovation, and offer new employment opportunities that have the potential of improving the community's human capital (Bezuneh et al., 1988).[28] Some analysts suggest that social protection programs help to address market failures and alleviate economic pressures by providing the beneficiaries with liquid assets and a reliable source of income (Gilligan et al., 2008). On balance, the net effect of food aid on agricultural production, labor markets and overall poverty alleviation may not be negative (Bezu and Holden, 2008).

[27] See Berhane et al. (2011), Bezu and Holden (2008), Little (2008), Yamano et al. (2005), Dorosh et al. (1995) and Bezuneh et al. (1988).

[28] Devereux (2008), Devereux et al. (2008), Hoddinott (2008) and Dercon (2005) provide further examples and references.

Food for Work Programs

Food for work programs are international aid initiatives that hire targeted populations and pay them with donor-provided cash or food. Several studies have examined the alleged benefits of food for work programs in terms of poverty reduction by investigating their impacts on food security and nutrition, food production and trade, soil conservation activities, accumulation of productive assets, formation of non-farm sectors and labor markets, enhancement of credit and insurance markets, and overall poverty alleviation and economic growth.[29]

The effects of those programs on short-term income, consumption and food security within affected households have consistently been estimated to be positive.[30] Also, some evidence suggests that, through the creation of public infrastructure and the encouragement of greater community involvement, programs based on public employment guarantees may be legitimate ways of helping the impoverished overcome chronic poverty and food insecurity in the long run (Mansouri and Rao, 2012; Barret and McPeak, 2006; Bezuneh et al., 1988).

[29] For further discussion of the impacts on food security and nutrition see Gilligan et al. (2008), Alderman et al. (2005) and Bezuneh et al. (1988). See Little (2008), Abdulai et al. (2005) and Hoddinott et al. (2004) for evidence of effects on trade and food production. Andersson (2010), Holden et al. (2004) and Gebremedhin et al. (2002) examine impacts on soil conservation activities. Effects on asset accumulation are documented by Gilligan and Hoddinott (2006), Barret et al. (2008) and Andersson (2010). For additional reading on the formation of informal labor markets see Gilligan et al. (2008), Bezu et al. (2008), Holden et al. (2004), Barrett et al. (2002), Asefa and Teklu (1999), Savadogo et al. (1998), Reardon et al. (1994), Rosenweig and Wolpin (1993) and Feder (1980). Refer to the work of Andersson et al. (2010), and Rosenweig and Wolpin (1993) for evidence on credit and insurance markets. Barrett et al. (2010), Agenor and Aizenman, (2010) and Lensink and Morrisey (2000) evaluate impacts on overall poverty alleviation and economic growth.

[30] See Uraguchi et al. (2011), Sulaiman et al. (2010), Reda et al. (2010), Solomon et al. (2010), Taffesse et al. (2008), Gilligan and Hoddinott (2008), Gilligan et al. (2008), Holden et al. (2004), Hoddinott et al. (2004), Dercon and Krishnan (2003), Barrett et al. (2002), and Bezuneh et al. (1988).

However, questions have been raised about the longer term benefits of food aid programs and their impacts on labor markets. Recent studies have suggested that food payments may not be sufficient to compensate for the caloric requirement of the work performed, resulting in poor health and malnutrition of the participants (Gobostwand et al. 2008). Other analysts find that food for work programs have limited effects on the dietary diversity of rural households as participants shift crop mixes from nutritious to higher priced commodities (Uraguchi and Zenebe, 2011; Bezuneh et al., 1988).

Some have asserted that the design of food for work programs is generally poorly informed and conceptually based on weak empirical evidence (Ravallion, 2012). They criticize the administrative and operational efficiency of food-for-work and food-for-training programs, question the adequacy food-based rather than cash forms of payment, the timing of payment deliveries, and doubt the efficient targeting of the programs.[31] However, overall, the narrow focus of most of these studies makes extrapolation difficult.

[31] Barrett et al. (2004) conclude that past failures of FFW are largely be due to a top-down approach. Administrators lacked the necessary information to efficiently accommodate labor and food donations. Gelan (2006) provides a comprehensive summary of the literature evaluating the relative effectiveness of in-cash and in-kind aid. His own findings suggest that cash-for-work programs would have larger positive effects on aggregate household welfare than food-for-work programs. In regards to timing of payment deliveries, the World Bank estimated that in the first year of the Ethiopian Productive Safety Net Program (PSNP) there were considerable delays with payments. The 2011 report states that six months into the program only 11 percent of the transfers had been completed—the target was to deliver 95 percent of the transfers during the first year of the program. Also, Gilligan et al. (2008) suggest the PSNP program has little impact on participants on average, in part due to transfer levels being far below program targets. Finally, there is a pervasive concern in the literature about the extent to which better-off communities—communities that are less geographically isolated, and with greater capacity, political networks, education or wealth—are more likely to benefit from community development programs (Mansouri and Rao, 2012). Some find that although the schemes are successful at targeting the poor, only those who are physically able can participate (Asefa and Teklu, 1999; Chowdhury and Osmani, 1983). Others find a

Technology Adoption and Diffusion

Historically, advances in science and technological innovation have been important determinants of growth and wealth accumulation (Alston et al., 2010). However, despite recent improvements in science and rapid reductions in the costs of technologies for agricultural production, improved extension services, easier access to credit and concerted efforts by governments and donors to alleviate poverty, rates of technology adoption and growth in agricultural production are well below expected levels in many developing agrarian societies (Finan, 1998).

Given the central role of technological change in fostering the development of agricultural sectors in tightly constrained contexts, the fact that apparently profitable technologies have often met resistance among smallholder farm families is an important paradox. This paradox has led researchers to focus on understanding the factors affecting adoption and diffusion of technological innovation among small agricultural enterprises in developing countries. A wide range of demand and supply side factors have been considered in the attempts to account for the limited adoption of yield-enhancing agricultural technologies in developing countries—particularly in Africa.

Numerous studies have examined the factors associated with the adoption of specific technologies. . Initially, studies of technology adoption by farmers in developing countries focused on descriptive statistics about the use and diffusion of new inputs. In

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disproportionate number of female- and aged-heads of households receiving food aid. Some studies even find that the work requirements of the EGS make the poor less likely to participate (Gilligan and Hoddinott, 2006).

recent years, however, the focus of interest has shifted towards the role of institutions and the impacts of technology adoption on farm production and farming practices, poverty and malnutrition, environmental decay, and a variety of other social and political issues.

Several hypotheses have been put forward to explain the lack of adoption of modern agricultural inputs among farmers in developing settings. These include limited knowledge and education (Asfaw and Admassie, 2004), assertions of risk aversion and behavioral biases (Duflo et al., 2006), lack of ready access to credit and financial markets (Croppenstedt, Demeke and Meschi, 2003), incomplete or missing insurance schemes (Dercon, 2002; Lamb, 2003; Zimmerman and Carter, 2003), short-term cash flow problems or lack of liquidity (Rosenweig and Wolpin, 1993), asymmetric information and coordination failures (Platteau, 2000; Fafchamps, 2004), lack of market access (Abrar, Morrissey, and Rayner, 2004), limited profitability of fertilizer use (Dadi, Burton, and Ozanne, 2004), high transaction costs (de Janvry et al., 1991), and the existence of poverty traps (Dercon and Christiansen, 2011). Recent anecdotal evidence also highlights the importance of household's limited ex post consumption smoothening capacity (Carson et al., 2005), as well as limited or untimely availability of technology related inputs (Dercon and Christiansen, 2011).[32]

[32] For detailed review of the literature see the following pieces of research: Foster and Rosenzweig (2010), who conduct a major survey of technology adoption at the household level in low-income agricultural settings; Barrett et al. (2010), who survey the past century's literature on agricultural development; Christiansen and Dercon (2011), who provide a comprehensive review of the recent research conducted to identify the determinants of technology adoption in agriculture and discuss the evidence on issues such as input availability, knowledge and education, risk preferences, profitability, and credit constraints; Bezu

The Process of Innovation: The S-shaped Curve

On balance, adoption and diffusion of innovations have been found to be somewhat specific to the context and the population under study. However, some trends are observed. Perhaps the most consistent empirical observation in the adoption and innovation literature has been that technology adoption and diffusion is in general a dynamic process that follows a sigmoid (S-shaped) path (Rubas, 2004).

In the initial stage, few agents adopt the newly introduced technology but as time goes on and more agents become users of the technology, the rate of adoption reaches a critical point where the innovation is biologically self-sustainable. Beyond the adoption threshold rate, usage picks up and increases rapidly until the benefits from additional units of the technology are negligible. At this point small-scale farmers slow down their use of the technology; in some cases they may even stop using the technology altogether and substitute it for an upgraded input. This ceiling point is also referred to as the "saturation level", and in most cases it is reached before all agents have adopted the technology.[33] Figure 8 illustrates the S-shaped path of innovation adoption and diffusion as it was originally presented by Everett Rogers in 1962.

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and Holden (2008), who discuss the impact of liquidity constraints; Duflo et al. (2010), who present evidence of apparent behavioral biases and *irrational* behavior. Also, Morris et al. (2007) provide a comprehensive review of the factors affecting fertilizer use in Africa, and Feder et al. (1985) review the international evidence.

[33] An extensive discussion on the main approaches used to explain the s-shaped path of innovation adoption and diffusion can be found in the work of Rubas (2004).

Variables Influencing Technology Adoption and Diffusion

Evidence from the literature suggests that adoption and intensification decisions are generally influenced by the interaction of characteristics from a wide range of factors. Generally, empirical evidence shows that the determinants of technology use fall into the broad categories of socio-economic and institutional factors, physical and technical aspects of farming, farmer-specific traits and perceptions, and individual preferences for risk.

Geographic characteristics related to the agro-ecology of a studied region have commonly been found to be key determinants of farmer behavior in general. Unfavorable soil fertility, erosion levels, land degradation, likelihood of flooding, likelihood of drought, and land scarcity are some of the biophysical conditions that consistently found to be significantly and substantially related with decreases in farmers' demand for technological inputs in sub-Saharan Africa.[34]

Institutional and infrastructural factors that are often found to have significant impacts on technology use include access to credit and financial markets, availability of formal and informal information about agricultural markets, quality and access to public infrastructure like road network and irrigation systems, access to public goods like health and education, access to agricultural extension service and membership in risk-sharing institutions, existence of operational rural labor markets, presence of

[34] This evidence can be found in the works of Bizoza (2012), Barrett and Marenya (2009), Chiany and Tsujii (2005), Benin et al. (2004), Baïdu-Forson (1999), Mwangi (1997), Adesina (1996), and Pitt and Sumodiningrat (1988).

supplementary sources of income like social safety net programs, and socio-cultural characteristics like local attitudes towards farming and conservation practices, perceptions of gender roles, and traditional norms of family dynamics.[35]

Farm revenue, farm size, distance to homestead, size of owned livestock herds, access to irrigation, asset ownership, and access to labor are usually used as proxies to measure household wealth and productive capacity and are generally positively related to input use.[36] Access to non-farm income has also been found to be a main determinant of technology use in many African countries.[37]

Finally, the literature also suggests that variations in household demographic characteristics like age, gender, ethnicity, immigrant status, educational attainment and potential behavioral biases are significant determinants of the technology adoption decision. [38] Interestingly, there is much less consensus in the literature about the overall effect of these characteristics on farmer behavior. Many studies reveal different and contradictory results on the effect of household-demographic characteristics on the

[35] For details in statistical methods and results see Christiansen, Dercon (2011), Asrat et al. (2010), Duflo et al. (2006), Bandiera and Rasul (2006), Wadood (2006), Chianu and Tsujii (2005), Abdoulaye and Sanders (2005), Lamb (2003), Holden and Shiferaw (2003),Croppensenstedt and Demeke (1996, 2003), Gebremedhin and Swinton (2002), Demeke et al. (1997), Croppensenstedt and Demeke (1996), Vlek (1990), Goode et al. (1993), Rosenzweig and Wolpin (1993), Feder and Zilberman (1985), and Shaw (1985).

[36] See Asrat et al. (2010), Barrett and Marenya (2009), Nkamleu (2008), Chianu, Tsujii (2005), Croppensensenstedt and Demeke (1996, 2003), Bationo et al. (1999), and Coffin et al. (1990).

[37] See for example Holden et al. (2008) and Ng'ong'ola (1993).

[38] Specifics of the empirical methodologies and obtained results from choice experiments and other econometric studies of demographic variables determining farm decisions can be found by reviewing the works of Bizoza (2012), Asrat et al. (2010), Fufa and Hassan (2010), Horna et al. (2008), Gine Yang (2007), Bandiera and Rasul (2006), Benin et al. (2004), Bationo et al. (1999), Claudio et al. (1998), Pietola et al. (1998), Croppensenstedt and Demeke (1996), Adesina and Zinnah (1993), and Coffin et al. (1990).

likelihood of input use, suggesting that results that are consistent in some communities may not be generate lessons that apply to societies in different contexts.

Theoretical Models

Technology adoption decisions are particularly complex when examined from the perspective of farm-households as economic agents. Within agricultural households, the intricate relationship between production and consumption via changes in prices and farm income limits the use of standard consumer models for the comparative statics analysis of microeconomic behavior in agrarian societies.

Agricultural smallholder household analyses modify the familiar utility-maximization problem in consumer theory by introducing production and time constraints that capture the endogeneity of farm income and resolve the apparent contradictions found in empirical research. As a flexible analytical framework, the agricultural household model has been modified to represent many different scenarios and used in analyses ranging from crop portfolio selection and technology adoption to deforestation and income diversification strategies (Taylor and Adelman, 2002).

Several studies have modified the household production model to accommodate idiosyncratic market failures and other economic barriers. De Janvry et al. (1991) introduce transaction costs to explain why households self-select into semi-autarkic situations. They show that increases in transaction costs drive households toward

autarky and, given no changes in production technology or available land to increase food production, shift away from cash-crop production.[39]

The micro-economic framework of agricultural household behavior has also been extended to account for the effects of uncertainty and risk. Platteau (2000) and Fafchamps (2004) use the agricultural household theoretical framework to assess the role of asymmetric information and coordination failures in rural economies (perhaps because of high costs of contract monitoring and enforcement). They also explore questions about unconventional market clearing mechanisms and the interaction between micro-level behavior and economic and policing institutions.

Uncertainty and personal risk preference have been widely studied as potential explanatory factors in the household's decisions regarding portfolio selection, input-output mixture, and technology adoption. To model behavior under uncertainty or to account for the subjective valuation of risk and choices, many studies incorporate stochastic parameters and processes into the standard agricultural household models (Feder, 1980; Binswanger, 1980).

There remains considerable disagreement on whether risk and uncertainty matter because individuals vary in the degree of subjective risk aversion. However, there is consistent evidence from studies examining the risk and farmer behavior showing that individuals modify their farming practices and choices of technology to

[39] The autarky prediction mentioned above, the possibility that agricultural input and output markets are less widely used in less-developed countries because market interactions are more complex and costly than in more advanced economies, has also been examined in several recent studies of imperfect information, unmanaged risk and missing economic institutions (Barret, 2011).

mitigate expected consequences of failed crops or failed market transactions (Barret, 2011).

Summary

The issue of technology adoption has received a great deal of treatment in the form of theoretical and econometric analysis. There is a broad consensus within the literature that technology adoption and diffusion are the result of a complex decision-making process, particularly when examined at the micro-economic level. Those decisions have been found to depend on a wide array of factors related to agro-ecological factors; farmer demographics and political, cultural and economic institutions of a particular social environment.

Some empirical results suggest that food aid distribution programs can encourage adoption of technologically advanced agricultural inputs (Gilligan et al., 2008; Bezu and Holden, 2008; Bezuneh et al., 1988).[40] However, evidence of this aspect of agricultural development remains limited. In examining the impacts of food aid on agricultural productivity via technological change, this thesis seeks to contribute to the limited empirical literature devoted this issue.

In the following chapters we develop a theoretical and an empirical model that we use to test the effects of food for work wages on fertilizer use in rural Ethiopia.

[40] Benuzeh et al. (1988) find that net results for representative farm households with FFW are 52 percent higher than those without FFW. 56 percent of the increased returns results from the induced effect of capital formation on agricultural production. Bezu and Holden (2008) find that FFW income increased probability of adoption by 1.5 percent but had no effect on intensity of use. Gilligan et al. (2008) find that PW-PSNP beneficiaries used 66 percent more fertilizer than non-participants.

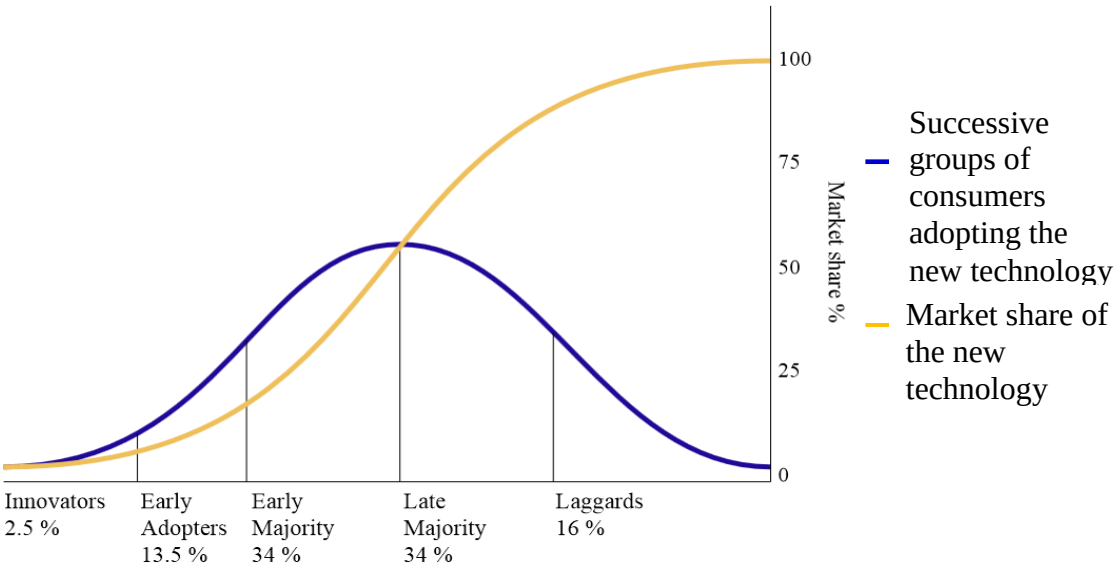


Figure 8. Diffusion of Innovations: The S-Shaped Curve (Rogers, 1962).

ECONOMIC THEORY

Agricultural Household Models

Agricultural household models are the basic building blocks of micro-level analytical research on economic behavior at the smallholder farm level in developing countries (Taylor & Adelman, 2002). They were introduced to examine paradoxical empirical findings that appeared to violate such as positive own-price elasticities of demand and lethargic supply responses to increases in crop prices.

In the general smallholder case, farm households are both consumers and producers of staple agricultural products. If they were only consumers of agricultural commodities, households would be unambiguously adversely affected by higher food prices; however, increases in staple crop prices lead to higher profits and larger incomes for smallholder farms that in turn may induce those household to modify their production and consumption choices. Thus, whether household welfare is enhanced by changes in food prices depends on whether the household has a marketable food surplus to sell or whether it has to supplement farm production with food purchases to meet its consumption needs.

The complex relationship between production and consumption decisions is therefore due in part to the effects of price changes on farm incomes. The existence of two transmission paths through which commodity prices and other exogenous shocks may affect smallholders' decisions raises questions about the relevance of standard

consumer models for the analysis of microeconomic behavior in agrarian societies. Agricultural household models of behavior modify the familiar utility maximization problem in consumer theory by introducing production and time constraints that account for the endogeneity of farm income and resolve the apparent contradictions found in empirical research.

For example, when labor markets are introduced through full income constraints, as is the case in this study, a utility maximization based household production model can be used to show that increases in market wages may result in a decline in the hours of labor supplied by households that are net providers of off-farm labor. Higher off-farm wages may induce farmers to work more time off the farm to increase their incomes. Subsequently, higher incomes allow them to afford higher consumption bundles. Because leisure is a normal good, higher incomes may also induce farmers to work fewer total hours on and off the farm.[41]

In this chapter we develop a household production model that allows farm labor to be allocated to leisure, on farm labor, off farm market labor, and food for work programs to obtain predictions and formulate hypotheses about the relation between food aid wages and the use of fertilizer. These hypotheses are examined empirically in Chapter 6.

[41] This phenomenon falls out of any labor supply model where income effects outweigh substitution effects and it is not unique to agricultural households.

Agricultural Household Model
with Food Aid Programs

Drawing on Singh, Squire and Strauss (1986), the household production model presented here is as a static, non-recursive representation of farmer behavior that assumes risk neutrality. Prices are assumed to be exogenous and deterministic and there are no markets for land or credit. In this model, households maximize utility subject to a time constraint, an income constraint and a production or technology constraint with the standard concavity properties.[42] Households obtain utility from the consumption of leisure, goods purchased in the market, and staple foods produced in the farm. For expositional convenience, the model treats staple foods and purchased goods, as a single composite consumption good.[43]

The above assumptions are typical of most static household production models. The innovation in this study involves the following additional elements that reflect the potential effects of food and cash for work programs. The first is a food-wage per unit of labor devoted to donor-funded public works programs (α), and the second the amount of labor devoted to such schemes (L_{PW}).

The extent to which farmers participate in public works programs is modeled in terms of the hours a household is willing to allocate to them. The agricultural technology adoption and intensification decision is characterized by the household's use

[42] The standard concavity properties imply positive but decreasing marginal utility and positive but diminishing returns to scale.

[43] Assuming a relatively large income share is devoted to the purchase of food goods by typical smallholder in developing countries, there is no loss of generality by imposing such condition.

of a capital input. Food aid wages are assumed to be exogenously set while the number of hours of labor devoted to public works (PW) projects is an endogenous decision. The household's optimization problem is:

$$\underset{X, L, C, L_e, L_{PW}}{Max}\ U(C, L_e)$$

$$s.t.$$

(1) $$PC + W_X X + WL_{hired} = PQ + WL_{off} + P\alpha L_{PW}$$

(2) $$Q = Q(X, L)$$

(3) $$T = L_{on} + L_{off} + L_e + L_{PW}$$

Equation (1) is the budget constraint, (2) is the production function and (3) is the time allocation constraint. The utility and production technology functions are assumed to exhibit standard concavity assumptions; that is, $U_C > 0,\ U_{CC} < 0,\ U_{L_e} > 0,$ $U_{L_e L_e} < 0,\ Q_X > 0,\ Q_{XX} < 0, Q_{L_i} > 0,\ Q_{L_i L_i} < 0,$ and $Q_{L_i X} > 0$. Variable definitions are as follows:

$P =$ Market price for farm output

$W =$ Market wage for labor

$W_X =$ Market price of the composite capital input

$\alpha =$ Food wage per unit of labor devoted to public works activities

$Q =$ Farm output

$M =$ Household income

$C =$ Composite consumption good

$X =$ Composite capital input for farm production

$L_{hired} =$ Hired farm labor

$L_e =$ Leisure

$L_{on} =$ Household farm labor

$L_{off} =$ Household nonfarm labor

$L =$ farm labor (the sum of L_{on} and L_{hired})

$L_{PW} =$ Labor allocated to public works programs (PW)

$T =$ Total time endowment of the farm household (sum of L_{on} , L_{off} , L_e and L_{PW})

$\alpha L_{PW} =$ in kind (food) compensation for labor allocated to public wokrs projects

$P\alpha L_{PW} =$ Monetary compensation for public works labor

The constraints in equations (1)-(3) can be combined to obtain the following *full* income constraint:

$$(4) \qquad PQ(X,L) + W(T - L_e - L_{PW} - L_{on}) + P\alpha L_{PW} = PC + W_X X + WL_{hired}$$

Hence,

$$PQ(X,L) - WL - W_X X + WT + L_{PW}(P\alpha - W) = PC + WL_e$$

The Langrangian for the optimization problem is:

$$(5) \qquad \text{Z: } U(C, L_e) + \lambda[PQ(X,L) - WL - W_X X + WT + L_{PW}(P\alpha - W) - PC - WL_e]$$

The first order conditions (FOCs) are:

$$(5a) \qquad Z_C: U_C - \lambda \text{P} = 0$$

$$(5b) \qquad Z_{L_e}: U_{L_e} - \lambda \text{W} = 0$$

$$(5c) \qquad Z_{Li}: \lambda\left(\text{P}\frac{\partial Q}{\partial L} - W\right) = 0$$

$$(5d) \qquad Z_X: \lambda\left(\text{P}\frac{\partial Q}{\partial X} - W_X\right) = 0$$

$$(5e) \qquad Z_{L_{PW}}: \lambda(P\alpha - W) = 0$$

$$(5f) \qquad Z_{\lambda}: PQ(X, L) - WL - W_X X + WT + L_{PW}(P\alpha - W) = PC + WL_e$$

From equations 5(a)-5(d) the standard tangency conditions and standard demands for production inputs and consumption good can be derived. Conditions 5(a) and 5(b) imply the marginal rate of substitution equals the price ratio for any two goods.[44] Conditions 5(c) and 5(d) imply that the value marginal product of labor equals the market wage, the value marginal product of X equals its market price, and the marginal rate of technical substitution equals the ratio of the inputs' prices.[45] Equation 5(e) implies that the money value of the food wage from participating in PW equals the market wage for labor. Condition 5(f) is a re-statement of the full income constraint.

In the absence of corner solutions, conditions 5(a) through 5(f) imply that the farm-household's utility maximizing bundle of goods and leisure occurs at a point tangent to the full income constraint, which is derived from both the farm-household's production frontier and the wage rate in the labor market. Thus, given an interior solution, the market wage rate equals the value of food aid wages and the value marginal productivity of farm labor ($W = P\alpha = \mathrm{P}\frac{\partial Q}{\partial L}$). This result informs the selection

[44] When solved together, 5(a) and 5(b) imply that $\frac{U_C}{P} = \lambda = \frac{U_{L_e}}{W}$, which means that the marginal benefit from consumption per dollar spent on consumption goods equals the marginal benefit from leisure per dollar given up. Subsequently, $\frac{U_C}{U_{L_e}} = \frac{P}{W}$. This implies that the marginal rate of substitution between consumption and leisure equals the ration between the price of consumption goods and the forgone market salary per unit of labor.

[45] 5(c) and 5(d) imply $P\frac{\partial Q}{\partial L} = W$ and $P\frac{\partial Q}{\partial X} = W_X$. Implying that, at the optimal level of use, the marginal benefit of production factors equals their marginal cost. Additionally, these equations imply $\frac{\partial Q}{\partial X} \cdot \frac{\partial Q}{\partial L} = \frac{W_X}{W}$, which means that the marginal rate of technical substitution equals the ratio of the inputs' prices.

mechanism guiding the household's choice about participating in PW programs (Holden et al., 2006). Households participate in PW programs only if the returns to farm work are as low as food aid wages and market wages, in which case households will allocate labor to equalize the marginal returns to labor in agriculture, salaried work and public works (if access to PW is unconstrained).

In this model, consumption decisions do not affect production decisions, implying that production is independent of household preferences and income. In contrast, production decisions about input uses affect consumption decisions via farm profits in the full income constraint. Through the optimal use of the inputs, X^* and L^*, the farm household selects the optimal production level, Q^*, and indirectly determines total farm-household income, M^*.

Households' demand functions and total income are as follows:

(6) $$C^* = C^*(\alpha, P, W, W_X, M^*_{(\alpha,P,W,W_X)})$$

(7) $$L_e{}^* = L_e{}^*(\alpha, P, W, W_X, M^*_{(\alpha,P,W,W_X)})$$

(8) $$L_{PW}{}^* = L_{PW}{}^*(\alpha, P, W, W_X, M^*_{(\alpha,P,W,W_X)})$$

(9) $$X^* = X^*(\alpha, P, W, W_X, M^*_{(\alpha,P,W,W_X)})$$

(10) $$L^* = L^*(\alpha, P, W, W_X, M^*_{(\alpha,P,W,W_X)})$$

where

(11) $$M^* = PQ^* - W_X X^* - WL^* + WT^* + L_{PW}{}^* \cdot (P\alpha - W)$$

As indicated by equations (6) through (11), food aid wages influence total farm profits through the household's production decisions; hence, food aid wages affect the

household's demand for inputs and the consumption good directly and indirectly through farm profits.

Comparative Static Analyses

In this section we introduce shift in some parameters and examine the comparative statics that evaluate the theoretical impact of an increase in the (marginal) price of the composite consumption and production good on consumption and production decisions, market wage rate on labor allocation decisions, and food wage on consumption and production behavior.

Consumption: In equation (6), food consumption depends on prices and income, but the price of food has an added effect on income via farm profits. Differentiating C with respect to P and using the Slutsky equation to show the full effect on food demand of a change in price, it follows that:

$$(12) \qquad \frac{\partial C}{\partial P} = \frac{\partial C}{\partial P}\Big|_{\Delta M^*=0} + \left(\frac{\partial C}{\partial M^*} \cdot \frac{\partial M^*}{\partial P}\right)$$

$$= \frac{\partial C}{\partial P}\Big|_{\Delta U=0} + \frac{\partial C}{\partial M^*} \cdot (Q - C + \alpha L_{PW})$$

Equation (12) implies that an increase in price unambiguously reduces consumption for households that are not self-sufficient in regards to food production (where $C > Q$) even when they complement own-farm food production with food aid wages (that is, $C > Q + \alpha L_{PW}$). However, (12) implies that households with a marketable food surplus (where $Q + \alpha L_{PW} > C$) may increase their consumption of the

composite good. This result may be obtained when the income effect of the price increase is sufficiently large. For a farm with initial marketable surplus, the effect of the price increase on consumption can be viewed as having two components. The first component is the increase in the household's full income because of the increase in the value of the consumption good in the market place. The second is what can be thought of as the household's income elasticity of demand (as reflected in its preference function). If the household's income elasticity of demand is sufficiently large, even a household with a small marketable surplus may choose to increase consumption of the composite commodity when its price increases.

Labor and Leisure: Comparative static effects of changes in the consumption of leisure in response to changes in the market wage are obtained by differentiating L_e with respect to W and, again, using the standard Slutsky equation:

$$(13) \qquad \frac{\partial L_e}{\partial W} = \left.\frac{\partial L_e}{\partial W}\right|_{\Delta M^*=0} + \left(\frac{\partial L_e}{\partial M^*} \cdot \frac{\partial M^*}{\partial W}\right)$$

$$= \left.\frac{\partial L_e}{\partial W}\right|_{\Delta M^*=0} + \frac{\partial L_e}{\partial M^*} \cdot (T - L - L_e - L_{PW})$$

$$= \left.\frac{\partial L_e}{\partial W}\right|_{\Delta U=0} + \frac{\partial L_e}{\partial M^*} \cdot \left(L_{off} - L_{hired}\right)$$

Given standard assumptions, $\left.\frac{\partial L_e}{\partial W}\right|_{\Delta U=0}$ is negative (the pure substation effect) and $\frac{\partial L_e}{\partial M^*}$ is positive (leisure is a normal or luxury good). Equation (13) implies that net purchasers of labor (where $L_{off} < L_{hired}$) will respond to increases in the market wage rate by reducing their leisure hours. However, for net sellers of off farm labor (where

$L_{off} > L_{hired}$) higher wages may or may not reduce leisure time. This may be the case of the landless farm workers, for example. [46]

Equation (13) implies that for both net sellers and net buyers of labor the effect of higher wages on the amount of time allocated to work activities (on or off the farm) is ambiguous. From equation (13), it follows that the availability of PW employment does not affect the household's labor-leisure allocation decision in response to changes in market wages. However, changes in market wages may induce farmers to modify their choice of labor allocated towards PW activities. The effects of a change in staple crop prices and wages on the labor use allocated to public works are as follows:

$$(14) \qquad \frac{\partial L_{PW}}{\partial P} = \frac{dL_{PW}}{dW} - \left(\frac{\partial L_{PW}}{\partial M^*} \cdot \frac{\partial M^*}{\partial P}\right)$$

$$= \frac{dL_{PW}}{dW} - \frac{\partial L_{PW}}{\partial M^*} \cdot (Q - C + \alpha L_{PW})$$

$$(15) \qquad \frac{\partial L_{PW}}{\partial W} = \frac{\partial L_{PW}}{\partial W}\Big|_{\Delta M^*=0} + \left(\frac{\partial L_{PW}}{\partial M^*} \cdot \frac{\partial M^*}{\partial W}\right)$$

$$= \frac{\partial L_{PW}}{\partial W}\Big|_{\Delta U=0} + \frac{\partial L_{PW}}{\partial M^*} \cdot \left(L_{off} - L_{hired}\right)$$

Equation (14) implies the effect of a change in P on L_{PW} cannot be determined without imposing restrictions on the properties and the interactions between the components of the expression. A farmer may be willing to work more hours on public works as the price of staple crops increases if, for example, the food received as salary

[46] It is feasible that households that are net sellers of labor may actually increase their consumption of leisure in response to an increase in the market wage for labor. This is a standard labor economics result illustrated by a backward bending labor supply curve. It occurs whenever the increase in income resulting from higher wages generates a positive income effect on leisure consumption that combined with a sufficiently large marketed labor surplus outweighs the substitution effect.

provides an economic alternative to maintain household food consumption without substantially altering household income (which would likely be the case for households that are more vulnerable to risks of food insecurity). However, instead farmers could choose devote more time and resources to farm production during times of high food prices, decreasing their allocation of family labor to PW employment.

Equation (15) provides some intuitive and unambiguous predictions about changes in the amount of farm labor allocated to PW as a result of a change in the market wage rate. For net sellers of labor, given that available off-farm work and public works require similar skills, the effect of an increase in W on L_{PW} is unambiguously negative. For these households, increases in the market wage result in a decrease in the labor allocated to PW work. However, increases in the market wage rate could induce net purchasers of labor to either reduce or increase the amount of household labor allocated to PW activities.

Marketable Surplus: Marketable surplus is the quantity of a crop that a household has available to sell on the market. In our model, it is expressed with the following identity:

$$MS \equiv Q - C + \alpha L_{PW} \tag{16}$$

Totally differentiating with respect to P, we obtain the following:

$$\frac{dMS}{dP} = \frac{dQ}{dP} - \frac{dC}{dP} + \alpha \frac{dL_{PW}}{dP} \tag{17}$$

$$= \frac{dQ}{dP} - \left.\frac{\partial C}{\partial P}\right|_{\Delta U=0} - \frac{\partial C}{\partial M^*} \cdot (Q - C + \alpha L_{PW}) + \alpha \frac{dL_{PW}}{dP}$$

This is the conventional analytical result that households' marketed surplus may either increase or decrease as a result of an increase in the market price of the composite commodity for either net buyers or net sellers of food (the consumption response to an increase in the market price of staples may outweigh the output response. However, as equation (17) illustrates, introducing food aid wages and PW employment into the model adds additional complexity to the sources of ambiguity in the predictions. Increases in the price of staples may lead households at higher risk of facing food insecurity (where $C > Q + \alpha L_{PW}$) to increase their marketable surplus if the higher price causes an increase in the amount of labor allocated to PW (if $\frac{dL_{PW}}{dP} > 0$).

Technology Use: The effects of a change in off farm wages and the price of the composite commodity on the use of the capital input, X, are ambiguous in this model, as they are in a standard household production model. Recall from equation (9) that the optimal level of capital input, X^*, is a function of P, W, W_X and α both directly and indirectly through M^*. Thus, the comparative statics with regards to capital input use are derived as follows:

$$(18) \qquad \frac{\partial X}{\partial P} = \frac{dX}{dP} - \frac{\partial X}{\partial M^*} \cdot \frac{\partial M^*}{\partial P}$$

$$= \frac{dX}{dP} - \frac{\partial X}{\partial M^*} \cdot (Q - C + \alpha L_{PW})$$

$$(19) \qquad \frac{\partial X}{\partial W} = \frac{dX}{dW} - \frac{\partial X}{\partial M^*} \cdot \left(L_{off} - L_{hired}\right)$$

$$(20) \qquad \frac{\partial X}{\partial \alpha} = \frac{dX}{d\alpha} - \frac{\partial X}{\partial M^*} \cdot PL_{PW}$$

As illustrated in equation (18), an increase in the price of the consumption commodity may or may not increase the household's use the capital input (fertilizer in the empirical models presented in Chapter 6). For example, an increase in the price of the composite consumption and production good may induce farmers to invest in farm production, indirectly impacting the use of yield-enhancing capital inputs. Conversely, capital inputs and consumption may be competing uses for the household's income. Some households may choose to allocate more of their income towards pricier consumption goods by sacrificing investments in the capital input.

Similarly, as illustrated in equation (19), how a household responds to a change in the market wage largely depends on the household's initial position in the labor market. Net buyers of labor may respond to increases in the market wage rate by substituting hired labor for capital inputs (this can occur if labor and capital are substitute inputs of production or if capital increases the marginal productivity of labor so that increases in the level of X allow farmers to attain same levels of production while hiring less labor). On the other hand, if labor and capital are complementary factors of production, net buyers of labor may choose to lower their use of both inputs. The effect on net sellers of labor is also ambiguous. For example, a higher wage increases a household's overall income and may therefore increase the use of the capital input in on-farm production. Alternatively, given the increase in market wages, a net seller of labor could choose to abandon farm production rely more heavily on off-

the farm work to sustain household consumption, reducing the household's use of the of the capital input on the farm.

Effects of Food Wages (α): By inspecting the first order conditions embodied in equations (6)-(11), it is relatively easy to see how a change in the food aid wage may affect a household's consumption, use of capital inputs and hired labor, and the allocation of the household's labor between leisure, on farm work, off farm work, and PW work. Even with a simple model, these effects are ambiguous and generally difficult to isolate without additional knowledge about the behavior of the parameters and restrictions over the domain of the variables.

Equation (20) shows the effect of increasing the food wage on technological input use, holding everything else constant. Although not captured directly in the above model, the following issues should be considered. Food aid wages and public works employment may affect households' consumption and production choices through many channels. Food-aid employment activities typically involve labor-intensive work such as road construction. If food payments do not suffice to compensate for the caloric requirement of the work performed, participation in public works could result in poor health and malnutrition. Additionally, strenuous physical work has direct impacts on farmers' productivity and farmers' demand for food, and therefore indirect impacts on the use of capital inputs in the farm. On the other hand, if the form of kind payment improves overall nutrition, food aid wages may provide additional health benefits to participants and enhance the marginal productivity of labor.

There may also be a psychological component related to food wages and a public works employment that could alter participants' behavior and farm decisions. Working conditions and contractual functionality (such as timely payment for the labor provided) may affect participants' morale and shape their expectations of future economic opportunities, thereby influencing farmers' productivity (which may occur if they are suddenly motivated and optimistic about the prospects of their future) and consumption-investment decisions: in light of prospect future benefits, farmers may choose to invest on production inputs or to allocate more of their income towards consumption in the present period.

Lastly, public works programs may also affect households' decisions through the infrastructural dividend from erected physical assets: constructed road networks facilitate access to market centers, schools and hospitals; similarly, built irrigation systems and soil conservation structures improve the productive capacity of cultivated lands. Ready access to markets and information may encourage farmers to develop their farms for commercial purposes and therefore increase their use of technological inputs. Greater productive potential derived from improved-quality soils may also induce farmers to intensify the use of capital inputs in their plots. However, if irrigation systems and other inputs are considered substitutes of production, the opposite may follow.

Implications for Estimation Models

The results obtained from the theoretical model indicate that public works programs in which participants receive food based wages may affect the use of technology related inputs such as fertilizer. However, the effects are complex and ambiguous, and participation in the public works program and the use of a technology or capital input are simultaneously determined. In addition, the use of the technology input and participation in the public works program will both by jointly affected by exogenous variables such as the price of the agricultural commodity produced by the farm and off-farm labor market conditions.

The absence of unambiguous predictions obtained from the theoretical analysis therefore highlights the need for empirical research to assess the effects of food for work programs household behavior in general. To test the hypotheses that multiple exogenous variables affect both decisions and that they are endogenously and simultaneously determined, we estimate an econometric model of participation in public works programs and chemical fertilizer adoption using data from rural Ethiopian households. The general form of the empirical model is as follows:

PW Participation $= f_1$(Gender, Age, Education, Household Size, Farm Size,
Farm Revenue, Nonfarm Income, Average Market Wage, Asset Ownership,
Livestock Ownership, Access to Irrigation, Access to Credit, Access to Public
Services, Access to Information, Direct Support Transfers, Soil Quality, Tree
Coverage; Previous Participation, Severity of Natural Shocks)

Fertilizer use $= f_2$(Gender, Age, Education, Household Size, Farm Size, Farm Revenue, Nonfarm Income, Average Market Wage, Asset Ownership, Livestock Ownership, Access to Irrigation, Access to Credit, Access to Public Services, Access to Information, Direct Support Transfers, Soil Quality, Tree Coverage; Other Inputs, Experience Handling Technologically Improved Inputs)

This general model is estimated using data from a survey of rural Ethiopian households. A detailed description of the data is presented in Chapter 5. Estimation procedures are discussed and described in Chapter 6.

Table 3. Comparative Statics Results: Refutable Predictions Derived from Micro-Economic Theory of the Farm-Household

Decision	Expression	Agent	Base Model	Food-Aid Wages Model
Consumption	∂C/∂P	Net seller of food	?	?
		Net buyer of food	-	-
	∂C/∂α	Net seller of food		?
		Net buyer of food		?
Leisure	$\partial L_e/\partial W$	Net seller of labor	?	?
		Net buyer of labor	-	-
	$\partial L_e/\partial \alpha$	Net seller of food		?
		Net buyer of food		?
PW Labor	∂LPW/∂α	Net seller of food		?
		Net buyer of food		?
	∂LPW/∂P	Net seller of food		?
		Net buyer of food		?
	∂LPW/∂W	Net seller of labor		-
		Net buyer of labor		?

Table 3. Comparative Statics Results: Refutable Predictions Derived from Micro-Economic Theory of the Farm-Household- continued

Decision	Expression	Agent	Base Model	Food-Aid Wages Model
Marketed Surplus	∂MS/∂P	Net seller of food	?	?
		Net buyer of food	+	?
	∂MS/∂α	Net seller of food		?
		Net buyer of food		?
Technology	∂X/∂P	Net seller of food	?	?
		Net buyer of food	?	?
	∂X/∂W	Net seller of labor	?	?
		Net buyer of labor	?	?
	∂X/∂α	Net seller of food		?
		Net buyer of food		?

DATA

Data Sources and Description

The data used in this analysis were obtained from the 2009 round of the Ethiopian Rural Household Survey (ERHS), a comprehensive survey conducted by the University of Addis Ababa and the Centre for the Study of African Economies (CSAE) in collaboration with the International Food Policy Research Institute (IFPRI). [47] The purpose of the survey is to collect periodic statistics on a comprehensive set of household characteristics to study the response of households to food crises.

The survey covers 1470 randomly selected households in 15 villages chosen to represent the diversity of farming systems in the country.[48] Within each village, samples are stratified by landless and female headed households. Respondents are personally interviewed and topics addressed in the survey include household demographics, agriculture and livestock ownership, food consumption habits, health indicators, and off-farm activities. The dataset also contains community-level data on access to labor markets, electricity and water, sewage and toilet facilities, health services, and education; NGO activities; migration patterns and local marketing conditions.

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[47] Stefan Dercon (Department of Economics, University of Oxford) and John Hoddinott (International Food Policy Research Institute) are the two major authors of the surveys and together with the Department of Economics and the University of Addis Ababa in Ethiopia, they oversight of the ERHS project. Dercon and Hoddinott (2011) describe survey and sampling methodology, definition of variables and measurement units, specific characteristics of surveyed populations and survey periods.

[48] In Ethiopia, rural districts are called Woredas. They are further divided into villages or Peasant Associations also referred to as *Kebeles*; they are the smallest administrative unit. Each Woreda consists of up to several villages. A cluster of villages is called a *Tabia.*

Variables Used and Description

The question posed by this study is whether or not public works programs encourage fertilizer use among rural Ethiopian households. In this study, we also seek to identify the factors that determine participation in food for work programs and therefore fertilizer use. We hypothesize each choice to be determined by similar explanatory variables that include demographic characteristics of the interviewed household, specifics about production environment of the farm, and regional characteristics that define the geography and the institutions found in the village where the respondent resides. Variable definitions and descriptive statistics are provided in table 4 at the end of this chapter.

The analysis of input use is focused on the use of chemical fertilizer measured as the number of kilograms of DAP or urea used in the household's farm in preparation for the largest harvest season in the 2007/2008 agricultural year.[49] Participation in public works is measured by an indicator variable that takes on the value of one when respondents had participated in public works programs administered by the Productive Safety Net Program (PSNP). Figure 9 shows the intensity of chemical fertilizer use (DAP or Urea) for respondents of ERHS. Figure 10 shows the level of participation in the Public Works component of the PSNP among the same population.

[49] The analysis of input adoption is focused on the use of chemical fertilizer because the data appear to be more consistent for this variable than for pesticides or improved seed varieties.

Of the 1470 observations in the ERHS dataset, only 183 are usable given the selection of variables suited for our empirical analysis. (Figure 11 depicts the variables with most missing observations by showing the progressive changes in sample size that occur when these are dropped.) A disproportionate number of these observations correspond to individuals from regions were fertilizer is used more intensively. Our sample focuses on households from the Tigray region and largely misrepresents the national fraction of rural households in the Oromia region. In addition, no observations are taken from the Southern Nations Nationalities and Peoples (SNNP) region. [50]

Of the farmers represented in the sample, 40 percent are illiterate (or at least had not received any form of formal education). The majority of them are middle-age men who head an average household of five people (12 percent of the interviewed households were headed by females). Around 60 percent of the households report suffering severe farm losses due to natural catastrophes during the past 5 years.

Over 90 percent of the farmers use some positive amount of fertilizer. Of that group, 79 percent use organic fertilizer while 83 percent apply chemical fertilizer; 68 percent use both. The sample average amount of chemical fertilizer per hectare of land during the Meher season is 19 kg. Yet, there is wide variation in the data of chemical fertilizer. Although the majority of fertilizer users apply between 4 and 20 kg of fertilizer per hectare, the average is likely to be driven by some extreme observations. The

[50] In the sample we used to estimate our models, 60 households (26 percent of the observations) belonged to villages in the Amhara region, 20 (8.6 percent) resided in the Oromia region, and 151 (65.4 percent) were situated in the Tigray region. Based on the Ethiopian Rural Housheold Survey, 33 percent of the country's rural households are situated in the Amhara region, 22 percent in the Oromia region, 11 percent in the Tigray region, and 44 percent in the SNNP region.

average farm revenue corresponding to the few intensive users of fertilizer quadruples the mean farm revenue of the examined sample.

In our sample, 5 percent of the respondents are PW participants (43 percent of them are females), 2 percent are beneficiaries of freely distributed assistance and 28 percent of them had been beneficiaries of food for work programs previous to the establishment of the PSNP. This composition largely misrepresents the rural population covered by ERHS: 18 percent of households are self-reported participants of public works programs; 13 percent are self-reported beneficiaries of freely distributed aid.

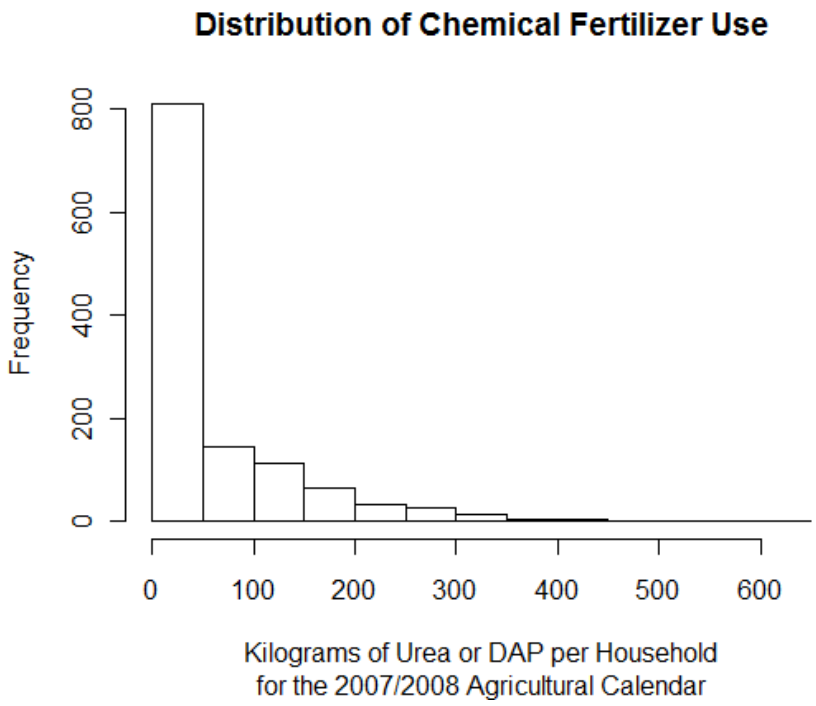


Figure 9. Histogram: Sample Distribution of Chemical Fertilizer Use.

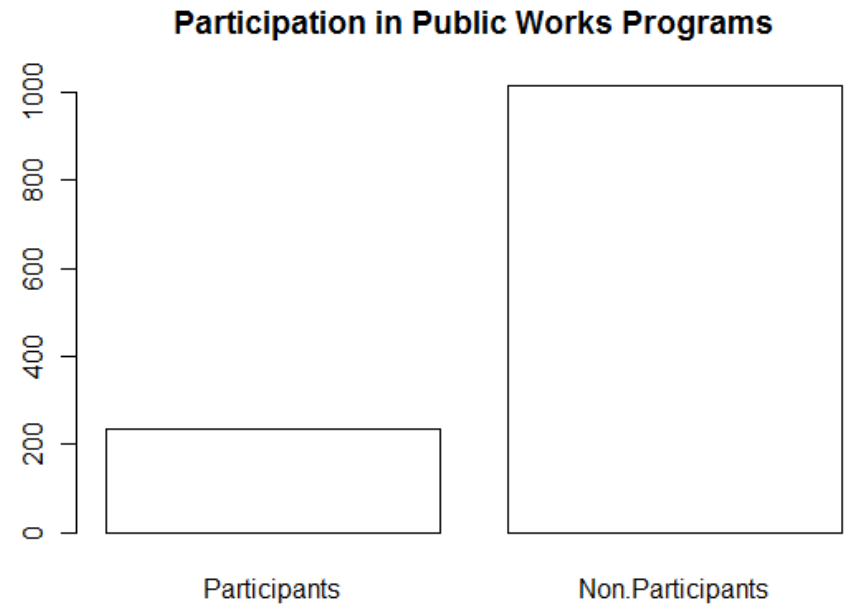


Figure 10. Histogram: Sample Distribution of Participation in Public Works.

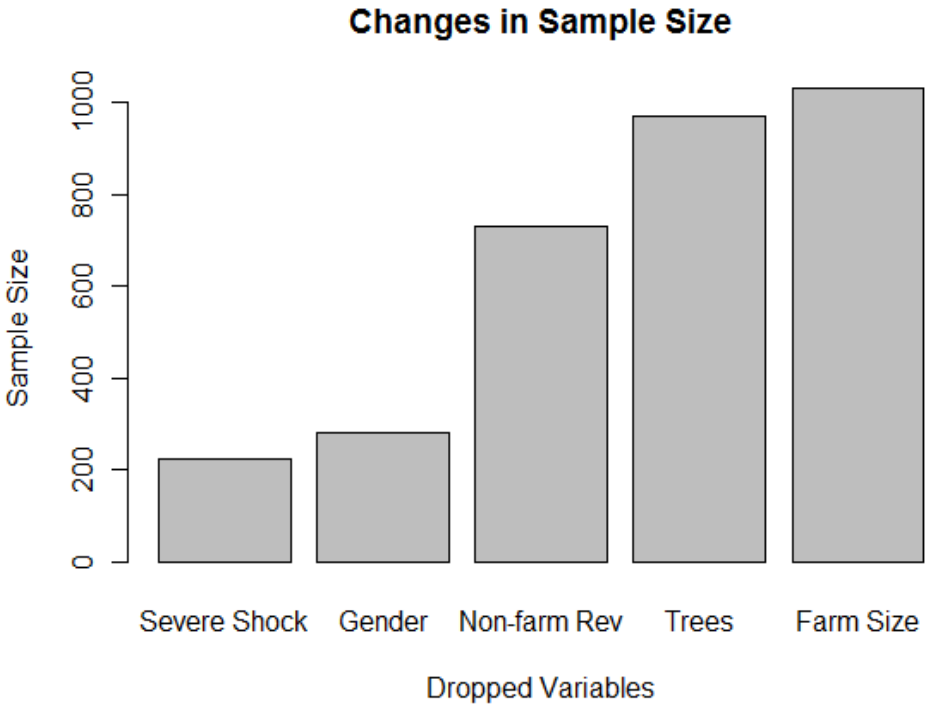


Figure 11. Changes in Sample Size: Variables Explaining Most Missing Information.

Table 4. Variable Definitions and Descriptive Statistics

Variable	Definition	Min	1st Q	Med	Mean	3rd Q.	Max	Sdev
Gender*	Gender	0	1	1	0.89	1	1	0.31
Age	Age	22	40	49	51	60	99	15.3
Literacy_Prg	Attended literacy progr.	0	0	0	0.18	0	1	0.38
Prim_Ed	Some primary educ.	0	0	0	0.17	0	1	0.37
Sec_Ed	Some secondary educ.	0	0	0	0.22	0	1	0.41
High_Ed	Some University educ.	0	0	0	0.01	0	1	0.09
HH_size	Family members	1	4	5	5	6	11	2.1
Farm_size	Farm size (hectares)	0	0.13	0.9	3	1.7	150	15.6
V_assets	Value of assets	0	116	222	340	485	3167	370.8
TLU ł	Tropical Livestock Units	0	0	2	3.5	4.2	27.9	4.7
Irrig	Access to irrigation	0	0	0	0.2	0	1	0.41
Farm_Rev	Farm revenue	0	0	160	1090	829	8340	5672.3
Nonfarm_Rev	Nonfarm revenue	0	96	180	497.6	410	13800	1235.2
DS	Direct Support beneficiary	0	0	0	0.02	0	1	0.15
Equibb	Member of Equibb	0	0	0	0.2	0	1	0.43
Market_W	Average market wage in the respondent's village	11.5	11.5	11.5	13.6	16.4	21.6	3.25
Ext_visits	Extension-service Visits	0	0	1	1.5	2	15	2.2
Sec_schools	Number of secondary schools in the respondent's village	0	0	1	0.7	1	2	0.56
Travel_time	Time to a market center (minutes)	0	5	10	21.	30	300	31.9
Soil_quality	Index of soil quality; 1 is "poor" and 3 is "good"	1.1	1.2	1.5	1.4	1.7	1.9	0.28
Trees	Number of trees in the respondent's farm	0	12	70	445.6	330	10000	1222.9
Manure	User of organic fertilizer	0	1	1	0.8	1	1	0.4
Severe_shock	Severely affected by a natural shock in any of the past 5 years	0	0	1	0.6	1	1	0.49
Fert	Level of chemical fertilizer in the last planting season	0	4	10	17.1	16	182	28.31
PW	Participant in PW of the PSNP	0	0	0	0.04	0	1	0.21
Prev_Fert	User of chemical fertilizer in any of the past 5 years	0	1	1	0.9	1	1	0.22
Prev_PW	Participant before the PSNP	0	0	0	0.28	1	1	0.45

* Summary statistics for variable *Gender* correspond to a sample with 183 observations; the other statistics were obtained from the larger sample.

ł Based on Ramakrishna and Demeke (2000), Tropical Livestock Units (TLU) values are 1 for cattle, horses, and mules, 0.15 for sheep and goats, 0.005 for poultry, 0.65 for donkeys, and 1.45 for camels.

EMPIRICAL METHODOLOGY

Empirical Models

The amount of fertilizer used on a hectare of land directly influences farm output and therefore food security. Also, food aid may relieve economic pressures, helping families to meet *basic* nutritional needs and invest additional income on chemical fertilizer. Alternatively, fertilizer and food aid wages may be considered risk management substitutes among farmers so that increases in aid receipts lead to decreases in the use of fertilizer and vice versa.

As shown in Chapter 5, the use of fertilizer and reliance on international aid are likely to affect one another. Furthermore, the decisions to intensify fertilizer use and participate in relief programs are likely to be determined simultaneously. Hence, a general representation of an econometric estimation model of the joint decision may be as follows:

$$PW_i = \alpha_0 + \alpha_1 X_i + \alpha_2 Y_i + \alpha_3 Z_i + \alpha_4 PREVIOUS_PW_i + \alpha_5 SEVERE_SHOCK_i + \delta_1 CHEM_FERT_i + \varepsilon_{1i}$$

$$FERT_i = \beta_0 + \beta_1 X_i + \beta_2 Y_i + \beta_3 Z_i + \beta_4 PREVIOUS_FERT_i + \beta_5 ORGANIC_i + \delta_2 PW_PARTi + \varepsilon_{2i}$$

where

PW_i is a binary measure of PW participation decision by farmer i; it takes on the value of 1 if the farmer participated in PSNP's public works and is zero otherwise;

$FERT_i$ is the amount of chemical fertilizer used by farmer i; it is measured in kilograms of fertilizer applied per plot;

$PREVIOUS_PW_i$ is a binary variable measuring whether any member in the household had worked in public works programs previous to the establishment of the PSNP;

$SEVERE_SHOCK_i$ is an indicator of (self-reported) severe crop damage suffered by the household in any of the previous five years;

$ORGANIC_i$ is a binary variable indicating whether or not a household used manure to cultivate their fields during the surveyed period; and

$PREVIOUS_FERT_i$ is a binary variable measuring whether any member in the household had used chemical fertilizer in any of the 5 years prior the survey period.

X_i is a vector of farmer-specific attributes such as gender and age;

Y_i is a vector of farm-specific variables such as farm size and ownership of productive assets; and

Z_i is a vector of regional characteristics like soil quality and degree of geographical isolation.

ε_{ni} is the error term.

The variables included in vector X are age, gender, household size and indicator variables for different levels of educational attainment. Vector Y includes variables that characterize the production environment of the farm, and off-farm opportunities for the employment of household labor. Variables that characterize farm capacity include farm revenue, an indicator variable for irrigation use, the total area and number of plots under cultivation, possession of livestock, possession of assets, and an indicator variable of membership in informal risk-sharing institutions. Other variables include nonfarm income, the average market wage in the area in which the household is located, and an indicator variable of free assistance receipts (food or cash).

Vector Z includes variables that define the socio-economic and agro-ecological situation of the region where the farmer resides. Variables that describe a farmer's ability to access information and services include the number of secondary schools, and a measure of distance to market centers as a function of time. Agro-ecological variables include a continuous variable representing tree coverage in the plot farmed by each household, and an index measure that indicates how adequate for cultivation the household's land is. Table 5 summarizes the expected effects of the exogenous variables in the two equations (positive, negative or indeterminate) which are discussed below

Variable Definitions and Expectations

Demographic Variables

Variables indicating the demographic characteristics of respondent farmers include age, gender, education and household size. Age is frequently used to capture the effect of a more complicated variable to measure, farmer's experience. A farmer's experience is not necessarily positively correlated with the propensity to use chemical fertilizer. Additionally, the natural correlation between age and physical ability implies farmer's experience may not be linearly related to participation in PW programs. Therefore, the effect of age on both dependent variables is indeterminate.

Gender plays an important role in determining the household's access to information and markets—especially in rural Africa where males tend to have greater opportunities to attend school, receive loans, join farmers groups, or find employment off the farm (Bittinger, 2010). The variable *Gender* takes on the value of 1 when the head of the household is a male; therefore, the coefficient associated with the variable is expected to be positive in both the fertilizer and participation equations.

Educational attainment may be capturing several attributes, including levels of overall economic success, farmers' attitudes towards new information, general mental and physical health, or availability of public services in the village. Moreover, it is unclear whether educational attainment is a linear indicator of any of these factors (Doss, 2003). Here, as in other studies, we include dummy variables for primary, secondary and post-secondary education, as well as an indicator of participation in

literacy programs. The expected relationship between dependent and education variables is indeterminate.

Off farm employment in local markets is likely to affect technology adoption and participation in public works. Household size is often used to measure a household's access to labor (Bittinger, 2010; Croppenstedt et al., 2003). In the case of input use, ready availability of labor at the time of harvest allows for more intensive use of fertilizer during the planting season. In addition, large households may use more chemical fertilizer to enhance crop production and sustain an extensive family, suggesting a positive relationship but weakening the case of causality. On the other hand, large households may lack the financial resources to invest in the purchase of chemical fertilizer, indicating a negative correlation. Overall, the relationship between family size and fertilizer use could be either positive or negative.

With respect to PW participation, on the one hand, large families may have more labor to sell in local markets and, presumably, more potential sources of income, and conceivably less need to obtain in-kind income through PW participation. On the other hand, larger families may have lower per capita real incomes and are therefore more likely to become participants in PW programs. In general, the relationship between household size and PW participation is also indeterminate.

Wealth Measures

Measures of wealth are often used to explain technology adoption. Wealth is expected to affect fertilizer use decisions. Wealthier farmers have greater access to

resources and may be able to manage food security risk without compromising the use of production inputs. Wealth may also be correlated with knowledge about production practices, which implies that common variables used to model wealth effects are farm size, livestock ownership, access to irrigation, and ownership of physical assets.

Farm size, through a wealth effect, is expected to have a negative effect on public works participation but a positive effect on fertilizer use. In addition, farm size serves as an indicator of information about other factors related to technology use and food security. Farm size may be correlated positively with economies of scale in using improved production technologies. Also, social status and prestige may be associated with large land holdings and may possibly reflect farmers' ability to obtain credit.

Similarly, using livestock ownership as a measure of wealth may be complicated by the fact that livestock provide draft power as well as manure. Farmers with more livestock may be wealthier and, therefore, less likely to participate in programs that provide emergency relief. They may also be more likely to adopt fertilizer as they are presumably more affluent than other households. However, if draft power and manure substitute fertilizer in farm production, having larger livestock herds would imply a lower propensity to use chemical fertilizer. In general, households that own larger livestock herds are expected adopters of chemical fertilizer but among the lower part of the distribution of intensive input users. Size of the household's herd and participation

in labor-intensive social security programs are expected to be negatively related. In this study we measure livestock in terms of Tropical Livestock Units or TLU.[51]

Access to irrigation may be a proxy for wealth because the high fixed costs associated with setting up irrigation systems limit the number of investing households (Bittinger, 2010). Since crop yields in irrigated agriculture are substantially less volatile than in rain-fed agriculture, households with access to irrigation systems are presumably less likely to face food insecurity. Therefore, access to irrigation systems and participation in public works are expected to be negatively correlated. However, as a factor of production, irrigation water may be a substitute or a complement of other inputs; therefore, its impact on chemical fertilizer use is indeterminate.

Finally, since increased wealth gives households more flexibility to bear risk and allocate financial resources to production inputs, asset ownership measured as the money value of non-agricultural assets owned by the household (these may include bicycles, TVs, radios or other consumer goods), is expected to positively affect the use of chemical fertilizer and negatively affect participation in public works programs.

Access to Credit and Cash

For the study of input adoption and participation in labor-intensive welfare programs, access to cash or credit is a characteristic of interest it may affect the ability of farmers to adopt technologies that require initial investments. Lack of access to cash

[51] Based on Ramakrishna and Demeke, 2000, TLU values are 1 for cattle, horses, and mules, 0.15 for sheep and goats, 0.005 for poultry, 0.65 for donkeys and 1.45 for camels.

and credit may also encourage farmers to participate in public works programs to alleviate immediate economic constraints. Because easy access to liquidity facilitates investment and makes households less reliant on transfers from social security programs, measures of access cash and credit accessibility are hypothesized to increase fertilizer use and reduce the likelihood of participation in public works programs.

Credit availability is often measured as a binary variable indicating whether or not the household *used* credit in the past. However, this measure is problematic as credit use does not distinguish between households who chose not to use available credit and farmers who *could* not access credit. Land ownership is often a prerequisite for obtaining credit.[52] If it is possible to assume that any farmer in a village who meets the land requirements had access to credit, farm size may be an adequate indicator of access to credit. Yet, it may still be appropriate to include a binary measure of credit accessibility. In rural Ethiopia, informal savings and credit, risk-sharing institutions such as *Equibs* and *Iddirs* are the source of loans for the large bulk of investors.[53] Thus, a measure of participation in informal risk-sharing institutions is included to improve the modeling of the credit variable.

[52] In Ethiopia, farmers must have at least 0.5 hectares under maize cultivation in order to participate in the credit scheme for maize (Doss, 2003). Farmers with smaller amounts of land will not have access to formal credit.

[53] For a detailed discussion in Iddirs and Equibs see "The Informal and Semi-Formal Financial Sectors in Ethiopia: a Study of the Iqqub, Iddir, and Savings and Credit Co-operatives" by Dejene Aredo (1993).

Access to cash is difficult to measure because of endogeneity issues.[54] To measure whether lack of cash is an impediment to the adoption of technology and a causal factor in labor market decisions, previous studies have used measures of farm revenue, non-farm income, and cash transfers and remittances. In this study, access to cash and credit will be modeled by equibb membership, non-farm income, farm revenue, and receipts of free assistance. The first is measured as an indicator variable that takes the value of 1 when any member of the household is part of an informal risk-sharing group. The second variable measures net income from off-farm activities in the 4 months previous to the survey time (measured in Ethiopian currency, birr). The third is a continuous variable indicating the net profits from agricultural activity by the household in the year preceding the survey. The fourth variable is a binary variable measuring whether the household has received free food or cash from the Productive Safety Net Program.

Presumably, the easier it is for a household to access cash either through income or credit, the more likely the household is to adopt and intensify the use of chemical fertilizer. In contrast, easier access to liquidity and more flexible financial constraints alleviate the household's dependency on welfare transfers. Therefore, it is reasonable to expect the impact of equibb membership, farm revenue and non-farm income to be positive on input adoption but negative on PW participation.

[54] For example, Berhane et al. (2011) show that receipt of a Public Works transfer increased the probability that a household entered a nonfarm business activity. It is possible that participants would have potential to take more loans to open a private business; conversely, it is possible that participants do not have the need to take loans as their livelihoods are more diversified.

The impact of direct support transfers on PW participation may largely depend on whether these programs are designed as complementary or substitute schemes. Similarly, economic intuition suggests the relation between input adoption and direct support receipts may ultimately depend on whether insufficient farm production is the cause or the consequence of poverty.

Access to Information

Farmers must have access to information about new technologies before they can consider adopting them. Extension services are one way in which farmers to gain information on new technologies; hence, access to extension services is often used as a measure of access to information. [55] Extension service visits are expected have a positive effect on fertilizer use; however, extension services may or may not have any effect on PW participation (although they may be correlated via other factors such as geographical isolation).

Other variables that reflect the ability for a household to access information and markets are gender, education, average market wage, number of secondary schools in the village, and travel time to market centers. As discussed above, men tend to have

[55] Using number of visits of extension agents as a proxy for access to information is often problematic. What is usually measured is whether a farmer *used* the extension service. However, this measure does not capture whether the information was available to the farmer; instead, it simply indicates whether the farmer took advantage of the resources. Furthermore, although access to extension may be correlated with technology use, the causal relationship is not clear—extension agents may identify farmers who are innovators and spend more time with them; thus, being an adopter may result in more extension visits. However, given the level of enthusiasm dedicated to outreach programs by the international community, it may still be prudent to include a variable indicating the number of visits by extension agents received by each household during the previous time period.

greater opportunities to access services such as education, credit and employment; also, farmers with higher education levels are likely to allocate resources more efficiently.

The opportunity cost of farming is represented by the average market wage for off-farm activities. In areas where the opportunity cost of farming is high, farmers may be less likely to use labor-intensive farm inputs, such as fertilizer. They are also less likely to devote time into the application to become public works participants.[56]

Secondary schools are likely to be positively correlated with a higher-skilled workforce; therefore, the number of secondary schools in the respondent's village may be directly related with more market interactions. Participation in public works is expected to decrease as the number of secondary schools increases; however, the relation between the number of secondary schools and fertilizer use in ambiguous.

Access to market centers is affected by road quality and geographical conditions such as mountainous regions and water bodies. Therefore, travel time captures the effects of all these variables. Overall, market proximity and faster access to agricultural marketing information is associated with increases in the use of fertilizer. However, the effect geographical isolation on participation in relief programs is ambiguous, particularly because of the endogeneity that arises from the targeting strategy of public works programs.[57]

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[56] There is record that the number of available positions for qualifying participants is limited; and that significant resources are generally required to obtain a position in PW programs. Anecdotal records suggest the selection process of applicants is highly subjective and that program officials are not immune to corruption (Calfat et al. 2010).

[57] In Ethiopia, public works projects typically involve the construction and improvement of roads, irrigation systems, schools, terraces, and soil and water conservation structures.

Agro-ecological Variables

Typically, agro-ecological measures are used to account for regional variation in both agricultural production and incidence of natural catastrophes. These variables also reflect differences in other factors such as quality of road infrastructure, ease of access to markets for inputs and outputs, prevalence of state presence in the area, likelihood of ethnic conflict and propensity for epidemic outbreaks. In this study, soil quality, tree coverage, and travel time are used to capture the effects of ecological processes operating on agricultural production systems.

Soil quality and tree coverage provide information about farming practices and farmers' agricultural expertise (farming practices such as grazing by livestock also affect environmental conditions in the household's plot).[58] These variables may be positively or negatively correlated with fertilizer adoption. Conversely, as noted above, travel time to market centers is expected to be inversely related to input use.

In the case of public works participation, the impact of agro-ecological factors on the decision is obscured by the logistics of the design of the projects themselves. If public works project were assigned to villages through randomization, there should not be any systematic relation between these agro-ecological factors and participation rates. However, public works projects are not randomly assigned; instead, they are allocated based on a complex combination of administrative and community-based

[58] For example, afforestation and reforestation are common practices in developing countries believed to improve the quality of previously degraded soils and promote biodiversity in the region. Thus, tree coverage and soil quality would reflect some of these trends.

targeting procedures. (A detailed description of this procedure is provided in Chapter 2.) Due to the highly subjective nature of the geographical distribution of public works projects, soil quality, tree coverage and distance to markets may be positively or negatively correlated the participation decision.

Other Variables

Two additional variables appear in each of the equations of the simultaneous equation models for which results are reported below. [59] In the participation decision, previous participation in public works and prevalence of severe (negative) natural shocks are used to identify the structural equation (prevalence of severe natural shocks provides a measure of household vulnerability to environmentally-related factors and is also included to control the effect of public works' geographical targeting). Both variables are expected to be positively correlated with public works participation. [60]

There is a lag between the time a household receives food wages and the time the household purchases production inputs (Bezu and Holden, 2008). Public works projects typically take place during the slack agricultural season to avoid competing with farm-activities for surplus labor, implying that if farmers were to use PW transfers for the purchase of inputs, they could not do so until the beginning of the *next* planting season. Therefore, including previous participation in public works can be viewed as

[59] The idea of using a system of simultaneous equations to estimate the relations of interest will be further explored and discussed in depth in the empirical section of this thesis project.
[60] In general, there appears to be consensus in the literature about the existence of a so-called *progressive buildup of institutional capacity* in the food aid delivery system, therefore, there is reason to expect previous participation in PW to heavily and positively influence the probability of participating in public works projects. For additional reading on this evidence see Clay et al. (1998)

adding a lagged variable that accounts for the timing effect imbedded in the seasonal nature of the agricultural calendar.

Previous use of chemical fertilizer and use of organic fertilizer are included in the structural model so that the input adoption equation is identified. More experienced farmers and farmers that rely on farming as their primary form of livelihood are more likely to benefit from yield-improving inputs in production. Therefore, if previous use of fertilizer is a good indicator of farmer's familiarity with modern inputs, and if use of manure accurately signals farmer's reliance on agriculture as a form of livelihood, then, it reasonable to hypothesize both variables to have a positive effect on fertilizer use.

Econometric Modeling Procedures

Four general hypotheses are examined in this study: (1) a range of exogenous factors systematically determine whether or not subsistence farmers in Ethiopia choose to participate in public works programs and use fertilizer; (2) participation in public works programs affects farmers' use of fertilizer; (3) the use of fertilizer affects public works participation decisions; and (4) both of these decisions are determined simultaneously rather than recursively.

To test these hypotheses we use instrumental variables and estimate a system of simultaneous equations with limited and binary dependent variables that model the relationship between participation in public works program and the adoption of

fertilizer by smallholder households in Ethiopia. This method is analogous to the Two-Stage Limited Dependent Variable (2SLDV) model proposed by Nelson and Olsen (1977).

The general procedure proposed by Nelson and Olsen is similar to Two-Stage Least Squares (2SLS) estimation in that it uses instrumental variables to correct for endogeneity. In the first stage of the 2SLDV process, reduced form predictions are obtained using the continuous fitted values retrieved from the selected estimation process—whether it is linear least squares, tobit, probit, or logit. In the second stage, the structural equations are estimated by replacing the endogenous (and possibly censored) right-hand side variables with the continuous fitted latent instruments constructed in the first stage. Therefore, for cases involving probability estimation, rather than using the rescaled fitted values obtained from the reduced form equation, the non-rescaled, linear predictors are used in the second stage of the model.

This procedure provides consistent and unbiased estimates. However, given the use of instruments in the second stage, the reported parameter standard errors are not accurate. Also, the latent nature of the endogenous dependent variables implies that the underlying relationship between explanatory and response factors differs fundamentally from conventional models. To estimate marginal effects we follow the procedure proposed by Atwood and Bittinger (2011).

Modeling PW Participation and Fertilizer
Use with Nelson and Olsen's 2SLDV

The structural form of the 2SLDV econometric model is the following:

$$(21) \qquad Y_1^* = \alpha_1 Y_2^* + \beta_{11} X_1 + \beta_{12} X_2 + \beta_{13} X_3 + \upsilon_1$$

$$(21b) \qquad Y_1 = \begin{cases} Y_1^* & if\ Y_1^* = 1 \\ 0 & otherwise \end{cases}$$

$$(22a) \qquad Y_2^* = \alpha_2 Y_1^* + \beta_{21} X_1 + \beta_{24} X_4 + \beta_{25} X_5 + \upsilon_2$$

$$(22b) \qquad Y_2 = \begin{cases} Y_2^* & if\ Y_2^* > 0 \\ 0 & otherwise \end{cases}$$

In equations (21) and (22), Y_1^* is a latent variable measuring participation in public works programs, and Y_2^* is a latent variable censored at zero representing the use of chemical fertilizer. Y_1^* and Y_2^* are observed only if farmers participate in public works or use positive amounts of fertilizer. The observed outcomes of Y_1^* and Y_2^* do not inform the researcher about how close were farmers from making the respective decision.

Omitting X_4 and X_5 from equation (21), and X_2 and X_3 from equation (22) results in model over-identification. All the other terms in equations (21) and (22) are as usually defined for simultaneous equations models.

Solving for the reduced form of the 2SLDV, the following system is obtained:

$$(23) \qquad Y_1^* = \pi_{11} X_1 + \pi_{12} X_2 + \pi_{13} X_3 + \pi_{14} X_4 + \pi_{15} X_5 + \nu_1$$

$$(24) \qquad Y_2^* = \pi_{21} X_1 + \pi_{22} X_2 + \pi_{23} X_3 + \pi_{24} X_4 + \pi_{25} X_5 + \nu_2$$

Equation (3) is a standard latent binary model of the public works participation decision estimated using a probit procedure. Equation (4) represents the latent censored model of fertilizer use and is estimated using a tobit procedure.

Since the methodology is analogous to 2SLS estimation, the reduced-form coefficient estimated are used to create instruments that are independent from the residuals. The instruments can be defined as:

$$(25) \qquad Y'_1 = \pi'_{11}X_1 + \pi'_{12}X_2 + \pi'_{13}X_3 + \pi'_{14}X_4 + \pi'_{15}X_5 + \nu_1^*$$

$$(26) \qquad Y'^*_2 = \pi'_{21}X_1 + \pi'_{22}X_2 + \pi'_{23}X_3 + \pi'_{24}X_4 + \pi'_{25}X_5 + \nu_2^*$$

Where Y'_1 and Y'^*_2 are the linear predictors obtained from reduced form equations (23) and (24). These instruments are substituted for their counterparts on the right-hand side of (21) and (22a). $Y'_1$and Y'^*_2 are at least asymptotically uncorrelated with the disturbances. The resulting equations are then treated as a single equation probit and a normal censored model. They are expressed as follows:

$$(27) \qquad Y_1 = \alpha_1 Y'^*_2 + \beta_{11}X_1 + \beta_{12}X_2 + \beta_{13}X_3 + \upsilon_1$$

$$= \alpha_1(\pi'_{21}X_1 + \pi'_{22}X_2 + \pi'_{23}X_3 + \pi'_{24}X_4 + \pi'_{25}X_5) + \beta_{11}X_1 + \beta_{12}X_2 + \beta_{13}X_3 + (\upsilon_1^* + \alpha_1 \nu_2^*)$$

$$(28) \qquad Y_2 = \alpha_2 Y'_1 + \beta_{21}X_1 + \beta_{24}X_4 + \beta_{25}X_5 + \upsilon_2$$

$$= \alpha_2(\pi'_{11}X_1 + \pi'_{12}X_2 + \pi'_{13}X_3 + \pi'_{14}X_4 + \pi'_{15}X_5) + \beta_{21}X_1 + \beta_{24}X_4 + \beta_{25}X_5 + (\upsilon_2^* + \alpha_2 \nu_1^*)$$

Maximum Likelihood Estimation (MLE) procedures are used to obtain unbiased estimates of the structural coefficients for equations (27) and (28) and to calculate the marginal effects of exogenous variables. The estimators of the true residuals in the original structural equation are obtained using nonlinear fitted values from the reduced equation and are therefore biased. In this study, to estimate accurate covariance

matrices and ensure unbiased t-statistics, the standard errors of the estimated coefficients in (27) and (28) are corrected following the methodology proposed by Atwood and Bittinger (2011).

Following Atwood and Bittinger (2011), we use a standard delete-k jackknife bootstrapping method to compute the standard errors.[61] Once standard errors are computed, latent variances of both limited and binary dependent variables are corrected in estimating marginal effects. Following Atwood and Bittinger, it is necessary to retrieve and correct the disturbances obtained from of the variance-covariance matrix corresponding to the reduced form equations (27) and (28).

Summary of the Econometric Modeling Procedure

The estimation procedure used in this study is as follows:

1. Estimate π_i in (23) and (24) by applying MLE to each of the equations in the simultaneous-equation system separately.
2. Create the instruments $Y_i' = \pi_i X_j$.
3. Replace the Y_1 and Y_2* on the right-hand side of (21) and (22) by the corresponding Y'_i and, treating these instruments as fixed regressors and the resulting equations as single equation models.

[61] For this project it is appropriate to find standard errors using a delete-k jackknife because its properties are favorable when dealing with the large outliers found in the data. Other reason for using jackknife is the overwhelming presence of non-linearity in the model (due to the use of binary and censored dependent variables) and the small sample size.

4. Estimate the structural parameters in (27) and (28) by MLE applied to each of the equations in the system separately.
5. Estimate standard errors and p-values using a standard jackknife bootstrapping method of 1000 draws with replacement.
6. Estimate the marginal effects following the methodology proposed by Atwood and Bittinger (2011).

Estimation Procedures

Decision to Participate in Public Works

The public works participation decision is measured as a binary variable indicating whether a household member received any payment, in the form of food or cash, for their work in PSNP projects in any of the 5 years previous to the survey period. The relationship between explanatory variables and the decision to participate in public works programs is estimated empirically as a binary probit model.

Formulation of a General Probit Model

Ethiopian farm-households are assumed to be risk-neutral utility-maximizers. Thus, a farmer will participate in public works if his expected utility under participation is greater than the expected utility under abstention. A latent variable, PW^*, indicates the underlying expected net benefit from participating in public works; it can be thought of as a measure of the likelihood that a farmer participates in public works.

The dependent variable PW^* is hypothesized to be explained by a set of exogenous variables and random deviations captured by an error term. This formulation can be expressed as:

$$(29) \qquad PW^* = X\beta + \varepsilon,$$

where X is a vector of explanatory variables, β is a set of parameters reflecting the impact of changes in X on the latent variable, and ε is the error term which is assumed to follow a standard normal distribution.

The analysis of a latent dependent variable (in this case the only observed values are 1 and 0) requires the elaboration of a model that is more suitable than a simple linear regression. One possible way to approach cases of latent binary dependent variables is to use a binary choice model. The use of a logit or a probit regression assures that the predictions from the model will resemble the underlying probability that the latent variable intends to represent. However, the probit estimation has several advantages over other binary choice models. Unlike a logit model, which assumes the error terms to be distributed logistically, a probit model assumes the error term be distributed normally; furthermore, probit estimation does not impose the independence from irrelevant alternatives (IIA) assumption. The probit model for public works participation is:

$$(30) \qquad Prob(PW^* = 1|X) = F(X, \beta)$$

$$Prob(PW^* = 0|X) = 1 - F(X, \beta),$$

where $PW_part = 1$ if a farmer participates in public works (when a farmer expects the net benefit from participating to be positive), X is a vector of explanatory variables, β is a set of parameters reflecting the impact of changes in X, and $F(\cdot)$ is the cumulative density function.

Assuming a normal distribution, the model is a probit regression of the form:

$$(31) \qquad E(PW_part|X) = 0 \cdot [1 - \Phi(X, \beta)] + 1 \cdot [\Phi(X, \beta)] = \Phi(X, \beta),$$

where $\Phi(\cdot)$ is the normal standard cumulative density function.

The nonlinear effects of changes in the explanatory variable on the probability that an individual will choose to participate in public works programs are reflected through the parameter vector β, which in a probit model is estimated using MLE.

The log-likelihood function is a transformation of the joint probability density function derived from the probability model represented in equation (29). The log-likelihood function that will be estimated using MLE is the following:

$$(32) \qquad lnL = \sum_{i=1}^{n} \{Y_i \cdot ln[\Phi(X\beta)] + (1 - Y_i) \cdot ln [1 - \Phi(X\beta)]\}$$

The maximum likelihood estimator, β, maximizes the log-likelihood function and is found through an iterative process (Greene, 2008). The parameter estimates in β, do not necessarily represent the marginal effects; therefore, it is advised to directly analyze them only for the purposes of inferring statistical significance and signing the relations proposed by the model. To calculate the marginal effects of explanatory variables on the public works participation it is important to transform the results from the MLE.

Following Greene (2008), the partial effects can be generally expressed as:

$$(33) \qquad \frac{\partial E(PW_part|X)}{\partial X} = \left\{\frac{dF(\frac{X\beta}{\sigma=1})}{d(\frac{X\beta}{\sigma=1})}\right\}\beta = F'\left(\frac{X\beta}{\sigma=1}\right)\beta = \phi(\frac{X\beta}{\sigma=1})\cdot\beta,$$

where $\phi(\cdot)$ is the standard normal density function.

Marginal Effects: In the public works participation decision, the average marginal effect is interpreted as the average percentage point change in the probability that farmers choose to participate in public works resulting from a discrete change in the explanatory variable. Thus, the accurate interpretation of the marginal effects may have important implications for various development reform policies. (For example, knowing that the decision to participate in public works is insensitive to changes in key parameters may lead to conclude that major structural changes to aid programs would have small behavioral effects.)

Correctly estimating the correlations between latent residuals from the structural equations increases the precision of the computed marginal effects.[62] After correcting variance-covariance matrix of estimated disturbances, the average marginal effect of the exogenous variables is calculated by taking the mean of all the individual marginal effects. (This method is preferable to computing the marginal effect of the average value of each regressor, particularly since some of the explanatory factors are

[62] When modeling a limited or a binary dependent variables an additional mapping is introduced to the process as probit estimation automatically rescales variance to be 1 in the reduced form, implying that the variance estimates will not be consistent or unbiased and invalidating them for the calculation of standard error and marginal effects. Atwood and Bittinger (2011) provide a detailed explanation of why non-corrected variances lead to biased marginal effects. The researchers present a method that is analogous to Thiel's variance correction but that can also be applied to models of simultaneous equations with one or more latent variables.

themselves measured by binary variables. Computing the average marginal effect using the mean value of the explanatory variable would imply using values that are not observed anywhere in the data.) This process is expressed by the following formula:

(34) $$\overline{\frac{\partial Prob(PW_part = 1|Xi)}{\partial Xi}} = \overline{\phi(X\beta/\sigma)}\beta,$$

Decision to Use Fertilizer

In principle, the adoption and intensification decisions can be made jointly or separately (Berhanu and Swinton, 2003). In this study, we treat the two decisions as single stochastic process, and therefore use a type I tobit estimator to model the input use decision.

Formulation of a Simple Tobit
with Censoring Point at Zero

A simple tobit procedure with censoring point at zero is used to model the fertilizer use decision. This representation is given by the following expression:

(35) $$Y^* = X\beta + \varepsilon$$

$$Y = \begin{cases} Y^* & if\ Y^* > 0 \\ 0 & if\ Y^* \leq 0 \end{cases}$$

Equation (35) describes the adoption and intensification of chemical fertilizer decisions as a function of X and ε. X is a vector of explanatory factors; ε is the term capturing random disturbances in the observations. ε is normally distributed and it is centered at zero with a standard deviation of σ. Y^* is a nonnegative and continuous partially observed dependent variable censored at zero; it is the underlying latent

variable representing the expected net benefit (expected utility) from fertilizer use. In turn, Y indicates the observed amount in kilograms of fertilizer used by farmer.

Marginal Effects: In tobit models, each marginal effect is decomposed in order to isolate the influence of the model on the probability of adoption from the effect it has on the intensity of adoption. [63] An additional consideration is the possible examination of different conditional means: those of the latent variable, the observed dependent variable, and the uncensored observed dependent variable (Y^*, Y and $\mathrm{Y}^* > 0$). Accordingly, the calculation and interpretation of the marginal effects depends on whether the researcher is concerned with the marginal effect of changes in the explanatory variables on a particular conditional expectation.

A principal objective of this study is to understand the determinants of fertilizer use in farming by all farmers. Therefore, the marginal analysis in this study focuses on the impact of exogenous variables on the censored dependent variable. The calculation of partial effects is derived using standard results on the moments of censored normal distributions and is expressed as follows:

(36) $$\frac{\partial E(Y|\boldsymbol{X})}{\partial X_i} = \Phi\left(\frac{X\beta}{\sigma}\right) \cdot \beta.$$

[63] An interesting feature of this simplified tobit model was discovered by McDonald and Moffitt (1980): that the total change in the unconditional expected value of Y^* could be decomposed into two intuitive parts. The first component indicates how responsive the amount of fertilizer used (in kilograms) under adoption by current users of the technology is to changes in X. The second component indicates how responsive the probability of adoption by non-users of the technology is to changes in X. Hence, the marginal effects on the adoption decision can be interpreted as change in the probability that a farmer chooses to adopt chemical fertilizer given a unit change in of X, while the marginal effects on the intensity of use decision can be interpreted as the change in the use of chemical fertilizer that results from a unit change increase in an explanatory variable, given that the farmer is a current user of the input.

Summary

In this chapter, an empirical framework that models the relationship between participation in a type of public works program and the use chemical fertilizer by smallholder households in Ethiopia have been developed and a general estimation model has been presented. Econometric estimation issues have been discussed and the estimation procedures used to obtain parameter estimates and estimates of the marginal effects of exogenous variables have been described for the Tobit structural equation for fertilizer use and the probit model of public works participation.

To estimate the empirical models we use cross-sectional data from the Ethiopian Rural Household Survey. We use instrumental variables to model a system of simultaneous equations with limited and binary dependent variables as proposed by Nelson and Olsen (1977). The reduced form estimates, standard errors, and p-values are calculated using standard jack-knife bootstrapping method of 1000 draws of 140 observations with replacement. Latent correlations and marginal effects are found using the estimation procedure proposed by Atwood and Bittinger (2011). In chapter seven we present and interpret the empirical results obtained from a sequence of increasingly parsimonious estimation models

Table 5. Explanatory Variables and Expected Signs*

Explanatory Variable	**Public Works Participation Expected Sign**	**Fertilizer Use Expected Sign**
Gender	+	+
Age	?	?
Literacy_Prg	?	?
Prim_Ed	?	?
Sec_Ed	?	?
High_Ed	?	?
HH_size	?	?
Farm_size	-	+
TLU	-	+
Irrig	-	?
V_assets	-	+
Equibb	-	+
Farm_Rev	-	+
Nonfarm_Rev	-	+
DS	?	?
Ext_visits	?	+
Market_W	-	-
Sec_schools	-	?
Travel_time	?	-
Soil_quality	?	?
Trees	?	?
Prev_PW	+	
Severe_shock	+	
Fertilizer	?	
Prev_Fert		+
Manure		+
PW		?

***** Variable definitions and summary statistics are provided in Table 4 at the end of Chapter 5.

RESULTS

In this chapter, we present estimation results for the general joint probit-Tobit model of public works participation and fertilizer use developed in Chapter 6 using data from the Ethiopian Rural Household Survey described in Chapter 5. Based on the results from the general model, we then estimate more parsimonious models for which we obtain the marginal effects of exogenous variables. The discussion of the results focuses on the more parsimonious models and is organized around the three categories of exogenous variables presented in Chapter 6: farmer-specific characteristics, variables related to farm capacity and household wealth, and region-specific characteristics.

Model Selection Process

The most general model estimated using the Ethiopian Rural Household Survey (ERHS) data has the following two-equation structure:

PW= f_1(Gender, Age, Age^2, Literacy_Prg, Prim_Ed, Sec_Ed, Hig_Ed, HH_size, Farm_size, V_assets, TLU, Irrig, Farm_Rev, Nonfarm_Rev, DS, Equib, Market_W, Ext_visits, Sec_Schools, Travel_time, Soil_quality, Trees, Fert; Prev_PW, Severe_Shock)

Fert= f_2(Gender, Age, Age^2, Literacy_Prg, Prim_Ed, Sec_Ed, Hig_Ed, HH_size, Farm_size, V_assets, TLU, Irrig, Farm_Rev, Nonfarm_Rev, DS, Equib, Market_W, Ext_visits, Sec_Schools, Travel_time, Soil_quality, Trees, PW; Manure, Prev_Fert)

The exogenous variables include household demographic characteristic, variables related to farm capacity and household wealth, and regional variables that reflect socio-

economic and biophysical conditions in the villages where respondents reside. Household demographic variables are Gender, Age, Literacy_Prg, Prim_Ed, Sec_Ed, Hig_Ed and HH_size. Variables related to farm capacity and household wealth are Farm_size, V_assets, TLU, Irrig, Manure, Prev_Fert, Severe_Shock, Farm_Rev, Nonfarm_Rev, DS, Prev_PW, Equib, Market_W, Ext_visits, Sec_Schools and Travel_time. Finally, variables describing the agro-ecology of the region are Trees and Soil_quality.

Results for this model are presented in table 6. In Table 6, several variables that were hypothesized to have potential effects on the public works participation decision, such as secondary and higher education, household size, direct support receipts, equib membership, number of high schools and previous participation in public works are not statistically significant; suggesting the use of a more parsimonious version of the model may be appropriate.

We explored progressively more truncated models. Variables that were not significant in specifications that involved minor modification were discarded for the final estimation. Tables 7 and 8 present the coefficient and standard errors for five alternative simultaneous equations models. Table 7 presents the results for the public works participation decision structural model while table 8 presents results for the chemical fertilizer decision structural model.

Public Works Participation

Gender: In the 2009 Ethiopian Rural Household Survey data set, information on gender is missing for a substantial number of observations. Omitting gender from the model increased the sample size from 183 to 231 observations. Although *Gender* was sometimes significant with a large effect on public works participation (results provided in Table 6 imply there is a difference of 50 percentage points between males and females in likelihood of participating in public works), dropping gender from the model generally resulted in declines in p-values for the regression coefficients associated with other variables. For these reasons, the variable representing gender was omitted from subsequent regressions.

The changes that occur when *Gender* is not included imply that women and men have different levels of human capital and economic capacity to access goods and services. Whenever *Gender* is not included in the regression, secondary and higher education become significant as do direct support transfers, access to credit and previous participation in public works. Conversely, farm revenue becomes insignificant. Average market wage continued to be significant but had a larger p-value. These results may reflect differences in the opportunity cost of time. Men may be more likely to receive formal education, find employment out of the farm household and have access to informal credit institutions.

Other Demographic Variables: In general, when demographic variables are dropped from the model, parameter signs do not change. Using the Akaike Information Criterion (AIC), the model's goodness of fit decreases when variables that reflect basic levels of human capital, such as *Age* and *Prim_Ed*, are omitted (AIC is 102 when they are excluded, and 98 when they are included). The opposite occurs when the variables *High_Ed* and *Literacy_Prg* are omitted (AIC falls from 113 to 98). These results suggest that *High_Ed* and *Literacy_Prg* may be redundant variables; therefore, they are not included in the final version of the model.

Wealth Variables: The results obtained after omitting various combinations of wealth variables from the model suggest that many of them have no effect on PW participation decisions. Whenever household wealth is not included, environmental factors no longer appear to have a role in determining the participation decision. This can be interpreted as there being a "natural incidence differential" between families living in regions with varying levels of agro-ecological potential. In other words, given a level of wealth, the decision to participate in public works made by households in less fertile regions is different from that of households located in more fertile regions.

Nonfarm_Rev exhibits some variation in the sample but variation in *Farm_Rev*, *TLU*, *V_assets* and *Irrig* is limited. This may explain why the latter four variables are not significant. Excluding *Farm_Rev*, *TLU*, *V_assets* and *Irrig* from the regression does not affect the model's overall goodness of fit as indicated by negligible changes in AIC (the

AIC statistics obtained for these models fall in the range between 97 and 98). Therefore, in the most parsimonious model we only control for variations in nonfarm wealth.

Other Variables: Results from different variations of the model suggest that *Farm-size* and *Soil_quality*, which are related to agricultural capacity, capture important effects on the participation decision. Also, minor changes indicate in model specification indicate that market accessibility is positively related to farm productivity (whenever access to services is included in the model the effect of variables related to agricultural productivity decreases). Finally, there is some evidence that *Travel_Time* and *Ext_visits* may be capturing similar effects. For example, extension service agents may only reach villages connected by road networks, in which case, both *Travel_Time* and *Ext_visits* could be reflecting overall remoteness or accessibility to a village. Therefore, one of the variables is omitted in the final estimation.

Fertilizer Use

Gender: Fertilizer use does not generally vary with the *Gender* variable. Although in one or two specifications the variable is significant and has relatively large marginal effects, the results are not robust to changes in model specification.

Other Variables: When controls of education, wealth, and access to markets are removed, previous use of fertilizer and use of manure in the plots are affected in undesirable ways for inference. Previous use of fertilizer is significant when these

variables are included but insignificant when excluded. Also, when education variables are omitted, the parameter values of *Manure* change sign. Additionally, when education variables are not included *PW* becomes insignificant but *HH_size* becomes significant and takes a positive sign.[64]

The more parsimonious version of the model, as suggested by the results discussed above, has the following form:

PW= f_1(Age, Age^2, Prim_Ed, Sec_Ed, HH_size, Farm_size, Nonfarm_Rev,
DS, Sec_Schools, Travel_time, Soil_quality, Fert;
Prev_PW, Severe_Shock)

Fert= f_2(Age, Age^2, Literacy_Prg, Prim_Ed, Sec_Ed, Hig_Ed, HH_size,
Farm_size, V_assets, TLU, Irrig, Farm_Rev, Nonfarm_Rev, DS, Equib,
Market_W, Ext_visits, Sec_Schools, Travel_time, Soil_quality, Trees, PW;
Manure, Prev_Fert)

Parameter estimates for this model are presented in Table 9.

Interpretation of Results

Only the effects of those variables in table 9 that are statistically significant are discussed here. As discussed above, the analysis is organized into three categories of

[64] That *HH_size* becomes significant may be revealing something interesting about family dynamics and sharing of knowledge in Ethiopian rural communities. If *HH_size* begins to reflect some of the effect of education, then it is reasonable to believe that larger families have more human capital than smaller families. Larger families may be able to afford more education than smaller families, suggesting that the relationship between household size and education is non-monotonic. In other words, there may be a critical number of available family workers at which education stops being a substitute and becomes a complement of farm-work.

exogenous variables: farmer-specific characteristics, variables related to farm capacity and household wealth, and region-specific characteristics.

Public Works Participation

Farmer-Specific Characteristics: As indicated by parameter estimates for the variables *Age* and *Age2*, the net effect of an increase in age of the household head on PW participation is negatively correlated with public works participation until the age of 90 years, at which point the effect of age becomes positive. Although consistently significant, this effect is small.

Results show a positive correlation between participation in public works and education of the household's head. Ceteris paribus, farmers with only some primary education are more likely to participate than illiterate farmers by 10 percentage points. The likelihood of participation is 5 percentage points higher for farmers with secondary education than for illiterate farmers.

Farm-Specific Characteristics: These include farm size, use of fertilizer, direct support receipts and previous participation in public works programs. As expected, the likelihood of PW participation is negatively related to farm size. The results indicate that a discrete increase of farm size of 1 hectare reduces the probability of participating in public works by an average of 1.3 percent. This effect is small given that the average size of landholdings in the sample is around two hectares.

Increases in the use fertilizer positively affect participation in public works. For every additional 10 kg of fertilizer used in the cultivated plot, the probability of participation increases by 0.9 percentage points. The magnitude of impact is small given that 17 kg per hectare is the sample average amount of fertilizer use.

The relationship between public works participation and access to direct support transfers is of particular interest. In theory, direct support (DS) is only available for farm households that are severely affected by environmental catastrophes or who are "physically unable" to participate in labor-intensive projects. To some extent, direct support transfers can be thought of as complements of public works wages during adverse years for agricultural activity but substitutes during good years. The results presented here indicate that being a recipient of freely distributed aid, in the form of food or cash, has a positive and economically significant effect on the decision to participate in public works. An increase of 11 percentage points in the probability of participating in public works is associated with the direct support indicator.[65]

Previous participation in public works is consistently significantly negatively related to the probability of participating again, but the effect is quantitatively negligible. Previous participation is associated with a 0.004 percentage point decrease in the probability of becoming a beneficiary.[66]

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[65] This result is paradoxical because there weren't major natural catastrophes between 2004 and 2009. The sign and magnitude of the effect could be revealing some inefficiency in the targeting of the program, or it could point out at a principal-agent type of problem. There is some empirical evidence supporting both of these possibilities (Mansuri and Rao, 2012).

[66] This result may be interpreted as evidence of a small success of the PSNP in bringing food insecure households out of poverty. Given the consistent empirical evidence suggesting there is a strong and

Region-Specific Characteristics: Variables defining the socio-economic and agro-ecological situation of the region where farmers resides include indicators of access to information and services as well as measures of agricultural potential. According to the results, the probability of participating in public works decreases by 6 percentage points for every additional secondary school in a farmer's village, suggesting that information and service accessibility may be related to the availability of safety net programs.[67]

Travel time to a market center reflects market accessibility and captures some geographical and infrastructural characteristics of the region in which farmers live. The marginal effect presented in table 9 indicates that for every additional 4 hours of travel farmers are 1 percentage point less likely to participate in public works. Considering that sample distance to market centers varies from zero to five hours, the economic impact of changes in this variable are negligible.

The results indicate a negative correlation between soil quality and public works participation. When soil quality changes from "bad" to "poor" or from "poor" to "good" there is a decrease of 6 percentage points in the likelihood that farmers participate in PW programs.[68] Finally, farmers who report having been severely affected by a natural

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weighty positive correlation between previous participation in food aid programs and the probability of becoming a beneficiary in the future, our results are somewhat controversial.

[67] As mentioned in previous chapters, there appears to be a general consensus in the literature about the existence of a so-called progressive buildup of institutional capacity in the food aid delivery system. It is possible that public works programs are systematically targeting locations with easier information and transportation accessibility, a situation that would be consistent with our results (for additional evidence see Clay et al., 1998; Mansouri and Rao, 2012).

[68] Since better soil quality is associated with lower vulnerability to food insecurity and therefore lower chances of being considered in food aid appeals, this result is intuitively appealing. Also, soil quality may be an indicator of other farmer characteristics that cannot be observed. For example, better soils may belong to farmers that practice soil conservation.

catastrophe (most likely to be a drought) are 1.3 percentage points less likely to participate in public works than other farmers.[69]

Fertilizer Use

Farmer-Specific Characteristics: The results presented in tables 7 and 9 indicate that higher levels of formal education are not monotonically associated with increases fertilizer use. Fertilizer use is 16 kg greater for households where the head of the family had received education beyond high-school level than for households headed by illiterate individuals. The observed differential is consistent with the idea that input optimization involves relatively complex analytical skills—at a minimum, it requires careful planning and understanding of the fertilization process.

Farm-Specific Characteristics: Variables indicating the agricultural characteristics of the farm and input use include farm size, previous use of chemical fertilizer, irrigation and use of manure. The results provide evidence in support of the hypothesis that technology intensification is a dynamic process.

The results shown in table 9 indicate that familiarity with technologically improved inputs, measured by relatively recent previous use of fertilizer, is positively

[69] Although this result seems counter-intuitive, when we separate the population of participants between those who were affected by natural catastrophes and those who were not, we find that they were significantly different in various controls. On average, participants who suffered severe farm losses due to natural catastrophes had slightly smaller farms, larger livestock herds, farm incomes that were over twice as large, and none of them were recipients of DS. Additionally, the population of severely affected participants had 4 times as large farm revenues as the whole population of severely affected farmers. That possibly explains the negative relation between the relation between severe shocks and PW participation.

correlated with fertilizer use and that the effect is relatively large. Fertilizer use is 50 kg larger for households which used chemical fertilizer in any of the previous five years than for other households.[70]

Farm-households with access to irrigation appear to reduce their use of chemical fertilizer by 14 kg per hectare than households without such access, suggesting that irrigation and fertilizer are substitute inputs of production and that households use fertilizer to compensate for poor water supply.[71] In contrast, manure and inorganic fertilizer appear to be complements: users of manure apply six more kg of chemical fertilizer than non-users.

Farm revenue, non-farm revenue and asset ownership are positively correlated with fertilizer use. The results indicate that, depending on the source of income, on average fertilizer use increases between 5 kg and 40 kg per hectare if income increases by 10000 Ethiopian birr, depending on the source of the income increase (five kg if the additional income was generated by farm operations and 40 kg if it originated through off-farm activities). [72]

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[70] In Ethiopia there are substantial differences in fertilizer use between regions, some believe the lower intensity of use to be related to soil type. Although it may still be important to include a region-specific dummy variable in order to capture variations in institutional, socio-political, religious, cultural and other relevant dimensions specific to the region, due to the perfect multicollinearity that arises when regional dummies together with agro-ecological variables that show little variance (soil quality for instance) are included, fixed effects are omitted in the econometric analysis.

[71] Bezu and Holden (2008) found similar effects of irrigation on fertilizer use; their estimated effect of access to irrigation was -18.8 kg per plot.

[72] We expect this result to be largely influenced by the restrictions imposed by the tobit model. It is possible that the effect of the variables mentioned above on intensity of use would be greater had we used a double hurdle or a heckman selection model to estimate the data.

Equib membership is significantly and positively related to the use of chemical fertilizer. However, the effect is small. The average predicted marginal effect of equib membership on fertilizer use is four additional kg per cultivated plot.

Finally, the regression results for fertilizer use provide no evidence that participating in the Ethiopian Productive Safety Net Program reduces the use of fertilizer. Direct support receipts have an estimated positive impact on fertilizer use. Beneficiaries used, on average, an additional 9 kg of fertilizer per hectare. Similarly, public works participants are estimated to use 1.8 more kg of fertilizer per hectare than non-participants.

Region-Specific Characteristics: The results in table 9 indicate soil quality is negatively correlated with fertilizer use. As soil quality increases (from "bad" to "poor" and from "poor" to "good"), farmers reduce their use of fertilizer by 8 kg per hectare; suggesting either that fertilizer is used to compensate for poor quality of soil or that fertilizer use may actually damage the soil. Both effects could occur simultaneously.[73]

Unexpected Results

It had been hypothesized that if average market wage reflects the opportunity cost of farming, whenever the opportunity cost of farming is high, farmers would dedicate less labor to farming activities. However, average market wage for nonfarm labor is found to be positively related to fertilizer use. For every 10 birr ($0.6) increment

[73] In their study of food-for-work programs in Ethiopia, Bezu and Holden (2008) estimate that poor quality soils decrease the use of chemical fertilizer by 7.9 kg.

in average market wages, fertilizer use increases by five kg. The observed positive relation between fertilizer use and average non-farm market wage may be reflecting overall regional economic performance or market and information accessibility.

The number of secondary schools was expected to be positively correlated with market interactions, and therefore fertilizer use. However, the empirical results indicate that for every additional secondary school in the village households use eight less kg of fertilizer. This counter-intuitive result may be driven by unobserved links between the number of secondary schools and other important socio-economic characteristics such as population pressure.[74]

Remoteness or geographical isolation, measured as the distance to market centers, is likely related to transportation-induced transaction costs and limited access to information; suggesting a negative relationship between *Travel_Time* and fertilizer use. However, the results presented in table 9 indicate that for every additional hour of travel farmers use five more kg of fertilizer. This result may derive from the lack of variation in the explanatory variable.[75]

The average marginal effect of an additional tropical livestock unit was positive as expected; however, the magnitude of impact seems small, given the emphasis placed in many studies on livestock ownership as a major component of smallholder farm

[74] Larger families may be too cash constrained to invest in expensive agricultural inputs such as fertilizer. Another possible explanation may be that families are choosing to invest in the human capital of their children over investments in agricultural inputs. This, together with Ethiopia's rapid population growth may be driving a higher demand for institutions offering secondary education.

[75] Bezu and Holden (2008) find a negative relationship between distance to market centers and fertilizer use in the Tigray region. The mean distance to market centers in their sample was 143 minutes with a standard deviation of 92. In our sample these statistics were 23 and 32, respectively.

wealth**.** A one unit change in herd size is associated with 260 more grams of fertilizer per cultivated plot.[76]

Summary

This chapter has presented the empirical results obtained from a probit-Tobit simultaneous equations model of public works program participation and fertilizer use by smallholder farmers in Ethiopia. The evidence from the econometric models indicates that farm households that participate in public works programs use more fertilizer than those who do not. Furthermore, fertilizer use is also positively associated with participation in other public support programs, in this case freely distributed aid and aid wages. Additionally, fertilizer appears to have a positive, although small, effect on the PW participation decision.

Other variables also affect these decisions. The previous use of both chemical and organic fertilizer appears to have substantial impacts on the amount of current fertilizer use. Variables measuring human capital, wealth and access to income also have a positive impact on fertilizer use. In contrast, soil quality and access to irrigation have negative impacts on the amount of fertilizer used by smallholder farmers.

[76] Livestock provide organic fertilizer, which may be perceived as a substitute for chemical fertilizer; in which case the sign would be negative. However, livestock are also known to serve as "repositories of wealth"; that is, they are used as an informal saving strategy among farmers. Therefore, livestock ownership may be reflecting a more complex household decision-making phenomenon than mere farm productivity choices. However, it is reasonable to label households with larger livestock herds as wealthier households who could afford modern agricultural inputs such as fertilizer. There are opposing forces at play; what is interesting in our results is to find that these impacts are almost exactly opposite.

Surprisingly, in this data set distance to markets is positively related to increased use of fertilizer while the number of secondary schools in the farmer's village has a negative effect.

Regression results for the public works participation decision indicate that lower education levels are statistically significantly related to higher likelihood participation. Instead, increases in farm size are negatively related to participation in public works. In addition, both number of secondary schools and quality of the soil have negative impacts on public works participation.

These findings indicate that safety net programs appear to facilitate the transformation and intensification of Ethiopia's agricultural system. In the next chapter we explore the economic significance and the policy implications from our results. We also discuss some ways in which the effects of PSNP transfers on the use of chemical fertilizer may translate into sector and economy-wide productivity gains and what these conclusions may imply for agricultural and international aid policy.

Table 6. Estimated Parameters Using 2SLDV: Most Comprehensive Model

Variable	coefficient	p-value		Variable	coefficient	p-value	
PW Participation Equation				Chemical Fertilizer Equation			
Fert	0.018	0.072	*	PW	4.542	0.004	***
Gender	7.870	0.005	***	Gender	-44.449	0.002	***
Age	0.058	0.146		Age	-0.235	0.273	
Age2	0.0004	0.162		Age2	0.002	0.327	
Prim_Ed	0.914	0.021	**	Literacy_Prg	5.617	0.039	**
Sec_Ed	-0.013	0.552		Prim_Ed	-3.984	0.065	*
High_Ed	-5.686	0.117		Sec_Ed	1.197	0.227	
Literacy_Prg	-0.385	0.073	*	High_Ed	48.465	0.001	***
HH_size	-0.007	0.309		HH_size	0.304	0.152	
Farm_size	-0.559	0.036	**	Farm_size	2.399	0.05	**
V_assets	-0.001	0.012	*	V_assets	0.008	0.006	***
TLU	0.070	0.039	**	TLU	0.725	0.026	**
Irrig	-1.093	0.046	**	Irrig	-8.090	0.061	*
Farm_Rev	0.000	0.096	*	Farm_Rev	0.003	0.012	**
Nonfarm_Rev	0.000	0.057	*	Nonfarm_Rev	0.004	0.016	**
DS	1.811	0.102		DS	17.235	0.03	**
Equib	0.301	0.107		Equib	2.696	0.064	*
Market_W	-0.149	0.018	**	Market_W	0.226	0.224	
Ext_visits	-0.138	0.04	**	Ext_visits	1.753	0.001	***
Sec_schools	-2.112	0.002	***	Sec_schools	-3.573	0.178	
Travel_time	-0.025	0.002	***	Travel_time	0.272	0.004	***
Soil_quality	-0.235	0.386		Soil_quality	-19.251	0.008	***
Trees	-0.001	0.004	***	Trees	0.006	0.008	***
Prev_PW	0.055	0.438		Prev_Fert	68.317	0	***
Severe_shock	-0.804	0.009	***	Manure	13.964	0.001	***

Degrees of Freedom: 170 Total (i.e. Null);
145 Residual
Null Deviance: 64.62
Residual Deviance: 39.68
AIC: 91.68

Notes: ***,**,* denote significance at the one, five and ten percent level

p-values were calculated as the probability that the effect of the impendent variable was equal to zero

Table 7. Estimated Model Parameters for the PW Participation Decision

Variable	Model 2		Model 3		Model 4		Model 5		Model 6	
Fert	0.024	***	0.016	***	0.015	***	0.014	***	0.014	***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Age	-0.006		-0.035	***	-0.032	**	-0.028	**	-0.040	***
	(0.003)		(0.000)		(0.000)		(0.000)		(0.000)	
Age2	0.000	**	0.000	***	0.000	***	0.000	**	0.000	***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Prim_Ed	1.020	***	1.149	***	1.103	***	0.838	***	1.193	***
	(0.25)		(0.000)		(0.126)		(0.09)		(0.126)	
Sec_Ed	0.541	**	0.653	**	0.544	**			0.570	**
	(0.284)		(0.189)		(0.189)				(0.158)	
High_Ed	-4.029	***					-3.819	***		
	(0.316)						(0.189)			
Lit_Prg	-0.538	***								
	(0.79)									
HH_size	-0.043	**	-0.031	*	-0.037	**	-0.067	**	-0.051	**
	(0.032)		(0.032)		(0.032)		(0.032)		(0.021)	
Farm_size	-0.197	***	-0.118	***	-0.143	***	-0.252	***	-0.157	***
	(0.063)		(0.032)		(0.032)		(0.063)		(0.032)	
V_assets	-0.001	***	-0.001	***	-0.001	***	-0.001	***		
	(0.000)		(0.000)		(0.000)		(0.000)			
TLU	0.019	**					0.011	**		
	(0.000)						(0.000)			
Irrig	0.273	**					0.364	**		
	(0.253)						(0.158)			
Farm_Rev	0.000									
	(0.000)									
Nonfarm_Rev	0.000	*							0.000	***
	(0.000)								(0.000)	
DS	1.273	**	1.234	**	1.167	**	1.213	**	1.436	**
	(3.478)		(1.075)		(1.075)		(1.264)		(1.201)	
Equib	0.281	**					0.313	***		
	(0.158)						(0.094)			
Market_W	0.002	***					0.021	*		
	(0.032)						(0.032)			
Ext_visits	-0.087	***	-0.068	***						
	(0.032)		(0.032)							
Sec_schools	-0.629	***	-0.686	***	-0.666	***	-0.334	**	-0.740	***
	(0.189)		(0.126)		(0.126)		(0.126)		(0.126)	
Travel_time	-0.007	***	-0.005	**	-0.004	**	-0.007	**	0.000	*
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Soil_quality	-0.675	**	-0.592	***	-0.648	***	-1.066	***	-0.709	***
	(0.316)		(0.221)		(0.221)		(0.284)		(0.252)	
Trees	-0.001	***	-0.001	***	-0.001	***				
	(0.000)		(0.000)		(0.000)					
Prev_PW	-0.199	**	-0.219	**	-0.193	**	-0.167	*	0.000	***
	(0.158)		(0.094)		(0.094)		(0.126)		(0.000)	
Severe_shock	-0.609	***	-0.606	***	-0.643	*	-0.587	***	-0.155	***
	(0.126)		(0.094)		(0.094)		(0.094)		(0.094)	

Table 7. Estimated Model Parameters for the PW Participation Decision-continued

Variable	Model 2	Model 3	Model 4	Model 5	Model 6
Degrees of Freedom:	224 Total; 200 Residual	224 Total; 208 Residual	224 Total; 209 Residual	224 Total; 206 Residual	224 Total; 209 Residual
Residual Deviance:	63.24	64.95	65.33	66.74	66.92
AIC:	113.2	98.95	97.33	104.7	98.92

Notes: ***,**,* denote significance at the one, five and ten percent level
p-values were calculated as the probability that the effect of the independent variable was equal to zero
Standard errors are presented in parenthesis; a value of 0.000 means it is less than 0.0001

Table 8. Estimated Model Parameters for the Chemical Fertilizer Decision

Variable	Model 2		Model 3		Model 4		Model 5		Model 6	
PW	2.610	**	0.789	*	0.370		-0.116		2.718	**
	(1.075)		(0.822)		(0.727)		(0.727)		(1.106)	
Age	-0.317	**	-0.497	**	-0.424	**	-0.346	**	-0.246	*
	(0.126)		(0.126)		(0.126)		(0.126)		(0.126)	
Age2	0.002	**	0.004	**	0.003	**	0.003	**	0.001	*
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Prim_Ed	2.251	*	2.100	**	2.901	**	4.268	***	2.072	
	(1.581)		(1.011)		(1.011)		(1.043)		(1.707)	
Sec_Ed	-1.370		-1.909	*					-1.139	***
	(1.296)		(0.980)						(1.201)	
High_Ed	34.836	***							24.189	*
	(6.039)								(3.921)	
Lit_Prg	3.905	**							2.563	
	(1.960)								(1.549)	
HH_size	-0.074		0.257	*	0.174		22.779	***	-0.037	
	(0.158)		(0.158)		(0.158)		(3.858)		(0.189)	
Farm_size	0.454	**	0.028	**	0.030	**	0.023	**	0.452	**
	(0.253)		(0.032)		(0.032)		(0.032)		(0.189)	
V_assets	0.006	***							0.003	**
	(0.000)								(0.000)	
TLU	0.328	***					0.477	***	0.397	***
	(0.094)						(0.094)		(0.094)	
Irrig	-19.713	***	-20.951	***	-21.093	***	-21.068	***	-20.663	***
	(1.707)		(1.296)		(1.296)		(1.359)		(1.517)	
Farm_Rev	0.001	***	0.001	***	0.001	***	0.001	***	0.001	***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Nonfarm_Rev	0.005	***	0.005	***	0.005	***	0.005	***	0.005	***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
DS	12.933	**	14.368	**	14.337	**	16.730	**	13.573	**
	(8.696)		(5.439)		(5.470)		(5.344)		(5.375)	
Equib	4.176	***					5.288	***	5.282	***
	(1.170)						(0.853)		(0.885)	
Market_W	0.764	***					0.895	***	0.827	**
	(0.221)						(0.221)		(0.221)	

Table 8. Estimated Model Parameters for the Chemical Fertilizer Decision-continued.

Variable	Model 2		Model 3		Model 4		Model 5		Model 6	
Ext_visits	1.705	***	1.645	***	1.613	***	1.492	***	1.523	***
	(0.221)		(0.221)		(0.189)		(0.189)		(0.189)	
Sec_schools	-11.953	***	-15.064	***	-15.510	***	-15.159	***	-12.671	***
	(2.023)		(1.201)		(1.201)		(1.170)		(1.770)	
Travel_time	0.134	***	0.133	***	0.132	***	0.120	***	0.121	***
	(0.032)		(0.032)		(0.032)		(0.032)		(0.032)	
Soil_quality	-11.389	***	-2.761	**	-2.966	**	-12.871	***	-11.669	***
	(2.403)		(1.581)		(1.549)		(2.118)		(2.276)	
Trees	0.001	**	0.000		0.000				0.001	**
	(0.000)		(0.000)		(0.000)				(0.000)	
Prev_Fert	76.167	***	-0.993	*	-0.904	*	0.350		76.574	***
	(7.463)		(0.695)		(0.695)		(0.600)		(6.893)	
Manure	9.596	***	-2.961	***	-3.052	***	-1.345	**	9.424	***
	(1.075)		(0.758)		(0.758)		(0.790)		(1.043)	

Notes: ***,**,* denote significance at the one, five and ten percent level;
Standard errors are presented beneath the estimated coefficient in parenthesis.

Table 9. Estimated Parameters Using 2SLDV: Most Parsimonious Model

Variable	coefficient	slope	p-value		Variable	coefficient	slope	p-value	
PW Participation Equation					*Chemical Fertilizer Equation*				
Fert	0.014	0.001	0	***	PW	2.718	1.792	0.02	**
	(0.004)					(1.111)			
Age	-0.040	-0.003	0.005	***	Age	-0.246	-0.162	0.059	*
	(0.015)					(0.135)			
Age2	0.000	0.000	0	***	Age2	0.001	0.001	0.08	*
	(0.000)					(0.001)			
Prim_Ed	1.193	0.097	0	***	Prim_Ed	2.072	1.366	0.104	
	(0.136)					(1.714)			
Sec_Ed	0.570	0.046	0.021	**	Sec_Ed	-1.139	-0.751	0.167	
	(0.169)					(1.215)			
High_Ed					High_Ed	24.189	15.946	0	***
						(3.926)			
Literacy_Prg					Literacy_Prg	2.563	1.690	0.061	*
						(1.534)			
HH_size	-0.051	-0.004	0.028	**	HH_size	-0.037	-0.024	0.383	
	(0.026)					(0.186)			
Farm_size	-0.157	-0.013	0	***	Farm_size	0.452	0.298	0.017	**
	(0.021)					(0.202)			
V_assets					V_assets	0.003	0.002	0.029	**
						(0.001)			
TLU					TLU	0.397	0.262	0	***
						(0.090)			
Irrig					Irrig	-20.663	-13.621	0	**
						(1.505)			
Farm_Rev					Farm_Rev	0.001	0.0005	0	***
						(0.000)			
Nonfarm_Rev	0.000	0.000	0.001	***	Nonfarm_Rev	0.005	0.004	0	***
	(0.000)					(0.000)			

Table 9. Estimated Parameters Using 2SLDV: Most Parsimonious Model-continued

DS	1.436	0.117	0.027	**	DS	13.573	8.948	0.025	**
	(1.204)					(5.390)			
Equib					Equib	5.282	3.482	0	***
						(0.877)			
Market_W					Market_W	0.827	0.545	0.015	**
						(0.234)			
Ext_visits					Ext_visits	1.523	1.004	0	***
						(0.191)			
Sec_schools	-0.740	-0.060	0	***	Sec_schools	-12.671	-8.353	0	***
	(0.139)					(1.755)			
Travel_time	0.000	-0.004	0.083	*	Travel_time	0.121	0.080	0.003	***
	(0.002)					(0.024)			
Soil_quality	-0.709	-0.058	0	***	Soil_quality	-11.669	-7.692	0	***
	(0.243)					(2.271)			
Trees					Trees	0.001	0.001	0.026	**
						(0.000)			
Prev_PW	0.000	0.000	0	***	Prev_Fert	76.574	50.478	0	***
	(0.000)					(6.890)			
Severe_shock	-0.155	-0.013	0.056	*	Manure	9.424	6.212	0	***
	(0.097)					(1.051)			

Notes: ***,**,* denote significance at the one, five and ten percent level
p-values were calculated as the probability that the effect of the independent variable was equal to zero
Standard errors are presented beneath the estimated coefficient in parenthesis;
A value of 0.000 means it is less than 0.0001

ECONOMIC AND POLICY IMPLICATIONS

In this study we examine the relation between fertilizer use by rural Ethiopian farmers and participation in public works administered by Ethiopia's Productive Safety Net Program (PSNP). Our empirical results provide no evidence that food for work programs and other income support programs adversely affect the adoption of fertilizer. In fact, the results suggest that the programs, to some extent, significantly encourage the use of chemical fertilizer. In addition, we find evidence that access to higher education, and community-based risk-spreading and credit-providing institutions are important factors for the development of Ethiopia's agricultural sectors. Finally, our findings support the case for agricultural policies to become integrated with long-term development projects as fertilizer use appears to be a dynamic process.

Our findings may be interpreted as evidence supporting the institutionalization of safety net programs in some regions of Ethiopia. In this chapter we compare our estimates to other Ethiopian economic data and provide a provocative discussion on whether the implementation of social protection programs is a viable policy instrument to solve the problem of transforming Ethiopia's agricultural system. We place particular attention to the possible unintended negative consequences of conditional transfers on farmer behavior. We also elaborate on our empirical results and discuss some implications for policies that seek to encourage fertilizer use in some regions of Ethiopia.

The Impact Differential between Unconditional and Conditional Transfers

The Productive Safety Net Program was launched in 2005. The initial phase of the program had a target caseload of 7.75 million people, and the total cost of the project was $370 million. Eighty five percent of the program's resources were distributed through food wages and the remaining fifteen via direct support handouts. We estimate that during the initial phase, beneficiaries of the program received on average 900 Ethiopian birr or around $48.[77]

Our results regarding fertilizer use and household income indicate that the average household would increase its use of chemical fertilizer by 40 kg following an increase in family income of at least 20 percent.[78] Based on 2005 average income per capita figures, we calculate participant households' income to have increased by 9 percent if every member of an average participant family were direct beneficiaries of the PSNP.

Based on our empirical findings, a pure income effect from PSNP transfers would translate into an increase in fertilizer use by 18 kg per beneficiary household. This would

[77] Our estimates are consistent with those offered by other researcher. For example, in a 2006 report by the Institute of Development Studies, Stephen Devereux and Rachel Sabates-Wheeler estimate that the total value of cash and food received by male-headed households was 912.9 Ethiopian Birr.

[78] Based on 2005 average income per capita figures, 10000 birr is a rough estimate of the average annual per capita income (The World Bank, 2012). Therefore, for households to increase their use of fertilizer by 40 kg, the income of the average household of 5 would have to increase by at least 20 percent.

be equivalent to doubling the amount of input used by average households.[79] Provided that doubling fertilizer use translated into a doubling of yields as suggested by some agricultural researchers, a pure income effect from PSNP transfers could translate into a doubling of agricultural production.[80] However, as evidence shows, PSNP benefits do not behave as we predict pure income transfers would.

In our study, there is an effect differential between pure transfers and conditional transfers that admits for interesting interpretations of potential fundamental differences between direct support beneficiaries and public works participants. According to our results, receiving direct support assistance was associated with a nine kg increase in fertilizer use, half of the estimated effect from a pure income transfer. In turn, participating in public works activities was related to a 1.8 kg increase in fertilizer use, a tenth of the predicted impact from pure income transfers.

By design, only chronically food insecure households with no physically abled members are entitled to direct support transfers. That these households are among the most vulnerable may explain why the overall impact of unconditional assistance on fertilizer use is lower than the expected effect of making additional income available to them. It is possible that direct support beneficiaries are using additional resources to meet basic consumption requirements rather than to invest in farm production; indicating that PSNP resources are adequately targeting disadvantaged populations.

[79] The average amount of chemical fertilizer per plot used by households in the sample we examined was 17. 21 kg. (According to World Bank data, the average consumption of fertilizer in 2007 was 16 kg per hectare of arable land, an indication that our sample average may be a close representation of the national average). Therefore, an increase of 18 kg is equivalent to doubling the amount of input used.
[80] For more details on these predictions see the work of Duflo et al. (2009).

The predicted trivial impact of public works participation on fertilizer use suggests that the labor requirement component of these food wages may impose additional incentives to which participants respond in a manner that almost offsets the predicted positive income effect that would result from the freely distributed assistance. We find this result interesting and consider it appropriate to elaborate on the possible forces behind this puzzling phenomenon. What unintended incentives could be attached to food wages that may be inducing participants to modify their choices of fertilizer use?

Fertilizer use increases farm production and is therefore associated with an increase in farm labor during the time of harvest. If participants in public works are allocating their labor towards off-farm activities and away from farm production they may choose to reduce their use of fertilizer in order to lower the amount of farm labor needed to harvest increased yields. However, public works activities are conducted during the slack season. Therefore, the potential discouraging effects on fertilizer use imposed by the labor requirement are not explained by lower labor availability during planting or harvesting seasons.

The effect differential on fertilizer use between beneficiaries of unconstrained and conditional transfers may be explained by differences in household allocation decisions of additional income. It is possible that, for whatever reason, public works participants are using aid subsidized wages to sustain higher levels of consumption instead of using them to improve the productivity of their farms. There is some

anecdotal evidence in favor of this hypothesis.[81] However, in our data we do not find systematic differences between public works participants and non-participants in household consumption decisions.[82] Instead, we suspect that the effect differential may be largely determined by delays in the payment of the transfers.

According to a World Bank assessment of the PSNP, in 2005 there were considerable delays with payment of transfers (some associated with the flow of funds from donors to governments, lack of capital equipment, limited availability of government notes in appropriate denominations, and sometimes payments were not made because public works activities were either not complete or not reported). By June 2005, half way through the first phase of the program, only 11 percent of transfers were completed. [83] After considering the seriousness of the payment issue, it is not so surprising to find that public works participants increased their fertilizer use by only a tenth of what they would have had they been given their food wages worth in additional income. It appears that the availability of PSNP wages, or the lack of it, may help explain why public works participants are likely to increase their use of chemical fertilizer by much lower amounts than direct support beneficiaries. However, the role of payment volatility is an issue beyond the scope of our study.

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[81] Barrett et al. (2001) find that non-farm earnings lead to more rapid growth in household consumption in rural Africa. Similarly, Holden et al. (2004) find that total agricultural production and farm input use are reduced when non-farm income becomes more readily available in the Ethiopian highlands.

[82] This observation is consistent with previous evaluations of the Productive Safety Net Program. Berhane et al. (2011) do not find significant differences in food consumption or caloric intake between participants and non-participants unless participants had been beneficiaries for 5 years.

[83] The World Bank (2011), “Program Performance Assessment Report”.

Other Implications

Our analysis provides some support in favor of safety net programs and comprehensive policy efforts that promote the adoption and intensification of technologically advanced agricultural inputs. In addition, the following lessons regarding fertilizer adoption in Ethiopia can be derived from our empirical results:

First, in our study the variable with the greatest explanatory power in the fertilizer use decision is familiarity with fertilizer as measured by previous use. This provides some evidence in favor of the hypotheses that technology intensification is a dynamic process and that it takes time for farmers to adjust their expectations to new knowledge and experience. The fluctuant nature of emergency relief efforts mechanisms has meant that the provision of emergency assistance is volatile and unreliable. Our results make a case for social protection programs to become integrated with long-term development projects and provide predictable and continuous relief in order to induce sustainable behavioral changes and further agricultural development.

Second, our evidence also shows that higher education is an important factor for the development of Ethiopia's agricultural sector. We found that for households headed by an individual who had received education beyond high-school level the expected use of fertilizer is 16 kg greater than that of households headed by illiterate individuals. (This positive impact is almost identical in magnitude and sign to the upper bound estimated effect of a 20 percent increase in household income.) Given the current trends in Ethiopian demographics, our results may provide evidence of a positive externality from

the scheduled expansion of Ethiopia's higher education system. Our analysis supports the continuation of current government efforts aimed at understanding the needs of rural families in order to design a formal education system that is able to provide them with relevant and practical human capital.[84]

Third, equib membership was found to be persistently significantly and positively related to fertilizer use. According to our results, average farmers belonging to these institutions use 23 percent more fertilizer than their counterparts. Our findings indicate that informal risk-sharing and credit providing associations may be important instruments to elude market failures in rural Ethiopia. However, it is particularly clear for the case of equib membership that causation is difficult to disentangle and complex to identify. Various records of anecdotal experience point out that farmers belonging to farmer groups have fundamentally different interests and attitudes towards farming than non-members. Thus, without further research, we do not find it appropriate to advocate for the institutionalization of risk-alleviating or credit-providing institutions.

Fourth, it is apparent in our data that more research is needed in the area of agro-ecological sustainability and chemical fertilizer use. It is difficult to disencumber the correlation between poor soil quality and increased use of chemical fertilizer. It is not clear whether farmers are using fertilizer to compensate for the poor quality of their

[84] Demographic trends in the country have driven a sharp increase in the demand for higher education. The number of university students quadrupled between 1997 and 2007, and the sector is expected to more than double in size by 2015[84]. To meet this increase in demand, with financial and technical support from the international community, the Ethiopian government has embarked on a massive higher education expansion and reform program. As of 2010, 10 federal universities were scheduled to open soon, and there were plans to inaugurate other 12 within a decade or so. This would mean that within a generation, Ethiopia's higher education sector will have expanded from 2 federal universities to 22.

soils or whether input intensification (maybe related to intensive cultivation) is driving the decay in soil quality. Given that community development projects devote many of their resources towards afforestation efforts and the construction of soil conservation structures like stone terraces, more scientific research on the biological stability of ecosystems in rural Ethiopia is recommended.

Finally, the negligible success of policy initiatives aimed at familiarizing smallholder households with modern technologies suggests there is room for improving government-sponsored agricultural extension service and outreach programs. Poor extension service delivery may be related to structural restrictions like limited communication infrastructure or to public choice phenomena. Improving existing communication networks, strengthening current information generation and delivery systems, changing the economic incentives provided by outreach initiatives, and increasing oversight of public officials may be viable approaches to enhance the performance of extension service delivery. However, none of these suggestions can be directly derived from our results.

Alternative Policy Options

Our results provide an optimistic evaluation of the design and potential effects of PSNP transfers. However, the observed impact differential between freely distributed assistance and public works wages raises questions about the adequacy of the program

to encourage fertilizer use. To complement this study's assessment of public works we use outside economic data and consider the PSNP's opportunity costs.

Assume the objective of the PSNP was to double farm production of the average beneficiary via increases in fertilizer use. A target load of 7.75 million people translates into 1.55 million average households. To increase each household's use of fertilizer by 18 kg (twice the effect of DS transfers and 10 times the effect of PW participation), 27.9 million kg of chemical fertilizer would be needed.

According to estimates by the International Food Policy Research Institute (IFPRI), in 2009 the selling price for farmers of DAP and Urea was $6756.18 and $496.21 per metric ton (MT), respectively. One metric ton of fertilizer (1000 kg) would suffice to meet the 18 kg target for 55 households. Therefore, the 279000 MT of chemical fertilizer required to meet the objective increase in fertilizer use would cost up to $18,837,522 (paying the 2009 price of urea). This amount is roughly 1.4 percent of the Ethiopian government's budget or 5 percent of the $370 million devoted to the PSNP in 2005.

It is apparent in the data that if the goal of social safety nets was to double agricultural productivity of the average beneficiary household by enhancing fertilizer use, the international community could reach this objective for a small fraction of what it currently spends on social protection programs.

Difficulties with Extrapolation

Our analyses suggest that donors and governments subsidizing community-based projects in rural Ethiopia may be misallocating resources. However, it is clear that our evaluation of the PSNP's impacts on fertilizer use oversimplifies the program's objectives and provides a myopic view of the overall benefits that may accrue from community development projects. Given the limitations of our study, we cannot answer with confidence whether or not the establishment of comprehensive social protection programs is an economically viable approach to encourage agricultural production and therefore alleviate the risks of food insecurity in Ethiopia.

A more complete evaluation of the PSNP's benefits to the country requires the examination of welfare changes at the aggregate level and a more complex set of analytical and measurement tools than the one available to us. However, for the sake of thorough and illustrative analysis, we examine recent trends in domestic economic performance in Ethiopia and compare them with our results. Simple examination of the data makes it evident that a corner has been turned in Ethiopia's sector and economy-wide productivity, particularly since 2005 when the PSNP was first launched. Figures 12 and 13 show Ethiopia's total GDP and GDP per capita per year (PPP) between 1984 (the year of the first great famine) and 2010. Figure 14 shows Ethiopia's GDP growth compared to regional economic performance between 1990 and 2010.

Summary

One of the lessons from the "Green Revolution" in Asia was that the world can effectively move millions of people out of poverty in a relatively short period of time when the infrastructure and the right incentives are in place. The analysis of the PSNP presented in this chapter generates lessons about how governments may tackle food insecurity by implementing comprehensive developmental safety nets. However, acknowledging the limitations of our study, care should be taken not to over interpret or base important reforms on our results.

In this chapter we examined the economic significance and the policy implications from the empirical analysis presented in Chapter 7. Our findings may be interpreted as supporting evidence for the institutionalization of safety net programs to encourage fertilizer adoption in some regions of Ethiopia. We also examined other sources of economic data on overall country economic performance and provided a provocative discussion on alternative ways to encourage fertilizer adoption in the studied region.

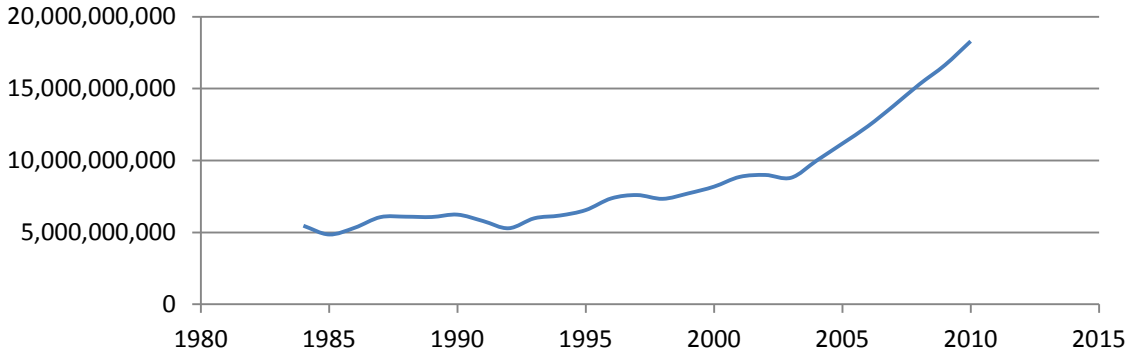


Figure 12. Ethiopia's GDP in constant 2000 US$ (The World Bank, 2012)

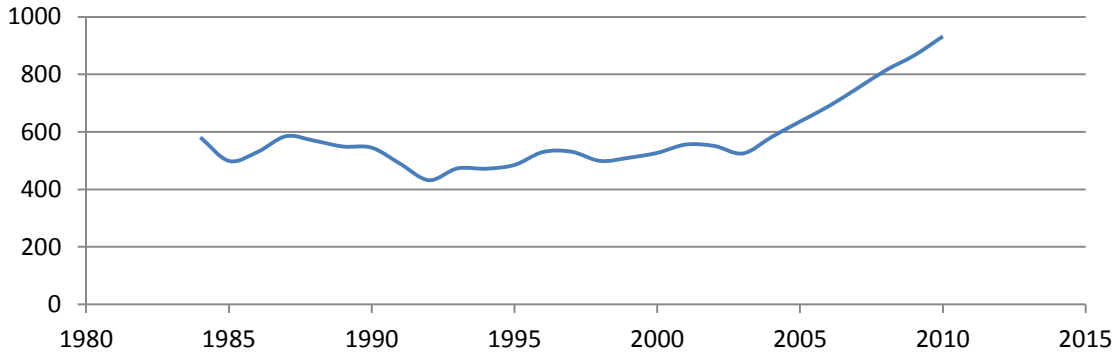


Figure 13. Ethiopia's GDP per capita, PPP in constant 2005 international$ (The World Bank, 2012)

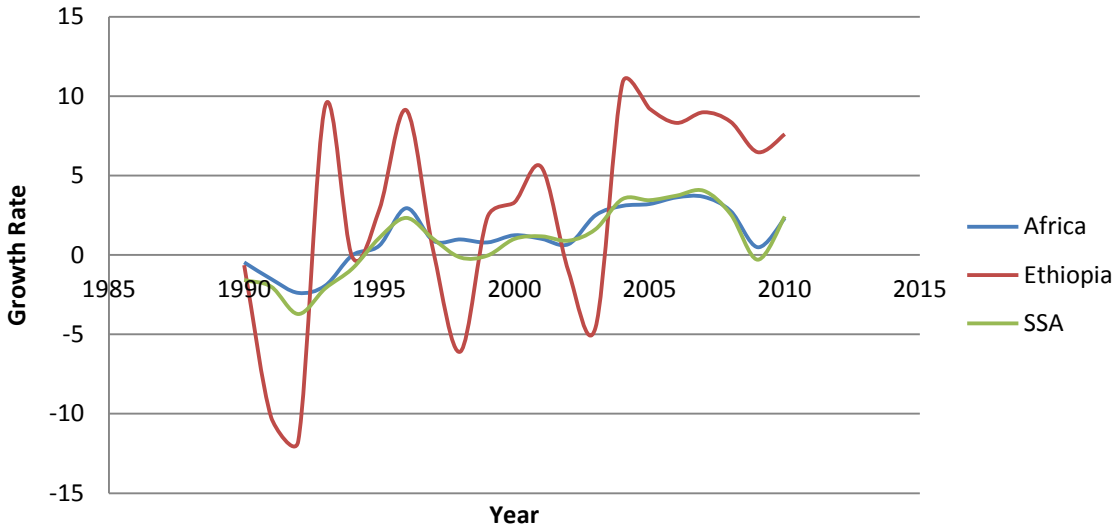


Figure 14. GDP Growth in African Countries and Regions (The World Bank, 2012)

CONLCUSIONS

Increasing the use modern agricultural inputs (in particular fertilizer) is seen by many agricultural experts as a prerequisite to increase agricultural production and therefore reduce the risks of food insecurity and chronic poverty in sub-Saharan Africa (Duflo et al., 2009). [85] Many policymakers advocate input subsidies to address low fertilizer use and improve food production. However, in many sub-Saharan African countries, these policies have failed to induce sustainable changes in farmers' production behavior.

Relatively recently, governments and international donors have begun to shift their support away from input subsidy strategies, which fail to address the structural economic constraints behind low technology adoption rates and often involve unsustainable fiscal costs, towards comprehensive welfare improving reforms as alternative policy options that could result in sustainable, long-run increases in farm productivity along with other desirable outcomes. In this study, we test whether one such comprehensive development program, the Ethiopian Productive Safety Net Program (PSNP), has the potential to help chronically food insecure farmers boost food production by encouraging the use of fertilizer.

Our contribution to the literature is twofold. First, we apply novel econometric techniques to correctly compute the marginal effects of a system of two simultaneous

[85] The International Fund of Agricultural Development estimated in 2011 that African farmers could double yields by doubling their fertilizer use (International Fund of Agricultural Development, 2011).

models with binary and censored latent dependent variables. Second, we use a unique sample of households from rural Ethiopia that permits us to examine the relation between fertilizer use and participation in a recently established safety net program.

This study provides insights that may have important implications in the areas of international aid and agricultural policy. Above all, our empirical evidence does not support the disincentive effects hypothesis that international aid discourages investment in farm production (a specific manifestation of the more general economic phenomenon of moral hazard). Instead, our results indicate that participants of PSNP public works use significantly greater amounts of fertilizer than their counterparts. Our results also identify various significant determinants of public works participation and fertilizer use. Key explanatory factors include education, farm size, household income, current and previous participation in alternative welfare programs, access to markets and services, and some regional biophysical and institutional characteristics.

We show that higher education is an important factor for the development of Ethiopia's agricultural sector through its effects on the use of modern agricultural technologies. Furthermore, our findings indicate that community-based risk-spreading and credit-providing institutions are important informal tools that help farmers circumvent various constraints that limit their use of fertilizer. Finally, the results presented in this study find previous use of fertilizer to be the most important determinant of current fertilizer use; providing empirical support for the case of social protection programs to become integrated with long-term development projects.

Final Remarks

Fertilizer use in Ethiopia has remained limited despite of government efforts to promote its adoption. Our analysis of the PSNP generates lessons about how governments may tackle low fertilizer use and food insecurity by implementing comprehensive developmental safety nets in rural Ethiopia. However, given the available analytical and measurement tools, whether or not the establishment of social protection programs is an economically superior policy instrument to improve agricultural production, alleviate the risks of food insecurity and encourage economic growth is a question we are not ready to answer.

We hope that the results and methodologies presented in this project capture the attention and interest of other development and agricultural researchers towards an important and widely neglected aspect of development that is closely related to chronic poverty, food security, agricultural research and development, and international assistance programs[86]. Both, donor and beneficiary countries could benefit from further research on the topic of agricultural development, comprehensive social protection programs, and public choice. At a minimum, the international community as a whole can benefit from rigorous empirical evidence to improve the delivery of donated resources.

[86] Public investment in agriculture declined by 0.6 percent per year, on average in the high income countries, from 1991-2000. Also, he share of foreign aid devoted to agriculture fell from nearly 17 percent in 1970 to just 4 percent by 2003 (Alston et al. 2000, Pardey et al. 2006, Raitzer and Kelley 2008).

REFERENCES CITED

Abdoulaye, T. and Sanders, J. (2005). "Stage and determinants of fertilizer in semiarid African agriculture: the Niger experience". *Agricultural Economics 32(2)*: 167-179.

Abdulai, A., Barrett, C. B. and Hoddinott, J. (2005). "Does food aid really have disincentive effects? New evidence from sub-Saharan Africa", *World Development, 33* (10): 1689- 1704.

Acemoglu, Daron (2009). Introduction to Modern Economic Growth. Princeton, New Jersey, Princeton University Press: 3-23.

Adegbola, P. and Gardebroek, C. (2007). "The effect of information on technology adoption and modification decisions". *Agricultural Economics 73(37)*: 55-65.

Adelman, I. and Taylor, J. (2003). "Agricultural household models: Genesis, evolution, and extensions". *Review of Economics of the Household 1*: 33-58.

Adesina, A. and Baidu-Forson, J. (1995). "Farmers' perceptions and adoption of new agricultural technology: Evidence from analysis in Burkina Faso and Guinea, West Africa". *Agricultural Economics* 13: 1-9.

Adesina, A. and Zinnah, M. M. (1993). "Technology characteristics, farmers' perceptions and adoption decisions: A Tobit model application in Sierra Leone". *Agricultural Economics, 9*: 297-311.

Adesina, A. (1996). "Factors affecting the adoption of fertilizers by rice farmers in Cote d'Ivoire". *Nutrient Cycling in Agroecosystems 46*: 29-39.

Agenor, P. and Aizenman, J. (2010). "Aid volatility and poverty traps". *Journal of Development Economics 91*: 1-7.

Ahmed, M. and Sanders, J. (2001). "Developing a fertilizer strategy for sub-Saharan Africa". In Abdoulaye, T. and Sanders, J. (2005). "Stage and determinants of fertilizer in semiarid African agriculture: the Niger experience". *Agricultural Economics 32(2)*: 167-179.

Akhter, A. and Zohir, S. K. K. (1995). "Bangladesh food-for-work program and alternatives to improve food security" *IFPRI.* Washington DC: International Food Policy Research Institute.

Alderman, H. and Sahn, D. E. (1996). "The effect of food subsidies on labor supply in Sri Lanka". *Economic Development and Cultural Change, 45:* 125-45.

Alderman, H., Christiaensen, L. and Yamano, T. (2005). "Child growth, shocks and food aid in rural Ethiopia". *American Journal of Agricultural Economics, 87*(2): 273-288.

Alem, Y., Bezabih, M., Kassie, M. and Zikhali, P. (2010). "Does fertilizer use respond to rainfall variability? Panel data evidence from Ethiopia". *Agricultural economics 41*: 165-175.

Alston, J.M., M.A. Andersen, J.S. James and P.G. Pardey (2010). *Persistence Pays: U.S.*

Agricultural Productivity Growth and the Benefits from Public R&D Spending. New York, Springer.

Alston, J. M., C. Chan-Kang, M. C. Marra, P. G. Pardey, and T.J.Wyatt.(2000). "A meta-analysis of the rates of return to agricultural RandD: Ex pede Herculem". IFPRI Research Report No. 113. Washington,D.C.: International Food Policy Research Institute.

Amare, M., Asfaw, S. and Calfat, G. (2010). "Food aid and rural poverty in Ethiopia". *IOB Discussion Paper 2010.5*. Antwerp, Belgium: Institute of Development Policy and Management.

Andersson, C. (2010). "Can a social safety net affect farmers' crop portfolios? A study of the Productive Safety Net Programme in Ethiopia". *Umeå University, Department of Economics.*

Andersson, C., Mekonnen, A. and Stage, J. (Forthcoming). "Impacts of the Productive Safety Net Programme in Ethiopia on livestock and tree holdings of rural households". *Journal of Development Economics.*

Appel, J. and Karlan, D. (2011). *More Than Good Intensions: How a New Economics Is Helping to Solve Global Poverty*. New York: Dutton. Print. Applied Econometrics, 4, 23-39.

Arellano, C., Bulir, A., Lane, T. and Lipschitz, L. (2009). "The dynamic implications of foreign aid and its variability". *Journal of Development Economics 88*: 87–102. January. In Agenor, P. and Aizenman, J. (2010). "Aid volatility and poverty traps". *Journal of Development Economics 91*: 1-7.

Asefa, S. and Teklu, T. (1999). “Who participates in labor-intensive public works in Sub-Saharan Africa? Evidence from rural Botswana and Kenya”. *World Development, 27:* 431-438.

Asrat, S., Carlsson, F., Yesuf, M. and Wale, E. (2010). “Farmers’ preferences for crop variety traits: Lessons for on-farm conservation and technology adoption”. *Ecological Economics 69*: 2394-2401.

Athanasios, A., Bezuneh, M. and Deaton, B. (1994). “Impacts of FFW on nutrition in rural Kenya”. *Agricultural economics* 11: 301-309.

Atwood, J. and Bittinger, A. (2011). “Developing consistent marginal effects in a simultaneous equation model with limited dependent variables”. Montana State University and University of Minnesota.

Awokuse, T. O. (2011). “Food aid impacts on recipient developing countries: A review of empirical methods and evidence”. *Journal of International Development, 23:* 493-514.

Ayele, G., Davis, K., Negash, M. and Spielman, D. (2011). “Rural innovation systems and networks: Findings from a study of Ethiopian smallholders”. *Agricultural Human Values 28*: 195-212.

Baïdu-Forson, J. (1999). “Factors Influencing Adoption of Land-Enhancing Technology in the Sahel: Lessons from a Case Study in Niger”. *Agricultural Economics 20*: 231–239.

Bandiera, O. and Rasul, I. (2006). “Social networks and technology adoption in Northern Mozambique”. *The Economic Journal, 116 (10)*: 869–902.

Baquet, A., Coble, K., Knight, T., Patrick, G. and Vergara, O. (2004). "Farm Income Variability and the Supply of Off-Farm Labor by Limited-Resource Farmers". *Faculty Publications: Agricultural Economics. Paper 64.*

Barreiro-Hurle, J. and Druilhe, Z. (2012). “Fertilizer subsidies in sub-Saharan Africa”. ESA Working paper No. 12-04. Agricultural Development Economics Division. Food and Agriculture Organization of the United Nations.

Barret, C. and Moser, M (2002). “The complex dynamics of smallholder technology adoption: The case of SRI in Madagascar”. Paper presented at the American Agricultural Economics Association annual meeting, Long Beach, California, July 28-31.

Barret, C.B. and McPeak, J. (2004). “Poverty traps and safety nets”. *USAID Pastoral Risk Management (PARIMA) project, Cornell University*. Ithaca, New York, USA.

Barrett, C.B. and Marenya, P. (2009). “Soil quality and fertilizer use rates among smallholder farmers in western Kenya”. *Agricultural Economics 40*: 561-572.

Barrett, C.B. and Minten, B. (2008). “Agricultural Technology, Productivity, and Poverty in Madagascar”. *World Development 36(5)*: 797-822.

Barrett, C.B. (2001). “Does food aid stabilize food availability?” *Economic Development and Cultural Change, 49*(2): 335-349.

Barrett, C.B., Bezuneh, M., Clay, D. and Reardon, T. (2000). “Heterogeneous constraints, incentives and income diversification strategies in rural”. *Mimeo*. In Barrett, C.B., Reardon, T., Webb, P. (2001). “Non-farm income diversification and household livelihood strategies in rural Africa: concepts, dynamics, and policy implications”. *Food Policy, 26*(4): 315–331.

Barrett, C.B., Carter, M.R., Timmer, C.P. (2010). “A century-long perspective on agricultural development”. *American Journal of Agricultural Economics, 92*(2): 447-468.

Barrett, C.B., Clay, D. and Holden, S. (2004). “Can food-for-work programmes reduce vulnerability?”. In Dercon, S (Ed.): *Insurance against poverty*. Oxford: University of Oxford.

Barrett, C.B., Hagos, F. and Holden, S. (2006). “Food-for-work for poverty reduction and promotion of sustainable land use: Can it work?”. *Environment and Development Economics, 11*(1): 15-38.

Barrett, C.B., Reardon, T. and Webb, P. (2001). “Non-farm income diversification and household livelihood strategies in rural Africa: concepts, dynamics, and policy implications”. *Food Policy, 26*(4): 315–331.

Barrett, C.B., Reardon, T. (2000). “Asset, activity, and income diversifications among African Agriculturalist: Some Practical Issues”. *Project report to USAID BASIS CRSP*, March 2000. In Barrett, C.B., Reardon, T., Webb, P. (2001). “Non-farm income diversification and household livelihood strategies in rural Africa: concepts, dynamics, and policy implications”. *Food Policy, 26*(4): 315–331.

Barrett,C. “Food Security and Food Assistance Programs.” In Alderman, H., Christiaensen, L. and Yamano, T. (2005). “Child growth, shocks and food aid in rural Ethiopia”. *American Journal of Agricultural Economics, 87*(2): 273-288.

Basant, R. (1987). “Agricultural technology and employment in India: A survey of recent research”. *Economic and Political Weekly, 22:* 1348-1364.

Basu, K. (1981). “Food for work programmes: Beyond roads that get washed away” *Economic and Political Weekly, 16*: 37-40.

Basu, K. (1996). “Relief programs: When it may be better to give food instead of cash”. *World Development, 24:* 91-96.

Bationo, A., Debrah, S.K. and Enyong, L.A. (1999). “Farmers’ perceptions and attitudes towards introduced soil-fertility enhancing technologies in western Africa”. *Nutrient Cycling in Agroecosystems, 53*: 177-187

Bauer, S., and Joshi, G. R. (2006). “Determinants of rice variety diversity on household farms in the Terai region of Nepal”. *International Association of Agricultural Economists.*

Belshaw, D., Lirenso, A. and Maxwell, S. (2008). “The disincentive effect of food-for-work on labour supply and agricultural intensification and diversification in Ethiopia”. *Journal of Agricultural Economics 45*(3): 351–359.

Beltran, J. C., Benedict, W., Doole, G. J. and Pannell, D. J. (2011). “Factors that affect the use of herbicides in Philippine rice farming systems”. *University of Western Australia, School of Agricultural and Resource Economics.*

Benin, S., Ehui, S., Gebremedhin, B., Pender, J. and Smale, M. (2004). “The economic determinants of cereal crop diversity on farms in the Ethiopian highlands”. *Agricultural Economics*, *31*:197–208.

Berhane, G., Handino, M., Hoddinott, J., Kumar, N., Lind, J., Sabates-Wheeler, R., Sima, F. , Tafera, M., Taffesse, A.S., Tedla, M. and Yohannes, Y. (2011). “Evaluating Ethiopia’s Food Security Program: Documenting progress in the implementation of the Productive Safety Nets Program and the Household Asset Building Programme”. Washington DC: International Food Policy Research Institute, University of Sussex: Institute of Development Studies, Dadimos Consultants.

Berhane, G., Hoddinott, J., Kumar, N. and Taffesse, A.S. (2011). “The impact of Ethiopia’s

Berry, P., Kherallah, M. and Minot, N. (2000). "Fertiliser Market Reform and the Determinants of Fertiliser Use in Benin and Malawi" *MSSD discussion paper No. 40.* Washington DC: International Food Policy Research Institute (IFPRI).

Besley, T. and Coate, S. (1992). "Workfare versus welfare incentive arguments for work requirements in poverty-alleviation programs". *American Economic Review, 82:* 249-61.

Besley, T., Case, A., May 1993. Modeling Technology Adoption in Developing Countries. American Economic Review 83, 396-402.

Bezu, S and Holden S. (2008). "Can food-for-work encourage agricultural production?". *Food Policy*, *33*: 541–549.

Bezuneh, M., Deaton, B. and Norton, G. W. (1988). "Food Aid Impacts in Rural Kenya". *American Journal of Agricultural Economics, 70:* 181-191.

Bezuneh, M., Deaton, B.J. and Norton, G.W. (1988). "Food aid impacts in rural Kenya". *American Journal of Agricultural Economics, 70* (1): 181–191.

Bisrat, Aklilu (1980). "The diffusion of fertilizer in Ethiopia: Pattern determinants and implications". *Journal of Developing Areas, 4(3)*: 387-399.

Bizoza, A. R. (2012). "Three State analysis of the adoption of soil and water conservation in the highlands of Rwanda". *Land Degradation and Development 23(3)*: .

Blackorby, C. and Donaldson, D. (1988). "Cash versus kind, self-selection, and efficient transfers". *American Economic Review, 78:* 691-700.

Bowless, S., Durlauf, S. and Karla Hoff (2006). Poverty Traps. Princeton University Press.

Brierley, J. S. and Semple, H. M. (2000). "A logit analysis of problems affecting domestic food production in Guyana". *Social and Economic Studies, 49*(1): 221-224.

Bulir, A. and Hamann, .A. (2003). "Aid volatility: An empirical assessment". *IMF Staff Papers 50*: 64–89 March. In Agenor, P. and Aizenman, J. (2010). "Aid volatility and poverty traps". *Journal of Development Economics 91*: 1-7.

Bulir, A. and Hamann, J. (2007). "Volatility of development aid: An update". *IMF Staff Papers 54*: 727–739. December. In Agenor, P. and Aizenman, J. (2010). "Aid volatility and poverty traps". *Journal of Development Economics 91*: 1-7.

Bumb, B.L. and Gregory, D.I. (2006). "Factors affecting the supply of fertilizer in sub-Saharan Africa". *Discussion paper #24. Agricultural and Rural Development Department,* The World Bank. Washington, D.C.

Calfat, G. and Reda, M. A. (2010). "Food aid impact on poverty reduction: Empirical evidence from rural households in Ethiopia". *Universiteit Antwerpen, Institute of Development Policy and Management (IOB).*

Chianu, J.N. and Tsujii, H. (2005). "Determinants of farmers' decision to adopt or not adopt inorganic fertilizer in the savannas of northern Nigeria". *Nutrient Cycling in Agroecosystems 70(3)*: 293-301.

Chowdhury, O. H. and Osmani, S. R. (1983). "Short run impacts of food for work programme in Bangladesh". *The Bangladesh Development Studies, 11:* 135-190.

Christiansen,L. and Dercon, S. (2011). "Consumption risk, technology adoption and poverty traps: Evidence from Ethiopia". *Journal of Development Economics 96*: 159-173.

Claudio, M. A., Franks, J. and Godoy, R. (1998). "Adoption of modern agricultural technologies by lowland indigenous groups in Bolivia: The role of households, villages, ethnicity, and markets". *Human Ecology,26:* 351-369.

Clay, D. C.; Molla, D. and Habtewold, D. (1998). "Food aid targeting in Ethiopia: A study of who needs it and who gets it". *Food Policy, 34*(3): 391-409.

Clay, D. C.; Molla, D. and Habtewold, D. (1998). "Food aid targeting in Ethiopia: A study of household food insecurity and food aid distributions". *Michigan State University, Department of Agricultural, Food, and Resource Economics.*

Coffin, G., Gunjal, K. and Kebede, Y. (1990). "Adoption of new technologies in Ethiopian agriculture: the case of Tegulet-Bulga district Shoa province". *Agricultural Economics, 4*(1): 27-43.

Crawford, E., Kelly, V. and Reardon, T. (1994). "Links between nonfarm income and farm investment in African households: Adding the capital market perspective". *American Journal of Agricultural Economics 76(5)*: 1172-1176.

Croppensenstedt, A. and Demeke, M. (1996). "Determinants of adoption and levels of demand for fertilizer for cereal growing farmers in Ethiopia". *Centre for the Study of African Economies Working Paper WPS/96-3* (University of Oxford).

Croppensenstedt, A. and Demeke, M. (2003). "Technology adoption in the presence of constraints: The case of fertilizer demand in Ethiopia". *Review of Development Economics 7(1)*: 58-70.

Dalrymple, D. (1979). "The adoption of high-yielding grain varieties in developing nations". *Agricultural History 53(4)*: 704-726.

De Janvry, A., Fafchamps, M. and Sadoulet, E. (1991). "Peasant household behaviour with missing markets: Some paradoxes explained". *The Economic Journal 101 (409)*: 1400-1417.

de Janvry, A., Fafchamps, M., and Sadoulet, E. (1991). Peasant Household Behaviour with Missing Markets: Some Paradoxes Explained. The Economic Journal , 101, 1400- 1417.

Dejene, A. (2001). "Gender and micro finance in Africa". *Microfinance development Review 2(1)*, AEMFI, Quarterly Bulletin, Addis Ababa.

Delgado, C., Matlon, P. and Reardon, T. (2007). "Determinants and effects of income diversification amongst farm households in Burkina Faso". *Journal of Development Studies 28(2)*: 264-296.

Demeke, M., Jayne, T.S and Said, A. (1997). "Promoting fertilizer use in Ethiopia: The implication of improving grain market performance, input market efficiency, and farm management". *Grain Market Research Project, Working Paper 5.* Addis Ababa, Ethiopia: Ministry of Economic Development and Cooperation.

Dercon, S. and J. Hoddinott. (2011). *The Ethiopian Rural Household Surveys: Introduction*. International Food Policy Research Institute, Washington, D.C. Photocopy.

Dercon, S. and Krishnan, P. (1996). "Income portfolios in rural Ethiopia and Tanzania: Choices and constraints". *Journal of Development Studies 32(6)*: 850-875.

Dercon, S. and Krishnan, P. (2003). "Food aid and informal insurance". *Center for the Study of African Economies Working Paper Series 2003- 01*.

Dercon, S., Vargas Hill, R.(2009). "Growth from agriculture in Ethiopia: Identifying key constraints". *Department for International Development (DFID), United Kingdom.*

Devereux, S. and K. Sharp (2006): “Trends in poverty and destitution in Wollo, Ethiopia”. *Journal of Development Studies*, *42*(4), 592-610.

Dimara, E., Skuras, D. (2003). “Adoption of agricultural innovation as a two-stage partial observability process”. *Agricultural Economics 28(28)*: 187-196.

Dorosh, P. A.; del Ninno, C. and Sahn, D. E. (1995). “Poverty alleviation in Mozambique: a multi-market analysis of the role of food aid”. *Agricultural Economics, 13:* 89-99

Doss, C. R. (2003). *Understanding farm-level technology adoption: lessons learned from CIMMYT’s micro surveys in Eastern Africa*. CIMMYT: International Maize and Wheat Improvement Center.

Duflo, E., Kremer, M. and Robinson, J. (2006). “Understanding technology adoption: Fertilizer in Western Kenya Evidence from field experiments” *MIT, NBER, CEPR and BREAD; Harvard University, NBER and BREAD, and Princeton University.*

Duflo, E., Kremer, M. and Robinson, J. (2011). “Nudging Farmers to Use Fertilizer: Theory and Experimental Evidence from Kenya.” American Economic Review 101 (6): 2350-2390.

Enfors, E. and Gordon, L. (2008). “Dealing with drought: The challenge of using water system technologies to break dryland poverty traps”. *Global Environmental Change 18*: 607-616.

Erenstein, O. (2006). “Intensification or extensification? Factors affecting technology use in peri-urban lowlands along an agro-ecological gradient in West Africa. *Agricultural Systems 90*: 132-158. Prepared for the *International Maize and Wheat Improvement Centre (CIMMYT).*

Ethiopia Rural Household Survey Dataset, 1989-2009. 2011. Washington, D.C.: International Food Policy Research Institute (IFPRI) (datasets). <http://www.ifpri.org/dataset/ethiopian-rural-household-surveys-erhs>.

Fafchamps, M. and Gubert, F. (2006). “The formation of risk sharing networks” *Journal of Development Economics 83*: 326-350.

Fafchamps, M. 2004. Market Institutions in Sub-Saharan Africa: Theory and Evidence. Cambridge, MA: MIT Press.

Feder, G. (1980). “Farm size, risk aversion, and the adoption of new technology under uncertainty”. *Oxford Economic Papers, 32*(2): 236-283.

Feder, G., Just, R., Zilberman, D. (1985). “Adoption of agricultural innovations in developing countries: A survey”. *Economic Development Cultural Change 30*: 59-76.

Fernandez-Cornejo, J., C. Hendricks and A. Mishra. (2005). “Technology adoption and off-farm household income: The case of herbicide-tolerant soybeans,” *Journal of Agricultural and Applied Economics 37*(3): 549-563.

Finan, T.J. (1998). “Time for change: Food aid and development”. *Bureau of Applied Research in Anthropology, University of Arizona.*

Fitzpatrick, J. and Storey, A. (1989). “Food aid and agricultural disincentives”. *Food Policy, 14*: 241-247.

Fofack, H. (2008). “Technology trap and poverty trap in sub-Saharan Africa”. *Policy Research Working Paper 4582. Poverty Reduction and Economic Management Division, The World Bank.*

Foster, A. and Rosenzweig, M. (2010). “Microeconomics of Technology Adoption”. *Annual Review of Economics 2*: 395-424.

Fufa, B., Hassan, R. M. (2010). “Determinants of fertilizer use on maize in Eastern Ethiopia: A weighter endogenous sampling analysis of the extend and intensity of adoption”. *Agrekon: Agricultural Economics Research, Policy and Practice in Southern Africa 45(1)*: 38-49.

Fulginiti, L., Perrin, R. and Yu, B. (2003). “Institutions and Agricultural Productivity in sub-Saharan Africa”. *Paper to be presented at the IAAE meeting, Durban, South Africa.*

Garfield, E. (1979). “The impact of technical change on the rural Kenyan household: Evidence from the integrated agricultural development progam”. *Working Paper 358. Institute for Development Studies, University of Nairobi.* Nairobi, Kenya.

Gebremedhin, B. and Swinton, S. M. (2002). “Investment in soil conservation in Northern Ethiopia: The role of land tenure security and public programs”. Staff Paper 2002-13. *Michigan State University, Department of Agricultural, Food, and Resource Economics.*

Gedamu, A. (2006). “Food for Work Program and its Implications on Food Security: A critical review with a practical example from the Amhara region, Ethiopia”. *Journal*

of Agriculture and Rural Development in the Tropics and Subtropics 107(2): 177-188.

Gelan, A. (2006). "Cash or food aid? A general equilibrium analysis for Ethiopia", *Development Policy Review*, *24*(5): 601-624.

Gelan, A. U. (2007). "Does food aid have disincentive effects on local production? A general equilibrium perspective on food aid in Ethiopia". *Food Policy, 32*: 436-458.

Gempesaw, C. and Lass, D. (1992) "The supply of off-farm labor: A random coefficients approach". *Agricultural and Applied Economics Association 74(2)*: 400-411.

Gilligan, D.O., Hoddinott, J., Kumar, N. and Taffesse, A.S. (2009). "An impact evaluation of Ethiopia's Productive Safety Nets Program". IFPRI. Washington, DC: International Food Research Institute.

Gilligan, D.O., Hoddinott, J., Taffesse, A.S. (2008). "An analysis of Ethiopia's Productive Safety Net Program and its linkages". IFPRI *Discussion Paper 839.* Washington, DC: International Food Policy Research Institute.

Gilligan, O.D. and Hoddinnot, J. (2006). "Is there persistence in the impact of emergency food aid? Evidence on consumption, food security and assets in rural Ethiopia". *American Journal of Agricultural Economics*, *89*(2): 225-242.

Gine, X. and Yang, D. (2007). "Insurance, credit, and technology adoption: Field experimental evidence from Malawi". *Policy Research Working Paper 4425, Development Research Group, The World Bank; Bureau for Research and Economic Analysis of Development (BREAD) and National Bureau of Economic Research (NBER).*

Gobotswang, K. S. (2004). "Poverty alleviation strategies in Botswana: The case of Labour-Intensive Public Works Programme (LIPWP)" *Botswana Notes and Records, 36:* 27-36.

Goode, F., Rauniyar, G. and Shields, M. (1993). "A longitudinal analysis of factors influencing increased technology adoption in Swaziland, 1985-1991". *The Journal of Developing Areas, 27*(4), 469-484.

Goodwin, B. and Mishra, A. (1997). "Farm income variability and the supply of off-farm labor". *American Journal of Agricultural Economics 79(8)*: 880-887.

Gordon, A., Meadows, K., Smith, D. R., Zwick, K. (2001). "Livelihood diversification in Uganda: patterns and determinants of change across two rural districts". *Food Policy 26*: 421-435.

Green, D. A. G. and Ng'ong'ola, D.H. (1993). "Factors Affecting Fertiliser Adoption in Less Developed Counties: An Application of Multivariate Logistic Analysis in Malawi". *Journal of Agricultural Economics 44(1)*: 99–109.

Greene, W. H. (2008). Econometric Analysis (6th Edition). New Jersey: Pearson Hall. Print.

Hay, R. W. (1988). "Famine incomes and employment: Has Botswana anything to teach Africa?". *World Development, 16:* 1113-1125.

Heady, E., Rogers, K. and Srivastava, U. (1972). "Modified price, production, and income impacts of food aid under market differentiated distribution". *American Journal of Agricultural Economics, 54*: 201-208.

Hernandez, M.A., and Torero, M., (2011). "Fertilizer Market Situation: Market Structure, Consumption and Trade Patterns, and Pricing Behavior". *Discussion Paper 01058.* Washington DC: International Food Policy Research Institute (IFPRI).

Hoddinott, J. (2004). "Examining the incentive effects of food aid on household behaviour in rural Ethiopia". *International Food Policy Research Institute (IFPRI)*

Holden, S., Shiferaw, B., (2004). "Land degradation, drought and food security in a less-favored area in the Ethiopian Highlands: a bio-economic model with market imperfections". *Agricultural Economics 30:* 31–49.

Holden, S., Shiferaw, B., Pender, J. (2004). "Non-farm income, household welfare, and sustainable land management in a less-favoured area in the Ethiopian highlands". *Food Policy 29*: 369–392.

Horna, J. D., von Oppen, M. and Smale, M. (2005). "Farmer willingness to pay for seed-related information: rice varieties in Nigeria and Benin". *International Food Policy Research Institute (IFPRI).*

Hudson, J. and Mosley, P. (2006). "Aid volatility, policy and development". *Unpublished, Wider Conference.* June. In Agenor, P. and Aizenman, J. (2010). "Aid volatility and poverty traps". *Journal of Development Economics 91*: 1-7.

Hudson, J. and Mosley, P. (2008). “The macroeconomic impact of aid volatility”. *Economics Letters 100*: 486–489. June. In Agenor, P. and Aizenman, J. (2010). “Aid volatility and poverty traps”. *Journal of Development Economics 91*: 1-7.

Huelsenbeck, J. P.; Crandall, K. A. (1997). "Phylogeny Estimation and Hypothesis Testing Using Maximum Likelihood". *Annual Review of Ecology and Systematics* 28: 437–466.

Huffman, W. and Lange, M. (1989). “Off-farm work decisions of husbands and wives: joint decision making”. *The Review of Economics and Statistics 71(3)*: 471-480.

Humphrey, L. (1999). “Food-for-Work in Ethiopia: Challenging the scope of project evaluations”. *IDS Working Paper 81. Prepared for the Poverty Research Programme project “Anti-poverty interventions in dryland Africa”.*

International Monetary Fund, Fiscal Policy Response to Scaled-Up Aid, Unpublished, Fiscal Affairs Department (Washington DC: June 2007). In Agenor, P. and Aizenman, J. (2010). “Aid volatility and poverty traps”. *Journal of Development Economics 91*: 1-7.

Janvry, A. and Sadoulet, E. (2001). “Income strategies among rural households in Mexico: The role of off-farm activities”. *World Development 29(3)*: 467-480.

Jayne, T. S., Negassa, A., and Myers, R. (1998). The Effect of Liberalization on Grain Prices and Marketing Margins in Ethiopia. MSU International Development Working Paper No. 68, Michigan State University, East Lansing.

Jones, A.M. (1989) A double-hurdle model of cigarette consumption, Journal of

Kelly, T., Naseem, A., Reardon, V. and Yanggen, D. (1998). “Incentives for Fertiliser Use in Sub-Saharan Africa: A Review of Empirical Evidence on Fertiliser Response and Profitability”. *Working Paper No. 70. Michigan State University, International Development, East Lansing, MI.*

Kharas, H. (2007). “Trends and issues in development aid”. *Working Paper No. 1*, *Wolfensohn Center for Development. Brookings Institution*. November. In Agenor, P. and Aizenman, J. (2010). “Aid volatility and poverty traps”. *Journal of Development Economics 91*: 1-7.

Knepper, E. (2002). “Factors affecting the use of fertilizer by small- and medium-sized farming households in Zambia, 1997 to 2000”. *Michigan State University, Department of Agriculture and Natural Resources.*

Kraay, A. and Raddatz, C. (2007). "Poverty traps, aid, and growth". *Journal of Development Economics 82*: 315-347.

Krishnan, P. , Dercon, S. (1996). "Income portfolios in rural Ethiopia and Tanzania: choices and constraints*". Journal of Development Studies 32* (6): 850–875. In Barrett, C.B., Reardon, T., Webb, P. (2001). "Non-farm income diversification and household livelihood strategies in rural Africa: concepts, dynamics, and policy implications". *Food Policy 26*(4): 315–331.

Kumar, S. and Webb, P. (1995). "Food and Cash for Work in Ethiopia: Experiences during Famine and Macroeconomic Reform." In von Braun, J. (2002). Employment for Poverty Reduction and Food Security. Washington DC: International Food Policy Research Institute (IFPRI).

Kumbhakar, SC. (1993): "Production risk, technical efficiency, and panel data". *Economics Letters 41*: 11–16.

Lamb, R. L. and Wadood, S. N. (2006). "Choice of crops and employment uncertainty in the off-farm labor market". *University Library of Munich, Germany.*

Lamb, R. L. (2003). "Use, risk, and off-farm labor markets in the semi-arid tropics of India". *American Journal of Agricultural Economics 85(2)*: 359-371.

Lanjouw, P., Quizon, J. and Sparrow, R. (2001). "Non-agricultural earnings in peri-urban areas of Tanzania: evidence from household survey data". *Food Policy 26*: 385-403.

Larson D. and Zerfu D. (2010). "Incomplete Markets and Fertilizer Use: Evidence from Ethiopia". Policy Research Working Paper 5235. The World Bank. Development Research Group, Agriculture and Rural Development Team.

Lensink, R. and Morrissey, O. (2000). "Aid instability as a measure of uncertainty and the positive impact of aid on growth". *Journal of Development Studies 36*: 31–49. February. In Agenor, P. and Aizenman, J. (2010). "Aid volatility and poverty traps". *Journal of Development Economics 91*: 1-7.

Lents, E. (2003). Annotated Bibliography of Food Aid Disincentive Effects. *Mimeo, Cornell University*, Ithaca, NY. In Abdulai, A., Barrett, C. B. and Hoddinott, J. (2005). "Does food aid really have disincentive effects? New evidence from sub-Saharan Africa", *World Development 33* (10): 1689- 1704.

Little, P.D. (2008). “Food aid dependency in Northeastern Ethiopia: myth or reality?” *World Development 36*(5): 860–874.

Maddala, G. S. (1983). Limited-Dependent and Qualitative Variables in Econometrics. Cambridge: Cambridge University Press.

Mansuri, G. and Rao, V. (2012). “Localizing development: Does participation work?”. The World Bank.Policy Research Report. Washington, D.C.

Markandya, A., Ponczek, V. and Yi, S. (2006) “What is the link between aid volatility and growth?”. *Unpublished, Wider Conference*. June. In Agenor, P. and Aizenman, J. (2010). “Aid volatility and poverty traps”. *Journal of Development Economics 91*: 1-7.

Mwangi, W. (1997). “Low use of fertilizers and low productivity in sub-Saharan Africa”. *Nutrient Cycling in Agroecosystems 47*: 135-147. Prepared for the *International Maize and Wheat Improvement Center (CIMMYT), Addis Ababa, Ethiopia.*

Ndiwa, N., Thornton, P., Shepherd, K. and Waithaka, M. (2007). “Factors affecting the use of fertilizers and manure by smallholders: the case of Vihiga, western Kenya”. *Nutrient Cycling in Agroecosystems 78(3)*: 211-224.

Neanidis, K. and Varvarigos, D. (2007). “The allocation of volatile aid and economic growth: Evidence and a Suggestive Theory”. *Working Paper 07*. Loughborough University. March. In Agenor, P. and Aizenman, J. (2010). “Aid volatility and poverty traps”. *Journal of Development Economics 91*: 1-7.

Nelson, F. and Olson, L. (1978). Specification and Estimation of a Simultaneous-Equation Model with Limited Dependent Variables. International Economic Review, 19 (3), 695-709.

Nkamleu, G. B. (2008). “Modeling farmers’ decisions on integrated soil nutrient management in sub-Saharan Africa: A multinomial logit analysis in Cameroon”. In: Bationo (ed). *Advances in integrated soil fertility management in sub-Saharan Africa: Challenges and opportunities.* Springer Publishers, Netherlands pp. 891-903.

Nkonya, E., Norman, D. and Schroeder, T. (2008). “Factors affecting adoption of improved maize seed and fertilizer in Northern Tanzania”. *Journal of Agricultural Economics 48(1)*: 1-12.

Pallage, S. and Robe, M. (2001). “Foreign aid and the business cycle”. *Review of International Economics 9*: 641–672. November. In Agenor, P. and Aizenman, J. (2010). “Aid volatility and poverty traps”. *Journal of Development Economics 91*: 1-7.

Perrin, R. and Ryan J. (1974). “Fertilizer response information and income gains: The case of potatoes in Peru”. *American Journal of Agricultural Economics, 56(2)*: 337-343.

Perrin, R. and Winkleman, D. (1976). “Impediments to technical progress on small versus large farms”. *American Journal of Agricultural Economics 58(5) Proceedings Issue (Dec, 1976)*: 888-894.

Perrin, R. K. (1972). “Optimal levels of Fertilization under risk: Comment”. *American Journal of Agricultural Economics, 54(4)*: 683-685.

Pietola, K., Reardon, T., Savadogo, K. (1998). “Adoption of improved land-use technologies to increase food security in Burkina Faso: relating animal traction productivity and nonfarm income”. *Agricultural Systems 58*(3): 441–464.

Pitt, M. M. and Sumodiningrat, G. (1988). “The determinants of rice variety choice in Indonesia”. *University of Minnesota, Economic Development Center.*

Platteau, J.P., 2000. Endogeneity in the rise of market order. In: Institutions, Social Norms, and Economic Development. Boston: Harwood Academic Publishers.

Porter, C. (2008) “Examining the impact of idiosyncratic and covariate shock on Ethiopian household’s consumption and income sources”. Mimeo, Oxford: Department of economics, Oxford University.

Productive Safety Nets and Household Asset Building Programme: 2006-2010”. IFPRI. Washington, DC: International Food Research Institute.

Ravallion, M. (1991). “Reaching the rural poor through public employment: Arguments, evidence, and lessons from South Asia”. *World Bank Research Observer, 6:* 153-75.

Ravallion, M. (1999). “Appraising workfare”. *World Bank Research Observer* 14, 1:31-48.

Ravallion, M., Datt, G., and Chaudhuri, S. (1999). “Does Maharashtra´s employment guarantee scheme guarantee employment? Effects of the 1988 wage increase”. *Economic Development and Cultural Change* 41, 2:251-75.

Reardon, T., Webb, P. (1992). “Drought Impact and Household Response in East and West Africa”. *Quarterly Journal of International Agriculture 31*(3): 230–247. In Barrett, C.B., Reardon, T., Webb, P. (2001). “Non-farm income diversification and household livelihood strategies in rural Africa: concepts, dynamics, and policy implications”. *Food Policy 26*(4): 315–331.

Rogers, E. M. 1962. Diffusion of innovation. New York: Free Press.

Rosenzweig, M.R., Wolpin, K.I. (1993). “Credit market constraints, consumption smoothing, and accumulation of durable production assets in low-income countries: investments in bullocks in India”. *Journal of Political Economy 101*(2): 223–244.

Rubas, D. 2004. Technology Adoption: Who is Likely to Adopt and How Does the Timing Affect the Benefits? PhD dissertation, Texas AandM University.

Shaw, A. B. (1985). “Constraints on agricultural innovation adoption”. *Economic Geography, 61:* 25-45.

Shultz, T. W. (1960). “Value of US farm surpluses to underdeveloped countries”. *Journal of Farm Economics, 42*(5): 1019-1030.

Spielman, D. (2005). “Innovation systems perspectives on developing-country agriculture: A critical review”. *Discussion Paper 2, International Service for National Agricultural Research (ISNAR).* Washington DC: International Food Policy Research Institute (IFPRI).

Sulaiman, M. (2010). “Incentive and crowding-out effects of food assistance: Evidence from the randomized evaluation of a food-for-training project in Southern Sudan”. *Suntory and Toyota International Centres for Economics and Related Disciplines, LSE.*

Sumner, D. (1982). “The off-farm labor supply of farmers”. *American Journal of Agricultural economics 64(3)*: 499-509.

Tedla, T. (2011). “Factors determining fertilizer adoption of the peasant farm sector in northern Ethiopia, Tigray region”. *Norwegian University of Life Sciences, Department of Economics and Resource Management.*

Uraguchi, Z. B. (2011). “Rural income transfer programs and rural household food security in Ethiopia”. *Journal of Asian and African Studies,* 1-19.

van der Berg, M. and Kumbi, G. (2006). “Poverty and the rural nonfarm economy in Oromia, Ethiopia”. *Agricultural Economics 35*: 469-475.

Vlek, P.L.G. (1990). “The role of fertilizers in sustaining agriculture in sub-Saharan Africa”. *Fertilizer Research 26*: 327-339. Prepared for the *International Fertilizer Development Center-Arica.* IFDC-Africa, Lome, Togo.

von Braun, J. (1995). *Employment for Poverty Reduction and Food security.* Washington DC: International Food Policy Research Institute (IFPRI).

von Braun, J. and Olofinbiyi, T. (2007). “Famine and food insecurity in Ethiopia”. *Food Policy for Developing Countries: The Role of Government in the Global Food System. Case Study # 7-4.* Cornell University in collaboration with University of Copenhagen, Wageningen University and IFPRI.

von Braun, J., Teklu, T. and Webb, P. (1991). “Labour Intensive Public Works for Food Security: Experience in Africa”. IFPRI *Food Subsidy Working Paper No. 6*. Washington DC: International Food Policy Research Institute.

von Braun, J., Yohannes, Y. and Webb, P., (1992). “Famine in Ethiopia: Policy Implications of Coping Failure at National and Household Levels”. *Discussion Paper 92*. Washington DC: International Food Policy Research Institute (IFPRI).

Wooldridge, J. (2009). Introductory Econometrics (4th Edition). Mason, OH: South-Western Cengage Learning. Print.

APPENDIX A

CODE USED FOR THIS THESIS

The following R-code requires the package *joecode*, which can be accessed through the website: http://www.montana.edu/econ/atwood/rdata/index.html.

Step (1): Bring in CSV files containing relevant raw data from the 2009 Ethiopian Rural Household Survey (ERHS) and subset data for the selected variables

```
#########################################################################

ERHS_2_binary <- read.csv("C:/Users/laura.villegas/Documents/ERHS_2_binary.csv")

ERHS_2_binary$Age2=(ERHS_2_binary$Age)^2

df1_na=as.data.frame(cbind(
 ERHS_2_binary$Urea_kg,
 ERHS_2_binary$PW_participation_between2000_and_today,
 ERHS_2_binary$Use_of_fertilizer_in_last_5years,
 ERHS_2_binary$PW_participant_beofrePSNP_Started,
 ERHS_2_binary$Age2,
 ERHS_2_binary$Age,
 ERHS_2_binary$Education_Literacy_Program.Church.Mosque_School,
 ERHS_2_binary$Education_Some_Primary,
 ERHS_2_binary$Education_Some_Secondary,
 ERHS_2_binary$Education_Some_higher_education,
 ERHS_2_binary$HH_size,
 ERHS_2_binary$Farm_size,
 ERHS_2_binary$Vassets,
 ERHS_2_binary$TLU,
 ERHS_2_binary$Irrigation_dummy,
 ERHS_2_binary$Farm_Revenue,
 ERHS_2_binary$Amount_earned_las_4months_birr,
 ERHS_2_binary$DS_beneficiaries_between2000_and_today,
 ERHS_2_binary$Member_of_equib,
 ERHS_2_binary$Average_market_wage,
 ERHS_2_binary$Number_of_visits_by_extension_agent,
 ERHS_2_binary$Number_Secondary_schools,
 ERHS_2_binary$Distance_fuel_minute,
 ERHS_2_binary$Soil_quality,
 ERHS_2_binary$Number_of_trees,
 ERHS_2_binary$Use_of_manure,
 ERHS_2_binary$Severily_hit_by_shock))
```

```
df1=df1_na[complete.cases(df1_na),]

colnames(df1)=c("Chem_fert", "PSNP_PW",
          "Prev_Fert", "Prev_PW",
          "Age2", "Age", "Literacy_Prg", "Prim_Ed", "Sec_Ed", "High_Ed", "HH_size",
          "Farm_size",  "V_assets", "TLU",  "Irrig", "Farm_Rev", "Nonfarm_Rev",
          "DS_PSNP", "Equibb",
           "Market_W","Ext_visits", "Sec_schools", "Travel_time",
           "Soil_quality", "Trees", "Manure", "Severe_shock")
colnames(df1)=c("y2","y1",
           "x201", "x101",
           "x1", "x2", "x3", "x4", "x5", "x6", "x7",
           "x8",  "x9", "x10",  "x11", "x12", "x13", "x14", "x15",
           "x16","x17", "x18", "x19",
           "x20", "x21", "x202", "x102")
#############################################################################
#y1=PSNP_PW, 2nd column; y2=Chem_fert, 1rst column;
#27 columns, 25 explanatory variables; 26 slots for the storing matrixes
#x101=Prev_PW, x102=severe shock
#x201=Prev_fert; x202=Manure
#############################################################################
Step (2): Require packages and define objects
#############################################################################
require(jcode)
require(jcode64)
require(AER)
#############################################################################
graphics.off()
#############################################################################
#Defining storage objects
M1='BIN'; M2='TOB'          #BIN for probit modeling, TOB for tobit
(ahat=matrix(0,2,26))
(bhat=matrix(0,2,26))
(ghat=diag(c(1,1)))

nboots=1000
AHAT=array(0,c(2,26,nboots))
BHAT=AHAT
GHAT=array(1,c(2,2,nboots))

y1cut=0;y2cut=0             # cut points for Tobit if model is 'TOB'
nobs2=50000                 # sample size for covariance estimation simulations
```

```
#############################################################################
 (nobs=nrow(df1))
#############################################################################
```

Step (3): Run public works participation and chemical fertilizer simultaneous equation regressions

```
#############################################################################
# Stage 1 Reduced Form
#############################################################################
#Equation 1
if(M1=='BIN') {
  reg11=glm(y1~x1+x2+x4+x5+x7+x8
          +x13+x14+x18+x19+x20+x21
          +x101+x102
          +x201+x202,family=binomial(link='probit'),data=df1)
  y11hat=reg11$linear
  varhat11=1.0
}
as.data.frame(table(reg11$coef)); #17 entries
ahat[1,1:3]=reg11$coef[1:3]
ahat[1,4]=0
ahat[1,5:6]=reg11$coef[4:5]
ahat[1,7]=0
ahat[1,8:9]=reg11$coef[6:7]
ahat[1,10:13]=0
ahat[1,14:15]=reg11$coef[8:9]
ahat[1,16:18]=0
ahat[1,19:21]=reg11$coef[10:12]
ahat[1,22:26]=reg11$coef[13:17]
#############################################################################
#Equation 2
if(M2=='TOB') {
  reg21=tobit(y2~x1+x2+x3+x4+x5+x6+x7+x8+x9+x10
           +x11+x12+x13+x14+x15+x16+x17+x18+x19+x20+x21
           +x101+x102
           +x201+x202,left=y2cut,data=df1)
  y21hat=reg21$linear.predictors
  varhat21=reg21$scale^2
}
as.data.frame(table(reg21$coef)); #26 entries
ahat[2,]=reg21$coef
#############################################################################
# Stage 2
```

```
#############################################################################
#Equation 1
if(M1=='BIN') {
  reg12=glm(y1~x1+x2+x4+x5+x7+x8
         +x13+x14+x18+x19+x20+x21
         +x101+x102
         +y21hat,family=binomial(link='probit'),data=df1)
  y12hat=reg12$linear
}
as.data.frame(table(reg12$coef)); #16 entries; -2 from reg11, + y21hat
bhat[1,1:3]=reg11$coef[1:3]
bhat[1,4]=0
bhat[1,5:6]=reg11$coef[4:5]
bhat[1,7]=0
bhat[1,8:9]=reg11$coef[6:7]
bhat[1,10:13]=0
bhat[1,14:15]=reg11$coef[8:9]
bhat[1,16:18]=0
bhat[1,19:21]=reg11$coef[10:12]
bhat[1,22]=0
bhat[1,23:24]=reg11$coef[13:14]
bhat[1,25:26]=0
#############################################################################
#Equation 2
if(M2=='TOB') {
  reg22=tobit(y2~x1+x2+x3+x4+x5+x6+x7+x8+x9+x10
          +x11+x12+x13+x14+x15+x16+x17+x18+x19+x20+x21
          +x201+x202
          +y11hat,left=y2cut,data=df1)
  y22hat=reg22$linear.predictors
}
as.data.frame(table(reg22$coef))#25 entries; -2 from reg21, + y11hat
bhat[2,1:22]=reg22$coef[1:22];bhat[2,25:26]=reg22$coef[23:24]
#############################################################################
#setting matrix of estimated coefficients of endogenous variables Chem_fert and PW
ghat[1,2]=-reg12$coeff[16]
ghat[2,1]=-reg22$coeff[25]
ghat
(ghat.inv=solve(ghat))
#############################################################################
```

Step (4): Variance Correction Process

```
#############################################################################
```

```
# Variance correction process
##############################################################################
#Defining functions and storage matrixes
rhofit=function(rhohat){
  (R=rho2cor(rhohat))
  (V=diag(varhat))
  (V3=cor2cov(R,V))
  (CHOL=chol(V3)) # Compute the Choleski factorization of a real symmetric positive-
definite square matrix.

# When it is applicable, the Cholesky decomposition is roughly twice as efficient as the
LU decomposition for solving systems of linear equations.\

# In a loose, metaphorical sense, this can be thought of as the matrix analogue of taking
the square root of a number.

  VSS=E %*% CHOL
  YTSS=YHAT+VSS
  YS=YTSS

  if(M1=='TOB') YS[,1]=ifelse(YS[,1]<y1cut,0,YS[,1])
  if(M1=='BIN') YS[,1]=ifelse(YS[,1]<0,0,1)

  if(M2=='TOB') YS[,2]=ifelse(YS[,2]<y2cut,0,YS[,2])
  if(M2=='BIN') YS[,2]=ifelse(YS[,2]<0,0,1)

# NOTE: We do not compare YSS[,1] to y1. We want to construct a metric that allows us
to #compare the properties of the system YS to the system [y1,y2,...] etc.

 (corS=cor(YS[,clist], method="spearman"))
  #abs(corS[1,2]-Srho.0)
  (corS[1,2]-Srho0)^2
}
##############################################################################
# set up data for covariance estimation
(Srho0=cor(df1$y1,df1$y2,method='spearman'))
YDATA=as.matrix(cbind(df1$y1,df1$y2))
varhat=c(varhat11,varhat21)
(nreps2=floor(nobs2/nobs))+1
ipick=rep(1:nobs,nreps2)
(nobs3=length(ipick))
Y1hat=y11hat[ipick]
```

```
Y2hat=y21hat[ipick]
YHAT=as.matrix(cbind(Y1hat,Y2hat))
E=matrix(rnorm(nobs3*2),nobs3,2)
clist=c(1,2)
rhohat=0.9434
rhofit(rhohat)
time0=seconds.local()
(rho12=optimize(rhofit,interval=c(-0.99,0.99))$minimum)
time1=seconds.local()
time1-time0
(R=rho2cor(rho12))
(V=diag(varhat))
(VVAR=cor2cov(R,V))
(UVAR=ghat %*% VVAR %*% t(ghat))
#############################################################################
```

Step (5): Computation of Marginal effects

```
#############################################################################
# marginal cdf's and pdf's for latent reduced form (stage 1)
pval11=1-pnorm(y1cut,y11hat,sqrt(VVAR[1,1]))
pval21=1-pnorm(y2cut,y21hat,sqrt(VVAR[2,2]))
dval11=dnorm(0,y11hat,sqrt(VVAR[1,1]))
dval21=dnorm(0,y21hat,sqrt(VVAR[2,2]))

# marginal cdf's and pdf's for latent structural model (stage 2)
pval12=1-pnorm(y1cut,y12hat,sqrt(UVAR[1,1]))
pval22=1-pnorm(y2cut,y22hat,sqrt(UVAR[2,2]))
dval12=dnorm(0,y12hat,sqrt(UVAR[1,1]))
dval22=dnorm(0,y22hat,sqrt(UVAR[2,2]))
#############################################################################
#we effectively compute the weights that are going to be used for the estimation of the
#marginal effects; following Greene,2008
#############################################################################
# Compute marginal effects
#############################################################################
# reduced form equations
#################################################################
#Equation 1
#For the probit estimation we use the density functions to compute marginal effects
if(M1=='BIN'){
  mv2a12=dval11*ahat[1,2]
  mv2a13=dval11*ahat[1,3]
  mv2a14=dval11*ahat[1,4]
```

```
  mv2a15=dval11*ahat[1,5]
  mv2a16=dval11*ahat[1,6]
  mv2a17=dval11*ahat[1,7]
  mv2a18=dval11*ahat[1,8]
  mv2a19=dval11*ahat[1,9]
  mv2a110=dval11*ahat[1,10]
  mv2a111=dval11*ahat[1,11]
  mv2a112=dval11*ahat[1,12]
  mv2a113=dval11*ahat[1,13]
  mv2a114=dval11*ahat[1,14]
  mv2a115=dval11*ahat[1,15]
  mv2a116=dval11*ahat[1,16]
  mv2a117=dval11*ahat[1,17]
  mv2a118=dval11*ahat[1,18]
  mv2a119=dval11*ahat[1,19]
  mv2a120=dval11*ahat[1,20]
  mv2a121=dval11*ahat[1,21]
  mv2a122=dval11*ahat[1,22]
  mv2a123=dval11*ahat[1,23]
  mv2a124=dval11*ahat[1,24]
  mv2a125=dval11*ahat[1,25]
  mv2a126=dval11*ahat[1,26]
}
#####################################################################
#Equation 2
#for the tobit estimation we use the pvalues
if(M2=='TOB'){
  mv2a22=pval21*ahat[2,2]
  mv2a23=pval21*ahat[2,3]
  mv2a24=pval21*ahat[2,4]
  mv2a25=pval21*ahat[2,5]
  mv2a26=pval21*ahat[2,6]
  mv2a27=pval21*ahat[2,7]
  mv2a28=pval21*ahat[2,8]
  mv2a29=pval21*ahat[2,9]
  mv2a210=pval21*ahat[2,10]
  mv2a211=pval21*ahat[2,11]
  mv2a212=pval21*ahat[2,12]
  mv2a213=pval21*ahat[2,13]
  mv2a214=pval21*ahat[2,14]
  mv2a215=pval21*ahat[2,15]
  mv2a216=pval21*ahat[2,16]
```

```
  mv2a217=pval21*ahat[2,17]
  mv2a218=pval21*ahat[2,18]
  mv2a219=pval21*ahat[2,19]
  mv2a220=pval21*ahat[2,20]
  mv2a221=pval21*ahat[2,21]
  mv2a222=pval21*ahat[2,22]
  mv2a223=pval21*ahat[2,23]
  mv2a224=pval21*ahat[2,24]
  mv2a225=pval21*ahat[2,25]
  mv2a226=pval21*ahat[2,26]
}

#####################################################################
#Structural model
#####################################################################
# Equation 1
if(M1=='BIN'){
  mv2g12=dval12*(-1*ghat[1,2])
  mv2b12=dval12*bhat[1,2]
  mv2b13=dval12*bhat[1,3]
  mv2b14=dval12*bhat[1,4]
  mv2b15=dval12*bhat[1,5]
  mv2b16=dval12*bhat[1,6]
  mv2b17=dval12*bhat[1,7]
  mv2b18=dval12*bhat[1,8]
  mv2b19=dval12*bhat[1,9]
  mv2b110=dval12*bhat[1,10]
  mv2b111=dval12*bhat[1,11]
  mv2b112=dval12*bhat[1,12]
  mv2b113=dval12*bhat[1,13]
  mv2b114=dval12*bhat[1,14]
  mv2b115=dval12*bhat[1,15]
  mv2b116=dval12*bhat[1,16]
  mv2b117=dval12*bhat[1,17]
  mv2b118=dval12*bhat[1,18]
  mv2b119=dval12*bhat[1,19]
  mv2b120=dval12*bhat[1,20]
  mv2b121=dval12*bhat[1,21]
  mv2b122=dval12*bhat[1,22]
  mv2b123=dval12*bhat[1,23]
  mv2b124=dval12*bhat[1,24]
  mvwts12=dval12
```

```
}
mean_mv_PW=as.data.frame(c(mean(mv2g12),mean(mv2b12),mean(mv2b13),mean(m
v2b14),mean(mv2b15),mean(mv2b16),mean(mv2b17),mean(mv2b18), mean(mv2b19),
mean(mv2b110),mean(mv2b111),mean(mv2b112),mean(mv2b113),mean(mv2b114),m
ean(mv2b115),mean(mv2b116),mean(mv2b117),mean(mv2b118),mean(mv2b119),mea
n(mv2b120), mean(mv2b121),mean(mv2b122),mean(mv2b123),mean(mv2b124)))
#################################################################
#Equation 2
if(M2=='TOB'){
  mv2g21=pval22*(-1*ghat[2,1])
  mv2b22=pval22*bhat[2,2]
  mv2b23=pval22*bhat[2,3]
  mv2b24=pval22*bhat[2,4]
  mv2b25=pval22*bhat[2,5]
  mv2b26=pval22*bhat[2,6]
  mv2b27=pval22*bhat[2,7]
  mv2b28=pval22*bhat[2,8]
  mv2b29=pval22*bhat[2,9]
  mv2b210=pval22*bhat[2,10]
  mv2b211=pval22*bhat[2,11]
  mv2b212=pval22*bhat[2,12]
  mv2b213=pval22*bhat[2,13]
  mv2b214=pval22*bhat[2,14]
  mv2b215=pval22*bhat[2,15]
  mv2b216=pval22*bhat[2,16]
  mv2b217=pval22*bhat[2,17]
  mv2b218=pval22*bhat[2,18]
  mv2b219=pval22*bhat[2,19]
  mv2b220=pval22*bhat[2,20]
  mv2b221=pval22*bhat[2,21]
  mv2b222=pval22*bhat[2,22]
  mv2b225=pval22*bhat[2,25]
  mv2b226=pval22*bhat[2,26]
  mvwts22=pval22
}

mean_mv_Chem=as.data.frame(c(mean(mv2g21), mean(mv2b22), mean(mv2b23),
mean(mv2b24),mean(mv2b25),mean(mv2b26),mean(mv2b27),mean(mv2b28),
mean(mv2b29),mean(mv2b210),mean(mv2b211),mean(mv2b212),mean(mv2b213),
mean(mv2b214),mean(mv2b215),mean(mv2b216),mean(mv2b217),mean(mv2b218),
mean(mv2b219),mean(mv2b220), mean(mv2b221),mean(mv2b222),mean(mv2b225),
mean(mv2b226)))
```

```
#################################################################
```
Step (6): Visual Inspection of Distribution of Marginal effects
```
#################################################################
#Equation 1
#histograms
png(file=paste("Z:/plots/mv_eq1-%03d.png",sep=''), width=960, height=960)
hist(mv2g12)
hist(mv2b12)
hist(mv2b13)
hist(mv2b14)
hist(mv2b15)
hist(mv2b16)
hist(mv2b17)
hist(mv2b18)
hist(mv2b19)
hist(mv2b110)
hist(mv2b111)
hist(mv2b112)
hist(mv2b113)
hist(mv2b114)
hist(mv2b115)
hist(mv2b116)
hist(mv2b117)
hist(mv2b118)
hist(mv2b119)
hist(mv2b120)
hist(mv2b121)
hist(mv2b122)
hist(mv2b123)
hist(mv2b124)
hist(mvwts12)
dev.off()
#################################################################
#Comparing marginal or "influenceable" farmers and farmers who apparently have
#already made a decision (no marginal effect is evident); are the characteristics for the
#people that are likely to be influenced by changes in X (those that can be moved over
#the margin) any different from the characteristics of the infra-marginal or non-
#influenceable population?

#Recall that the average marginal effect is not truly representative for any individual in
#the sample, it is preferable to report the average marginal effects for entire population
#together with the average marginal effects correponsing to both populations
```

```
#mentioned above. This is useful for future sensitivity analysis; if we artificially increase
#the mean of a regressor (shift a parameter), what is the likelihood of participation?

hist(mvwts12)
df1$mvwts12=mvwts12
df1_unaffected_eq1=subset(df1,mvwts12<=0.05)
df1_affected_eq1=subset(df1,mvwts12>0.05)

as.data.frame(summary(df1))
as.data.frame(summary(df1_unaffected_eq1))
as.data.frame(summary(df1_affected_eq1))
sumstats_me_eq1=cbind(as.data.frame(summary(df1_unaffected_eq1)),
as.data.frame(summary(df1_affected_eq1)))

sumstats_me_eq1=sumstats_me_eq1[c(2,3,6)]
colnames(sumstats_me_eq1)=c("variable", "statistic_unaffected", "statistic_affected")
write.csv(sumstats_me_eq1, file = "Z:/sumstats_me_eq1.csv")

#################################################################
#Examining covariance
#is it appropriate to examine changes in explanatory variables in isolation or are they
#tightly related? Do responses change jointly or independently? This analysis is
#important for policy recommendations. How do the regressor covary?
#If they mode together, it does not make sense to suggest changing only one thing at a
#time. It may be adequate to look at their joint effect, there may be cross-effects:
#increasing marginal return to x1 from a unit change in x2; or, there may be off-setting
#effects: the benefit on y1 from increasing x1 is offset by the cost in y1 occurring from
#the reduction in x2

interesting_eq1=df1_affected_eq1[,c('y1', 'y2', 'x1', 'x4', 'x8', 'x9', 'x10', 'x12', 'x13', 'x14',
'x15', 'x17', 'x19', 'x21')]
pairs(interesting_eq1)

interesting2_eq1=df1_affected_eq1[,c('y1', 'y2', 'x4','x9','x12','x13','x14','x15')]
pairs(interesting2_eq1)

interesting3_eq1=df1_affected_eq1[,c('y1', 'y2', 'x4', 'x9','x10','x15','x19','x21')]
pairs(interesting3_eq1)
#################################################################
#Equation 2
#histograms
png(file=paste("Z:/plots/mv_eq2-%03d.png",sep=''), width=960, height=960)
```

```
hist(mv2g21)
hist(mv2b22)
hist(mv2b23)
hist(mv2b24)
hist(mv2b25)
hist(mv2b26)
hist(mv2b27)
hist(mv2b28)
hist(mv2b29)
hist(mv2b210)
hist(mv2b211)
hist(mv2b212)
hist(mv2b213)
hist(mv2b214)
hist(mv2b215)
hist(mv2b216)
hist(mv2b217)
hist(mv2b218)
hist(mv2b219)
hist(mv2b220)
hist(mv2b221)
hist(mv2b222)
hist(mv2b225)
hist(mv2b226)
hist(mvwts22)
dev.off()
#####################################################################
#Comparing marginal and infra-marginal farmers. This is useful for future sensitivity
#analysis--> if we artificially increase the mean of a regressor (shift a parameter), what is
#the change in fertilizer use?
hist(mvwts22)
df1$mvwts22=mvwts22
df1_unaffected_eq2=subset(df1,mvwts22<=0.5)
df1_affected_eq2=subset(df1,mvwts22>0.5)

as.data.frame(summary(df1))
as.data.frame(summary(df1_unaffected_eq2))
as.data.frame(summary(df1_affected_eq2))
sumstats_me_eq2=cbind(as.data.frame(summary(df1_unaffected_eq2)),
as.data.frame(summary(df1_affected_eq2)))

sumstats_me_eq2=sumstats_me_eq2[c(2,3,6)]
```

```
colnames(sumstats_me_eq2)=c("variable", "statistic_unaffected", "statistic_affected")
write.csv(sumstats_me_eq2, file = "Z:/sumstats_me_eq2.csv")
#################################################################
#Report mean marginal effect for all variables, and include histogram/distribution of
#marginal effects for variables of particular interest
hist(mv2a12)
mean(mv2a12)
bhat[1,2]

#################################################################
#Examining covariance:

interesting_eq2=df1_affected_eq2[,c('y1', 'y2', 'x201', 'x101', 'x3', 'x4', 'x5', 'x8', 'x9',
'x10', 'x11', 'x12', 'x13', 'x17', 'x19', 'x202')]
pairs(interesting_eq2)

interesting2_eq2=df1_affected_eq2[,c('y1', 'y2', 'x201', 'x101', 'x4', 'x11', 'x17', 'x19',
'x202')]
pairs(interesting2_eq2)

interesting3_eq2=df1_affected_eq2[,c('y1', 'y2', 'x201', 'x101', 'x4','x10','x202')]
pairs(interesting3_eq2)
#################################################################
Step (7): Bootstrapping Standard Errors and Parameter Estimates
#################################################################
# bootstrap the parameter estimates
# Set objects and functions
set.seed(2012)
j=1
for( j in 1:nboots){
 pickum=sample(1:nobs,225,replace=F)
 df2=df1[pickum,]
#################################################################
 #Equation 1
 if(M1=='BIN') {
  reg11=glm(y1~x1+x2+x4+x5+x7+x8
        +x13+x14+x18+x19+x20+x21
         +x101+x102
         +x201+x202,family=binomial(link='probit'),data=df2)
  y11hat=reg11$linear
  varhat11=1.0
 }
```

```
AHAT[1,1:3,j]=reg11$coef[1:3]
AHAT[1,4,j]=0
AHAT[1,5:6,j]=reg11$coef[4:5]
AHAT[1,7,j]=0
AHAT[1,8:9,j]=reg11$coef[6:7]
AHAT[1,10:13,j]=0
AHAT[1,14:15,j]=reg11$coef[8:9]
AHAT[1,16:18,j]=0
AHAT[1,19:21,j]=reg11$coef[10:12]
AHAT[1,22:26,j]=reg11$coef[13:17]
#####################################################################
#Equation 2
if(M2=='TOB') {
   reg21=tobit(y2~x1+x2+x3+x4+x5+x6+x7+x8+x9+x10
            +x11+x12+x13+x14+x15+x16+x17+x18+x19+x20+x21
            +x101+x102
            +x201+x202,left=y2cut,data=df2)
   y21hat=reg21$linear.predictors
   varhat21=reg21$scale^2
 }
 AHAT[2,,j]=reg21$coef
#####################################################################
# Stage 2
#####################################################################
#Equation 1
 if(M1=='BIN') {
   reg12=glm(y1~x1+x2+x4+x5+x7+x8
          +x13+x14+x18+x19+x20+x21
          +x101+x102
          +y21hat,family=binomial(link='probit'),data=df2)
   y12hat=reg12$linear
 }
BHAT[1,1:3,j]=reg11$coef[1:3]
BHAT[1,4,j]=0
BHAT[1,5:6,j]=reg11$coef[4:5]
BHAT[1,7,j]=0
BHAT[1,8:9,j]=reg11$coef[6:7]
BHAT[1,10:13,j]=0
BHAT[1,14:15,j]=reg11$coef[8:9]
BHAT[1,16:18,j]=0
BHAT[1,19:21,j]=reg11$coef[10:12]
BHAT[1,22,j]=0
```

```
BHAT[1,23:24,j]=reg11$coef[13:14]
BHAT[1,25:26,j]=0
#################################################################
#Equation 2
if(M2=='TOB') {
   reg22=tobit(y2~x1+x2+x3+x4+x5+x6+x7+x8+x9+x10
            +x11+x12+x13+x14+x15+x16+x17+x18+x19+x20+x21
            +x201+x202
            +y11hat,left=y2cut,data=df2)
   y22hat=reg22$linear.predictors
  }
  BHAT[2,1:22,j]=reg22$coef[1:22]
  BHAT[2,25:26,j]=reg22$coef[23:24]

  plot(j,j,main=paste('rep',j,'of',nboots))

#Getting a distribution of estimated coefficients for the endogenous variables
  GHAT[1,2,j]=-reg12$coeff[16]
  GHAT[2,1,j]=-reg22$coeff[25]

} #end loop on bootstrap
#################################################################
#Notes on bootstrapping:
#Big difference between simple delete bootstrap (pickum=sample(1:nobs, 140,
replace=F); effectively selects 40 to drop)
#Jacknife is more robust to outliers
#much larger variance with sample a replacement than with jacknife
#AHAT= bootstrapped coefficients from stage 1
#BHAT= bootstrapped coefficients from stage 2
#ahat=coefficients from stage 1
#bhat=coefficients from stage 2
#Ghat=var-cov matrix
#################################################################
#VISUAL INSPECTION, are standard errors normally distributed?

qqnorm(AHAT[1,2,])
qqline(AHAT[1,2,])

qqnorm(BHAT[1,2,])
qqline(BHAT[1,2,])

#################################################################
```

Step (8): Calculating P-values

```
#####################################################################
#P-VALUES
#What proportion of the observations are below that value?
#What is the chance of this coeficient==0, thus the probability of rejecting significance?
#We can construct a 95% confidence interval and see if zero lies within the interval
#Constructing a 1-tail test for negative parameters.

#Defining functions
pvals_pos=function(x0,x){
  length(x[x<x0])/length(x)
}
pvals_neg=function(x0,x){
  length(x[x>x0])/length(x)
}
#####################################################################
# Creating loop to calculate and store p-values
#####################################################################
# Equation 1, M1=Probit

PVALS=array(0,c(2,26))
j=1

for( j in 1:26){

  #VISUAL INSPECTION

qqnorm(BHAT[1,j,])
qqline(BHAT[1,j,])

#Calculating PVALS
#what is the chance of this coeficient==0, thus the probability of rejecting significance?

 pvals_pos=function(x0,x){
    length(x[x<x0])/length(x)
  }

  pvals_neg=function(x0,x){
    length(x[x>x0])/length(x)
  }
```

```
 if(bhat[1,j] >= '0') {
  PVALS[1,j]=pvals_pos(0,BHAT[1,j,])
 }

 if(bhat[1,j] < '0') {
  PVALS[1,j]=pvals_neg(0,BHAT[1,j,])
 }

} #end loop
#####################################################################
#Equation 2, M2=Tobit

j=1

for( j in 1:26){

#VISUAL INSPECTION,

 qqnorm(BHAT[2,j,])
 qqline(BHAT[2,j,])

  #PVALS
#what is the chance of this coeficient==0, thus the probability of rejecting significance?

pvals_pos=function(x0,x){
  length(x[x<x0])/length(x)
 }

 pvals_neg=function(x0,x){
  length(x[x>x0])/length(x)
 }

 if(bhat[2,j] >= '0') {
  PVALS[2,j]=pvals_pos(0,BHAT[2,j,])
 }

 if(bhat[2,j] < '0') {
  PVALS[2,j]=pvals_neg(0,BHAT[2,j,])
 }

} #end loop
```

```
(PVALS_DF=as.data.frame(PVALS))
colnames(PVALS_DF)=c("Intercept",
                "Age2", "Age", "Literacy_Prg", "Prim_Ed", "Sec_Ed", "High_Ed", "HH_size",
                "Farm_size",  "V_assets", "TLU",  "Irrig", "Farm_Rev", "Nonfarm_Rev",
"DS_PSNP", "Equibb",
                "Market_W","Ext_visits", "Sec_schools", "Travel_time",
                "Soil_quality", "Trees",
                "Prev_PW", "Severe_shock",
                "Prev_fert", "Manure")

#I will have 26 entries for both models because I am using the reduced form estimates

#bhat[1,25]; bhat[1,26]; bhat[2,23] and bhat[2,24] have entries of zero. They
#correspond to the variables used to over-identify the system

#Using BHAT,
#BHAT[1,25,]; BHAT[1,26,]; BHAT[2,23,] and BHAT[2,24,]  have entries of zero. They
#correspond to the variables used to over-identify the system.
################################################################
#Examining the distribution of estimated coefficients for the endogenous variables

#VISUAL INSPECTION

qqnorm(GHAT[1,2,])
qqline(GHAT[1,2,])

qqnorm(GHAT[2,1,])
qqline(GHAT[2,1,])

#PVALS

ghat[1,2]
ghat[2,1]

if(ghat[1,2] >= '0') {
  PVALS_DF$Chem_ferthat=c(pvals_pos(0,GHAT[1,2,]),0)
}

if(ghat[1,2] < '0') {
  PVALS_DF$Chem_ferthat=c(pvals_neg(0,GHAT[1,2,]),0)
}
```

```
PVALS_DF$Chem_ferthat #2 rows....why?
pvals_neg(0,GHAT[1,2,])
# pvals(0,GHAT[1,2,])=0.213, 21% are above zero--> not significantly different from
zero(?)


if(ghat[2,1] >= '0') {
  PVALS_DF$PW_parthat=c(0,pvals_pos(0,GHAT[2,1,]))
}

if(ghat[2,1] < '0') {
  PVALS_DF$PW_parthat=c(0,pvals_neg(0,GHAT[2,1,]))
}

PVALS_DF$PW_parthat #2 rows....why?
pvals_neg(0,GHAT[2,1,])
# pvals(0,GHAT[1,2,])=0.22, 22% are above zero--> not significantly different from
zero(?)

PVALS_DF
#####################################################################
```

Step (9): Setting data frames organizing estimated coefficients, marginal effects, standard errors and p-values

```
#####################################################################

mean_mv_PW=as.data.frame(c(mean(mv2g12), mean(mv2b12), mean(mv2b13),
mean(mv2b14), mean(mv2b15), mean(mv2b16), mean(mv2b17), mean(mv2b18),
mean(mv2b19), mean(mv2b110), mean(mv2b111), mean(mv2b112), mean(mv2b113),
mean(mv2b114), mean(mv2b115), mean(mv2b116),mean(mv2b117), mean(mv2b118),
mean(mv2b119), mean(mv2b120), mean(mv2b121), mean(mv2b122), mean(mv2b123),
mean(mv2b124)))

coef_PW=as.data.frame(c((-1*ghat[1,2]), bhat[1,2], bhat[1,3], bhat[1,4], bhat[1,5],
bhat[1,6], bhat[1,7], bhat[1,8], bhat[1,9], bhat[1,10], bhat[1,11], bhat[1,12], bhat[1,13],
bhat[1,14], bhat[1,15], bhat[1,16], bhat[1,17], bhat[1,18], bhat[1,19], bhat[1,20],
bhat[1,21], bhat[1,22], bhat[1,23], bhat[1,24]))

se_PW=as.data.frame(c(sd(GHAT[1,2,]),
sd(BHAT[1,2,]), sd(BHAT[1,3,]),sd(BHAT[1,4,]),sd(BHAT[1,5,]),
sd(BHAT[1,6,]),sd(BHAT[1,7,]),sd(BHAT[1,8,]),sd(BHAT[1,9,]),
sd(BHAT[1,10,]),sd(BHAT[1,11,]),sd(BHAT[1,12,]),sd(BHAT[1,13,]),
sd(BHAT[1,14,]),sd(BHAT[1,15,]),sd(BHAT[1,16,]),sd(BHAT[1,17,]),
```

```
sd(BHAT[1,18,]),sd(BHAT[1,19,]),sd(BHAT[1,20,]),sd(BHAT[1,21,]),
sd(BHAT[1,22,]),sd(BHAT[1,23,]),sd(BHAT[1,24,])))

pval_PW=PVALS_DF[1,]
pval_PW=pval_PW[c(27, 2:24)]
pval_PW=t(pval_PW)

dim(mean_mv_PW)
dim(coef_PW)
dim(se_PW)
dim(pval_PW)

table_PW=as.data.frame(cbind(coef_PW,mean_mv_PW,se_PW,pval_PW))
colnames(table_PW)=c("coefficient_estimates", "mean_marginal_effect",
"standard_error", "p-value")
#################################################################

mean_mv_Chem=as.data.frame(c(mean(mv2g21), mean(mv2b22), mean(mv2b23),
mean(mv2b24), mean(mv2b25), mean(mv2b26), mean(mv2b27), mean(mv2b28),
mean(mv2b29), mean(mv2b210), mean(mv2b211), mean(mv2b212), mean(mv2b213),
mean(mv2b214), mean(mv2b215), mean(mv2b216), mean(mv2b217), mean(mv2b218),
mean(mv2b219), mean(mv2b220), mean(mv2b221), mean(mv2b222), mean(mv2b225),
mean(mv2b226)))

coef_Chem=as.data.frame(c((-1*ghat[2,1]), bhat[2,2], bhat[2,3], bhat[2,4], bhat[2,5],
bhat[2,6], bhat[2,7], bhat[2,8], bhat[2,9], bhat[2,10], bhat[2,11], bhat[2,12], bhat[2,13],
bhat[2,14], bhat[2,15], bhat[2,16],  bhat[2,17], bhat[2,18], bhat[2,19], bhat[2,20],
bhat[2,21], bhat[2,22], bhat[2,25], bhat[2,26]))

se_Chem=as.data.frame(c(sd(GHAT[2,1,]),
sd(BHAT[2,2,]), sd(BHAT[2,3,]),sd(BHAT[2,4,]),sd(BHAT[2,5,]),sd(BHAT[2,6,]),
sd(BHAT[2,7,]),sd(BHAT[2,8,]),sd(BHAT[2,9,]),sd(BHAT[2,10,]),sd(BHAT[2,11,]),
sd(BHAT[2,12,]),sd(BHAT[2,13,]),sd(BHAT[2,14,]),sd(BHAT[2,15,]),sd(BHAT[2,16,]),
sd(BHAT[2,17,]),sd(BHAT[2,18,]),sd(BHAT[2,19,]),sd(BHAT[2,20,]),sd(BHAT[2,21,]),
sd(BHAT[2,22,]),sd(BHAT[2,25,]),sd(BHAT[2,26,])))

pval_Chem=PVALS_DF[2,]
pval_Chem=pval_Chem[c(28, 2:22, 25:26)]
pval_Chem=t(pval_Chem)

dim(mean_mv_Chem)
dim(coef_Chem)
```

```
dim(se_Chem)
dim(pval_Chem)

table_Chem=as.data.frame(cbind(coef_Chem,mean_mv_Chem,se_Chem,pval_Chem))
colnames(table_Chem)=c("coefficient_estimates", "mean_marginal_effect",
"standard_error", "p-value")

table_Chem

write.csv(table_PW, file = "C:/Users/laura.villegas/Documents/Table_PW.csv")
write.csv(table_Chem, file = "C:/Users/laura.villegas/Documents/Table_Chem.csv")
```