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DISSERTATION

Agrarian Households in Semi-Arid Tropics

Evaluating Policy Options

Arnab Mukherji

This document was submitted as a dissertation in September 2006 in partial fulfillment of the requirements of the doctoral degree in public policy analysis at the Pardee RAND Graduate School. The faculty committee that supervised and approved the dissertation consisted of James R. Hosek (Chair), Ranjitha Puskur, Greg K. Ridgeway, and Neeraj Sood.

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Abstract

Approximately 165 million people, about a fifth of the world's poor, are known to be resource scarce agrarian households, or "smallholders", living in rain fed semi-arid tropical areas (SATs). Uncertainty in livelihoods in SATs is higher than in other areas of intensive farming with short burst of intense rainfall, high soil erosion and cycles of drought. Chapter 2 describes economic condition of the smallholders, their significance, and the state of knowledge on some micro-interventions that have been used to reduce the uncertainty in their incomes.

Chapter 3, following Rosenzweig and Wolpin (1993), characterizes decision making in risky environments by formulating a structural dynamic model of agricultural investment (in bullocks) for smallholders. This incorporates key characteristics of decision making for smallholders e.g. income uncertainty, no rental market, credit constraints, and preferences over mean and variance of incomes. The model's utility function primitives are calibrated using data from the ICRISAT village level studies. Once the calibrated parameters are obtained, counterfactual policy simulations identify which ones are most successful at preserving household wealth. The interventions I consider are a) livestock intervention, b) a soil and water conservation intervention and c) an employment guarantee scheme (that allows households a fixed income during droughts). I find that livestock management and soil and water conservation have a minimal impact on asset holdings, while the employment guarantee scheme provides substantial asset protection throughout the lifetime of these households. However, the livestock intervention is the most cost-effective intervention.

Chapter 4 evaluates an agricultural CDD that was designed and implemented by a village development committee in the semi-arid tropics of Madhya Pradesh, India. I use non-parametric propensity score adjusted difference in difference models and retrospective data from a field study to evaluate the effects of this CDD on a variety of outcomes. The findings suggest that the CDD led to: (1) a decrease in agricultural income but no change in total income, (2) a reduction in the incidence of skipped meals and collecting non-timber forest produce, and (3) reduction in sharecropping in favor of independent farming. This study is based on an original data set collected by the author.

Chapter 5 concludes with policy implications and a discussion of areas of research that will further improve policy design and implementation.

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Chapter 1

Introduction and Research Questions

1.1 Introduction

A fairly well known fact is that approximately one fifth of the world's population lives on less than a US dollar a day[1]. These 1.1 billion poor people are not uniformly distributed, even within developing countries, and estimates suggest that about 560 million live in the Semi-Arid Tropics[2](SAT). A subset of this, about 165 million people, are believed to be extremely resource scarce and dependent on subsistence farming in rain fed areas in the SATs (Ryan and Spencer 2001). Agricultural livelihoods in general are known to operate in a risky production environment, however, the scale of uncertainty for rain dependent households in the SATs is substantially higher. Not only is the temporal and spatial distribution of rainfall highly unpredictable, but

[1]See http://earthtrends.wri.org/ for facts, data, and definitions on poverty.

[2]The SATs include those tropical regions of the world where rainfall exceeds potential evaporation four to six months of the year. Mean annual rainfall is known range from 400 to 1200 mm (Walker and Ryan 1990). It is also home to about 1.4 billion people across 55 countries in the world. Collectively, it occupies about 40% of the world's surface area (Dobie 2001).

it also receives most of this rainfall in a matter of a few days making soil erosion an additional problem[3].

Without access to formal market based mechanisms to pool risk, small holders have been observed to rely on many innovative individual, and sometimes community-specific, risk management devices[4]. In a seminal paper, Townsend (1994) was among the first to show that household consumption is correlated with average village consumption and importantly is less influenced by fluctuations in own incomes, showing that households were able to have a smoother consumption profile than if they had been solely dependent on their incomes. However, empirical research also finds that such mechanisms do not provide adequate insurance to households (Morduch 2003). Such gaps in insurance in a high risk environment not only lead to catastrophic consequences for households but are also responsible for retarded growth possibilities and persistent inequities (Zimmerman and Carter 2003). From a public policy point of view this raises the question of how households may be able to transition from economic profiles that tend to self-perpetuate in poverty to ones that allow households to experience economic growth and improvements in welfare.

Historically, interventions in the agricultural sector have been macroeconomic and financially supported through centralized programs (see Binswanger and Deininger 1997, and FAO 2000 for a review of agrarian poli-

[3]It is estimated that annual rainfall in most SATs are distributed across just a 100 hours in the entire year (Agarwal 2000).

[4]For example, Walker and Ryan (1990) record borrowing, seasonal migration, selling assets, crop diversification, Jodha (1986) records the role of common pool resources like forest areas, grazing lands etc. and their increasing importance in droughts, Akresh (2004) discusses the role of child fostering in Africa in response to income shocks, and Rosenzweig and Stark (1989) find evidence to support the hypothesis that households marry their daughters off to locationaly distant, yet kinship related households with low correlations of weather shocks to improve chances for consumption smoothing. Fafchamps (2004) and Dercon (2005) also provide recent reviews of this literature

cies over the last few decades). Rapid expansion of irrigation networks, infrastructure, subsidized credit, disseminating knowledge through research and extension activities and the spread of high-yielding variety seeds and related technology have contributed to the rapid increase and global sufficiency in food production. However, much of these gains have been driven by modern agricultural enterprizes and have ignored the smallholder working often on less favored lands (high aridity, variable rainfall, poor soil quality, etc.). Thus, in spite of global sufficiency there are local failures in meeting minimum subsistence food consumption standards.

1.2 Research Objectives:

This dissertation has three research objectives. First, it seeks to describe the conditions and constraints within which smallholders seek to earn a livelihood. Household preferences, agricultural and institutional constraints within which these households operate, and options available to them, all collectively determine how these households respond to a highly uncertain production environment. While a number of papers have described different aspects pertinent to this, this dissertation combines these insights together specifically for small holders.

Second, it seeks to identify the nature of income changes that policy interventions need to provide or to target to help smallholders stay out of poverty. Smallholder households operate in an inherently dynamic environment where decisions made today affect future income and consumption possibilities. To characterize their decision making in a credit constrained environment, with uncertain rainfall states and uncertain returns on owned assets, a stochastic dynamic program is developed whose utility parameters are calibrated using the ICRISAT VLS data. This provides a framework within which counter-

factual policy simulation are undertaken. Specifically, the dissertation looks at how micro policies such as livestock management, watershed development projects and employment guarantees schemes change a household optimal decisions and its impacts on the long term productive asset holding behavior of a household.

Thirdly, it discusses the appropriate program design within which public policy interventions need to be placed. At one end are centralized programs that implement a consistent set of rules for the target population that potentially allow beneficiaries a common set of guidelines within which to participate in the program. At the other end are decentralized, community based, or driven, projects which are designed, managed and monitored by the community within which the intervention takes place. Such programs have the advantage of being able to use local information to configure the project to local needs, however, may also suffer from elite capture. Programs under both models of implementation have seen successes as well as failures. This dissertation also contributes to this debate by evaluating the impact of a community driven intervention in central India and documents the kinds of intended and unintended benefits that such programs can lead to.

1.3 Organization of the Dissertation

This dissertation focusses on some policy issues related to the small farmer. In particular, Chapter 2 describes the emergence of the smallholder as the appropriate target unit for various kinds of micro-interventions that aim to reduce poverty and foster growth in personal incomes. It also describes the state of knowledge about two kinds of interventions that directly target different aspects of the small holders agro-economic profiles: soil and water conservation, and employment guarantee schemes. Chapter 3 builds a behavioral

dynamic model of a household's decisions about holding a productive asset. Using panel data from the ICRISAT VLS studies. I calibrate utility function primitives and conduct counterfactual policy simulations. Chapter 4 seeks to evaluate the ability of a village development committee in designing its own intervention based on a field study carried out in Sheopur district, Madhya Pradesh, India. Finally, chapter 5 reviews the findings of this dissertation and concludes.

Chapter 2

The “Smallholder”: A Review

2.1 The “Smallholder”

The term “*smallholder*” has become quite ubiquitous in research and policy settings and is often used interchangeably with family farms, or peasant farmers. Not surprisingly, there is no exact defining set of attributes for the smallholder as many different lifestyles may be resource scare or “small” in many different ways. Some of the alternative definitions or characterization of the small holder are:

“ *.. as a farmer (crop or livestock) practicing a mix of commercial and subsistence production or either, where the family provides the majority of labor and the farm provides the principal source of income.*”

(Narayanan and Gulati 2002)

“*... operated units in which most labor and enterprise come from the farm family, which puts much of its working time into the farm.*”

(Lipton 2005)

“*Smallholders are persons with agriculture as the main occupation and source of income, and little or none of the following resources: land, water,*

financial resources, human resources, information resources. They generally manage these resources effectively within the constraints of climate and institutional (including legal) frameworks. ... The shortage of resources available to smallholder households causes severe constraints for income generation, and reduces the level of household food security. This situation applies to approximately 500 million households (1.8 billion people), among which the world's poorest; their relative number decreases slowly, but the absolute number still increases"

(IWMI 2004)

Thus, smallholders are households whose access to bio-economic resources and institutional support (e.g. credit markets) is sufficiently constrained to make sustained income growth and livelihood stability difficult to attain. A key issue is that consumption needs are pretty steady over time while income receipts tend to be uncertain for a number of reasons specific to both agriculture, as well as the semi-arid tropics[1]. In a seminal paper Deaton (1991) showed that in such environments households tend to hold assets as a buffer stock to tide over poor realizations of income; essentially, assets act as an insurance instrument allowing households to save in good states of the world and deplete it in poor states of the world. In addition, if households are impatient (i.e. prefer consumption today to deferring consumption to the future) then savings and investments tends to be sub-optimal to levels necessary for perfect consumption smoothing behavior. Thus, households would tend to experience key shortages in consumption and will fail to fully self-insure against adverse income shocks.

[1]Fluctuations in income may be covariate and affect many households in a region, such as with rainfall fluctuations, price variations, and economic fluctuation induced by epidemics and wars. Alternatively, shocks could also be idiosyncratic and affect a single household such a,s with ill health, or with the death of a household member. (Morduch 1995) discusses how households cope with different types of risk.

However, the problem is more systemic then just smallholders being impatient at subsistence consumption levels. As (Dercon 2005, Chapeter 1) points out, uncertainty in returns from asset ownership, the covariance in value of assets and adverse income shocks, and discrete nature of some of these assets (like livestock, pumps, tractors, etc.) makes realizing the value of assets owned difficult and so their use as buffer stocks inadequate. Apart from their role as a buffer stock, some of these assets are critical to agricultural income, and often determine the types of contracts that a smallholder may be able to bargain for in local land and labor markets. Consequently, income fluctuations have implications not only for current consumption, and the pattern of investment, but also for future income streams as households resort to a wide variety of consumption smoothing and income smoothing strategies[2]. This may often imply being locked into behaviors, technologies, and most importantly income generating profiles that are self-perpetuating and may hurt growth prospects for individual households as shown in a simulation study by Zimmerman and Carter (2003).

This chapter provides emerging trends on different aspects of livelihood for the smallholder. Specifically, Section 2.2 discusses fragmentation of farm sizes for smallholders as well as the increasing difference in productivity of subsistence agriculture and modern agricultural systems; Section 2.3 discusses some estimates of returns on public investment in semi-arid tropics; Section 2.4 presents evidence from two micro intervention that tries to directly target households - water management strategies and employment guarantee schemes and Section 2.5 concludes.

[2]Actions chosen in anticipation of shocks, such as having a household member in non-farm employment or choosing robust but low productivity seeds (Walker and Ryan 1990), are ex-ante risk mitigating actions. Action in which household respond to the shock, such as migrating in search of work after rains fail, or borrowing, are ex-post risk mitigating actions.

2.2 Smallholders: Emerging Polarization in Agriculture

Table 2.1: Average Size of Farms, by Countries 1880 - 2000 (Hectares)

Country	1880-5	1910	1950	1970	1980	1990	2000
A: Developed Nations							
USA	56	56	87	157.61	159.13	186.95	178.35
Canada	40	65	113	-	-	242	273.38
Belgium	6.3	-	6.8	8.71	12.37	16.06	23.12
England	33	32	33	55.07	65.42	55.07	70.86
Germany	6	5.5	-	14.18	17.04	30.26	40.47
B: Developing Nations							
India	-	-	-	2.3	2	1.55	1.41
Indonesia	-	-	-	-	0.56	0.54	-
Pakistan	-	-	-	5.29	4.68	3.78	3.09
Philippines	-	-	-	3.61	2.85	2.16	2.04
Turkey	-	-	-	-	6.24	5.76	5.99
Ethiopia	-	-	-	-	1.43	0.8	1.03
Thailand	-	-	-	-	3.72	3.36	3.16

NOTES:

(1) 1970 - 2000 data source: World Census of Agriculture, various issues

(2) 1880 - 1950 data source: (Federico 2005)

Small holders in developing countries today are more numerous than ever before and with arable land in inelastic supply, this has meant declining farm sizes. The World Census of Agriculture provides trends in average farm sizes in countries. This, combined with other data in Table 2.1 shows an important bifurcation in time trends for farm size holdings in developed and developing nations. Developed countries today have average farm sizes that are several times larger than their average farm sizes in 1950s, for some, the increase is as much as four times. On the other hand farm sizes in developing countries have tended to fall, or at best stagnate. With data availability on devel-

oped countries going back further in time it is possible to see that over the past century farm sizes have on average increased by three to seven times as more and more people have increasingly moved away from agriculture. Not only is the smallholder lifestyle the most common lifestyle in the world today, but it also constitutes a substantial share of the world's rural and total poor. Almost paradoxically, in spite of this poverty, collectively, small holder produce is a substantial fraction of produce in developing countries. In sub-saharan Africa, smallholders account for 90% of agricultural production, while in India, they were known to produce more than 40% of the total agricultural produce. Smallholders also own and manage a significant share of the world's livestock and contribute actively to dairy production, poultry farming etc. (Narayanan and Gulati 2002). Thus, in spite of diminishing farm sizes in developing countries small holders remain economically significant.

Apart from the bifurcation in farm sizes, a differences also exist in the level of technology used and the labor productivity experienced between developed and developing countries. Modern agricultural technology in developed nations makes for a far larger labor productivity than is possible with the traditional technologies in use in developing nations. This difference in productivity between modern farming and subsistence farming was already in evidence by the 1950s. Estimates suggest that, under best conditions, subsistence agrarian systems are able to provide a maximum net productivity of 1000 kg of cereal equivalent per worker. At the other end of the spectrum we find systems of cultivation that are fully mechanized and allow a maximum net productivity of 30,000 kg of cereal equivalent per worker. Not surprisingly, the size of this productivity differential has varied over time. In 1950s the ratio of net productivity from manual farming to mechanized farming was at 1:30; by the year 2000 this difference had grown to 1:500, in spite rapid increases in productivity seen due to the adoption of green revolution tech-

nology in developing countries (FAO 2000). While global food production is adequate to meet demands for food, food insecurity has continued to affect the lives of a vast majority of people in developing countries (many of whom are also smallholders); best estimates suggest that over 850 million people (about one person in eight) are chronically unable to meet their nutritional needs (FAO 2004).

A key question that stems from our earlier discussion of differences in technology and labor productivity is : are small farms in semi-arid tropics the appropriate unit of farming on efficiency grounds alone? The stylized negative relationship between farm size and land productivity[3] would suggest that it is indeed so. Many public policy interventions, such as land reforms to reduce land concentration, aim to exploit this negative relationship. More recent research suggests that this negative relationship maybe biased by unobservable differences (for example technology used, or soil quality) that affect both labor productivity and farm size choices; thus, for example, if agriculture on nutrient (or moisture) deficient soils requires higher effort from the smallholder and that such soils are more likely on a smaller farms then estimated coefficients from regression models omitting soil quality would overestimate the relationship between farm size and labor productivity.

Fan and Chang-Kang (2005) provide a recent literature review on the inverse relationship between labor productivity and reports that studies which have controlled for soil quality, for the distribution of irrigated to non-irrigated land holdings, and the proportion of farm labor that came from a household (as opposed to being hired) tend to show a weak or non-significant

[3]Sen (1962) was the first to note that farmers with smaller land holdings had a higher productivity per unit of land than larger farmers. Subsequently, a number of other researchers have found this relationship using household surveys as well as aggregate national (or state level) data, particularly in the context of Asian agriculture. Cornia (1986) also does a cross-country study and finds it holds for 12 of 15 countries.

relationship between farm size and labor productivity. This suggests that the hypothesis that households with small farm sizes would have higher labor productivity may not hold on richer soils (or for those using better farm technology, or have access to more secure irrigation), as may be expected from the differences in labor productivity in developed and underdeveloped countries. However, as argued by Hazell (2003), smallholders as farming units have comparative advantage in labor using technologies in developing countries due to its relative scarcity with respect to land and capital. In addition, such smallholder farming plays a key role in containing food scarcity by ensuring some home production. Other arguments in support of smallholder farming stem from its ability to slow down rural urban migration and limit the extent of poverty by providing a baseline level of income that would be difficult to replicate within any public redistribution system. Key gains in livelihoods are however needed for the smallholder, in particular, infrastructure, eduction, better production technologies, and institutions with which to participate in the increasingly global market place (Hazell and Diao 2005).

2.3 Investments in Less Favored Areas

Interestingly, research is beginning to find some evidence that public investments in less favored areas (e.g. poor soils, low and unstable rainfall, steep slopes, and short growing seasons) may have returns comparable to areas with access to better soil and rainfall and may play a key role in reducing poverty. Historically, public investment in agriculture has been significantly higher in irrigated and high potential agrarian areas as returns have been highest in such areas. Policy makers have also traditionally believed that maximizing productivity would be sufficient to reduce poverty through the stimulation it would receive through the Keynesian multiplier. Overtime it is increasingly becoming clear that such investments are failing to reduce

poverty because much of the poor are in fact in less favored areas and don't benefit from public investments in superior agricultural areas. For example, Fan and Hazell (2001) report that in 1993 there 184 million rural poor in India, of which 154 lived in rain fed areas, and of 50.2 million rural poor in China in 1996, 31.6 million lived in the low-agricultural potential area.

Apart from not targeting the poor directly or indirectly, there is some evidence that the standard high yielding variety technology may lead to a number of bio-economic problems. While substantial gains in agricultural production has been possible through the green revolution[4], long term experience with this technology shows that there are serious environmental costs of using this technology (e.g. water logging, groundwater contamination, eutorphication of water bodies,[5] increased salinity and alkalinity of soil, loss of crop genetic diversity etc.). Preliminary research is also beginning to show certain organic alternatives to green revolution technology that rely on manure addition, and/or reduced tillage appear to do at least as well as the green technology package (Tillman 1998, Shah et al. 1998, and Drinkwater et al. 1998).

While technological alternatives to the green revolution are still being understood and standardized an important question is what role can direct investment in less favored areas play in encouraging agricultural production and reducing poverty? Fan and Chang-Kang (2004) use disaggregated data on returns to investments in high-yielding variety (HYV) technology and find that a) there are limited gains from investing in HVY technology in low-potential rain fed areas and b) such investments were not effective in re-

[4]Khush (2001) provides a review of the successes of green technology and also discuss some aspects of its future usefulness. Hazell (2003) also discusses the poverty reducing role that the technology has played for those who could access it

[5]"... contamination by organic and inorganic nutrients that cause oxygen depletion, spread of toxic species and changes in the structure of aquatic food webs ..." (Tillman 1998), Also see Mukherji (2004, Chapter 3) for related discussions.

ducing poverty even in rain fed areas. Fan et al. (2000) using state-level data for India over a 23 year period from 1970, show that rural poverty declines are most rapid with government expenditures on rural road and agricultural technology. Such investments not only have largest poverty reduction impacts per rupee spent, but also generate higher productivity growth. Apart from government spending on education, which has the third largest marginal impact on rural poverty and productivity growth, other investments (including irrigation, soil and water conservation, health, and rural and community development) have only modest impacts on growth and poverty per additional rupee spent.

An important area of investment is in technology development as well as adoption through extension activities. A lot of focus has been placed on watershed development initiatives since they directly influence some of the constraints that household in rain fed semi-arid tropics face (e.g. soil conservation, recharging groundwater, increasing the ability to farm over larger lengths of time in the agricultural year etc.). Shah et al. (1998, Chapter 8) discuss watershed planning in the Indian context and discuss how to optimally design components of the initiative to raise farm productivity, meeting household food budgets, easing the water constraint in the watershed, meeting fertilizer needs from within the watershed, and ensuring fodder needs of livestock are meet as well. These kinds of project require investments in infrastructure to control water flow in the watershed, and training and learning opportunities for those who manage the watershed. Much of these kinds of interventions are resource management interventions which help attain efficiency, however, the efficiency frontier itself needs expansion.

Finally, an important way to ease concerns of food security in the future could be through expanding agricultural output of smallholders. Shah et al. (1998), again using data from 1991-92 for India, predicted that to meet

forecasted needs by 2006, 50% of the necessary increase must come from non-irrigated agriculture. (G. S. Bhalla and Kerr 1999) using somewhat more recent data make predictions for India in 2020. Future consumption patterns and demand for grain is difficult to predict based on past trends because of emerging trends in consumption with greater income growth, more access to information about food, and alternative foods themselves. Shah et al. (1998) did back of the envelope calculation for India using data from 1991-92 and suggest that at the then available rates of expansion of population, food grain production, irrigation and technological gains, close to 50% of the gains needed to mature future demand in 2006 must come from growth in rain fed arid and semi-arid areas.

2.4 Micro Interventions for Smallholders in Less Favored Areas

2.4.1 Watershed Development Programs

Securing water supply is a key requirement for successful agriculture. Historically, governments have placed a large amount of emphasis on building irrigation networks for such purposes. However, the rate of expansion of area under irrigation has remained relatively stable since mid- 1970s and increasing this runs into various environmental, economic and political issues (FAO 1990). Government policy instruments that attempt to provide secure access to water, for example, large-scale irrigation networks (multi-purpose dams and canal irrigation) or ground water extraction, have exhausted much of the gains that these could provide. In India's context, large-scale irrigation systems have reached a plateau in their coverage and expansion since mid-1980s. Much of the recent expansion in irrigation coverage has been through groundwater extraction i.e. tube-wells, bore-wells etc. So much so, that currently 50% of all irrigation in India is from ground water extraction alone

(Rao 2000). For rain fed areas maximizing the productive use of rainfall is likely to be a key strategy in ensuring that stable livelihoods are possible for smallholders.

The FAO defines *water harvesting*[6] as " the process of collecting and concentrating rainfall as runoff from larger catchments to be used in a smaller area". Thus, these programs work with shaping land contours[7] to encourage water seepage into soil rather than running off and thereby increasing soil moisture and labor productivity. Rural households can potentially grow crop that requires more water, or farm more intensively during the agricultural year. Evidence on the efficacy of these interventions have been mixed, but most studies find that watershed development programs ease many of the soil and water management constraints that smallholders face (Joshi et al. 2004; Kerr 2002; and Chopra and Gulati 2001). The problem that arises is how are these programs to be implemented.

Governance Issues:

Water management programs essentially try and alter the natural flow of rain water in ways that allow households to use it (either through ground water recharge, or creating storage tanks, or simply controlling its speed) and hence the loss in top-soil. Structures and interventions need to be built and this typically requires land, labor and various social and legal mechanisms by which optimal structures can be designed, built and maintained. The public goods nature of watershed development is central to designing a functional

[6] Water harvesting is a generic term referring to a class of rainwater management principles. Two sub-classes are Soil and Water Conservation (SWC) and Watershed Development Programs (WDP). SWCs initiatives are undertaken at the level of the farm where field specific structures are built and managed. Watershed harvesting however, takes place over larger tracts of land and requires co-ordination across farmers for effective implementation.

[7] Watershed structures consists of farms ponds, open dug wells ("cisterns"), underground dykes, gabion structures, contour trenches, gully plugs, etc. Shah et al. (1998) provide some description of these along with visuals of some of these structures.

intervention. Costs and benefits must be distributed to the beneficiaries and if these interventions are to play a role in reducing poverty the exact distribution of the costs and benefits matter (Joshi et al. 2004).

WDP projects typically experience significant implementation issues because of the nature of collective community action that is needed to maintain them. Purely technocratic interventions that optimally place these structures without due consideration to such land relations and the management responsibilities of the beneficiaries have traditionally been found to be plagued with maintenance issues (Kerr 2002, Farrington et. al., Walker and Ryan 1990). Thus, governance is a key issue in ensuring that communities are able to regulate the distribution of labor costs, land donations, and other maintenance work needed to keep the many structures (check dams, gulley plugs, drain lines, field bunds etc) that are critical for the soil and water conservation intervention. Like other community driven projects, community driven watershed projects have a number of advantages of operation, provided the local institutions (e.g. village development committees, water boards, etc.) within which they operate are effective (Mansuri and Rao 2004). The essential gain from decentralized schemes comes from being able to design programs that are responsive to local needs, abilities, and preferences. However, the gains from using such information tend to diminish with larger socioeconomic heterogeneity as possibilities of increased inequity arise when local sub-groups are able to dominate decision making (for example, decision maybe gender biased, or caste biased with costs and benefits of the program distributed in a skewed fashion). Two important arenas of policy discussion have arisen to which there are no obvious answers in this arena a) how to manage large catchment areas when building highly effective watershed harvesting structures to reduce the flow of water for communities downstream and b) how to develop guidelines that systematically allows for the replication of micro-watershed programs on a larger scale.

Evidence:

Early evaluations of watershed development projects have found that their adoption and maintenance has been poor due to high costs of implementation, little maintenance, and poor distribution of benefits (Walker and Ryan 1990, pp 302-305). More recently, watershed interventions have been paying more attention to not only the technical aspects of the intervention, but the socio-economic context within which it operates. A key focus that has also emerged is to look at interventions not just at the watershed level, but also at the farm level. Studies of small-scale initiatives have found that it offers advantages over larger watershed based initiatives on a number of dimensions. For example, it has been found that water collected in 10 tiny check dams with a catchments area of 1 Ha (= 2.47 acres) each, collects more water than one large dam with a catchments area of 10 Ha (Rao 2002). Evaluations also find that they are able to reduce soil erosion during the rainy seasons and maintain higher soil moisture during the dry season, as well as reduce time taken to collect drinking water ((Ishahm and Kakhonen 2002) and (Kerr 2002)). These micro-initiatives have the ability to increase access to 90% of the rural population who depend on ground-water for drinking purposes alone. Some assessments suggest that in India alone as much as 64 million Ha of additional water can be collected through artificial recharge by harnessing surplus monsoon run-off (Rao 2002).

Shah et al. (1998) provide an extensive review of literature on benefits and costs of using watershed development programs (WDPs). They cite studies that show that WDPs provide households with ability to undertake extra risk coping strategies (e.g. intercropping and sequential cropping), reduce the coefficient of variation of yields by as much as 50% and increase yields in the order of 50-60% and cropping intensity by 40-60%. Intercrop-

ping and sequential cropping are not new strategies to deal with uncertainty in agriculture, but they are able to achieve much higher productivity levels when combined with soil and water conservation. Apart from increasing the mean and reducing the variation in agricultural output for beneficiary households, watershed development programs (WDP) also reduce soil erosion, recharge ground water, reverse deforestation, regenerate wastelands, and provide a forum for community participation and development activities to involve households that have traditionally been ignored in decision making about local public policy.

A key problem with seeking inference in an observational setting is that there are no obvious benchmarks, or counterfactual states against which to compare the effect of an intervention; in observational settings no objective measure exists of what the outcomes would have been for those who got the treatment, had they not received it. Kerr (2002) uses an instrumental variable approach solution to such endogenous program placement by using variation from a variable that is strongly correlated with the endogenous variable (the treatment indicator), and affects the outcome variable only through its correlation with the treatment variable. Finding such variables are often difficult and problematic since there is no testable way to ensure that the instrument affects the outcomes only through program placement. Kerr (2002) uses a large set of village-level explanatory variables as instruments for endogenous program placement. Some of the variables used are distance to nearest bus stop, paved road, number of communal groups in the village etc. If village level facilities and the likelihood of receiving a water management program are determined by an omitted variable (for example: the local political representative's skill at collecting village development funds, or villagers are motivated and aware of programs and how the hierocracy functions), then the problem of endogenous program placement remains unresolved.

Kerr (2002)'s work, however, is the most through in the literature looking at the effect of watershed interventions, and looks at a number of interesting outcomes. Their study design randomly selects 70 villages from two states in India and classifies them into one of 5 mutually exclusive assignment categories;[8] villages had access to either a WDP under central government management, or under the state government project management, or under non-government (non-profit) management, or under joint non-government organization and government management, or had no WDPs. While endogenous program placement remains a threat to internal validity the evidence suggests that water management interventions have important effects on of soil erosion in the upper catchment area of a watershed, erosion status of uncultivated land, availability of products from common access lands that are often key to livelihoods in drylands (eg: grass, fodder, fuel, etc.), and farmer's self-perception of the impact of water harvesting on availability of water for agriculture.

The evaluation found that all watershed programs had a positive and significant effect on increasing the frequency of irrigation within a growing season, and on reducing soil erosion in upper catchment areas and on uncultivated land, when compared to village that had no WDPs. Within the group of villages that had WDPs in place, villages with WDPs under both non-government and government management had the largest effects suggesting that a combination of participatory methods and centralization provides a balanced framework that may potentially overcome shortcoming of both

[8]Both central government and state government management have well specified rules within which the bureaucracy functions; little, or no local participation was encouraged at the time the programs were evaluated. Non-government projects typically rely on participatory methods to involve households to not only learn specific local needs but also to involve households in designing, executing and managing WDPs; partnership projects tend to share aspects of the two with technological aspects following a centralized design while involving the community and ensuring their participation is the non-government organization's responsibility.

strict centralized programs, as well as decentralized programs. While program beneficiaries tend to report positive perceptions of the programs effects on raising water tables, surprisingly, this perception was not borne out by measurements of the water table. Finally, in villages which had common lands, there is evidence to suggest that access to common lands declined after the programs were set up; this decline was higher for the partnership projects. Thus, rain water management strategies have an ex-ante role for stabilizing incomes that would tend to not only reduce the impact of rainfall (e.g. securing excess grazing, reducing soil erosion, preserving soil quality etc.). Rain water harvesting strategies can provide important ex-ante income stabilizing options for households who share the watershed. However, one shortcoming is that the reported decline in access to common lands can have potentially serious impacts on the very poor who extract their needs from common lands for survival (Jodha 1986).

2.4.2 Employment Guarantee Schemes

An employment guarantee scheme (EGS) provides assured employment (usually on local public works) and wage payments (either in cash or kind) to eligible households to ensure they meet certain minimum consumption thresholds. Such programs have been extensively used to provide poverty relief historically[9] and continue to be used in both developing and developed countries today (eg: Maharastra Rural Employment Guarantee Scheme (MEGS) since 1979, and National Rural Employment Guarantee Scheme (REGS) since 2005, in India, and the Temporary Assistance to Needy Families (TANF) since 1996 in the US, with an earlier version dating back to 1935). This section discusses the rationale and some evidence on success of such schemes.

[9] Poor Employment Act of 1817 in Great Britain, and charity workshops in pre-French Revolution France. References to it are even available in *Arthashartra*, a 4th Century BC text by Katuyila that advises kings on the ideal way to govern a nation state.

Conceptually, an employment guarantee scheme (paid either in cash or in kind) allows households access to a risk-less income stream in the current period. Thus, the scheme sets a secure floor to the income distribution for those who opt into the scheme. Not only does this provide a current income floor, such guarantees also increase the set of options that households can exercise to cope with risk. Without the guarantee, households may still be able to meet current consumption needs but the cost of doing so from own resources might negatively impact future income streams (e.g. sell household assets, starvation, withdrawing children from school etc.). Meeting current subsistence needs in a stochastic setting with incomplete credit markets would require households to maintain their savings in a liquid form. Morduch (1999) discuses in detail this interlinkage between current poverty and future vulnerability and how household may be made less "at risk" through various initiatives including workfare programs. Apart from providing an income floor, and protecting savings and/or future income streams, such schemes also provide a legal infrastructure within which households may exercise the right to basic entitlements to food as originally conceptualized by Sen (1981) and initiate legal process should they be denied access to the guarantee.

A key question then is where to set the income floor? Subbarao (1997) provides a cross-country review of various aspect of using employment guarantee like programs as a safety net for a number of developing countries. His findings suggests that: 1) the floor should be set no higher than the ruling market wages in the region to reduce mis-targeting; 2) programs run during the slack season in the agricultural year lower the transfer of benefits (in comparison to year round programs) but also insure that its more likely to be used for consumptions smoothing and income stabilization. However, such programs are appropriate only if poverty in the target population is transient; with chronic poverty it is important to have a safety net over the

entire year; and 3) public work programs may also be used for alternative objectives (to income stabilization) such as greater women's participation, reducing participation costs for beneficiaries and even allowing private sector participation.

Evidence

In the context of looking at impacts of employment guarantee schemes on smallholders, I focus almost exclusively on the experiences of the Maharastra Rural Employment Guarantee Scheme (MEGS). The MEGS not only targeted smallholders, many of whom are in semi-arid districts of India, but also has a rich body of studies evaluating different aspects of the MEGS. Exposure to uncertain rainfall, lack of access to credit markets, and seasonal nature of agricultural production even in good rainfall years often exposes households to variable lengths of time where income earning potential is at or below subsistence levels. A key concern is the type of risk-mitigating activities that households may engage in to keep consumption above subsistence levels. In a dynamic setting such pressures may force households to hold sub-optimal levels of assets and skills that may reinforce repeated exposure to such risks.

The MEGS guarantees unskilled manual work on piece rates to all adults in the state of Maharashtra. With wages well below alternatives (such as agricultural wages) until 1988, and no choice in type of work this scheme is believed to be self-targeting and excludes households that are able to find work. The adult seeking employment must register with a "Village Level Worker" who then is obliged to provide work within a distance of 8 kms, and within a time frame of 15 days from the day of request for work (presumably on each request for work). The essential source of gain for households through the MEGS is through the low but secure income it provides to adults

as well as the rural infrastructure that is generated by the work (better roads, soil and water conservations structures, afforestation, flood prone area development etc.). Another indirect benefit of having the scheme is to improve wage bargaining opportunities in the informal sector for the very poor.

Targeting: An important criteria for judging the success of EGS type schemes is how well it is targeted. Some studies have reported accurate targeting while others have reported poor targeting of the MEGS. This is largely due to differences in both the definition of what constitutes the poor, as well as changes in the program over time. Gaiha (2000) reviews some of these studies and present evidence to suggest that targeting in the program worsened over time. Table 2.2 presents errors in program targeting using data from the ICRISAT VLS studies for the period 1979-89 from two villages in Maharasthra. $\hat{E}$ measures the fraction of the non-poor beneficiaries amongst the total non poor in the two villages and is a measure of excessive coverage. $\hat{F}$ measures the fraction of the poor who were excluded in total number of poor in the village and indicates the failure of the MEGS in covering the target audience and finally, S measures the ratio of non-poor participants in total participants. Thus over time, the MEGS became more restrictive for the non-poor ($\hat{E}$ falls), as well as more exclusionary of the poor ($\hat{F}$ rises). The exclusion effect has been stronger than the restriction effect because over the same time period more people non-poor people were beneficiaries of the program.

An additional set of concerns have been noted by Deshingkar and Johnson (2003) on food for work programs[10] that maybe pertinent to this discussion. In an original year long field study conducted in six villages in Andhra Prdesh, the authors find that a number of things undermine the ideal design

[10]Payment in kind (e.g food) rather than money is often a way of implementing EGS whereby the allocation of the benefits is in kind to limit its use to home consumption of food.

of workfare programs. They find that local public works are not chosen by locally elected village level decision making bodies (the *Gram Sabha*) but are still frequently mandated by state governments. Apart from lack of project choices being revealed, issues also arise with the use of contractors (private operators) to oversee the work. This leads to work assignments being determined by the contractor and frequently, the use of labor saving capital equipment to get the work done denying the very poor work.

Table 2.2: Targeting Errors in 1979 and 1989

Year	% Non-Poor Beneficiaries in total Non-poor $\hat{E}$	% Poor Non-Beneficiaries in total Poor $\hat{F}$	% Non-Poor Beneficiaries in total Participants S
1979	15.67	80.70	38.89
1989	7.21	85.71	54.76

Source:(Gaiha 2000)

Benefits of MEGS: On an average about 60% of the program beneficiaries are believed to have been poor. The MEGS wages were a substantial part of the income of all beneficiaries (for both poor and non-poor participants); after subtracting the opportunity cost of working on the MEGS (using non-farm wage rates) the net direct benefit is estimated to be about 60% of the gross MEGS earnings at the poverty line (Gaiha and Imai 2005). Clearly, without the MEGS most of the beneficiary households would have to forego some consumption, sell necessary assets, migrate in search of wage labor[11], etc.

[11] Almost all WDPs also have this component of providing wage labour during non-cropping season for a certain number of days per family. In addition, the possibility of a third crop due to availability of water, reduces migration. This is seen by most households as the most important benefit (Kerr 2002)

Apart from the direct benefit of the MEGS piece rates the other potential sources of benefit could have been improvements in agricultural wages as the guarantee provides a higher floor on wages available, and by improved productivity of farming through community infrastructure development. It is also reasonable to expect that this is likely to lead to protection of household assets from distress sales, however there is limited study of this so far. Gaiha and Imai (2005) discuss these issues; they report that agricultural wages tend to follow movements in MEGS and non-farm wages reported by households in the ICRISAT sample. Specifically, a Rupee increase in agricultural wages is likely to lead to a Rs. 0.17 increase in agricultural wages in the short-run and to a Rs. 0.28 increase in the long-run. Evidence on asset creation is mixed, while assets do get created, much of the benefits from these assets accrue to richer farmers. Simulation studies consistently show a high potential for poverty alleviation from programs like the MEGS provided the distribution of benefits from assets created through MEGS are distributed adequately.

2.5 Conclusion

Smallholders in semi-arid tropics form a substantial part of the poor and while they are already participating actively in the world economy and but are likely to remain a significant share of the total poor in the near future. Operating in a very uncertain production environment without institutional support has historically meant that these households adopt costly risk management strategies that ensure subsistence consumption but reduce growth possibilities. Public policy interventions that are able to strengthen the resilience of smallholders to adverse events are key to reducing poverty.

Smallholders in rain fed semiarid tropic (more generally less favored areas) are unlikely to see major improvements in access to irrigation, or be able

to benefit from replicating the use of green technology. However, research also finds that investments into roads and agricultural research would provide the largest marginal returns to investors. Shah et al. (1998) put this more forcefully to say that future food security of developing countries will crucially depend upon the rates of growth of agricultural output observed for the smallholder.

Public policy initiatives that allow smallholders to maintain incomes, increase labor productivity, and improve agricultural growth are possible and needed to reduce poverty. This chapter reviews the literature on two mechanisms, not necessarily mutually exclusive, within which smallholders may not only experience secure subsistence consumption but also sustained income growth. Watershed development programs, when implemented in a participatory setting to encourage community participation, are able to improve levels of soil moisture that such households have access to. It also helps conserve soil productivity by reducing soil erosion that takes places when the rains do arrive. Finally, they play a key role in reducing the coefficient of variation of output as well as significantly raising the mean level of produce by increasing the cropping intensity in the agricultural year. Employment guarantee schemes (EGS) play an important complementary role to watershed development projects. By providing an income floor to households, it enables households to maintain subsistence levels of consumption without having to dis-save or disinvest productive assets. These are likely to have important impacts on households ability to move out of poverty and stay out of poverty.

Both policies are sensitive to program design and implementation practices. While the EGS is believed to be self-targeting and so benefit only the poor, there exists evidence to show that many program beneficiaries were not poor. In fact in some instances private contractors were hired to man-

age the workfare program and this has reduced participation from the poor. Similarly, watershed development project suffer from threats of elite capture where by the community participation process is subvert by individuals or community sub-groups that are able to minimize their share of group costs and maximize their share of group benefits. Careful and flexible social programs are needed to ensure that smallholders in semiarid tropic are able to share in the growth process.

Chapter 3

A Dynamic Model of a Bullock Economy

3.1 Introduction

Smallholders in semi-arid tropics are known to be not only resource scarce, but also to seek a livelihood in a very risky production environment. While missing insurance markets imply that consumption and production decisions are interlinked and have to be self-financed, uncertainty in income realization implies that the pattern of investment undertaken is likely to determined by both its liquidity and its profitability (Deaton 1991; Rosenzweig and Wolpin 1993 and Dercon 1998). Risk coping strategies that households undertake (either in anticipation, or after the realization) of income shocks have been well documented in the literature[1]. A key question that arises in this context is: while risk-coping mechanisms may help households meet current subsis-

[1]The literature on risk-coping behavior is large; (Walker and Ryan 1990), (Morduch 1995), and (Dercon 2005) provide a detailed review of much of the work in this area. Also see (Holzman and Jorgensen 2000) who conceptualize the notion of "social protection" i.e. having different interventions in place to deal with multiple sources of risk (e.g. retirement funds, health insurance, micro-finance schemes etc.) in livelihoods. The concern here relates to income and consumption smoothing activities that households may choose to take in anticipation of, or after, poor states of the world are realized.

tence, does it also make future income growth difficult to realize?

One of the most significant insights from neoclassical growth models, assuming complete markets, no uncertainty, and constant savings, is that in spite of different starting endowments of resources, growth will over time lead to a convergence in average incomes, wealth, utilities, etc. However, persistence in poverty can be generated under a number of different assumption about the characteristics of income (or wealth) to the basic neoclassical model; stochastic incomes, imperfect credit markets, and others sources of non-convexity in income generating processes (e.g. indivisibilities of investment etc.) all generate models of income growth with some amount of hysteresis. Fafchamps (2005) provides a recent review of this literature and shows that the nature of risk-coping behavior, along with size of asset yields, possibilities for asset accumulation, and savings behavior are critical determinants of the level of inequality. Zimmerman and Carter (2003) use a stochastic dynamic programming framework, to simulate decision making over time with households that are exposed to stochastic income streams, subsistence consumption constraints, and use asset and consumption smoothing strategies; interestingly, they find that households strategies and income profiles bifurcate with richer households following consumption smoothing and poorer households being forced to use asset smoothing. In a related context, Banerjee and Newman (1993) model the interaction between economic development and agents' occupational choices, and discuss examples under which initial inequalities in distribution of wealth may be perpetuated in the long-run. Each of these models looks at situations in which the income generation process is non-linear and so either initial conditions persist, or the impact of shocks on wealth persists.

Jalan and Ravallion (2005) test for the presence of such non-linearities in income dynamics using panel data from rural China. They estimate a gener-

alized method of moments estimator to estimate income changes as a cubic function of its own lagged values and find evidence of non-linearity in income processes. While poor Chinese households are able to return to pre-shock level incomes given time like the richer Chinese households, they return to the pre-shock levels more slowly. Dercon (1998) shows that households in Tanzania who have a higher endowment of resources (land and labor) are more likely to be able to cross the minimum threshold needed to enter into cattle rearing in an economy where cattle ownership is associated with higher incomes. The entry cost provides the basis for bifurcation in the activities that households undertake and incomes they earn. Thus, there is evidence to suggest that specificities of income generating processes and indivisibilities in assets hamper income growth.

From a public policy perspective, thus, it is important to think about interventions that help households cope with risk in ways that not only help meet subsistence needs but also support their future income growth. This paper builds on this idea and conducts policy simulations to see the impact of alternative policy choices on a household's ability to respond to repeated droughts, as well as on their lifetime utility levels. The simulation is calibrated using panel data from the ICRISAT village level studies (the same data used by Rosenzweig and Wolpin (1993)). Specifically, utility function primitives (risk aversion, discount rates, and minimum consumption levels) at the individual household level are calibrated and used in a model of inter-temporal decision making in a stochastic environment to derive optimal decisions. This provides the benchmark framework against which various counterfactual policy simulations are conducted.

An inter-temporal model of household decision making is formulated following the work of Rosenzweig and Wolpin (1993), henceforth (RW), where the chief form of productive capital is bullocks. While households in the

sample do hold other assets during the 9 year study period these tend to be small in comparison to the amount invested in bullocks[2]. The only change in the model that I make to the original model is to leave out modeling pump purchases since I am interested in asset dynamics and household do not appear to use pumps as a buffer stock.

The structure of the paper is as follows: Section 3.2 discusses the importance of bullocks in agricultural decision for households, Section 3.3 presents a simple dynamic model of stock adjustment with rainfall uncertainty; Section 3.4 discusses the calibration based on the analytic file created from the ICRISAT VLS; Section 3.5 discusses some of the findings from the policy experiments.

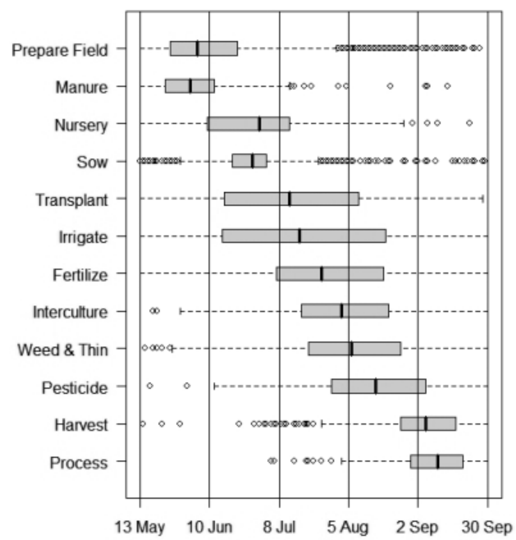
3.2 A Bullock Economy

Agriculture is the major source of income for small and marginal land owning households in rural areas, particularly in India's semi-arid tropics. Agricultural production is a complicated process not only because of the many sub-activities that need to take place, but also because the timing and sequencing of these sub-activities is critical in determining final output. Thus, field preparation must precede sowing, and sowing in turn is followed by irrigation, weeding, administering pesticides, etc. until the crop is finally harvested, processed, and either kept for home consumption, or sold in the market for income. Each of these activities is critical to determining the size of the final crop produce.

[2]Rosenzweig and Wolpin (1993) report that in the 1983 wave of the data bullocks represent the greatest non-real estate wealth for all land owning households in the study sample (50% for small farmers, 33% for medium farmers, and 27% for large farmer). Much of the rest is maintained as crop inventory. Since we look at possibilities for productive investment we focus directly on bullock holdings that have both a store of value and act as an investment at the same time.

Figure 3.1 presents the distribution of days, from the 25th to the 75th percentile, on which major farm activities were carried out by 120 households over the period 1975-84 for the period from 20th May to 30th September. In spite of some variation in the day on which activities were carried out, the sequencing of all farm activities is stable.

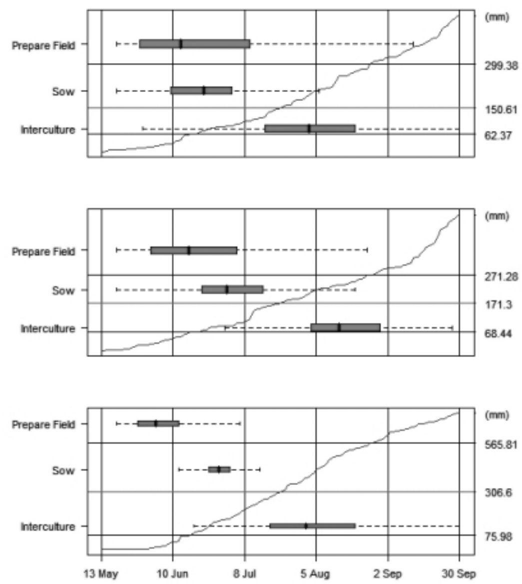
Figure 3.1: Timeline for Farm Activities & Rainfall



Note: Box plots of days of different farm activities to prepare the Rainy Season crop. Data from the Y-files (ICRISAT VLS data)

A key asset for farming is access to a team of bullocks. Amongst the activities in Figure 3.1 bullocks are essential to plowing the soil (part of field preparation), sowing seeds, and for weeding (or transplanting). Figure 3.2 presents box plots of the three bullock intensive activities in relation to the 10 year average cumulative rainfall distribution for each of the three ICRISAT VLS study villages. Bullock ownership is very important and valued for a number of reasons. a) The traction needed to plough the dry and hardened soil before the south west monsoon sets is sufficiently high to require bullock or mechanical power. b) Renting bullocks is not an option because each

Figure 3.2: Timeline for Bullock Intensive Activities & Rainfall



Note: Box plots of days of different *bullock using* farm activities to prepare the Rainy Season crop. Data from the Y-files (ICRISAT VLS data)

bullock owners demand for bullock services is contemporaneous[3] and few, if any, keep surplus bullocks; c) a potential moral hazard problem arises in the renting of bullocks since costs of maltreatment of the bullock while away on rent must be bourn by the bullock owner; d) ownership of bullocks is an important factor in determining the nature of contracts that smallholders are able to negotiate on land rental markets; e) bullock ownership acts as store of liquid wealth that the household can cash in when needed at bullock fairs and f) owning bullocks allows the household to engage in a range of ancillary

[3] Plowing and sowing are ideally done in a dry soil profile because later plantation is associated with crop losses (Walker and Ryan 1990, pp. 33). In addition, plowing and sowing are both less labor intensive when the soil is dry and planting seeds before the rainfall ensures uniform crop growth as germination starts with the first contact with moisture, making harvesting and if necessary marketing decision easier. I would like to thank Ranjitha Puskur for pointing this out to me.

activities such as transportation, grinding grains etc.

Walker and Ryan (1990) describe the rainfall profile of each of these villages in detail; Aurepalle and Shirapur (top two panels respectively in Figure 3.2) have a mean rainfall of 630 mm annually and a coefficient of variation of 31% and 35% respectively. Rainfall is assured in Kanzara (the bottom panel in Figure 3.2) with a higher mean of 890 mm with a lower coefficient of variation at 22%. The time line for the plot is over the planting phase of the *Kharif* (rainy season) crop. Two points emerge from these diagrams: a) on average the demand for bullocks on the farm is pretty consistent throughout the planting phase making bullock sharing a limited possibility; b) the distribution of days on which an activity is done is tighter for Kanzara than for the other two villages. Thus, owning bullocks is not only important for farming, but this importance is likely to be increasing in the rainfall uncertainty that such households may experience.

3.3 A Bullock Model

The decision facing a household at the end of each agricultural year is to choose the fraction of current income to invest in expanding future consumption possibilities and what to consume today. An upper bound on this on this fraction is placed by current subsistence consumption. This decision problem is modeled as a discrete state and discrete time Markov decision problem.

The smallholder begins each agricultural year with a stock of bullocks and calves that were determined by actions taken in the preceding agricultural year. While a number of activities are critical to determining crop income we focus here on behavior that explicitly affects accumulation of bullock stock (household wealth) i.e. the decision to invest and sell bullocks and the

decision to invest in calves. Once the smallholder observes itself to be in state s_t it chooses action a_t from its set of feasible actions. The current state and the action taken in it completely determine the income, $f(s_t, a_t)$ that the household receives at the end of the period[4]. Both the state space and action space are sets with countably finite elements. The state transition from period t to $t+1$ is controlled by actions taken in period t, i.e. a_t, and by the stochastic process governing shocks that affect the household. The action space is bounded not only by its finite set of values, but also by subsistence consumption requirement i.e. $c_t > C_{min}$. The transition process consists of shocks that affect households uniformly, such as rainfall, as well as variable that are idiosyncratic in that they affect a single household such as livestock death, or a household specific shock (described in detail later). A key characteristic of this transition is that it depends only on the state space that the household is in at time, i.e. s_t, and the action taken in that period, i.e. a_t; thus, $s_{t+1} = g(s_t, a_t)$ where $g(.)$ is the state transition function. The transition process is Markovian in the sense that it is independent of history outside of the current states space. I next describe the state space, the payoff matrix, and the markov process in greater detail.

3.3.1 State Space, Time Line for Events, and Actions:

A state point $s_t \in S$ is characterized by seven discrete variables: 1) the number of bullocks currently owned (B_t), 2) the number of calves that are between one and two years of age ($C2_t$), 3) the number of calves that are between two and three years of age ($C3_t$), 4) the level of rainfall received

[4]While s_t and a_t fully determine $f(s_t, a_t)$, s_t is fully revealed after the livestock mortality shocks are revealed at the end of period t. From the income creation perspective, see equation 3.1, rainfall, bullock ownership, and a household specific shock, $i.Shock_t$, determine (current) income which is the sum of net cash inflows into the household (predominantly crop income). See Figure 4.3. Even after rainfall is realized, current income remains uncertain till incomes are realized. Hence, there is uncertainty in incomes not only across agricultural years (because R_{t+1} is unknown in period t), but also uncertainty within the current period (because $i.Shock_t$ is unknown till incomes are realized).

(R_t), 5) an idiosyncratic shock drawn from a household specific binomial distribution ($i.Shock_t$), 6) a bullock fatality drawn from a binomial distribution and 7) a calf fatality, also drawn from a binomial distribution. Each of these variables take on values given by the range of their distributions in the ICRSAT VLS data.

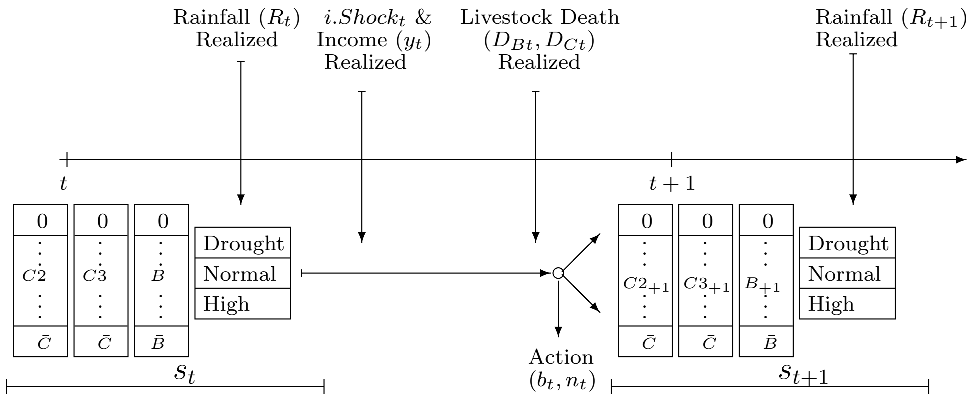
For medium sized farmers the ICRISAT data shows an ownership of no more than 2 bullocks[5] and thus, $B_t \in \{0, 1, 2\}$. For the sake of consistency the number of calves that are held at any point in time are also restricted to two; $C2_t, C3_t \in \{0, 1, 2\}$. The rainfall distribution is assumed to take on discrete values, $R_t \in R \equiv \{Drought, Normal, High\}$[6], and is distributed independently and identically over space and time with probability mass points at $\{\pi_i\}_1^3$. These rainfall probabilities are estimated from the data by the sample frequency of observing each of these rainfall states. Finally, both bullock and calf mortality are binary variables and all mortalities are assumed to occur at the end of current agricultural year as a simplification. Two additional assumptions are made: all livestock mortality takes place after the crop has been realized; and only calves between the age of one and two years of age experience mortality. Taken together, the state space is described by $\{s_t \in S | s_t = (B_t, C2_t, C3_t, R_t, i.Shock_t, D_{Bt}, D_{Ct})\}$ where S has 648 state points[7].

[5] 7% of the sample has more than 2 bullocks and 2% more than three. These have been recoded to 2 for the purpose of this exercise.

[6] Rainfall is measures in mm in the data set and is inherently a continuous variable. Rainfall states are constructed by normalizing the rainfall distribution for each village (subtracting mean and dividing by standard deviation) and binning values of less then -0.5 as being drought years, more than 0.5 being high rainfall years and everything else as being a normal rainfall year. A number of indices exist to identify rainfall quality, almost all of the declare a drought for rainfall below -0.5 as a drought, see (?) for details.

[7] The state space is characterized by 3 Bullock levels, 3 less than two year old calf levels, 3 less than three year old calf levels, 3 rainfall levels, 2 individual shock levels, 2 bullock deaths and 2 calf deaths, i.e. $3^4 \times 2^3 = 648$ states.

Figure 3.3: Time line for Events in the Agricultural Year



A household enters t knowing $C2$, $C3$ and B; once R_t and $i.Shock_t$ are realized income is known. Once livestock death is revealed, s_t is known; household chooses (b_t, n_t) and moves to $t+1$, where b_t is the number of bullocks bought or sold, and n_t is the number of calves bred

Figure 4.3 is a graphic that shows the transition from a state at time t to $t+1$. On entering time period t, a household is aware of only $(B_t, C2_t, C3_t)$, i.e. 3 of the seven variables that determine the state space s_t. The remaining four, $\{R_t, i.Shock_t, D_{Bt}, D_{Ct}\}$, are determined exogenous to what the household can influence and is realized at different points of the agricultural year. I assume that all deaths happen at the end of period while rainfall is realized right after starting period t. A household's income, y_t is realized before the end of period t and at this point the household chooses an action from the set of feasible actions.

A household's action space is defined by two variables: 1) the number of bullocks bought (or sold) ($b_t \in \{-2, -1, 0, 1, 2\}$, and 2) the number of calves bred ($c_t \in \{0, 1, 2\}$). Thus, while the action space has 15 possible elements, not all of them will always be feasible at each of the possible state points (for eg: when owning 0 bullocks a household cannot sell bullocks, or a household's income realization being too small to buy bullocks, or invest in calves). All

actions are taken at the end of the year, just before the new agricultural year starts and right after crop output is realized, as shown in Figure 4.3.

3.3.2 Markov Chain

The Markov chain is a three dimensional matrix; for each possible action (of which there are 15 total), the Markov chain gives the probability of transaction from each possible state today (of which there are 648) to each possible state in the next period (of which there are also 648). These probabilities are decision parameters of the decision problem for the household and for each action, that probability of the transition from state s_t to s_{t+1} is given by the joint probability of the exogenous shocks that determine state s_{t+1}. The Markov matrix's is of dimension $15 \times 648 \times 648$.

There are four sources of uncertainty in the decision problem, rainfall, household shocks, bullock death and calf deaths. Rainfall shocks are independently and identically distributed and therefore, its realization is common across households in the same village. While the binomial distribution for draws of bullock death is common to all households, each household has its own draw of bullock deaths. Likewise for calf deaths[8].Idiosyncratic shocks are household specific and each households has its own binomial distribution for a good year verses a bad year. I discuss the calculation of these probabilities in the calibration section.

[8]While both livestock mortality, or survival rates, are treated as exogenous to the decision process, they are potentially policy actionable with changing quality of care, and investments in improving the animal itself. This is possibility we explore during policy simulations

3.3.3 Preferences, and Payoff Matrices

Rainfall quality, bullock ownership, and the household specific shock determine the income distribution that a smallholder receives[9]. With income being a random variable, the smallholder's preferences over incomes at each of the the state space elements is assumed to take on a mean-standard deviation form that depends on three of the seven state space variables (the others do not affect current income but are needed to capture the state space transition function $g(.)$). Thus, household h's income in time period t may be written as :

$$y_{th} = y(R_t, B_{th}) + i.Shock_{th} \tag{3.1}$$

where $y(.)$ is the income that a household can expect to receive on receiving R_t level of rainfall and owning B_{th} number of bullocks, $i.Shock_{th} \in \{i.Shock.Low_h, i.Shock.High_h\}$ is the idiosyncratic shock that the household is exposed to (see details of how these were calculated in the calibration section). Smallholders are aware of the first two moments of the income distribution at each rainfall and bullock ownership combination i.e.($\mu(R_t, B_{th})$,$\sigma(R_t, B_{th})$) $\forall R_t \in R, B_{th} \in \{0, 1, 2\}$ and their moments enter the smallholder's expected utility, as discussed below. Current income y_t has two potential allocations - present consumption (C_t) or investment. The trade-off then is between consuming today and forgoing consumption now to raise income realizations in the future. The value of current period consumption is given by a CRRA utility function:

$$U(C_t; \alpha, s_t) = \frac{1}{1-\alpha} C_t(s_t)^{1-\alpha} \tag{3.2}$$

where α is a parameter capturing relative risk aversion for smallholders.

[9]Livestock deaths are assumed to take place after crop incomes is realized.

Finally, a household's equation of motion for its wealth holding is given by:

$$\begin{aligned} B_{t+1} &= B_t + b_t + C3_t - D_{Bt} \\ C3_{t+1} &= C2_t - D_{Ct} \\ C2_{t+1} &= n_t \end{aligned} \tag{3.3}$$

where b_t is the investment (or disinvestment) in bullock stock that occurs and n_t is the number of calves that the household may have chosen to breed (for simplicity I assume that breeding attempts are always successful). The cost of making this adjustment is simply the price of the bullock in the market and also determines the budget constraint for the household. Assuming that there is a tight budget constraint in each period (no borrowing possibilities exist) the per period budget constraint is:

$$C_t = y_t - p_B b_t - p_C n_t \tag{3.4}$$

where p_B is the price of the bullock and p_C is the breeding cost for calves.

3.3.4 Intertemporal Decision Making

Decisions made today by the household are likely to affect it in the future in a world where production and consumption decisions are closely linked. Thus, a disinvestment in current bullock stock will allow for greater consumption possibilities today at the cost of a income stream with a higher mean in the future. Households are assumed to be infinitely lived agents that will continue to remain predominantly agricultural without technological progress. In addition, I assume that the current specification is sufficient to ensure that actions taken today are independent of actions taken in the past, i.e. the principle of optimality holds, we may specify this decision problem in the

form of a Bellman equation as[10]:

$$
\begin{aligned}
V(s_t;\alpha,c_{min},\delta,p_C) \quad &= \quad Max_{(b_t,n_t)\in A}\{U(C_t;\alpha,B_t,R_t)+ \\
&\qquad \delta E[V(s_{t+1};\alpha,c_{min},\delta,p_C)]\} \\
s.t. \quad &\qquad \text{Budget Constraint: } C_t = y_t - p_B b_t - p_C n_t \\
&\qquad \text{State Space Transition: } s_{t+1} = g(s_t,b_t,n_t) \\
&\qquad \text{Consumption Constraint: } C_t > C_{min} \\
&\qquad \text{Feasibility Constraints: } (b_t,n_t)\in A; \\
&\qquad B_{t+1},B_t \in \{0,1,2\}
\end{aligned} \tag{3.5}
$$

where $\delta \in [0,1]$ is the discount rate for the future consumption stream, and following RW, c_{min} is the minimum consumption that a household needs to have without which making any investment is not feasible. This formulation assumes that some kind of disaster insurance does exist, as pointed out in RW, thereby underestimating the size of the effect that uncertainty has on household decisions. The expectation is over the future realization of the rainfall state, bullock death, calf death, and the idiosyncratic shock that the household may receive and is encapsulated via transitions in the Markov matrix. Since we assume this is an infinite horizon problem, a solution to the Equation 3.5 is a mapping from the state space to the action space, i.e. the optimal action for the household for each state:

$$(b(s;\alpha,c_{min},\delta),n(s;\alpha,c_{min},\delta))^*, \forall s \in S. \tag{3.6}$$

In Equation 3.5, $V(.)$ is a vector fixed point in the functional space and is analytically difficult to solve for. With $\delta < 1$ and assuming monotonicity

[10]Suppose that the health of the household head matters to the consumption stream and that health is affected by current consumption. In such a situation, unless we explicitly model health as a state variable, or impose a minimum consumption requirement such as we do here, decisions taken today may raise bullock stocks but may also alter health and so fail the principal of optimality. Adding an extra state variable on health and allowing for health adjustments would still make it feasible to use a DP.

of $V(.)$, the fixed point mapping is a strong contraction and hence, in the case of the infinite horizon value function, a unique solution exists and may be computed to arbitrary levels of accuracy using function iteration or policy iteration. I solve for $V()$ using policy iteration where the the Bellman equation is recast as a root finding problem and Newton's method is used to iteratively seek the value function. This works well unless the Markov transition matrix is of a high dimension with mostly non-zero cells (Miranda and Fackler 2002). With policy iteration, for a given set of primitive values (i.e. $(\alpha, \delta, c_{min}, p_C)$ and finitely many actions and states, an exact optimal policy solution is possible. This is implemented using the CompEcon toolbox developed by Miranda and Fackler (2002).

3.4 Calibration

3.4.1 Calibrating Utility Function Primitives

To solve the decision problem it is necessary to formulate a Markov transition matrix to define the probabilistic arrival rates of exogenous shocks, and a payoff matrix that specifies the payoff for each point in the state space and for each action. To specify these matrices, data from the ICRISAT VLS studies is used. Following RW, middle land holding households in the data set are used; for a total of 25 such households 9 complete years of observation are available from the L-Schedule. The L-Schedule provides data on household transactions at a frequency of 3-4 weeks, over the entire 9 years. From this yearly income totals are calculated as the net cash inflow into the household.

Table 3.1 presents values of all calibrated parameters that are used to completely define the decision process. Apart from the utility function primitives all other parameters were calibrated from the moments of their empirical distribution in the VLS data set. Thus, for example, a household's annual

income, y_{th}, is measured as the sum of net cash inflows into the household on crop, animal husbandry, and trade and handicrafts accounts. Crop incomes make up for the most significant chunks of this income[11]. A household's expected mean and variance of the income distribution from owning i bullocks in rainfall state j is calculated by its sample analogues, i.e.:

$$\begin{aligned} \hat{\mu}[y(R_t = j, B_{th} = i)] &= \frac{\sum_h \sum_t y_{th} I(R_t = j \& B_{th} = i)}{\sum_h \sum_t I(R_t = j \& B_{th} = i)} \\ \hat{\sigma}^2[y(R_t = j, B_{th} = i)] &= \frac{\sum_h \sum_t (y_{th} - \hat{\mu})^2 I(R_t = j \& B_{th} = i)}{\sum_h \sum_t I(R_t = j \& B_{th} = i)} \end{aligned} \tag{3.7}$$

where $I()$ is the indicator function. Table 3.1 presents the expectations about the mean and spread of income generated at each possible bullock and rainfall combination that would be seen in each household's state space.

These expectations about incomes are adjusted by the household's period specific idiosyncratic shock $i.Shock_{th}$ that is realized well into the agricultural year (see Figure 3.1). Each household has T values for draws from their household specific idiosyncratic shock. The distribution of these shocks for a household is calculated from the difference between the income predicted by their state space and the actual income observed i.e. by using equation 3.1. This gives us T draws from a household specific idiosyncratic distribution which is treated as a draw from a binomial distribution with bad shocks being realized when $I.Shock_t$ is lower than a household specific mean shock

[11]Crop income and wage labor constitute the two major components of income. Most household earned some income from each of animal husbandry, trade and handicrafts, wage labor and agriculture in the 9 year period. Most land owning households predominantly relied on income come from agriculture. In none of the villages did the mean share of non-farm income exceed 30% (Walker and Ryan 1990, Chapter 4). While non-farm income is also more likely to suffer from measurement error, the entire income is used for this study since households were found to not have adequate income to purchase bullocks at the frequency observed in the data when we exclude these smaller components of income.

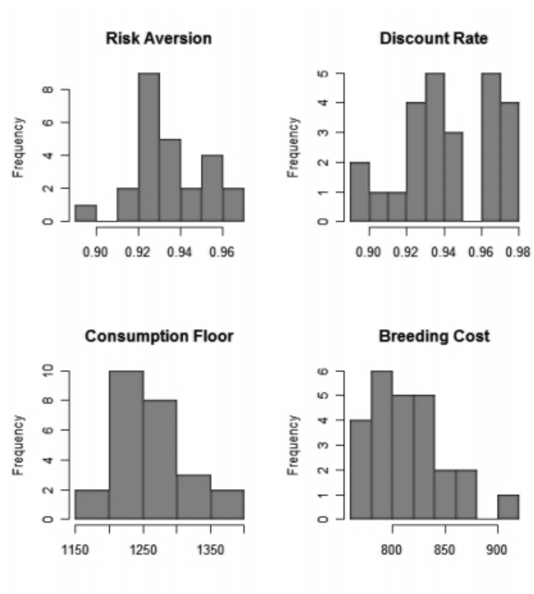
$E(i.shock_h)$, defined as below:

$$
\begin{aligned}
E(i.shock_h) &= \frac{\sum_{t=1}^{T} i.Shock_{th}}{T}, \forall h \\
i.Shock.Low_h &= \frac{\sum_{t=1}^{T} i.Shock_{th} * I(i.Shock_{th} < E(i.Shock_h))}{\sum_{t=1}^{T} I(i.Shock_{th} < E(i.Shock_h))} \\
i.Shock.High_h &= \frac{\sum_{t=1}^{T} i.Shock_{th} * I(i.Shock_{th} > E(i.Shock_h))}{\sum_{t=1}^{T} I(i.Shock_{th} > E(i.Shock_h))} \\
P(i.Shock.Low_h) &= \frac{\sum_{t=1}^{T} I(i.Shock_{th} < E(i.Shock_h))}{T} \qquad (3.8)
\end{aligned}
$$

These calculations are made for each of the 25 households in the sample and the values estimated for these are presented in Table A.1 in the appendix. For each household this specifies the frequency with which bad shocks are realized and the values of the shock experienced. Thus, household level heterogeneity enters the model both through the Markov matrix (through the frequency with which poor shocks are realized) and the payoff matrix (the size of the good (or bad) shock that the household experiences). The remaining values that are calibrated using the sample mean are the probability of the three rainfall states (see footnote 6 for details on rainfall states), and the probability of death of bullocks and calves.

The set of parameters which are not directly observed, such as the utility function primitives, were calibrated by searching for their best values that explains observed investment behavior in the data set. The objective function used to measure the quality of prediction at each potential parameter value is square error in predicting household bullock ownership. Table 3.2 presents the steps involved in the optimization process used to identify the parameters $\{\alpha, \delta, c_{min}, p_c\}$. The algorithm begins by initializing the action space, the state space, and the Markov matrix. The state and action spaces are common across households, while the Markov matrix is different only because each household has its own rate of experiencing negative idiosyncratic shock years.

Figure 3.4: Distribution of Parameters from 25 households



None of the unknown parameters are needed for the elements of the decision problem we set this up in Steps 1-5 in Table 3.2. The utility parameters however affect the households' payoff matrix. In step 6.1 I set up a grid of possible parameter values in a four dimensional parameter spaces over the likely range of these parameters[12]. For each point in the grid space a unique pay off function for the household is calculated. The Bellman equation is now fully specified for the grid point i, and may be solved numerically for the policy vector $(b,n)^{hi}$ using the CompEcon toolkit in MatLab (Miranda and Fackler 2002). This optimal policy vector is used to calculate predicted bullock stocks held by household h and one can calculate the square loss in

[12] $\alpha, \delta \in [0.85, 0.99]$ with a step size of 0.01, while $c_{min} \in [1100, 1500]$ with a step of Rs. 20, and $p_c \in [1100, 1500]$ also with a step of Rs. 20. The entire dimension of the grid space for each household is of 75600 possible configurations

Table 3.1: Calibrated Parameters of the Decision Problem

Parameters	**Source**	**Values used**		**RW Estimates**	
Preferences and Action Costs		Mean	SD	Mean	SD
Relative Risk Aversion (α)	Calibrated	0.93	0.03	0.96	0.0017
Discount Rate (δ)	Calibrated	0.92	0.04	0.95	NA
Consumption Floor (c_{min})	Calibrated	1257	43	1469	28.4
Breeding Costs (p_C)	Calibrated	823	35	857	8.35
Price of a Bullock (p_B)	Sample	999		999	
Markov Matrix components					
Drought	Sample	0.29			
Normal	Sample	0.34			
High	Sample	0.37			
Bullock Death	Sample	0.01			
Calf Death	Sample	0.03			
Asset & Rainfall Indexed Incomes		μ	σ		
$R_t = Drought, B_t = 0$	Sample	976.19	1,059.01		
$R_t = Drought, B_t = 1$	Sample	1,749.51	584.02		
$R_t = Drought, B_t = 2$	Sample	1,845.96	4,960.50		
$R_t = Normal, B_t = 0$	Sample	1,504.21	1,622.54		
$R_t = Normal, B_t = 1$	Sample	2,074.56	3,471.41		
$R_t = Normal, B_t = 2$	Sample	2,385.16	5,567.21		
$R_t = High, B_t = 0$	Sample	1,628.08	1,740.33		
$R_t = High, B_t = 1$	Sample	1,415.47	2,034.24		
$R_t = High, B_t = 2$	Sample	2,275.07	4,856.93		

prediction in Step 6.5 as below:

$$L_h(\alpha, \delta, c_{min}, p_C) = \sum_t (B_{th} - \hat{B}_{th}(\alpha, \delta, c_{min}, p_C))^2 \tag{3.9}$$

Searching over the g grid points we find the parameter configuration(s) for which L_h is minimized and these are the utility function primitives for which the observed behavior is best predicted. A total of 25 different optimization problems are solved.

For most households the loss minimizing vector of parameter values was

Table 3.2: Algorithm for Calibrating Decision Parameters

Steps	Action Taken
	Initializations
Step 1	Specify Action and State Space elements
Step 2	Calculate Rainfall, and Livestock fatality
Step 3	Calculate the probability of $i.shock_t$ for each household
Step 4	Calculate means and standard deviations of income
Step 5	Calculate Markov Matrix $[\Pi]_{15\times 648\times 648}$
	Individual Parameter Grid
Step 6.1	For each household h in sample (25 households)
Step 6.2	For each value i in $[\alpha, \delta, c_{min}, p_c]_{g\times 2}$ grid
	Solve for Individual Decision Rules
Step 6.3.1	Calculate payoff matrix $[P^h(R, B; \alpha^i, \delta^i, c^i_{min}, p^i_c)]_{648\times 15}$
Step 6.3.2	Solve Bellman Equation using CompEcon Script to get optimal policy $(b, n)^{hi} = f^h(\alpha^i, \beta^i, c^i_{min}, p^i_c)$
Step 6.4	Make predictions for $\hat{B}^h_t$ for periods 2, to T
Step 6.5	Calculate Household Loss function: $L^{hi} = \sum_{t=2}^{T}(B^h_t - \hat{B}^{hi}_t)^2$
Step 6.6	$\{\alpha^h, \delta^h, c^h_{min}, p_c h\}^* = \arg max L^{hi}$

Table 3.3: Actual and Predicted Sample wide Bullock Holdings

	Actual	Predicted
1975	21	21
1976	21	19
1977	21	18
1978	27	23
1979	25	23
1980	25	24
1981	24	25
1982	24	20
1983	22	18

not unique. While the loss function $L()$ is able to take on values in the range $[0, 2^8]$ (one of the largest errors one can make is predicting 0 for each of eight periods when the household owns two bullocks in each of those periods),

the loss function is flat for fairly large ranges of values, particularly, for the risk aversion and discount rate parameters[13]. For each case where multiple solution vectors were obtained, the values of each parameter were averaged across these solutions. These averaged parameter values jointly determine a central point over the entire region in which the loss function is flat and so is a good measure of the parameters compatible with observed behavior of the household[14]. Figure 3.5 gives the distribution of parameter values that were identified as the unique solution for each household. The first two moments of the distribution of each of these parameters are presented in Table 3.1 and compared with RW's estimates. It is interesting to note that households tend be more risk averse, and tend to discount the future a little more than originally estimated by RW by allowing for a more risk sensitive utility parametrization. Finally, the validity of the model's predictions were also tested using a chi-square goodness of fit statistics at the sample level for each year. Table 3.3 presents the distribution of actual bullocks owned and the distribution of predicted bullock ownership at the loss minimizing parameter values of each of the household's utility functions.

[13] In a simulation based paper, Elbers et al. (2005) report their attempt at recovering parameters estimated by RW using the same data. They begin with estimates reported by RW and generate a simulated data set using these parameters. Using the simulated data set they attempt to recover the original parameters and find that risk aversion and discount rate parameters have little impact on their log-likelihood function. Plots of the joint sampling distribution of the discount rate and risk aversion show that risk aversion estimates span the entire grid that Elbers et al. (2005) choose to search on, while the discount rate takes on values between 0.90 and 0.99. Their estimates on minimum consumption are close to those reported by RW and they don't model calves or breeding

[14] One way to think about these parameter across the different households is that these households have a time invariant parameter value that can be uncovered using a fixed effect (random effect) specification of running a regression of the 25 parameter value on household dummy variables.

3.4.2 Sensitivity Analysis Exercises

Comparative static exercises are not possible in the absence of closed form functional relationships between the optimal policy rule and the utility parameters that were calibrated earlier. However, it is possible to study the optimal decision rule itself for changes in parameter values and we report on the sensitivity of the optimal policy rule to the underlying decision parameters in Table 3.4.

Table 3.4: Sensitivity of Decisions, $(\hat{b}, \hat{n})^*$, to $(\alpha, \delta, c_{min}, p_C)$

$\hat{n}(.)$	0	1	2	0	1	2
$\hat{b}(.)$	A = (0.96,0.95,1469,857)			B = (0.96, 0.95, 2000, 857)		
-2	0	18	90	0	36	72
-1	90	90	45	162	72	0
0	288	27	0	306	0	0
1	0	0	0	0	0	0
2	0	0	0	0	0	0
	C = (0.96,0.75, 1469, 857)			D = (0.76, 0.75, 1469, 857)		
-2	0	18	90	63	27	18
-1	96	97	29	235	0	0
0	297	21	0	305	0	0
1	0	0	0	0	0	0
2	0	0	0	0	0	0
	E = (0.96,0.95, 200, 80)			F = (0.90, 0.93, 1257,823)		
-2	0	0	108	0	21	87
-1	0	0	193	132	53	21
0	0	21	300	292	24	0
1	0	0	21	11	7	0
2	0	5	0	0	0	0

Each cell value x_{ij} is the number of states spaces out of a total of 648 for which the household would choose a bullock investment level i and a calf breeding level j for a given configuration of parameters. This table uses household 40 in Aurapalle to demonstrate how the distribution of actions changes with different configurations of the state space. Configuration F is the loss minimizing one for this household.

We look at the effect of 6 alternative configuration of the parameter space

and see how this changes the optimal policy that the household will take if behaving as a utility maximizing agent. Configuration A sets the model parameters to those estimated by RW. All other parameter configurations are chosen as departures from Configuration A to check if the model predicts expected behavior in response to changes in these parameters. At A, households will not be investing directly into bullock ownership but rather will invest calves who grow up to be bullocks. On 288 of the possible 648 state points the household will retain their holding of bullock stocks and not invest in any calves. In 333 (= 648 - 288 - 27), the household is selling one or more of its bullocks and also investing in calves, however, it also is investing in one or more calves at 270 (= 648 - 288- 90) states points. The actual profile would be dependent not just on the decision rule but also on the actual transitions, and exogenous shocks that the household see. Thus, with configuration A, much of the bullock dynamics would be played out through sales, and breeding of calves as opposed to explicit purchase of bullocks.

Configuration B departs from A by raising the consumption floor for the household from Rs. 1469 to 2000. With higher commitments to household subsistence consumption households are less likely to engage in investing in bullocks. At 306 of the 648 state space points the household neither invests (nor disinvests) in bullock stock, nor breeds calves, and in an additional 162 state space points, household sell one bullock. In 180 of the state space points the household invests in one or more bullock, but at each of these points the household is trading a bullock (or more) for a calf.

Configuration C departs from A, by reducing the discount rate parameter from 0.95 to 0.75. With a reduction in the discount rate we'd expect households to care more about current consumption and reduce investment activities. Some evidence of this behavior is seen as the number of states in which a household invests in bullocks declines and the number of states in

which the optimal response is to maintain, or disinvest, bullock stocks without any increase in calf stocks increases. Configuration D departs from C by reducing the risk aversion parameter and we see that households reduce the investment of calves and disinvest at most state points 298 state points, with not investing in either bullock or calves at another 305 state points. There are very few transaction in bullocks that take place with configurations like D.

Configuration E is one in which breeding calves is relatively inexpensive and we see that the optimal decision rule reflect this change in parameter value with the household opting to breed 2 bullocks in almost every period. Finally, Configuration F is closest to the parameter values that were identified for almost all the households. Under configuration E, the optimal policy is to invest in bullocks at 18 state space points and breeding calves takes place in 213 state space points. Thus, the optimal policy is flexible enough to accommodate a fairly wide variety of behaviors, and for all parameter changes, the optimal policy appears to change behavior in a way we'd expect it to.

3.5 Policy Experiments

3.5.1 The Policies

For policy experiments I consider three policy alternatives for these households. These are a livestock intervention, a soil and water conservation intervention and an employment guarantee scheme. Using the utility functions parameters calibrated earlier, each household's decision rule is resolved under the changes that these interventions introduce in the decision making environment of the household - i.e. either the Markov chain (the livestock intervention) or the payoff function (watershed intervention) or the action space (the employment guarantee scheme). I discuss how each of these in-

terventions alter the household decision problem below.

The livestock intervention is conceptualized as a process that enables households to keep their livestock alive longer. Livestock is not only a key part of farming, but it also, provides an alternative source of income. The most basic improvements in livestock, from a farming perspective, consists of improvements in health care, control of infectious diseases, and parasites (through improved vaccination), followed by improvements in feed, and cross-breeding to combine local traits with stronger and healthier animals (Delgado et al. 1999, Chapter 3). Impact evaluation studies suggest that veterinary interventions are able to provide large and statistically significant reduction in mortality rates for large and small livestock animals. Schreuder et al. (1996) in an observational study of a Dutch sponsored veterinary intervention in Afghanistan found that districts with the intervention experienced mortality rates that were significantly lower than other districts that had no intervention. Mortality rates for calves and adult cattle were reduced by 25% and 30% respectively[15]. This is conceptualized in the present simulation as a program that that helps livestock survive to adulthood better and be more resistent to drought conditions as an adult. Explicit rates of survival for bullocks and calves are not available in the data set, however the transactions schedule records both deaths of owned livestock. Over the entire sample (including small and large farmers) 9 bullock deaths and 23 calf deaths are reported and so baseline mortality rates used in the problem are 1.2% and 3% respectively. For the intervention, I assume that better livestock management provides households with the opportunity to reduce the probability of mortality by half. A priori, it is expected that such an intervention will lead to declines in bullock purchases and breeding as households experience mortality less frequently. From the perspective of our dynamic program

[15] The study reports a favorable cost benefit ratio of 1.8-4.8 and the low program costs are attributed to it's being run by volunteers and managed by a non-profit.

this intervention affects household decisions by changing the frequency with which households find themselves in states in which there is a livestock death.

The literature evaluating the impacts of Watershed Development Programs (WDPs) suggests that large and persistent effects on agricultural productivity are possible with successful implementation and management. Shah et al. (1998) report that WDPs allow households to practice intercropping as well as grow more crops in the agricultural year increasing incomes by as much as 40-60% points and an almost 50% decline in the coefficient of variation. In addition, better rainfall management implies that earlier losses in soil productivity are prevented as soil erosion is checked (Ishahm and Kakhonen 2002). The potential benefits of scaling up such interventions is large with studies showing that it can conserve enough water to meet water requirements of of over 90% of the rural population (in India), who currently depend upon expensive ground water extraction, can be met through such programs (Rao 2002). Many studies have also found that it is important place such WDP programs in a setting that encourages community participation and management since such programs appear to do better than other purely technical ones (Kerr 2002, Ishahm and Kakhonen 2002, and Walker and Ryan 1990). In the simulation, this intervention is modeled as one that improves mean income realization by 50% for the same rainfall and bullock stock values. In addition, this is also accompanied by a 20% declines in the coefficient of variation has on household decisions (these numbers are close to gains in incomes are reported in studies of individual watersheds rather than from an evaluation of a national program (Shah et al. 1998)). The larger income affects households by changing its feasible action set at each state point. For example, investments into bullocks, or calves requires a fixed entry cost that households may not have been able to afford earlier as argued by Dercon (1998). The gains from an improvement in means at the current levels may allow households to cross the minimum subsistence consumption

thresholds by a large enough amount to purchase a bullock[16].

The last intervention is conceptualized as an employment guarantee scheme (EGS) that becomes available to households only during drought seasons. In India, EGS programs have varied substantially in design and implementation over time. Limits on when households can move into benefit from such programs differ, as do the benefits the get while they are on the program, and the length of time they can be on the program (see Chapter 2 for details). In the developing countries much of the debate as involved around the appropriate wages that people receive while on the EGS (Subbarao 1997). A general feature of such programs is to keep wages at, or just below, the minimum wage so that the benefits become self-targeting; targeting is known to worsen with rising wages (Gaiha 2000). There are also substantial general equilibrium effects of such programs since it improves the outside opportunities for the very poor, and so their bargaining position improves in making wage contracts (Gaiha and Imai 2005). In the context of the simulation, the employment guarantee scheme is conceptualized as an expansion in the households action space. In only periods of drought, households, apart from investing (disinvesting) in bullocks, and breeding calves, have the additional option of working on EGS related projects and receiving a secure income (zero standard deviation). The income is set at the estimated consumption minimum and this option is not available for better rainfall years[17].

[16]For example, a household with no bullocks in a high rainfall period can expect to make an average income of Rs. 1,628 with a standard deviation of Rs. 1740 (see Table 3.1). On realizing the mean income the household spends about Rs. 1257 on consumption needs and is left with Rs. 371 which is too small to either breed a calf or invest in a bullock. If he experiences a 50 % incomes then he makes Rs. 2,442 and after meeting minimum consumption needs has Rs. 1,185 and can invest in a bullock or breed a calf.

[17]In India the National Rural Employment Guarantee Scheme is program that provides assured employment for a duration of 100 days at wages set at the state minimum in India. While the minimum wage varies between 50 - 150 per day across states, it is interesting to note that even at the minimum the household makes Rs. 5,000 which is sufficient to buy a bullock at current prices. In our data set too the minimum consumption is close to the average bullock purchase price.

3.5.2 Evaluation

I evaluate the performance of these three policy options in two dimensions a) life time utility improvements or the welfare changes that are induced under alternative policy regimes and b) effect of repeated exposure to a drought (i.e. two or more consecutive years of drought) on household asset holdings. In addition, I also look at a few simple estimates of the cost of implementing these policies. The simulation is set up by drawing 40 year shocks values for rainfall, idiosyncratic shock, bullock deaths and calf deaths for each of the 25 households. Each household has its own unique set of utility parameters and therefore its own decision rules for behavior at each of the state points. I populate the simulation by randomly drawing bullock and calf holdings for each of the 25 households in the first period. All subsequent state transitions are then defined by the pre-drawn shocks and the decisions made in each period. Utility and bullock holdings for each household in each period are stored and the experiment is repeated 500 times with separate draws of the shock profiles.

For a given policy option, Π (where Π is a scenario in which households adopt decision rules that reflect either behavior under the benchmark environment (Π_0), or the livestock management environment (Π_1), or the soil and water conservation environment Π_2, or the employment guarantee scheme environment Π_3), the simulation tracks each household's utility stream and bullock ownership (or wealth) stream $(B^{\Pi}_{th}, U^{\Pi}_{th}), \forall t, \Pi$. Simple utility differences are calculated across policy regimes to identify the one which does the best for the entire sample. Also, I look at distributional differences across bullock holdings in each policy scenario with increasing periods of drought years.

Table 3.5: Average Bullock holdings under for different Rainfall shocks, by Policy

Policy: Benchmark Responses				
# of Bullocks	# of Years of Successive Drought			
	0	1	2	3
0	41.15	15.19	3.73	3.73
1	10.62	3.33	0.68	0.68
2	15.17	4.29	0.72	0.72
Policy: Livestock Management				
# of Bullocks	# of Years of Successive Drought			
	0	1	2	3
0	40.69	14.95	3.69	3.69
1	10.78	3.41	0.67	0.67
2	15.48	4.45	0.76	0.76
Policy: Soil and Water Conservation				
# of Bullocks	# of Years of Successive Drought			
	0	1	2	3
0	36.15	14.19	2.73	3.73
1	10.62	3.33	0.68	0.68
2	20.17	5.29	1.72	0.72
Policy: Employment Guarantee Scheme				
# of Bullocks	# of Years of Successive Drought			
	0	1	2	3
0	9.47	2.47	0.61	0.54
1	3.69	0.79	0.14	0.14
2	54.73	18.79	4.27	4.34

Each panel shows distributions of bullock holding for different drought intensities. Each cell represents the sample average of time spent in the 40 year period at a bullock and drought level, for a policy scenario.

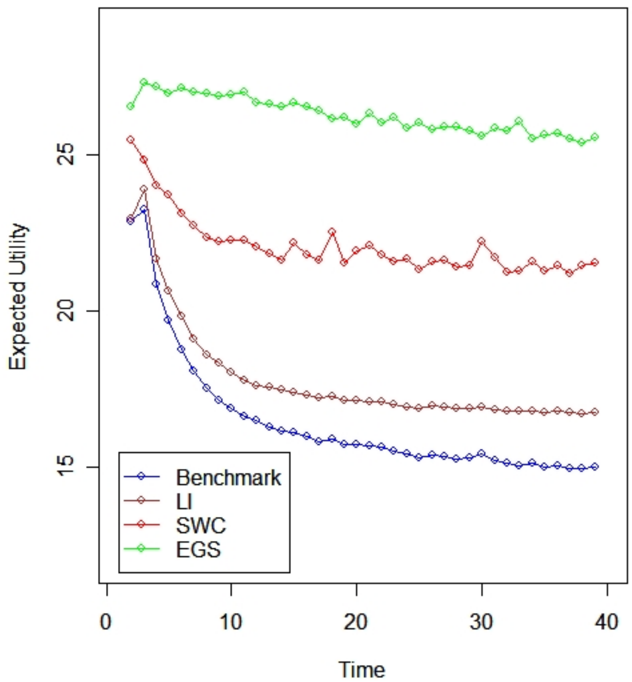
Table 3.5 tabulates the distribution of bullock stock holdings over the 40 year period when exposed to varying lengths of drought. For each policy, the number represents the percentage of the entire 40 year span that is spent at a specific bullock holding level when exposed to repeated droughts. Two or more consecutive droughts are quite rare and occur in about 10% of the

household years[18]. In the benchmark scenario, on being exposed to a two or more droughts I find in 75% of household years, households tend to own no bullocks. This is true when both the livestock intervention and the soil and water conservation intervention are in place. The employment guarantee scheme however provides substantively different asset holdings for households when exposed to repeated drought years. In over 80% of the household years in which repeated droughts are observed, households are found to keep 2 bullocks. Thus, the option of having an employment guarantee scheme allows the households the option to meet minimum consumption needs without having to sell their productive assets.

Figure 3.5 plots the sample average of the expected utility that households would have under alternative policy options for the 40 year period. A few things to note are a) in each replication households may start with different livestock holdings, but for each household the holding is identical across the policy experiments. Different decision rules are followed for each policy regime and consequently households begin their 40 year utility profile at different utility levels; b) under the benchmark all households on average experience a steady decline in utility levels over time as it is difficult to accumulate savings that allow the household to return to pre-shock levels of income; c) household experience larger utility levels than the benchmark under the livestock intervention. Bullocks and calves die less frequently needing the household to adjust their stocks less frequently. However, the overall decline in utility levels over time persists; d) utility under the watershed development intervention is higher than the benchmark situation for each year; while households have higher incomes for each period in this scenario households continue to be exposed to the same (in frequency and magnitude) rainfall, idiosyncratic, and livestock shocks as the baseline, and so their in-

[18] This is strictly function of the probability distribution that was calibrated from the ICRISAT VLS studies. In fact, repeat droughts are quite common and currently parts of Ethiopia are in the fourth consecutive year of their drought.

Figure 3.5: 40 year average Utility Paths for different Policies



comes continue to be affected by large shocks; e) the employment guarantee scheme (EGS) provides the highest lifetime utility path in every period. Providing risk free income at the consumption minimum is adequate to reduce the household's need to sell its livestock to maintain minimum consumption levels. While the general decline in utility levels is also seen for the EGS scenario, this is far more gradual than any of the other scenarios. Such insurance provides a risk free income floor to the distribution of households allowing households to continue to hold their assets for far longer.

Table 3.6 presents summaries statistics for average yearly utility levels

Table 3.6: Utility Distribution Across Policy Alternatives

	Average Utility				Lifetime Discounted Utility			
Policy	Mean	Median	SD	Gain	Mean	Median	SD	Gain
Benchmark	16.56	15.72	2.10	-	645.93	495.93	264.85	-
LI	17.88	17.14	1.73	1.33	697.64	533.17	296.11	51.70
WDP	22.14	21.78	0.99	5.58	863.67	908.56	262.95	217.73
EGS	26.22	26.16	0.61	9.65	1022.66	1141.83	253.62	376.72

LI: Livestock Initiative; WDP: Watershed Development Program;
EGS: Employment Guarantee Scheme

and lifetime discounted utility levels, across the policy choices. The livestock intervention provides only marginal improvements in utility levels over the benchmark scenario. This intervention halves mortality rates for livestock and while that has utility gains, the general profile of declining household utilities persists as in the benchmark case. Both the WDP and the EGS interventions provide larger gains than the livestock intervention with the EGS intervention providing the highest gains amongst the policy options. A key difference between the two is that while WDP provide a mean improvement in productivity (as well as decline in the standard deviation) the EGS provide a consumption floor. Thus, while under each of the benchmark, the WDP and the EGS policies the households experience the same shock profile in expectation, the income distributions are altered in different ways from the benchmark scenario. The income floor under the EGS appears to protect the household's asset levels from distress sales and this not only allows the household to access their pre-shock level bullock holding indexed income distribution, it also implies that the household does not have to save to return to the pre-shock bullock holding levels.

Each of these interventions needs to be financed either from public or private funds. The traditional source of funds is usually the government, however, alternative paradigms for managing such programs exists as well.

Table 3.7: Benefit Cost Ratios for the Interventions

Policy	Lifetime Utility Gain	Costs (Rs.)	Utility per Rs. 1000
LI	51.70	17.34	2,941.18
WDP	217.30	829.40	261.63
EGS	376.72	364.53	1,031.47

L1: Livestock Intervention; WDP: Watershed Development Program; EGS: Employment Guarantee Scheme

Most of these are typically partnership programs between government departments and private and non-profit organizations with each taking on separate roles in managing the intervention (see discussion by Kerr (2002) and Ishahm and Kakhonen (2002) for discussions in the watershed development program context). There are significant administrative costs of implementing such programs as well as monitoring costs. Cost data on these programs are necessary to look at a full cost benefit analysis of these programs.

However, it is possible to undertake a simple back of the envelope type calculation of the program costs for each of the interventions (without administrative costs) using knowledge about each of the program components. Under the livestock intervention (LI) each household's probability of bullock death and calf death declines by half to 0.5% and 1.5% respectively. For the government, the per person expected cost under the scheme would be $0.005 * 999 + 0.015 * 823 = 17.34$. Similarly, to finance the gains of the WDP, assuming that the distribution of the bullock stock is as it was in the first period (i.e. 50% own no bullocks, 20% own one, and 30% own two), the government can expect to pay the difference in expected values of the incomes from the intervention and the benchmark[19], i.e. Rs. 829.40. The EGS is in

[19]This number is problematic as a measure of the cost to the government for the WDP since its a measure of the size of the benefitJoshi et al. (2004, Table 6, pp 22) reports that

operation only when there is a drought, and assuming everyone chooses to join the program, the maximal expect cost would be $0.29 * 1257 = 364.53$. Thus, better livestock management, while giving the smallest lifetime benefits is also the most cost-effective way of providing these benefits.

3.6 Conclusion

Persistence in poverty is a key attribute of most smallholders in less favored areas, such as the semi arid tropics. This paper seeks to look at how different components of a household's income generating process influences it's investment and consumptions decisions. A household is always responsible for meeting its consumption needs as well as investing in capital. In the absence of markets for credit and risk, the household must self-insure and with subsistence consumption often at risk is likely to choose strategies that maintain subsistence rather than expand incomes. In such a world a clearer understanding of the different ways in which a household's income may be influenced is important to design public policy interventions that help households move out of, and stay out of absolute poverty.

To understand the framework within which smallholder households make decisions I formulate a model of inter-temporal decision making under uncertainty, with credit constraints. The basic decision that a household makes every period is how much to invest (disinvest) in its stock of immediately productive capital (i.e. bullocks), how much to invest stocks that may become productive in the future if it survives (i.e. calves), and how much to consume. The model follows the work of Rosenzweig and Wolpin (1993) and

on average it costs around Rs. 5,640 per hectare to implement a watershed development project. These are medium land owning category households and so they would have two or more hectares of land and so would cost Rs. 11,280, or in 1983 Rs. about Rs. 2927, or more than twice the expenditure needed to meet minimum consumption levels

uses the same ICRISAT VLS data set to calibrate primitive parameters (risk aversion, discount rates, minimum consumption and breeding costs) that determine the decision a household will take at a given point in the state space. A few departures are made from RW's original formulation, in particular, households are assumed to have preferences not only over the mean income (and consumption) realization, but also over the standard deviation in income realizations for household with similar bullock holdings. I calibrated the primitive parameters of the decision problem for the household using data on livestock holdings, rainfall and income realizations from the ICRISAT VLS data. While parameter estimators were clearly identified for the consumption floor and calf breeding costs, parameters for risk aversion and discount rates were more difficult to identify (RW do not calibrate both and assume the discount rate is 0.95).

These parameters were used to simulate a household's lifetime (defined as 40 years) wealth accumulation behavior and the utility realizations. These policy interventions affected either the stochastic environment (Livestock Intervention), or the income distributions that are realized at different states points (Wateshed Development Projects(WDP)) and the Employment Guarantee Scheme (EGS)). The WDP interventions differs from the EGS intervention in important ways in which how it affects household incomes. The WDP intervention increase incomes across all state space points so that both the income is higher and standard errors in income realizations are lower. The EGS provides households with the option of insurance at the minimum consumption levels by providing a floor to households who choose to opt in and does not affect incomes in non-drought states (as compared to the benchmark).

This paper finds that on average households have the highest levels of utility under the EGS scheme. Not only is the mean utility level the highest but

the variance of this utility over time is the smallest reflecting that households are most successful in protecting their incomes and assets from unpredictable shocks. Watershed development programs (WDP) also provide households with important gains. While these gains are smaller than those realized under the EGS scheme, households do better than the benchmark situation in each year and over the entire lifetime. An important failure of the WDP is that it does not significantly change the bullock holdings in drought situations form those observed in the benchmark situation (see Table 3.5), and consequently households are unable to reach the utility levels found under the EGS scheme. The insurance aspect of the EGS plays an important role in helping individual household accumulate productive wealth, even when the income distribution in non-drought years does not change from the benchmark case. However, in terms of the costs of these three interventions, the livestock intervention is the cheapest and gives the highest average lifetime utility for every dollar spent. While the livestock intervention is the most cost effective intervention, there appear to be limits to the size of gains that can be had since livestock mortality rates are already quite low.

Finally, the interventions that were considered for the simulation exercises were kept simple to allow the study of how changing a single aspect of a household's decision making environment changes it decisions, lifetime asset holding and utility levels. Actual policies tend to be more complicated in design and try and set up multiple changes in a household's decision environment at the same time. Thus, for example, a watershed development project typically not only improves crop productivity as we modeled it, but it also provides some opportunities for wage labor in the slack season giving it a flavor of the EGS scheme. Some integrated watershed development projects also make the provision for livestock management as well. The impacts of such integrated programs are more complex, however, our results clearly show that a) a household's decisions are affected by both the mean and the vari-

ance of the asset indexed income distribution that households receive; thus, interventions that are mean increasing and variance reducing (such as the watershed management) are an important way to encourage income growth; b) asset maintenance strategies play an important role for households in a risky production environment by breaking the dependence on personal wealth for subsistence consumption needs; c) income growth strategies alone, such as the watershed management programs, do not protect households from shocks and therefore, much of the potential gains from higher productivity would not materialize into lifetime asset gains and d) livestock management too provides gains, however, these are just as susceptible to loss as households must still self-finance consumption needs in bad states of the world. The income floor that EGS-type interventions provide plays a key role not only for households with little or no assets, but is also likely to enable households to achieve persistent income growth!

Chapter 4

Treatment Effects of a Community Intervention

4.1 Introduction

Community driven development (CDD)[1] projects have attracted a lot of interest as an alternative mechanism to top-down centralized programs for managing local public goods. The World Bank's portfolio of CDD projects is estimated to be close to 7 billion US dollars in 2003 alone (Mansuri and Rao 2004). A growing body of literature discusses the ability of CDD to create poverty reducing infrastructure, as well as the mechanisms by which such institutions are realized. Some recent examples of this are Rao and Ibanez (2003), who look at participation in CDDs supported by the World Bank's Jamaica social investment fund; Miguel and Gugerty (2004) and Alesina, Baqir, and Easterly (1999) who discuss local collective action in Kenya and

[1] A working definition of CDD used by the World Bank is : "CDD gives control of decisions and resources to community groups. These groups often work in partnership with demand-responsive support organizations and service providers, including elected local governments, the private sector, NGOs, and central government agencies. CDD is a way to provide social and infrastructure services, organize economic activity and resource management, empower poor people, improve governance, and enhance security of the poorest." (Donninger et al. 2004)

US respectively; Khwaja (2003) who looks at the effect of community heterogeneity and task complexity on CDD project maintenance; and Aggarwal (2000) on maintenance of group-owned wells through cooperation among very small user groups.

Can village development committees design interventions that provide measurable gains to their own livelihoods? The key advantage of decentralized development is its potential to exploit local information in designing projects that are needed locally and to distribute its benefits to those who need them the most. However, this advantage may not be realized if subgroups within the community have the ability and incentive to distort the incidence of net project benefits away from targeted subgroups. Current research reports a few common findings across different studies; A) Greater within community homogeneity (ethnic, cast, religion based or economic) makes it easier for communities to co-operate in collective activities. Thus, Alesina et al. (1999) show that less ethnically diverse cities report higher shares of spending in the provisions of local public goods (e.g. education, roads etc.), Khwaja (2003) reports that in a group of community maintained projects in northern Pakistan, greater social heterogeneity is negatively associated with project maintenance. Similarly, Miguel and Gugerty (2004) find that less ethically diverse communities in Kenya are better able to impose social sanctions and tend to have higher provision for community wells and primary education. B) CDD projects tend to be susceptible to "elite capture", Rao and Ibanez (2003) find that the Jamaican social investment fund tends to be elite-driven and decision-making focuses on a few active participants; C) Technically demanding projects or projects with high transaction costs (related to negotiating, monitoring or enforcing project responsibilities) are more difficult to sustain in a community driven process (see Khwaja 2003 and Aggarwal 2000).

This paper reports on the livelihood effects of an agricultural development initiative that was developed and implemented by the village development committee (VDC) of a Sahariya tribal village in Madhya Pradesh. A number of features makes this evaluation potentially interesting:

1. All households in the sample are Sahariya Adivasi and thus, the sample exhibits low social and economic heterogeneity;

2. The intervention itself consisted of simple tasks (digging, or laying walls) and contributions of labor by households were easy to monitor;

3. A year long pre-initiative phase was dedicated to simply building community participation;

4. Detailed data about the functioning of this VDC and its initiative is available through the VDC logbook. For each meeting we can trace the agenda of the meeting, financial transactions, if any, and decisions taken.

In addition, this study uses the same questionnaire for both the treatment and control groups as recommended by Heckman et al. (1997). Thus, the study setting is simpler than programs that have been studied and allows us to abstract from issues that typically complicate a study of a CDD intervention (e.g. multi-site studies, with different programs in each site, or heterogenous target populations, as in Alesina et al. (1999) or Rao and Ibanez (2003)). This gives us the chance to focus on intervention design, its implementation and effects without such potential sources of bias.

The intervention is evaluated using a unique retrospective dataset that observes 168 households for 4 seasons (3 growing seasons and the summer season). The control group is drawn from surrounding villages that had similar socioeconomic profiles and did not have any agricultural improvement initiative underway. I estimate the effects of the intervention on agricultural

outcomes (crop income, total income, sharecropping behavior etc.) as well as risk management outcomes (skipping meals, borrowing to finance consumption, or migration in response to sever consumption scarcities).

A key problem in seeking inference in a non-randomized setting stems from the fact that many potential sources of bias (selection into treatment, pre-treatment differences, etc.) makes ideal comparison groups difficult to find. To mitigate some of these concerns for bias this study took a number of steps: first, control villages were selected with similar agricultural and village level characteristics (e.g. similar soil characteristics, tribal composition, positions relative to soil etc.); second, covariate distributions of households in the selected control villages were transformed to match the covariate distribution of the intervention households using propensity scores estimated using a highly flexible non-parametric boosted regression algorithm (McCaffrey, Ridgeway, and Morral 2004); and a flexible semi-parametric Difference-in-Difference estimator (also known as the nonequivalent group study design)is used to identify the treatment effect after controlling for time invariant unobserved factors (Abadie 2005).

The rest of the paper is arranged as follows: section 2 discusses the study area, the livelihoods of households in the area, the intervention design and the sample design; section 3 discusses the estimation strategy, section 4 discusses the results and section 5 concludes with a discussion of the findings.

4.2 Study Details

4.2.1 Study Area

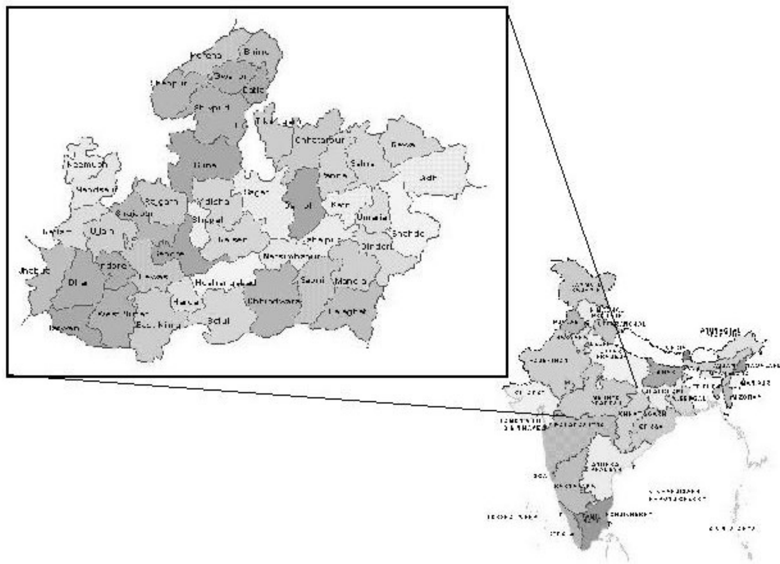
The field study was carried out in a group of villages in sub-district Bijaipur, of Sheopur[2] district, in the state of Madhya Pradesh, India (see Figure 1 and Figure 2 to place the study area on a map). Sheopur is officially recognized as one of the 200 poorest districts, out of a total of 604 districts, in India. The district has a population of approximately 560,000 individuals, of whom about 20% are Sahariya tribal households. Currently, the district's literacy rate is 27% with men being 3 times as likely to be literate as women. The Ministry of Tribal Welfare of the Central Government lists the Sahariya as a "scheduled tribe"[3] that lives in low population density areas, are economically impoverished, and have little or no access to basic amenities (schooling, health centers etc.) or to employment opportunities Ministry of Tribal Welfare (2005). A distinctive feature of land regulations in Madhya Pradesh is that non-tribal households cannot obtain land previously owned by tribal households (see Section 179, MP Land Revenue Code)[4].

[2]Basic district level information about Sheopur is available from web sites maintained of the Government of Madhya Pradesh (http://www.mpgovt.nic.in) & the District office of Sheopur (http://sheopur.nic.in/). For anecdotal evidence on the state of livelihoods for Sahariya Adivasis, see Sen and Vivek (2003), a report to the Commissioner for the Right to Food, assessing the quality of social security networks in the area, written in response to starvation deaths reported in the media during the drought of 2002.

[3]Tribal households make up about 8% of the national population; this has been, and continues to be, a marginalized community. Shah et al. (1998) provides a detailed sketch of tribal households in India. A few stylized facts are tribal households a) tend to live in tribal enclaves with limited interaction with non-tribal households; b) tend to live in ecologically poor areas (94% of the population lives either in arid regions, or in hilly areas, or in forest areas); c) own larger plots of land than non-tribal households and also have a larger dependence on agricultural wage labor rather than crop income; and d) tend to have lower rates of access to assured irrigation than non-tribal households.

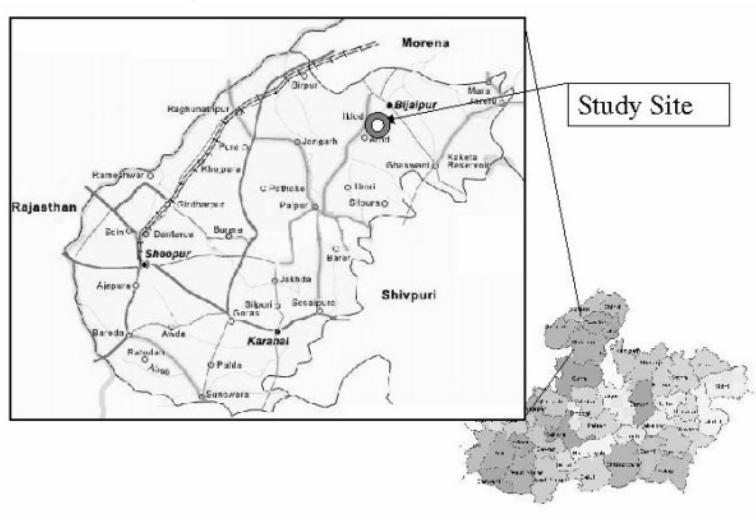
[4]Singh and Dikshit (2005) provide a detailed discussion of a number of public policy programs in operation in Madhya Pradesh. They also document the evolution of the Madhya Pradesh Land Revenue Code (MPLRC) of 1959 and its implications for different scheduled tribes(see page 15).

Figure 4.1: State of Madhya Pradesh in India



Source: Census of India, 2001

Figure 4.2: District of Sheopur in Madhya Pradesh



Source: http://www.mapsofindia.com

About 22% of the total land area in this district is used for agriculture, of which 60% is irrigated, and belongs to the moist semi-arid tropics of central India (Vijayshanker 2005). The south-west monsoons bring about 75% of the annual rainfall for this area, and this is also the most important source of irrigation for the study villages as there are no irrigation projects in the area that they can use as an alternative. Over the period 1998-2003, this sub-district experienced highly variable rainfall with an average coefficient of variation of 42%[5]. In good rainfall years households are able to plant two crops, a rainy season crop over the months of July to November, and a later, post-rainy season crop from December to April. In normal rainfall years households are able to cultivate at most one crop during the rainy season, while in drought years households are principally dependent on migration in search of work unless drought relief work is initiated in an area close to their home. The study area's predominant rainy season crops are millet and sesame, while mustard, wheat, and other pulses are grown in the post-rainy season. Apart from being strictly rain dependent the study villages also tend to have poor soil quality; the soil exhibits chronic nitrogen deficiency combined with instances of potassium and phosphorus deficiency.

Many households in the area do not practice farming independently since the consequences of a loss are simply catastrophic. With limitations on selling land, "reverse" sharecropping has emerged as a practice to augment the level of investments made into each crop, and allows some farmers to field two crops. Such reverse sharecropping contracts are between the Sahariya households and richer non-Sahariya farmers from nearby non-tribal villages. These richer farmers will be referred to as investors in the rest of the discussion. These investors enter into a flexible cost-cum-output sharing, or *Batai* contracts with Sahariya farmers where output shares rates ranging from 25%

[5]Rainfall was recorded at 857, 540, 378, 483, 214, 764, 686, 606 mm. for the period 1998 to 2005 from the block revenue officer in Bijaipur, Sheopur district, M.P.

of output to the more usual 50% of output. This range recognizes the diversity in the asset holding, household labor, and ability to purchase inputs that a Sahariya household has access to[6]. Under these contracts the tribal household provides all the labor (sometimes is even supported by hired labor whose wages are paid by the investor). At the time of harvest produce is separated into costs and surplus, each of which is shared according to the pre-arranged sharing rules. Another common, but unrelated, farming practice is "*saavat*" (tilling the soil in the rainy season, but not planting) and farming only in the post-rainy season to take advantage of the increased soil moisture from the rains.

4.2.2 The Agricultural Intervention and Sample Design

The study area is close to the Kuno National Park currently being developed as a site to relocate the vanishing Asiatic lion from its current and only abode, the Gir National Park in Gujrat (Wildlife Institute of India 1995). Samrakshan Trust (ST), a non-partisan, non-profit organization working with human and animal livelihood conflicts, has been working in the study area from 1999. The agricultural year 2002-03 saw 35 of the 48 districts in Madhya Pradesh, including Sheopur, experiencing droughts and limited employment opportu-

[6] By and large 3 kinds of *Batai* are practiced - 1/3rd sharecropping (*Teesra Hissa ka Bataie*): sharecropper chooses crop type, type & level of inputs (e.g. frequency of ploughed, manure, frequency of irrigation, threshing, fertilizer use etc.); here the production risk is borne by the sharecropper; 1/2 sharecropping (*Adheria*): sharecropper and the adivasi farmer share input costs and gross output; 1/4th sharecropping (*Ji ka Bat*): unlike the other two, here the adivasi leaves his land and works on someone else plots and is a way to employ households with surplus labor. Two meals, lodging and 1/4th output net of costs is usually paid in return for providing labor over the entire season. These are generic names for the contracts; actually observed contracts tend to be more complex with opportunities to negotiate many aspects. Setting up a new contract is usually a very long time consuming process.

nities. After initial mobilization by Samrakshan's trained social mobilizers[7], the intervention village, Agraa, setup its village development committee during this year with the purpose of discussing the village's current development problems . Eventually, the government of Inidia's Food for Work program was set up in this district to provide relief against the drought, however, the village development committee continued meeting on a monthly basis.

Once membership to the Agraa VDC (AVDC) stabilized (40-45 members) ST field staff began training members to minute meeting proceedings, maintain log books, start a small savings schemes and maintain records of financial transactions by the committee as a whole. AVDC norms for member entry and exit, and ways to bring problems related to a household into the AVDCs knowledge were also set up. The agricultural year of 2002-3 saw ST discussion facilitator initiate discussions on what would be the properties of the ideal agricultural support program. These meetings helped identify four perceived threats to agricultural incomes:

- Loss of crop due to raids by cattle and forest animals;
- Insufficient water to support irrigation in the post-rainy seasons;
- Loss of soil fertility due to soil erosion;
- Lack of Bullocks to till the fields during plantation.

An intervention that tried to target each of these issues within budget of Rs. 2,25,000 (USD 5,000)[8] was proposed. The proposed intervention had the following components:

[7]Samrakshan Trust's staff had previously undergone training with MYRADA ,(www.myrada.org) a non-profit organization that has been engaged in creating community infrastructure from 1970s.

[8]Financial support was available to the AVDC through donations made to Samrakshan Trust by the Barbara Delano Foundation (http://www.bdfoundation.org/) and the Portland Chapter of India's Development Foundation. Voluntary donations in kind (land, and labor donation) were also made by the Agraa AVDC members.

1. Building a collective crop protection wall to reduce crop loss through raids by stray domestic animals as well as wild animals from the nearby reserve forest;

2. Digging, or deepening, dug wells to improve access to irrigation;

3. Building small check dams to prevent soil erosion;

4. Provision of "bullock" loans to AVDC members

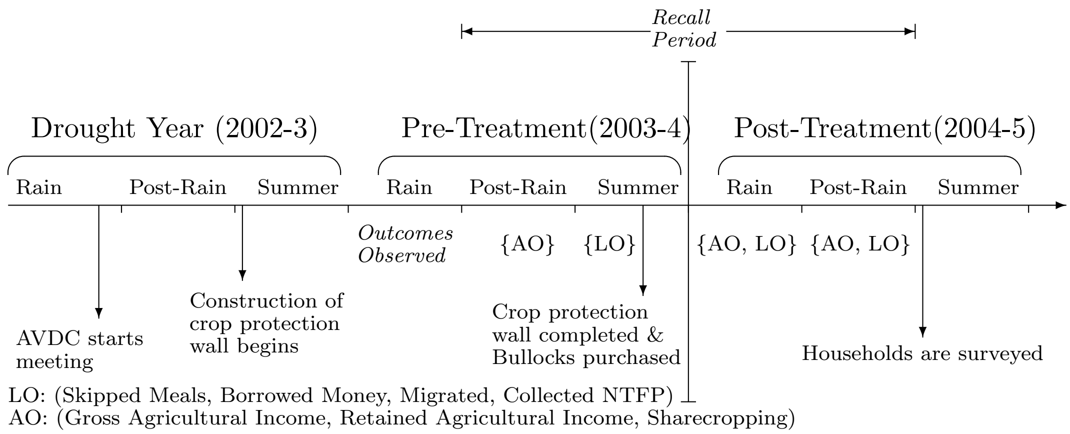
At the time of the survey 1), 2) and 4) were in place, while 3) had been temporarily postponed because it was extremely labor intensive. The time-line of the work on the project spans the entire agricultural year of 2003 (i.e. March 2003 to July 2004). As labor tends to be scarce during the two growing seasons. much of the construction activity was spread out over the summer of 2003 and 2004[9]. In the summer of 2003, 895 meters, less than half, of the crop protection wall was built; the entire wall (2556 meters long) was completed in the summer of 2004. The 2003-04 crops were thus exposed to raids by animals as earlier years were. The 11 wells were also completed over the course of 2003-04, but a survey carried out by the ST-staff showed that only 2 of these were ever used for irrigation [10].

Finally, Rs. 65,000 were advanced to the AVDC to purchase 14 bullocks-pairs on 22nd July 2004, just in time to purchase bullocks from the annual livestock fair that takes place before the new agricultural year starts. Thus, in this study we evaluate the effect of the community participation in the process of identifying the components of the agricultural intervention, and creating a

[9]Weddings and festivals are slated for the summer months; all the volunteered labor for the intervention also took place in the summer. We fielded the survey in summer to take advantage of this seasonal decline in labor demand as well.

[10]Of the potential 208 bighas (52.6 acres) of land that could have been irrigated in Agraa, only 46 bighas (11.63 acres) were irrigated in the agricultural year of 2003-04. The dug-wells, partly due to poor construction and partly due to a lack of access to pumps, failed to provide irrigation security to AVDC members. Pump survey details are available from author on request

Figure 4.3: Timeline for Agraa Agricultural Intervention



crop protection wall, and the access to bullocks through the loans. I use observations from the 2003-04 winter and summer seasons as pre-intervention observations, and observations from the agricultural year of 2004-05 as the post-intervention period, as seen in Figure 4.3.

Data was collected over the summer season of the agricultural year 2004-05 (i.e. April-June 2005) and the recall period was chosen to be 16 months based on our experiences during pre-tests in the field[11]. Recall data is increasingly used in survey data on developing countries (see for example the Demographic and Health Surveys (DHS), or the Malaysian Family Life Surveys (MFLS) or the Health and Retirement Surveys (HRS)), and there are some concerns about reliability of using such data. Smith and Thomas (2003) use two waves of MFLS data to look at the retrospective life histories of individuals that were collected 12 years apart and provide evidence on the

[11]Local vocabulary distinguishes between present year ("*een saal*") and the immediate past year ("*paar saal*"),nut events further back in time have no explicit vocabulary and must be referred to in relation to the present or the immediate past. Initially, I'd hoped to collect data for 2003-04 rains as well, however this proved to be difficult as some of the households began confusing outcomes and activities from the 2004-05 rains, needing recall from 4 months back, with activities from rains 2003-4 needing recall from 20 months back.

quality of long-term recall data. Comparing migration related recall with recall from 12 years later, Smith and Thomas (2003) find that respondents tend remember "salient" moves while their memory of migration for short duration tend to fade. "Salient" moves are ones that are correlated with meaningful lifetime events such as a birth, death, marriage etc. in the respondent's household. (Beckett et al. 2001), also using the MFLS, report that respondents appear to have the strongest memories of events and incidents themselves, rather than details of the incidents, particularly when they also co-occur with events that are important in the respondents lifetime.

To improve quality of recall and reduce systematic bias while collecting data in the field we developed various kinds of recall assist "keys" during the pre-test to help prompt and triangulate responses; for example, a) if a household reported use of either irrigation in the dry season, or manure use, or pesticide use, then sharecropping and borrowing entries were cross checked; b) a few items were repeated in the questionnaire to trigger recall in slightly differing contexts (e.g. borrowing (for both risk-mitigation and separate borrowing section), non-timber forest produce collection (for both diet section and income section) etc.); and c) key events in each season were identified to prompt memory (e.g. a usually dry tank in the area, was full of water during the pos-rainy season of 2003-04 and improved irrigation, or, relating harvests to child birth's etc.). Relating retrospective events to salient events in life, as well as providing prompts have been used in similar contexts as well to collect retrospective data (Beckett et al. 2001). The 16 month recall period essentially asked each household head to recall activities from the prior post-rainy season, the summer season, the rainy season and the ongoing post-rainy season. The final sample design for the study is presented in Table 4.1; of the 44 household registered in the Agraa village development committee (AVDC) logbook, the survey interviewed 41 households, and of the 145 households that were identified in the control group, 127 were interviewed.

Table 4.1: Sample Design

Intervention	Agricultural		Sample Size	
Status	Year	Season	Control	Treatment
Before	2003-04	Post-Rains	127	41
Before		Summer	127	41
After	2004-05	Rains	127	41
After		Post-Rains	127	41

4.2.3 Comparing the Treatment and Control Groups

Data for the study is drawn from four villages that were identified from two focus groups; one with farmers and share-croppers and another with local hires on the staff at Samrakshan Trust(ST). The objective of these discussion were to identify villages that were similar to the treatment village, Agraa, on a number of agricultural and socio-economic dimensions. Focus group members were asked to discuss and comment on the suitability of a number of surrounding villages as being comparable to the intervention village. These discussions identified the following dimensions as important ways in which villages differed in the area:

- Tribal composition (non-tribal farmers were subjectively identified as better farmers);
- Proximity to river (better irrigation potential);
- Soil type;
- Land holding sizes;
- Access to well-irrigation;
- Access to reserve forest and commons
- Similar levels of social cohesion

The focus group with the ST staff members also revealed that they valued working in communities that were less socially fractured as it took less time to build a village development committee that met on a regular basis with substantial representation.

For the study I identified three control villages and Table 4.2 presents the covariate distribution of these village when compared to the treatment. These villages were selected on the basis of aggregate data available with the Land Records officer[12]. Once the control villages were identified, household lists for interviews were constructed from electoral rolls, administrative data on households below the poverty line, and from a census of the study villages by the field investigators.

Information in Table 4.2 is supplemented with data from the field work to cover areas of concern raised during the focus groups. All the study villages tend be largely tribal, and specifically Sahariya tribal. All the study villages are quite remote from the crop produce market at which they can buy or sell agricultural output. Measures of collective community activity are not obvious and based on suggestion from the focus groups I use three indicators a) the extent of village participation in Sahariya weddings, b) the length of time community groups (e.g. Women Self Help groups) have been active, and the number of village spokespersons[13]. The only significant difference across the treatment and control group is that the households in the control village on average owns 2.5 bighas[14] more than the treatment village.

[12]I am extremely grateful to Asmita Kabra and other Samrakshan staff for getting the data from the *patwaris*'s office as well as helping me conduct the focus groups.

[13] A village spokesperson, or a *patel*, is a person of social importance in the village who conveys village opinion to outsiders, and also settles minor disputes; in fractured communities, each faction tends to recognize a separate *patel*.

[14]A bigha is a unit of measurement for land that varies across different states in India. In central India is approximately 0.2529 hectares http://tinyurl.com/fj3p8

4.3 Methods

Households, when systemically exposed to the risk of fluctuating incomes, tends to rely on a number of different ways to insure themselves against low incomes. A rich literature looks at the role of consumption and income smoothing, both theoretically, such as Fafchamps (2004), and empirically (Walker and Ryan (1990), and Townsend (1994)). Morduch (1995) and Fafchamps (2004) discuss different ex-ante and ex-post risk mitigating household strategies that have been documented and their relationship to managing fluctuations in consumption and income. From the perspective of the intervention one may therefore be interested not only in program specific outcomes (which I call Agricultural Outcomes (AO)), but also in how households have changed their ex-post risk management strategies (which I call Livelihood Outcomes (LO). Changes in AO reflect the direct impacts of the intervention, while changes in LO reflect how the intervention has reduced the households dependence on methods that may have high costs of their own (e.g. decline in health, asset holdings, etc.).

For agricultural outcomes I look at agricultural incomes and at the decision to enter into sharecropping contracts. Since sharecropping contracts are frequent I also distinguish between gross agricultural income (which is a measure of productivity) and retained income. Retained income (or disposable income) is identical to gross income for household farming independently. For households working under a sharecropping contract, the retained income is the net income left after payments to the investor have been made. For livelihood, or ex-post risk mitigating, outcomes I look at a set of activities identified by Walker and Ryan (1990) (and references therein); specifically, I look at the reported incidence of skipping meals because there was no food at home, of borrowing money to finance consumption, of having family members migrate to support consumption and collecting NTFP (non-timber forest produce) to support consumption. In the results section, we see each

of these are important ways in which households manage their consumption requirements.

4.3.1 Estimators and Identification

Establishing the causal effect of the agricultural intervention on the Agraa village development committee (AVDC) members requires knowledge about the outcomes of the AVDC members had they not participated. A fundamental problem here is that there is no obvious way to know what would have happened to these households had they not participated in the intervention. Putting this formally into the notation of a standard Neyman-Fisher-Roy-Rubin binary evaluation framework suppose each individual is indexed by i and D_i denotes i's treatment status (i.e. $D_i \in \{0, 1\}$, where $D_i = 1$ denotes that individual was a AVDC member, and 0 otherwise). For each individual the vector (y_{i0}, y_{i1}) denotes the potential outcomes that may be realizable under each level of treatment. Once treatment assignment has been made, we observe $y_i = D_i y_{i0} + (1 - D_i)y_{i1}$ i.e. only one of these states, conditional on treatment assignment that i experiences. Consequently, the obvious individual causal treatment effect of an intervention, $(\delta_i = y_{i1} - y_{i0})$, cannot be estimated.

The problem of making causal inferences from just observational data is usually resolved by: a) aggregating the missing counterfactual problem from the individual level to the sample level to reduce the dimensions of the missing data problem; b) making assumptions specific to the structure of treatment assignment, for example: "SUTVA" (see footnote 15), or the socio-economic environment of the program being invariant to the presence of the program; c) making assumptions about the correlation structure between potential outcomes, the treatment assignment, and other variables (observed and unobserved); and d) a range of auxiliary assumptions, contingent on the estimator of interest. Randomization of treatment assignment is a usually

preferred alternative to observational studies[15] because it controls the correlation structure by making potential outcomes independent of treatment assignment. Subsequent comparison of means is sufficient to do the analysis without needing either c) or d).

In the absence of cleanly understood variation in treatment assignment, a number of potential sources of bias may enter. Thus, for example, the non-profit Samrakshan Trust may have extra information (for e.g. motivation, needs, entrepreneurial spirit etc. specific to the AVDC members that I do not see) about the communities and may have supported the AVDC because they believed it would be the most successful; in such a case I would overestimate the effect of the AVDC. Many of these unobserved variables are likely to be specific to the community, or in this case, the village[16]. With repeated observations on households, spanning a 15 month recall period, I use a difference in difference specification to control for time-invariant unobservable variation that may otherwise bias treatment effects. Suppose, off-farm migration related opportunities are higher in one of the control villages then

[15]Randomization requires key structural and behavioral restrictions on the data to identify the mean effect of the treatment (i.e. a) and b) still need to be made, but no requirements are placed on either c) or d). Some of the requirements that randomization have to meet are 1) Stable Unit Treatment Value Assumption (SUTVA) requires that i's outcomes from participation (or not) are not affected by j's participation. 2) No general equilibrium effects of the program, i.e. how people interact in the program, market equilibrium in relevant markets etc. are independent of the existence of the program (i.e the program is small in contrast to the population) (for a detailed discussion of this see Irwin Garfinkel and Micahlopolous ()). 3) Awareness about randomization may change the information set with which individuals enter the program, and this may change the participant's expectations and behavior in the program; (Heckman (1992) elaborates on the restrictions imposed by these assumptions on the evaluation framework, and more generally the case for, and against randomization as an evaluation tool).

[16]Tribal villages continue to be isolated from much of the rest of India; the nearest metalled roads was 25 km. away from the study site. To quote Townsend (1994) writing about the ICRISAT villages, also in the semi-arid tropic of India "Many families have been present for generations; contemporary residents live, eat work in the village; ... village residents have relatively good information about the ability, effort, and output of one another". Villages tend to be self-reliant socio-economic entities and any difference across villages are likely to be time persistent

this will imply that the observed difference in incidence of migration between the treatment and control group is larger than what would have been had they been exactly the same. Access to off-farm migration opportunities are unobserved in the sample and thus, may be a source of bias in our estimates. In so far as the effect of this (and other) unobserved variables are constant over time, a difference-in-difference specification will control for such time invariant differences.

With repeated observations on the same household, spanning before and after the intervention, the potential outcomes for a household may be written as $(y_{i1}^{Pre}, y_{i0}^{Pre}, y_{i1}^{Post}, y_{i0}^{Post})$. For the estimator of interest, the average effect of the treatment on the treated (ATT)[17], the relevant missing counterfactual for members of the AVDC is y_{i0}^{Post} , i.e. the outcomes that would have been observed had there been no intervention in the post-intervention period. The key identifying assumptions for the difference in difference (DiD) estimator are:

- (DiD.1) $E(y_0^{Post} - y_0^{Pre}|x, D = 1) = E(y_0^{Post} - y_0^{Pre}|x, D = 0)$
- (DiD.2) $0 < P(D = 1) \& P(D = 1|x) < 1$

DiD.1 is the traditional *parallel trends* assumption that allows us to impute values for the missing counterfactual from the control group. DiD.2 requires that the probability of treatment assignment be strictly positive and the conditional assignment to treatment be strictly less than one. Following Meyer (1995), in a traditional parametric OLS setting, only DiD.1 is assumed

[17]In the cross-sectional context the ATT is estimated as $\Delta = E(y_1 - y_0|X, D = 1) = E(Y_1|X, D = 1) - E(Y_0|X, D = 1)$; the missing counterfactual is $E(Y_0|X, D = 1)$. This is typically estimated by transforming $E(Y_0|X, D = 0)$. Generally, $\hat{E}(Y_0|X, D = 1) = \sum_{i \in Control} W(x_i)y_i$, where different, but closely related, $W(x_i)$ have been used; for example, see Woolridge (2001),Hirano, Imbens, and Ridder (2003) and McCaffrey, Ridgeway, and Morral (2004) for alternative specifications of $W(x_i)$.

(apart from linearity and error distribution) and is specified as :

$$y_{it} = \alpha_1 AVDC_i + \alpha^1 Post_t + \alpha(AVDC_i * Post_t) + \beta x_{it} + \varepsilon_{it} \tag{4.1}$$

where y_{it} is the observed outcome in season t for household i, $AVDC_i$ is an indicator for being in the intervention village, $Post_t$ is an indicator variable for the post treatment period and the α captures the effect of AVDC. x_{it} are season varying covariates in (e.g. size of plot under cultivation, number of days household was engaged in migratory labor, or local wage labor, money borrowed, and average distance travelled to collect non-timber forest produce from the reserve forest). For each OLS model, I cluster standard errors at the village level.

Biases may still exist however, for example, Ashenfelter (1978) evaluated the Manpower Development and Training Act to find, amongst other things, that trainees experienced unprecedented declines in earnings in the year before training was provided, over and above declines seen in the control group. This makes individuals in the treatment group more likely to be selected into the program. Thus, unit specific, individual transitory changes in the pre-training period, such as explicitly not looking for work in before the training to become eligible to participate in the MDTA will overestimate the effect of receiving training. In the context of this study, if members of the AVDC were diligently conducting their monthly meetings and discussions to make it more likely that their VDC would be picked for the intervention, then it is likely that we'd underestimate the effect of the intervention as such diligence will fade once financial support has been promised.

Such concerns are usually higher when treatment and control groups are not balanced on covariates that are thought to be correlated to output dynamics (for example, households who have more experience at farming (proxy for lower time discounting) may appreciate future agricultural benefits more

and may be more willing to work hard on both their farms as well as with the intervention). With finite data, the problem of resolving distributional heterogeneity in observables across treatment assignment is resolved using a result due to Rosenbaum and Rubin (1983). They show that if the set of observed covariates is rich enough to justify conditional independence of the potential outcomes to treatment assignment, then conditioning on a balancing function (such as a propensity score $p(x) = (P(D = 1|X)$ is sufficient for conditional independence. This provides an easy scale on which distributional differences across treatment assignment may be resolved.

While the Rosenbaum and Rubin (1983) result was meant for cross-sectional data, more recently, Heckman, Ichimura, Smith, and Todd (1998), and later Abadie (2005) propose nonparametric, propensity score based generalization to the difference-in-difference models to correct for distributional differences. Abadie (2005) suggests a simple two step process in using estimators that force distributions of observed covariates to be balanced when estimating a DiD estimator (without making assumption on the functional form). Using assumptions DiD.1 and DiD.2, Abadie (2005) derives the semi-parametric difference in difference estimator as:

$$\begin{aligned} E(y_1^{Post} - y_0^{Post}|x, D = 1) &= E(y_1^{Post} - y_0^{Pre}|X, D = 1) \\ &\quad -E(y_0^{Post} - y_0^{Pre}|X, D = 0) \\ &= E\left(\frac{y_1 - y_0}{P(D = 1)}\frac{D - P(D = 1|x)}{1 - P(D = 1|x)}\right) \end{aligned} \tag{4.2}$$

Propensity scores are first estimated to get $\hat{p}(x)$ and the sample analogue of equation 4.2 is calculated as:

$$\hat{E}(y_1^{Post} - y_0^{Post}|X, D = 1) = \frac{1}{N}\left(\sum_{i \in D=1} \frac{y_{i1} - y_{i0}}{\hat{p}(D = 1)}\right)$$

$$-\frac{1}{N}\left(\sum_{i\in D=0}\frac{y_{i1}-y_{i0}}{\hat{p}(D=1)}w_i(x_i)\right) \quad (4.3)$$

where $w_i(x_i) = \frac{\hat{p}(D=1|x)}{1-\hat{p}(D=1|x)}$ is the odds ratio for each control group household to be in the treatment group. In equation (4.3) the weights essentially transform the distribution of the covariates for the control group so that it matches the treatment by weighting up cases that are more likely to be in treatment while weighting down cases which are unlikely to be in treatment. Weighting also affects the effective sample size of the control group since individual with low odds of participating in treatment are down weighted. McCaffrey, Ridgeway, and Morral (2004) show that the effective sample size for the control group may be calculated as:

$$ESS = \frac{(\sum_{i\in\{D=0\}} w_i)^2}{\sum_{i\in\{D=0\}} w_i^2} \quad (4.4)$$

An attempt is made to investigate if the treatment effect varies with households who had access to both a crop protection wall and bullocks, over and above the effect of just the crop protection wall.

Finally, while we have adjusted for observable differences between the treatment and control group, matched the distributions of covariate at baseline, and removed the effect of time invariant unobservable variables, there still remains the possibility of the time varying, unobservable variables that could be co-related to treatment assignment that make the estimates potentially biased. However, in the literature, this is an improvement over other studies both due to the use of the propensity score adjustment on baseline covariates, as well as, difference-in-difference estimator.

4.3.2 Estimating the Propensity Score

Propensity score models are implemented in a range of ways across disciplines; these differences may be reduced to two dimensions a) models used to estimate the propensity score $\hat{p}(x)$ and b) the estimator to use to transform the covariate distributions of the control group to match the treatment group. Diagnostics to judge the quality of the propensity score model are also important. I discuss each of these for this study below.

An early example of using propensity score methods is Rosenbaum and Rubin (1984). There the propensity score is estimated using logistical regression. Subsequently, sub-classes are formed based on the propensity score where treatment effect estimates are calculated for the sub-class within which treatment and control groups have balanced covariates. More recently, interest has shifted to using non-parametric estimation techniques for estimating $\hat{p}(D = 1|x)$, as well as to constructing the appropriate control group (k-nearest neighbors, kernel matching, local linear regression, or weighting)(see Heckman, Ichimura, Smith, and Todd (1998), Hirano, Imbens, and Ridder (2003) and McCaffrey, Ridgeway, and Morral (2004)).

For this study, following McCaffrey, Ridgeway, and Morral (2004), I use generalized boosted models to estimate $\hat{p}(x)$. Generalized boosted regression models (GBM) offers a number of advantages over conventional methods to estimate the propensity scores. GBM is a data-adaptive modelling algorithm that iteratively fits shallow (i.e. with few splits), classification and regression trees to collectively build highly complex model able to capture non-linear relationships in a multivariate settings. These models offer a couple of advantages:

1. being based on classification and regression tree it is able to deal with ordinal, and continuous variables, as well as with missing variables easily;

2. the class of functions that it can estimate is highly flexible and may be optimized to seek covariate balance across treatment assignment[18];

3. a number of function search parameters (e.g. degree of interaction across covariates, or contribution of each iteration of the model search to the overall predictive model etc.).

In estimating the propensity score function, a major advantage of GBM is that it automates model selection for a given data set and an optimization criteria. All propensity score models attempt to minimize distributional differences with differing measures of difference[19]. I use the average Kolmogrov-Smirnoff (KS) test statistic as a cumulative measure of the distributional differences across treatment assignment. The prediction model for balancing covariates that is selected is the one which minimizes the average KS statistic (see Figure B.1).

The KS statistic performs a nonparametric test for each covariate where the null hypothesis is that the unweighted empirical distribution for the treatment group and the weighted empirical distribution for the control group were drawn from the same distribution Durbin (1973). The KS statistic may be calculated for each covariate, with each set of weights that is generated at each iteration. Once the average KS-statistic is at a minima within a subjectively wide range of iterations we stop GBM and use these weights (and the propensity scores) as the optimal weights.

[18] http://cran.r-project.org/src/contrib/Descriptions/twang.html provides code, data handling scripts and diagnostics to judge the quality of the estimate propensity scores. R is an open-source software environment for statistical computing and graphics.

[19] Other possible measures are the Mahalnobis distance, or the average standardized effect sizes as used in McCaffrey, Ridgeway, and Morral (2004)

Table 4.2: Variables used to identify Treatment and Control Villages

	Treatment Village Agraa		Control Villages		T-Value (Absolute Value)
Caste/Tribe					
Sahirya	100%		97%		-
Gujjars	0%		2%		-
Others	0%		1%		-
Remoteness Measures					
Crop Produce Market	24 km		35 km		-
Public Distribution System	0 km		3 km		-
Bus Stand	0 km		2 km		-
Community Groups	*Years*	*Members*	*Years*	*Members*	
Women's Self Help Group	2	31	2	35	
Musicians' Group	4	40	4	15	
Social Cohesion					
# of *Patels*	1		4/3		-
Wedding Attendance	100%		80%		-
Type of Soil					
Black	21%		24%		0.40
Red	25%		27%		0.18
Yellow	15%		13%		0.32
Domat	29%		23%		0.75
Land Holding (*bigha*)	6.51		8.98		2.61**
Distance to Reserve Forest					
Rains (km)	3.82		4.34		0.90
Post Rains (km)	4.63		5.21		1.56
Summer (km)	4.76		4.78		0.06
Indebtedness					
Rains (Rs.)	1006.34		740.15		0.76
Post Rains (Rs.)	261.58		382.67		0.69
Summer (Rs.)	1175.61		1070.71		0.24
Plots Relative to River					
Higher Bank	100%		80%		-
Lower Bank	0%		20%		-
Irrigated (*bigha*)	3.07		2.21		1.16
Protected (*bigha*)	4.90		3.72		1.41

Sources:
1. *Patwari* Land Records Officer records
2. Sheopur Village Study
3. Focus Groups
4. ** Significant at 5% level of significance

4.4 Results

4.4.1 Descriptive Statistics and the Propensity Score Models

Table 4.3: Seasonal distribution of Household Labor Days, by Occupation

Labor Category	**Rains**		**Post Rains**		**Summer**	
	Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*
Agriculture	105	75	85	80	-	-
Local Labor	24	25	23	21	23	24
Migrant Labor	42	45	29	25	32	21
NTFP Collection	59	69	79	47	59	38
Total Days Worked	230	74	216	55	114	41

1. Sample size 672 (168 households X 4 seasons)
2. Rainy Season spans July-November; Post-Rainy Season spans December-March Summer spans April to June
3. Survey spans Post Rainy Season 2003-4 to Post-Rainy Season 2004-5

Data from this field study shows the use of similar ex-post risk mitigating behaviors (e.g. migrating, distress borrowing etc.) in this study as has been reported in the literature (Walker and Ryan 1990 and (Fafchamps 2004)). Household heads were asked how much time a household would allocate to each income activity in each season. Apart from coping explicitly with consumption shortages, households explicitly attempt to diversify their income sources seasonally to reduce income fluctuations. Table 4.3 presents the mean number of days a household member spent on a specific activity. A season is spread over 120 days and about 85% of the sample have 3 persons in the working age group (defined as being older than 15). Table 4.3 suggests that households reallocate their labor every season and allocate it between four different income sources. The major allocation of labor is in the agricultural sector. There is a substantial amount of underlying heterogeneity, as

Table 4.4: Seasonal Distribution of Income (in Rs.) by Occupation

Labor Category	**Rains**		**Post Rains**		**Summer**	
	Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*
Agriculture	2,254	3,516	7,018	6,931	-	-
Local Labor	3,795	21,036	1,781	9,744	3,240	15,527
Migrant Labor	2,807	3,984	3,295	11,450	1,750	2,173
NTFP Collection	78	206	246	430	397	746
Total Income	3586	14367	6029	11388	2692	10798

1. Sample size 672 (168 households X 4 seasons)
2. Rainy Season spans July-November; Post-Rainy Season spans December-March Summer spans April to June
3. Survey spans Post Rainy Season 2003-4 to Post-Rainy Season 2004-5

well as possible measurement error in these numbers given the high variances.

Table 4.4 reports average income by source for these households. Agriculture is not a commercial activity in this area, and therefore, agriculture incomes reflect the value of the produce had they sold it in a government fair price shop. All other numbers are reported incomes that household received by activity category and season. Agriculture is a major income source for these households however, and there is substantial seasonal dependence on local wages and income earned while on migration. Sales of non-timber forest produce (NTFP) (i.e. collected forest produce from the nearby reserve forest) appear to be insignificant in comparison to other income sources, however, I observed between 0 and 60 visits every season to the reserve forests; much of the dependence on forest is for home use and is not marketed. Table 4.5 presents data for the summer of 2003-04 and the rains and post rainy season for the agricultural year of 2004-05. These are responses to questions that asked the survey respondent, the household head, if the household head faced shortages at home in providing the next cooked meal. If the household answered yes, the respondent would then be asked an open ended question

that asked how the household coped with this situation. At the end of the discussion, the field investigator classified these responses into one of these five categories. The summer season is the most oppressive with the highest rates of incidence for each type of distress activity. The start of the rainy season, before the quality of the rainfall for the years is revealed, is also a period of extraordinary stress as households tend to be low on grain stocks, and many are looking to invest in the next crop, and may migrate or borrow to temporarily tide over the shortage.

Table B.1 provides summary statistics on all the variables used in the propensity score models. Not surprisingly, in spite of attempting to choose control villages that looked a lot like the treatment village, important household level differences between the two groups are observed. Statistically significant differences (on both the two test statistics for difference in means (column (5)) (t-test) and column (7) (Kolmogrov-Smirnoff test)) are observed at baseline between the treatment and control group; thus, the treatment group on average has households that are a little larger, with households heads about 5 years older, with more adults in the family and with more number of people who can sign their names in the family. AVDC members also tend to have smaller farmyards, are less likely to own bicycles, but more likely to own ploughs, and have few other assets (eg radio, locally made music decks, watches, etc); also thatched houses are significantly more common in the control group. In terms of plot characteristics, AVDC members tend to have a larger share of *domat* type soil[20], own smaller plots, and are more likely to own a plough to farm their plot. There are significant differences on each of our outcome variable as well. Finally, the effective sample size, as cal-

[20] *Domat*literally means two types and refers too a mixture of two or more grained soils on the same plot. In general, *domath* tends to be most valued since it is a robust soil and performs well in both good and bad rain seasons. Black soils tends to outperform *domath* in years of good rainfall but tends to crack and this destroys the crop in bad rain years and so is more risky to farm on. These are both superior to the other categories, in which yellow is better than red

culated according to Equation 4.4 of the balanced control group is 54, and so for each season I have an effective sample size of 54 households in the control group and 41 in the treatment group for the non-parametric estimates.

Table 4.5: Participating in a Distress Activity, by Season

Distress Activity	Rains	Post-Rains	Summer
Skipping Meals	21	8	33
Consumption Loans	43	18	36
Migration	4	13	33
Sell Household Asset	2	4	6
Depend on NTFP	24	24	27

1. Sample size 672 (168 households X 4 seasons)

1. See footnote for Table 1 for other details

Table B.1 also provides the effect of propensity score adjustment on the control group (column (4)). After propensity score weighting, the transformed distribution of covariates has a distribution for the control groups matches the distribution of the control group. Only one variable " other assets" [21] shows some sign of lack of balance, while the KS statistic shows balance the t-stat shows differences exists; with the frequency of ownership of "other" assets being very low this is unlikely to affect either treatment assignment or outcomes.

Next, there is an important data issue; not all households in the sample are farming each season. Table 6 shows the distribution of the sample according to the different possible agricultural profiles that may have been possible in the 3 growing periods that we observe. Thus, households may either choose not to farm in a season, or may have chosen to farm and have suffered a crop failure[22]. In this sense agricultural outcomes for some house-

[21] This variable was an indicator for ownership of entertainment equipment such as radios, "music deck" etc.

[22] Since we asked household heads specifically about the agricultural activities in a season

holds are censored. Table 6 presents the sample stratified by the kind of planting profile that I observe. While there is wide variation in the kinds of profiles seen in the data a substantial amount of the treatment group is not censored (24 out of 41 households grow crops in all three seasons, and 33 households have both before and after observations, and so would be the sample we used to estimate the DiD estimator) in the sample frame. In addition, Figure B.2 shows that if we look at the data based on the crop profiles, there is overlap in the propensity score estimated, particularly for profiles where before and after observations are seen[23]. Thus, we appear to have a good set of propensity scores that achieve balance in covariate distributions across treatment assignment and that there is overlap in propensity scores for the subset of the data that we care about the most - when we observe before and after observations.

4.4.2 Difference-in-Difference Models

Tables 4.7 presents results from our Difference in Difference specifications. (A restricted version of these estimates are presented in Table B.2 where the sample consists of household with only agricultural profile (111)).

Both parametric OLS estimates and non-parametric difference in difference estimates present similar results. Gains in crop income tend to be small, positive, and statistically not significant (either in levels or logs). An exception is the OLS treatment effect estimate for the log of crop income; it suggests a small, and negative growth of -2.7% points for crop incomes

(planting, irrigation, etc.) we can distinguish between crop-failure and choosing not to farm. We cannot though differentiate between the many reasons that household may have chosen to not farm (e.g. it may be have chosen to leave the plot fallow, or may not have access to credit and savings to start a crop)

[23]A household growing a crop in each season has a profile of 111, while a household growing just before and after has a profile 101, thus we look at household with profiles {101,110,111} to check if we have good balance on those observations that identify the DID estimator.

Table 4.6: Agricultural Profiles of Sample Households

Agricultural History	**Treatment Status**		**Frequency**
	Control	**Agraa**	
000	3	3	3.57%
010	24	2	15.48%
100	15	3	10.71%
101	14	3	10.12%
110	27	6	19.64%
111	33	24	33.93%
Total	127	41	168

0 indicates no crop output; 1 indicates non-zero crop produce. Thus, 000 indicates no produce in three planting season, while 111 indicates positive produce in three seasons. The three season are Post-Rainy Season 2003-04, the Rainy Season 2004-05, and the Post-Rainy Season 2004-05.

for the AVDC members in the post-rainy season. However, this estimate is not significant for the non-parametric model. Total income shows large and negative estimates for both rainy and post-rainy season for the OLS models, while they are smaller and positive for the DiD models; however, none of these estimates are significant.

Incidence of sharecropping amongst AVDC members shows a consistent and large decline across both seasons and both OLS and non-parametric models. Conditioning on the subset for whom we see output in all seasons, the 111 sub-group, the coefficient remains negative and significant; estimates range from 13-21% declines in share cropping for the rainy season, and from 15-34% declines in sharecropping for the dry season, suggesting that a larger fraction of AVDC member were farming independently rather than with larger farmers from nearby villages as they had done in the past.

Households also consistently report a significantly lower incidence of skipping meals because there was no food at home to eat. In the rainy season AVDC members report a decline in the frequency of skipping a meal from 10-29 percentage points on different models. The non-parametric model reports smaller estimates. Declines in the incidence of skipping meals is also present

Table 4.7: Difference-in-Difference Estimates with Entire Sample

	Full Sample			
	OLS		Non-Parametric	
	T.E.	*Std. Error*	*T.E.*	*Std. Error*
Panel A: Rains				
Crop Income (Rs.)	148.70	1732.76	23.39	495.01
Log(Crop Income)	-2.19	1.37	0.34	1.51
Crop Retained Income (Rs.)	-9.70	1574.79	160.14	380.48
Log(Crop Retained Income)	1.21	1.76	0.35	1.50
Total Income (Rs.)	-1208.66	2760.89	65.81	600.60
Log(Total Income)	-0.08	0.76	-0.18	0.55
Share Cropping	-0.15*	0.08	-0.13***	0.03
Skipped a Meal	-0.24*	0.13	-0.10**	0.04
Borrowed Money	-0.16*	0.09	-0.07	0.09
Migrated	-0.11*	0.06	0.04	0.03
Collected NTFP	0.01	0.06	-0.09**	0.04
Panel B: Post Rains				
Crop Income (Rs.)	-2849.90	1938.16	416.16	1953.62
Log(Crop Income)	-2.712**	1.06	2.11	1.57
Crop Retained Income (Rs.)	237.83	1903.37	1629.19	1609.16
Log(Crop Retained Income)	1.05	1.54	2.75*	1.51
Total Income (Rs.)	-3671.40	2517.18	714.97	1955.72
Log(Total Income)	-0.86	0.58	0.33	0.28
Share Cropping	-0.34***	0.12	-0.18***	0.07
Skipped a Meal	-0.05**	0.02	-0.06**	0.03
Borrowed Money	0.13	0.10	-0.03	0.08
Migrated	0.01	0.04	-0.04	0.04
Collected NTFP	0.04	0.06	-0.06	0.04

Notes: OLS standard errors are Huber Eicher White standard errors. Each OLS DiD model also had the amount of land cultivated, days of local wage labor, days of migratory wage labor, amount of money borrowed, distance travelled to collect NTFP and a count of number of NTFP variables collected for sale in a season as control variables; * Significant at 10%, **Significant at 5%, ***Significant at 1%

for estimates in the post-rainy season as well, and while they continue to be significant, the size of these effects are about 1/2-1/5 smaller than what is seen in the rainy season and range between 5-19 per cent points. Clearly, seasonality plays an important role in the lives of these households and the intervention's impact is strongest on risk mitigation when it is the easiest season of the year (i.e. the rainy season).

Amongst other risk mitigating variables, dependence on NTFP also ex-

hibits 7-9 per cent point declines in incidence on the non-parametric models. These are however not found on the OLS models when the distributions are not matched for treatment and control variables. Incidence of borrowing to support consumption, and migrating to support consumption also show significant declines, though only in the rainy season and on the OLS models. Overall, the strongest and most robust findings are for the decline in incidence of share cropping and in reported need for skipping meals.

4.4.3 Crop Wall Vs. Crop Wall and Bullock Loans

The intervention as it was finally in place during data collection had two levels. All 41 households had their crops behind the community crop protection wall for the agricultural year of 2004-05. A subset of 20 households had access to a bullock pair during the agricultural year. These models are estimated by extending equation (4.2) as in Abadie (2005). Identification stems from assuming outcomes of the treatment group, whatever their level, would have changed identically to the control group had the treatment not taken place.

Table 4.8 presents the results from this estimation. The results are similar to those found in the entire sample. Households do not tend to experience significant gains on agricultural outcomes. The table also suggests that households who received only the crop protection wall show statistically significant reductions in share-cropping when compared to the control households, rather than those who received both the crop protection wall as well as had access to bullocks for agriculture in the rainy season. In the dry season both sub-categories of the treatment group report significant declines.

Table 4.8: Crop Wall Vs. Crop Wall and Bullock Loans

	Rainy Season		**Post Rainy Season**	
Outcome	*Crop Wall*	*Full*	*Crop Wall*	*Full*
Crop Income	-630.20	116.40	-4245.00	-3300.00
	462.60	645.60	2868.00	2459.00
Log(Crop)	-1.65	0.40	-4.12**	-0.15
	1.68	1.64	1.76	1.56
Crop Ret'd Income	-463.34	75.34	-1237.70	-884.20
	403.50	464.54	2449.00	1826.50
Log(Crop Ret'd)	-1.61	0.43	-3.72	0.15
	1.68	1.63	2.70	1.50
Total Income (Rs.)	-1058.32	82.15	-400.45	-291.30
	688.76	884.00	2807.00	480.00
Log(Total Income)	-0.23	1.14	-0.41	-0.06
	0.89	0.41	0.34	0.32
Share Cropping	-0.07**	-0.04	-0.39***	-0.25***
	0.03	0.04	0.06	0.09
Skipped a Meal	-0.14*	-0.15**	-0.07***	-0.04
	0.06	0.05	0.02	0.04
Borrowed Money	-0.14	-0.14	-0.05	0.04
	0.10	0.11	0.07	0.08
Migrated	0.02	0.01	-0.11*	-0.12**
	0.04	0.04	0.06	0.05
Collected NTFP	-0.20***	-0.12***	-0.15***	-0.15***
	0.04	0.06	0.06	0.05

NOTE: "Full" implies having access to both the crop wall and bullocks

4.5 Discussion

Community driven development programs tend to be viewed as an alternative mechanism to top-down centralized programs of fostering development. This paper evaluates a community based agricultural initiative in rural India to test if the community can successfully design and manage its own community driven development program. Given the low socioeconomic heterogeneity, simple non-technical intervention related tasks, and absence of "elite" social groups in the community, this study can uniquely focus on group functionality without other potential sources of bias. A number of lessons are learned from this.

The Agraa Village Development Committee started meeting in the face of district wide drought during the agricultural year 2002-03. It designed an agricultural intervention for its members that focussed on increasing crop security from grazing by wild animals, building check-dams, deepening or building new wells and augmenting the stock of drought animals critical for ploughing hard and dry soils once rains set in. The AVDC was able to implement its "ideal" initiative only in part; with labor being voluntary, and in extremely short-supply during the agricultural season, most of the construction activity (digging wells, or building walls) was done during the summer. At the time of this study, check-dams to harvest rain water remain to be built. In addition, the investments made in building dug-wells have not been realized due to the mix of poorly constructed wells, as well as not planning for pumps to extract water effectively from the wells. Thus, both technical and managerial aspects of the project implementation could have been better and perhaps outside consultation of the project plans once proposed by the community from an expert group would have prevented such oversights.

The restricted initiative that was implemented shows mixed findings. The strongest effects are shown for the decline in the incidence of sharecropping

amongst farming households as well as a decline in the reported incidence of skipping meals at home because of consumption shortages. Sharecropping has been an important phenomena in the area and historically AVDC members have tended to farm with inputs from richer farmers in nearby villages. Reported rates at which sharecropping is done indicate that AVDC members traditionally get anywhere between 25 - 50% of the gross produce after deducting input costs. Thus, a decline in sharecropping indicates the perception that member are more willing to farm independently. However, crop income, retained crop income, and total income do not show statistically observable gains, in fact on some specifications, they show statistically significant declines.

A possible interpretation of this is that with the AVDC intervention (, in particular, with the bullock loans) members perceived that there was no need to enter into sharecropping contracts. However, the benefits of sharecropping extend beyond the benefits that intervention was providing (e.g. advice on when to irrigate, frequency of ploughing, composition of fertilizer used, etc.). Thus, choosing to become independent also denies these farmers access to such complementary inputs that may come with sharecropping. An unintended consequence of the AVDC intervention has been that farmers opt into being independent even though that may be a riskier option. A clear and frequently mentioned benefit during focus groups from the intervention has been that households now sleep better in their beds at night, rather than spending the nights on the field protecting their crops from grazing by stray animals.

The study does not indicate if its better to have undergone a centralized program or not. It does show decentralized program can have significant effects, even if weak affects in the immediate short-term. The failure to build check dams, not planning for pumps, and the poor construction of wells is informative in that it suggests that communities may overcommit itself at project design stage to plans that may not be realistic.

Chapter 5

Conclusions

Agriculture always has, and continues to play an important role in economic development today. A majority of the poor in the world today continue to depend on agriculture as their dominant source of income and many more rely on it along with some alternatives. This dissertation describes the constraints, endowments, and uncertainties with which smallholders in semi-arid tropics seek to establish a livelihood. In addition, it also looks at the lifetime consequences of policy interventions that affect some of the constraints and income distributions that smallholders are likely to see using data from the ICRISAT VLS studies. Finally, it also looks at a case study of a community based agricultural initiative amongst a group of small holders in the semi-arid tropics of India.

5.0.1 Literature Review:

Smallholders in semi-arid tropics are not only a substantial part of the world's poor today, but also play an important economic role in promoting food security in developing nations. In nations in sub-Saharan Africa, they account for 90% of the produce, while in India they account for 40% of the national produce (Narayanan and Gulati 2002). Interestingly, as originally hypothesized

by Shah et al. (1998, pp. 44), empirical evidence now exists to show that marginal returns to investments in less favored areas (with predominantly smallholder households) are higher than in fertile areas that have already seen growth through the adoption of green revolution technologies over the past three decades. Fan, Hazell, and Thorat (2000) and Fan and Chang-Kang (2004) show that today, returns to public investments in roads and agricultural research for less favored areas are amongst the highest possible in a range of possibilities that include similar investments with irrigation coverage.

A number of policy responses that have traditionally been used to raise agrarian productivity are not available/feasible for small holders in semi-arid tropics. For example, expanding irrigation networks through large irrigation and dam projects, or extending the use of green technology for small farmer in semi-arid tropics is not possible (Shah et al. 1998, Chapter 4). Focus is increasingly being placed on policies that target agricultural production and income security for such households at the individual or community level. In this context, two promising and well studied interventions are watershed development programs and employment guarantee programs.

5.0.2 Policy Impacts:

Smallholders are known to be risk-averse, close to subsistence consumption, face uncertain incomes, and have little access to formal risk institutions. Consequently, smallholders (and similar households who do not have access to smoothly functioning credit markets and face uncertain incomes) must self-finance subsistence needs as well as investments in productive capital. Public policy may be used to ease one, or more, of these constraints faced by these small holders. Chapter 3 looks at three alternative ways of easing constraints for these households. For each alternative, the chapter uses two

measures to evaluate the performance of these households under each of these policies a) ability of households to retain productive capital when exposed to repeated covariate shocks (droughts) and b) average expected lifetime utility levels that are attained under each policy option.

The three alternatives considered are a) a livestock intervention that teaches smallholders to maintain and care for their livestock so that fatality rates for bullocks and calves are halved. This reduces the probability of experiencing states in which livestock fatalities occur; b) a watershed intervention that changes the income distribution of household at each level of bullock ownership that raises the mean income and reduces its spread; c) an employment guarantee scheme that provides households access to assured income (zero standard deviation) at the minimum consumption level for each household. In Chapter 3, we see that while under each of these interventions households experienced utility gains, by far the largest gains came from the employment guarantee scheme. The employment guarantee scheme was also the most successful at helping households retain bullock stocks when faced with repeated droughts. However, the most cost-effective program is the livestock intervention.

The simulation shows that the way policy interventions influence income distribution are particularly important. While all three intervention affect the income distribution that household receive (the livestock intervention by changing the frequency of the livestock shocks and so the expected incomes in the future, the watershed intervention by changing means and standard deviations of incomes, and the EGS by providing an income floor), the insurance role played by the optional income floor in the EGS is the most successful intervention at maintaining productive assets. A key reason is that only under the EGS intervention (due to the income floor) is it possible for the smallholder to treat his productive asset as simply an investment good. Under

all other scenarios, the household is forced to also use its bullock stock as a store of value to be used to self-finance consumption needs when bad states of nature are realized. Thus, by maintaining productive capital at higher rates during the entire lifetime of the household the EGS provides consistent access to income distributions that are higher than the ones experienced in other scenarios.

5.0.3 Program Design

The level of centralization needed for effective policy interventions is a key question in public policy debates. Advantages of decentralization stem from the greater flexibility of the program to learn about local issues, needs and respond to these which are often difficult to anticipate in centralized schemes. Well designed centralized programs on the other hand have the ability to deliver uniform programs that can bring expertise and knowledge to bear about different aspects of the program.

The field study is an example of decentralized development that takes advantage of local conditions, requirements and provides evidence that close co-ordination with a responsible non-profit may help design programs that bring about desired goals. Two issues that this case study reveal are a) technical details of the intervention can be overlooked during program design (in this case planning for pumps and dispersal of water from dug wells was not thought of at the planning stage) and b) program beneficiaries have every incentive to overcommit themselves to work at program initiation stage. Neither of these appear to be a priori insurmountable problems and combining decentralized programs with an element of centralization and program oversight through a partnership with government appears to be possible work around. There already is evidence to support that such programs work well for watershed interventions.

The dissertation shows that smallholder livelihoods are likely to benefit considerably from interventions that help protect and create personal productive assets. While improvements in labor productivity due to watershed programs bring important gains, households continue to be fully exposed to various sources of income shock. Ideally, an integrated program that not only provides an employment guarantee, but also implements infrastructural improvements such as associated with watershed programs would be an ideal strategy for promoting income stabilization and poverty reduction for small holders. Implementation of these interventions can potentially be decentralized provided there are sufficient safeguards in place that prevent local communities from making technical errors in program design. Further research on the cost structures of these intervention would allow a full cost-benefit calculation that is currently left for future research.

Appendices

Appendix A

Dynamic Program

Table A.1: Household Specific Distribution of *i.Shock*

Household ID	bad.p	idiosync.low	idiosync.high	low.t	high.t
Aurepalle.40	0.78	-434.375	1176.816	-4.54918	6.587832
Aurepalle.41	0.44	-790.688	-66.5922	-5.06687	-0.4771
Aurepalle.43	0.67	-514.476	-71.1213	-7.90641	-0.77286
Aurepalle.44	0.22	-1053.91	-444.011	-16.3891	-12.9175
Aurepalle.45	0.67	-1656.79	2973.351	-2.06124	2.61573
Aurepalle.46	0.56	-645.177	1648.46	-1.24953	2.855551
Aurepalle.48	0.44	-834.233	538.6524	-3.1604	2.281491
Aurepalle.49	0.56	-470.939	-74.3001	-8.83738	-1.24708
Shirapur.40	0.44	-1625.15	1465.589	-5.61669	5.66312
Shirapur.41	0.56	-902.795	305.3421	-6.00533	1.816686
Shirapur.42	0.44	-600.527	-291.131	-12.0049	-6.50683
Shirapur.43	0.56	-864.508	1759.557	-2.90963	5.296849
Shirapur.45	0.56	-1058.79	-357.405	-7.94561	-2.39897
Shirapur.48	0.33	-912.154	-359.141	-7.85734	-4.37509
Shirapur.49	0.56	-346.39	165.9937	-3.08121	1.320663
Kanzara.40	0.67	-1181.28	1160.089	-3.21645	2.23357
Kanzara.41	0.67	174.9409	5091.735	0.347742	7.156773
Kanzara.42	0.56	-751.13	-127.444	-6.43521	-0.97659
Kanzara.43	0.56	-323.868	702.1266	-1.31475	2.549394
Kanzara.44	0.56	-42.6994	1306.509	-0.24121	6.601426
Kanzara.45	0.67	-132.674	921.891	-1.08147	5.313659
Kanzara.46	0.44	-158.427	555.8607	-1.32085	5.181385
Kanzara.47	0.44	-1071.95	866.7054	-1.89482	1.71286
Kanzara.48	0.44	601.34	2254.051	2.401323	10.06351
Kanzara.49	0.56	-531.048	184.7856	-3.71745	1.156975

Appendix B

Field Study

This appendix presents some of the tables describing the quality of the balance achieved on the pre-treatment characteristics of the propensity score model. In addition, it also presents tables that were used to test for robustness of the effects, as well as the effect of different treatment intensities (i.e. the effect of the crop wall and access to bullocks verses just the crop wall, verses no intervention) and the sensitivity of the results to the intervention.

B.0.4 Balance Table for Propensity Score Model

Table B.1: Pretreatment Characteristics and Group Differences on all baseline variables before and after propensity score weighting

	AVDC	**Controls**		**T-stat**		**KS-stat**	
Variables	Mean	Mean	PS adj.	Obs.	PS adj.	Obs.	PS adj.
	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A: Household Level							
Size	5.78	5.25	5.45	1.66*	0.91	0.13	0.10
	1.74	1.93	1.76				

Continued . . .

Table B.1 *Continued*

Variables	**AVDC** **Mean**	**Controls** Mean	PS adj.	**T-stat** Obs.	PS adj.	**KS-stat** Obs.	PS adj.
	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age of Head	42.34	38.39	42.30	1.78*	1.14	0.23*	0.10
	13.19	11.66	14.65				
% Female	0.47	0.45	0.47	0.56	-0.27	0.12	0.09
	0.18	0.17	0.17				
# of Adults	2.73	2.45	2.53	1.72*	1.04	0.14	0.08
	0.98	0.83	0.83				
# of Children	3.05	2.80	2.92	0.86	0.41	0.10	0.06
	1.55	1.74	1.59				
# of who can sign	0.63	0.48	0.56	1.87*	0.59	0.12	0.04
	0.62	0.53	0.54				
Livestock Owned							
Chicken	0.68	1.08	1.02	-1.16	-0.88	0.09	0.10
	1.77	2.33	2.16				
Cow	1.63	1.21	0.92	0.61	1.05	0.08	0.06
	4.28	2.34	1.77				
% Households Assets Owning							
Cycle	0.05	0.23	0.11	-3.57***	-1.36	0.18	0.06
	0.22	0.42	0.32				
Watch	0.27	0.24	0.23	0.30	0.41	0.02	0.04
	0.45	0.43	0.43				
Pump	0.02	0.02	0.03	0.03	-0.08	0.02	0.00
	0.16	0.15	0.16				
Plough	0.78	0.62	0.69	2.03**	0.97	0.16	0.09
	0.42	0.49	0.46				

Continued . . .

Table B.1 *Continued*

Variables	**AVDC** **Mean**	**Controls** Mean	PS adj.	**T-stat** Obs.	PS adj.	**KS-stat** Obs.	PS adj.
	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Other Assets	0.00	0.07	0.03	-3.1***	-2.43**	0.27**	0.13
	0.00	0.26	0.17				
House Type							
Brick	0.05	0.03	0.06	0.47	-0.26	0.02	0.01
(Pakka)	0.22	0.18	0.24				
Stone	0.56	0.45	0.66	1.00	-0.65	0.09	0.06
(Pathore)	0.63	0.61	0.76				
Thatched	0.51	0.68	0.48	-1.76*	0.27	0.18	0.02
(Katcha/Tapiya)	0.68	0.60	0.58				
B: Plot Level							
Type of Soil							
Black	0.21	0.26	0.26	-0.63	-0.61	0.10	0.07
(Kala)	0.40	0.39	0.42				
Red	0.25	0.26	0.16	-0.05	1.27	0.06	0.14
(Laal)	0.40	0.41	0.34				
Yellow	0.15	0.13	0.21	0.28	-0.68	0.05	0.10
(Peela)	0.36	0.31	0.39				
Two grained	0.29	0.14	0.23	2.42**	0.47	0.20	0.08
(Domat)	0.44	0.33	0.40				
Other Soil	0.15	0.20	0.21	-0.77	-0.76	0.05	0.07
	0.36	0.40	0.41				
Plot Size	6.51	8.98	6.79	-2.63***	-0.57	0.24**	0.08
	4.63	6.19	6.00				
Farmyard Size	0.49	0.66	0.51	-1.68*	-0.11	0.25**	0.07

Continued . . .

Table B.1 *Continued*

Variables	AVDC Mean	Controls Mean	Controls PS adj.	T-stat Obs.	T-stat PS adj.	KS-stat Obs.	KS-stat PS adj.
	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	0.59	0.53	0.53				
C: Baseline Outcomes							
Crop Income (Rs.)	6956.88	3272.76	4339.91	2.32**	1.55	0.28**	0.22
	9697.52	5884.34	5879.99				
Log(Crop Income)	4.50	-0.63	1.52	3.98***	1.71*	0.28**	0.22
	7.05	7.72	7.82				
Ret. Crop Income	4382.23	1847.80	2517.44	1.85*	1.29	0.18	0.11
	8638.52	3430.73	4188.31				
Log(Ret. Crop Income)	1.98	-0.67	1.37	1.96*	0.39	0.18	0.11
	7.63	7.43	7.49				
Total Income (Rs.)	12136.54	5950.00	6150.46	1.62	1.59	0.24**	0.19
	23906.71	10720.48	7800.36				
Log (Total Income)	8.66	7.70	8.23	3.38***	2.03**	0.24**	0.19
	1.12	2.53	1.49				
Sharecrop ? (0/1)	0.43	0.48	0.47	-0.45	-0.25	0.05	0.03
	0.50	0.50	0.50				
Risk Responses (%)							
Skipped Meals	0.34	0.32	0.32	0.22	0.18	0.02	0.02
	0.48	0.47	0.47				
Borrowed Money	0.37	0.35	0.32	0.22	0.45	0.02	0.04
	0.49	0.48	0.47				
Migrated	0.12	0.28	0.12	-2.37**	0.04	0.15	0.00
	0.33	0.45	0.33				

Continued . . .

Table B.1 *Continued*

Variables	AVDC Mean	Controls Mean	Controls PS adj.	T-stat Obs.	T-stat PS adj.	KS-stat Obs.	KS-stat PS adj.
	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Collected NTFP	0.07	0.24	0.13	-3.06***	-1.09	0.17	0.06
	0.26	0.43	0.34				

NOTES:

1. Asymptotic Standard Errors presented below means;
2. KS statistic is calculated using a permutation test with 200 iterations yielding a precision of 3% to the true p-values, as opposed to an analytic approximation;
3. *b*: measured in *bighas* approx 5/8th of an acre;
4. *Significant at 10%, **Significant at 5%, ***Significant at 1%;
5. ps() call placed with following parameters: (n.trees = 5000; interaction depth = 3; shrinkage = 0.005);
6. ESS is the effective sample size of the control group after weighting.

B.0.5 Sensitivity Analysis

The identifying assumption for the analysis, DiD.1, requires that I observe a rich set of covariates so that conditional on these covariates, the change in outcomes over time is independent of program participation. Unobserved variables may remain that bias the treatment effect estimate. Following Rosenbaum (2002), hidden bias is said to exist when for two different sample households, j and k with exactly the same observed covariates $x_{jt} = x_{kt}$ (and so with the same estimated propensity score) have different (true) propensity scores. Thus, with $w_i = p_i/(1 - p_i)$ denoting the true odds of treatment participation, for all j and k with $x_{jt} = x_{kt}$, then a study is said to be sensitive

Table B.2: Difference in Difference Estimate with Crop Profile = “111”’

	Agriculture Profile = ’111’			
	OLS		**Non-Parametric**	
Outcomes	*T.E.*	*Std. Error*	*T.E.*	*Std. Error*
Panel A: Rains				
Crop Income (Rs.)	464.41	2187.12	223.45	564.06
Log(Crop Income)	-3.27*	1.7	-0.66	2.19
Crop Retained Income (Rs.)	142.68	1035.86	57.66	531.54
Log(Crop Retained Income)	-0.83	2.11	-0.63	2.18
Total Income (Rs.)	-2500.01	2957.21	-205.70	669.66
Log(Total Income)	-0.65	0.95	-0.79	0.66
Share Cropping	-0.21*	0.12	-0.18***	0.02
Skipped a Meal	-0.29*	0.17	-0.20**	0.09
Borrowed Money	-0.23	0.20	0.00	0.14
Migrated	0.08	0.13	-0.02	0.01
Collected NTFP	0.03	0.14	-0.07***	0.03
Panel B: Post Rains				
Crop Income (Rs.)	-949.61	2,698.09	350.29	3638.83
Log(Crop Income)	0.40	1.56	0.98	1.80
Crop Retained Income (Rs.)	662.04	2,840.46	1298.77	2860.99
Log(Crop Retained Income)	-0.94	0.768	1.24	1.79
Total Income (Rs.)	-2,050.23	2,500.20	-905.80	3589.28
Log(Total Income)	0.61	0.50	-0.13	0.32
Share Cropping	-0.16*	0.09	-0.15*	0.08
Skipped a Meal	-0.19***	0.06	-0.11**	0.04
Borrowed Money	0.06	0.15	0.11	0.08
Migrated	0.07	0.16	-0.02	0.06
Collected NTFP	-0.03	0.06	-0.09**	0.04

Notes: OLS standard errors are Huber Eicher White standard errors. Each OLS DiD model also had the amount of land cultivated, days of local wage labor, days of migratory wage labor, amount of money borrowed, distance travelled to collect NTFP and a count of number of NTFP variables collected for sale in a season as control variables; * Significant at 10%, **Significant at 5%, ***Significant at 1%

to hidden bias if for a value of τ close to one treatment effect estimates are different from when τ is one. The study is insensitive if large values of τ are needed to alter the study’s inferences.

$$\frac{1}{\tau} \leq \frac{w_j}{w_k} \leq \tau \tag{B.1}$$

Table B.3: Crop Protection Wall. Vs. the Full AVDC Intervention

Crop Profile '111'	**Rainy Season**		**Post Rainy Season**	
Outcome	*Crop Wall*	*Full*	*Crop Wall*	*Full*
Crop Income	237.80	214.00	-5982.00	-9183.00
	834.80	640.40	6756.00	5290.00
Log(Crop)	-0.14	-2.94	-3.69*	2.81**
	2.27	2.48	2.02	1.23
Crop Ret'd Income	264.05	150.65	-532.20	-4101.90
	780.01	620.30	5734.60	3896.40
Log(Crop Ret'd)	-0.10	-2.89	-3.19	-2.32
	2.71	2.40	2.02	1.22
Total Income (Rs.)	159.00	524.17	-6275.00	-8188.00
	781.00	708.21	6642.00	5236.00
Log(Total Income)	-1.67	-0.03	-0.82	-0.59
	1.50	0.26	0.51	0.36
Share Cropping	-0.09*	-0.08*	-0.42***	-0.30***
	0.05	0.05	0.10	0.12
Skipped a Meal	-0.09	-0.15	-0.10	-0.05
	0.13	0.09	0.60	0.07
Borrowed Money	-0.04	-0.18	0.01	0.04
	0.19	0.15	0.12	0.10
Migrated	-0.04	-0.04	-0.13*	-0.08
	0.03	0.03	0.07	0.08
Collected NTFP	-0.15*	-0.16	-0.09	-0.15
	0.07	0.07	0.14	0.10

To implement the above idea two things are needed - the correlation between the unobserved variable and program participation, and the relationship between the unobserved variable and the outcomes of the study. Ridgeway (2006) implements this idea by comparing each individual's weight to what it would have been had a covariate been missing; suppose we do observe x^k, but for the moment we assume that it is in fact missing; then we can construct $\hat{a}_i^k = \hat{w}_i(x_i^j, x_i^k)/\hat{w}_i(x_i^j)$ where j refers to the subset of vectors observed, except x^k , $\hat{w}_i(x_i^j, x_i^k)$ is the odds of receiving treatment when we include x_k in the propensity score model and $\hat{w}_i(x_i^j)$ is the odds of participation when x^k is excluded from the propensity score model. Thus, with $\hat{a}_i^k$ we

have a measure of the effect of the unobserved x_k on individual i. Thus, at the observed $Cor(x^k, y_0) = \rho_k^O$, I can estimate the change in the outcome for those who received the intervention, had they not participated as:

$$\hat{E}(y_0^{Post} - y_0^{Pre}|x, D=1) = \frac{1}{N}\left(\sum_{i\in\{D=0\}} \frac{y_{i1} - y_{i0}}{\hat{p}(D=1)} a_i \hat{w}_i(x_i)\right) \tag{B.2}$$

A range of possible correlations are constructed by permuting the $\hat{a}^k$ to get a sense of how robust the treatment effect is; the maximal correlation is given by $Cor(\hat{a}_{P_1}^k, y)$ and the minimum by $Cor(\hat{a}_{P_0}^k, y)$, where $\hat{a}_{P_1}^k$ is that permutation of the $\hat{a}^k$ where the highest a_i are assigned to the highest y_i, while $\hat{a}_{P_0}^k$ is that permutation of the $\hat{a}^k$ where the highest a_i is assigned to the smallest y_i. These permutations also establish the range of possible values that the counterfactual $(\hat{E}(y_0^{Post} - y_0^{Pre}|x, D=1))$ can take. Interpolating within this range one may also numerically solve for the correlation level ρ_k^* at which the treatment effect is zero. Larger values of ρ_k^* relative to ρ_k^O would suggest that omitted variables of type k are an unlikely source of hidden bias for the study. I report the sensitivity analysis only for the share cropping model and for the skipping meals model[1]. The sensitivity analysis suggests that our findings are robust for certain categories of omitted variables while for others it is weak.

Thus, for share cropping in the rainy season (see Table (B.4)), if baseline total income had not been observed then we'd need it to be 4 times as strong as it currently is to set the observed decline in sharecropping to zero. Similarly if we had not observed the distance traveled to collect NTFP produce then we'd need for the variable to be only 3/4th as strongly correlated as the distance measure to set the treatment effect to zero. Thus, the

[1]The sensitivity analysis was carried out by dropping each of the over 40 covraites that were used in the propensity score model, for each of the 11 outcomes variables. They have not been reported because of space constraints.

model is more sensitive to unobserved variables if we are concerned about variables such as distance travelled to the nearest reserve forest (or owning a pump) and less so for variables such as baseline total income (or if household was migrating or borrowing in distress in the summer season). The median, across 40 variables in the propensity score model, suggests that the omitted variables' correlation needs to be 1.8 (3) times stronger than the one we see in the rainy (post-rainy) season. Similarly, for skipping a meal, the median strength of the unobserved variable needs to 1.7 (2.39) times stronger than the one we see for the observed treatment decline in incidence of skipping meals during the rainy (post-rainy) season to be set to zero. Since we do see these variables, the unobserved variables has to be fairly strongly correlated to outcome or treatment assignment (or both) to matter. Given the rich specification of covariates I am less concerned about this issue.

While estimating the sensitivity of the results to the predictors I used all 40+ variables. However, while presenting results I look at the top 12 most predictive variables that together explain about 70% of the variation in treatment assignment. These predictive models were estimated using generalized boosted regression models and implemented in R as the *gbm* library.

Table B.4: Sensitivity Analysis: Sharecropping in Rainy Season

Variable Name	E0	a.cor	a.mincor	a.maxcor	minE0	maxE0	Break Even Correlation	Strength
Plot size	0.04	-0.19	-0.45	0.76	0.02	0.06	-0.29	1.56
% female	0.04	-0.01	-0.52	0.63	0.03	0.05	-0.02	1.88
Age of household head	0.05	-0.20	-0.52	0.67	0.03	0.05	-0.27	1.40
Size of farmyard	0.05	-0.22	-0.45	0.69	0.03	0.05	0.61	2.82
Area planted	0.04	-0.19	-0.55	0.71	0.03	0.05	-0.19	1.01
# of Adults	0.05	-0.20	-0.50	0.69	0.03	0.05	-0.27	1.31
# of members who sign	0.04	0.04	-0.56	0.64	0.03	0.05	0.22	5.52
Household size	0.04	-0.19	-0.61	0.59	0.03	0.05	-0.91	4.69
Red soil type	0.05	-0.25	-0.50	0.66	0.03	0.05	-0.11	0.44
# of Children	0.04	-0.03	-0.51	0.70	0.03	0.05	0.02	0.56
Black soil type	0.05	-0.27	-0.56	0.63	0.03	0.05	-0.46	1.73
# of Cows owned	0.04	0.08	-0.58	0.64	0.03	0.04	0.01	0.13

Notes:

E0 : $\hat{E}(y_0^{Post} - y_0^{Pre}|x, D = 1)$

a.cor : observed correlation between variable and outcome - sharecropping

a.mincor : minimum possible correlation between variable and outcome

a.maxcor : maximum possible correlation between variable and outcome

minE0 : minimum possible value for $\hat{E}(y_0^{Post} - y_0^{Pre}|x, D = 1)$

Break Even cor : size of correlation at which treatment effect is zero

Strength : Break Even Cor/a.cor

Table B.5: Sensitivity Analysis: Sharecropping in Post-Rainy Season

Variable Names	E0	a.cor	a.mincor	a.maxcor	minE0	maxE0	Break Even Correlation	Strength
Plot Size	0.25	-0.16	-0.56	0.81	0.13	0.37	-0.58	3.74
% female	0.24	-0.28	-0.77	0.78	0.15	0.29	0.91	3.24
Age of Head	0.20	0.35	-0.67	0.82	0.16	0.29	0.49	1.39
Size of farmyard	0.23	0.04	-0.71	0.82	0.15	0.30	-0.47	12.02
Red soil type	0.22	0.02	-0.76	0.78	0.17	0.26	-0.40	17.65
# of Adults	0.22	-0.05	-0.72	0.74	0.16	0.27	-0.13	2.54
Household size	0.24	-0.21	-0.72	0.83	0.18	0.26	0.28	1.32
# who can sign	0.22	0.03	-0.73	0.81	0.16	0.28	0.46	15.89
# of Children	0.21	0.16	-0.74	0.80	0.17	0.27	0.35	2.26
# of Adults	0.22	-0.03	-0.78	0.76	0.17	0.26	0.21	8.23
Area Planted	0.21	0.15	-0.68	0.77	0.17	0.28	0.19	1.26
# of Cows owned	0.22	-0.03	-0.76	0.72	0.18	0.26	-0.43	12.54

Notes:

E0 : $\hat{E}(y_0^{Post} - y_0^{Pre}|x, D = 1)$

a.cor : observed correlation between variable and outcome - sharecropping

a.mincor : minimum possible correlation between variable and outcome

a.maxcor : maximum possible correlation between variable and outcome

minE0 : minimum possible value for $\hat{E}(y_0^{Post} - y_0^{Pre}|x, D = 1)$

Break Even cor : size of correlation at which treatment effect is zero

Strength : Break Even Cor/a.cor

Table B.6: Sensitivity Analysis: Skipped a Meal in the Rainy Season

Variable Names	E0	a.cor	a.mincor	a.maxcor	minE0	maxE0	Break Even Correlation	Strength
plotsize	0.10	-0.05	-0.55	0.75	0.06	0.15	0.01	0.14
sex	0.09	0.12	-0.67	0.73	0.06	0.13	0.00	0.01
ageHHH	0.09	-0.13	-0.66	0.72	0.07	0.12	-0.15	1.17
farmyard	0.10	-0.07	-0.62	0.80	0.07	0.13	-0.12	1.63
planted	0.08	0.14	-0.58	0.79	0.07	0.12	0.05	0.33
c.adults	0.10	-0.03	-0.65	0.76	0.07	0.12	-0.13	4.85
c.sig	0.10	-0.10	-0.67	0.72	0.06	0.12	0.12	1.24
hh.size	0.09	0.13	-0.73	0.70	0.07	0.11	-0.16	1.18
red	0.09	-0.12	-0.66	0.74	0.07	0.11	-0.08	0.66
c.children	0.10	-0.16	-0.69	0.75	0.07	0.12	-0.19	1.21
black	0.09	-0.02	-0.68	0.75	0.07	0.11	0.19	9.47
cow	0.09	0.00	-0.72	0.73	0.07	0.11	0.02	16.34

Notes:
E0 : $\hat{E}(y_0^{Post} - y_0^{Pre}|x, D = 1)$
a.cor : observed correlation between variable and outcome - sharecropping
a.mincor : minimum possible correlation between variable and outcome
a.maxcor : maximum possible correlation between variable and outcome
minE0 : minimum possible value for $\hat{E}(y_0^{Post} - y_0^{Pre}|x, D = 1)$
Break Even cor : size of correlation at which treatment effect is zero
Strength : Break Even Cor/a.cor

Table B.7: Sensitivity Analysis: Skipped a Meal in Post-Rainy Season

Variable Names	E0	a.cor	a.mincor	a.maxcor	minE0	maxE0	Break Even Correlation	Strength
Plot Size	0.1	-0.05	-0.55	0.75	0.06	0.15	0.08	1.39
% female	0.09	0.12	-0.67	0.73	0.06	0.13	-0.29	2.53
Age of Head	0.09	-0.13	-0.66	0.72	0.07	0.12	-0.15	1.17
Size of farmyard	0.1	-0.07	-0.62	0.8	0.07	0.13	-0.12	1.63
Area Planted	0.08	0.14	-0.58	0.79	0.07	0.12	0.46	3.3
# of Adults	0.1	-0.03	-0.65	0.76	0.07	0.12	-0.19	7.11
# who can sign	0.1	-0.1	-0.67	0.72	0.06	0.12	0.12	1.24
Household size	0.09	0.13	-0.73	0.7	0.07	0.11	-0.16	1.18
Red soil type	0.09	-0.12	-0.66	0.74	0.07	0.11	-0.18	1.49
# of Children	0.1	-0.16	-0.69	0.75	0.07	0.12	-0.19	1.21
Black soil type	0.09	-0.02	-0.68	0.75	0.07	0.11	0.02	0.95
# of Cows owned	0.09	0	-0.72	0.73	0.07	0.11	0.02	16.34

Notes:

E0 : $\hat{E}(y_0^{Post} - y_0^{Pre}|x, D = 1)$

a.cor : observed correlation between variable and outcome - sharecropping

a.mincor : minimum possible correlation between variable and outcome

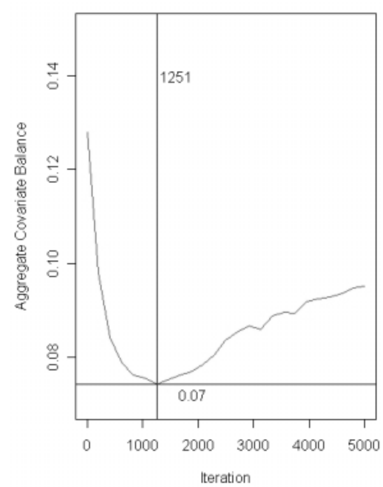
a.maxcor : maximum possible correlation between variable and outcome

minE0 : minimum possible value for $\hat{E}(y_0^{Post} - y_0^{Pre}|x, D = 1)$

Break Even cor : size of correlation at which treatment effect is zero

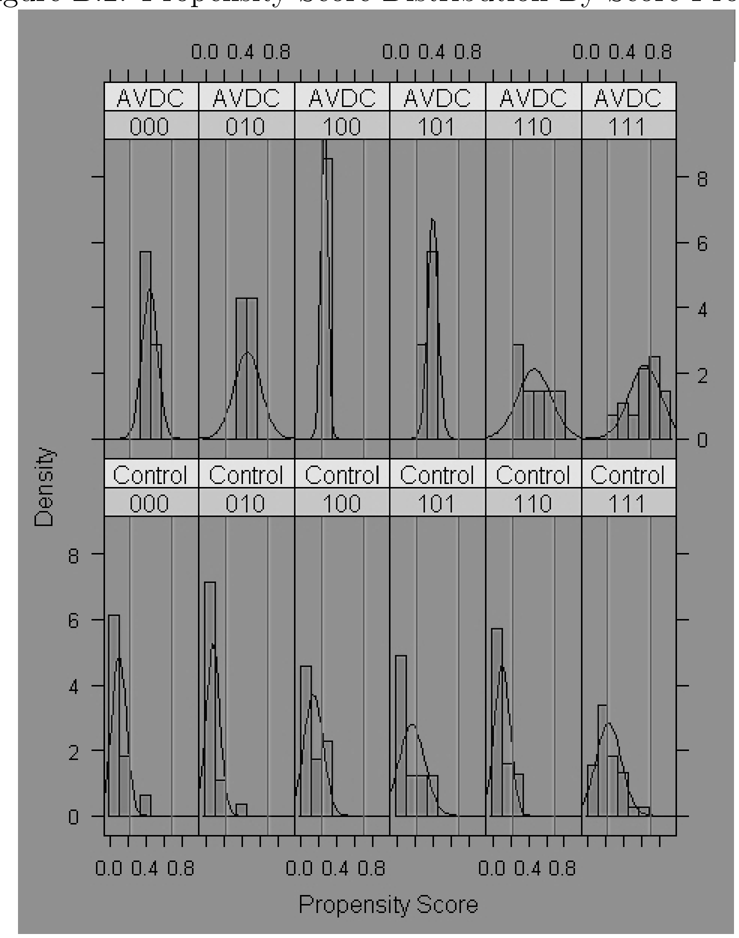
Strength : Break Even Cor/a.cor

Figure B.1: Kolmogrov-Smirnoff Statistic by GBM Iteration



NOTE: Average Covariate Balance reports the average KS statistic calculated for each covariate to test if the empirical distributions across treatment and control groups are identical. Lower average value indicate smaller differences. The range of p-values for all KS-stat variables in the rainy season propensity score model is [0.23, 1], and is [0.17, 1] for the post-rainy season propensity score model. They differ in only the changes seen in the time varying covariates.

Figure B.2: Propensity Score Distribution By Score Profile



NOTE: Each panel plots the density function for the propensity score for each crop profile and each treatment assignment. AVDC is the Agraa Village Development Committee and is the treatment group. Each panel has two vertical lines, the left line is the left tail for the propensity score distribution for the AVDC members while the right vertical line is the right tail of the propensity score distribution of the control group observations. The area in between the two vertical lines is the region of overlap of propensity scores across treatment assignment.

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