Distinguishing between Chronic and Transient Poverty in Mozambique

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Abstract

The main purpose of the study is to identify household characteristics which can 1) distinguish between the chronic poor and transient poor and 2) be feasibly implemented as targeting criterion in poverty interventions. Data for this study was drawn from Mozambique's 2008/09 Household Budget Survey and consisted of 10,832 observations. This study fills a gap in the literature by structurally determining the impact of common shocks (drought, floods and cyclones, agricultural pests, illness, death, and theft) on 1) food expenditures at the household level and 2) poverty rates at the national level. The results of the study indicate that shocks are one of the key determinants of household food expenditures. The expected impact of shocks in aggregate increases the national poverty rate by 9%. However, the impact of specific shocks on household food expenditures varies across regions and households. Further, the variables which are strongly correlated with chronic poverty differ from the variables strongly correlated with transient poverty. These results suggest the need to both more rapidly identify and enroll households exposed to shocks in short-term social protection programs and continue to improve methods targeting the chronic poor in long-term programs.

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1. Chronic poor: households whose food expenditures per person per day are below the national food poverty line without exposure to a shock or shocks.

2. Transient poor: households who food expenditures per person per day are above the national food poverty line without exposure to a shock, but are below the national food poverty line with exposure to a shock or shocks.

3. Vulnerable households: households who are expected to fall below the national food poverty line with exposure to a shock or shocks. Synonymous with transient poor households.

4. Covariate shocks: shocks where exposure is strongly correlated geographically across households and can be identified based upon regional or community characteristics.

5. Idiosyncratic shocks: shocks where exposure is based upon specific aspects of the household and is not strongly correlated across households.

Chapter 1: The Problem of Poverty in Mozambique

1.1 Introduction to the Problem

Mozambique is a unique country in Sub-Saharan Africa, as it has maintained a fairly stable economy and political environment since the ceasefire of a 16 year civil war in 1992. While receiving considerable recognition for its reconstruction efforts, Mozambique still suffers from high poverty levels, with a national poverty headcount ratio of 54.1% (WB, 2009). The incidence of poverty also shows a large regional variance, ranging from 36.1% in Sofala to 80.7% in Inhambane (WB 2010). Similarly, chronic malnutrition for children under 5 years of age ranges from 21% in Maputo City to 56% in Cabo Delgado, with a national average of 41% in 2003 (WB 2010). Efforts to reduce poverty and food insecurity are complicated by Mozambique's vulnerability to covariate and idiosyncratic shocks. In Mozambique, common covariate shocks, or shocks whose occurrence is correlated between households, are mostly climatic and weather related. A 2007 FAO report labeled 20 of the 128 districts in Mozambique "highly prone to drought", 30 prone to flooding, and seven to both (FAO 2007). Idiosyncratic shocks, including HIV and AIDS, tuberculosis, malaria, and theft, are specific to the individual household and uncorrelated with other households. In the face of these shocks, households can be forced to rely upon social networks or public programs for transfers to smooth consumption. If the transfers are not sufficient, households may resort to negative coping mechanisms, including asset depletion and withdrawing children from school. Thus, shocks can have a significant effect not only on immediate consumption, but on long-term expected consumption by reducing investment in human and physical capital. As households are exposed to more than one shock, or repeated shocks, their ability to use positive coping mechanisms to smooth consumption are increasingly diminished. Thus, exposure to these covariate and idiosyncratic shocks can keep Mozambican households from escaping poverty or may push households above the poverty line into a state of transient poverty and food insecurity.

Administrators of poverty alleviation programs are increasingly recognizing the need to distinguish between the chronic and transient poor. In this paper, chronic poor are defined as households whose estimated food expenditures are below the food poverty line in the absence of a shock. The transient poor are defined as households that are not chronically poor, but whose estimated food expenditures are expected to fall below the food poverty line with an external shock. Thus, vulnerability in this paper refers to households who are likely to become transient poor with exposure to a shock. Programs addressing households who are vulnerable to transient poverty provide a safety net and a means to prevent households from resorting to negative coping mechanisms. Interventions may focus on mitigating either exposure to, or impacts from, short or medium term negative shocks. Programs targeted towards reducing chronic poverty are geared towards moving households out of the "poverty trap". These interventions can include adult training programs or school feeding programs that seek to foster income generating activities and develop human capital. Acknowledging the separate and distinct causes and factors of chronic and transient poverty can lead to the design of more effective programs to reduce total poverty.

1.2 Problem Statement

Households who are poor today may not be the same as those households that are poor in the future, as external shocks move households in and out of poverty. An analysis of the impact of common shocks on poverty rates is essential to distinguish between the two components of total poverty: chronic poverty and transient poverty. Thus, addressing the persistently high poverty rates in Mozambique requires the identification of poverty's causes, such as low assets, household characteristics, and exposure to negative covariate and idiosyncratic shocks.

Social assistance programs can to be tailored to address the unique needs of the chronic and transient poor by distinguishing households in each group and identifying variables strongly correlated with the groups.

1.3 Objectives

The objective of this study is to identify distinct variables and conditions which are related to chronic poverty and to transient poverty.

Sub-objectives include:

1. To predict the change in Mozambican household food expenditures (per person per day) due to the assets and conditions of the household and to exposure to common negative events.
2. To categorize households as the chronic poor, transient poor with exposure to negative shocks, and non-poor by comparing predicted food expenditures to national food poverty lines.
3. To select potential targeting indicators based on strong correlations between indicators and household status as chronically or transiently poor under sub-objective 2. Potential indicators should be easily collected through a household screening questionnaire and readily verifiable.

1.4 Hypotheses

There are two main hypotheses tested in the model. The first is that households' characteristics are highly correlated with households' food expenditure levels. Second, we hypothesize external shocks have a significant, negative impact on household food expenditure and that the impact on food expenditures is likely to vary across shocks.

The major maintained hypothesis of the model is that household well-being is accurately determined using household's food expenditures per person per day. We assume that households who do not have food expenditures sufficient to purchase enough food to meet minimum daily caloric recommendations, through food purchases or home production, are food insecure and at a lower level of well-being than households who are able to afford this basket of foods. Similarly, we assume households unable to consume minimum levels of basic food calories are poor and have a lower level of well-being and should be targeted by social assistance programs.

1.5 Summary of Procedures

The main purpose of this paper is to identify specific variables which are highly correlated with chronic and transient poverty in Mozambique and can be realistically applied as targeting criteria for poverty interventions. We develop an ex-ante approach to identify households likely to become poor based upon exposure to common household shocks by structurally determining the impact of shocks on food expenditures. Transient poverty suggests a temporary movement into poverty and ideally is identified using panel data. However, due to the unavailability of panel data, the model presented in this paper uses cross-sectional data from Mozambique's 2008/09 Household Budget Survey (IOF) to predict household well-being in the face of common shocks (NIS 2009). Estimates of food expenditures assess the household's ability to meet their basic needs and are based on observed household characteristics and exposure to specific, arguably endogenous, shocks. Household food expenditures are estimated using the endogenous treatment effects (ETE) model and poverty classifications are made based upon comparisons to a national food poverty line. Households whose food expenditures are estimated to fall below the food poverty line on average based on food expenditure levels in the absence of shocks are considered to be chronically poor. Households whose food expenditures are estimated to fall below the food poverty line only with exposure to shocks are defined as the transient poor. Using the households' poverty classification obtained in the ETE model, a multinomial logit regression (MNL) model is developed to predict the probability of a household falling into each of the three poverty groups. Variables from the MNL model are drawn from the current poverty literature on Mozambique and the results of the treatment equation in the ETE model. Further, the variables are easily identifiable and verifiable, allowing them to be used as targeting criteria for poverty interventions.

1.6 Organization of Thesis

The reminder of the paper is organized as follows. Chapter two provides a brief background on Mozambique's post-war economic growth and the individual characteristics and factors underlying poverty in Mozambique. The conceptual framework is established in chapter four and chapter five develops the model specification and empirical analysis. Chapter six presents the results of the analyses and discusses their implications. Chapter seven summaries the results and how they can be used to guide program targeting and social assistance policy decisions. In addition, chapter seven will note the limitations of the methodology and highlight key areas for future research.

Chapter 2: An Overview of Poverty in Mozambique and Poverty's Influential Factors

2.1 Mozambique's Post-war Economic Growth

Countries in Sub-Saharan Africa persistently have the highest poverty rates globally, and Mozambique is no exception. Three centuries of low investments in economic, social, and human development under Portuguese colonial rule ended in 1975 (Simler *et al* 2004). Just two years later, a 16 year civil war began and Mozambique's scarce infrastructure, schools, and health posts were destroyed. When a ceasefire was declared in 1992, Mozambique was in a dismal state. Since then, however, the country has sustained impressive aggregate economic growth. Over the past decade Mozambique's GDP has increased by an average of 9% annually (CIA 2010). Gains in GDP can be attributed to Mozambique's commitment to rebuilding a demolished infrastructure and shifting to a more open, market-oriented economy (Simler *et al* 2004). The new government also focused on expanding investment and expertise in export agriculture, land tenure reforms, and privatization of state farms and industries (Eriksen and Silva 2009). Post-war Mozambique has also sought to improve living standards universally, strengthen the economic conditions of the underprivileged, and improve social safety nets for its poorest citizens (Simler *et al* 2004).

However, Mozambique's GDP per capita (PPP) is one of the world's lowest at $900 and 54% of the population remains below the poverty line (CIA 2010). Poverty rates also reveal large regional discrepancies, ranging from 36.1% in Sofala to 80.7% in Inhambane (WB 2010). With such a high percentage of Mozambique's population facing economic hardship, clear identification of those who are currently poor, or at risk of becoming poor, is necessary. Understanding household vulnerability to poverty is particularly important in Mozambique, given the high frequency of exposure to covariate shocks (flooding, droughts, and cyclones) which persistently disrupt household consumption levels. In addition, exposure to idiosyncratic shocks, such as job loss and illness, generate hardship for individual households. These external events can prevent poor households from escaping the poverty trap as assets are depleted and household resources are taken away from long-term investments, like education, in order to meet immediate needs. For the same reasons, non-poor households can be pushed below the poverty line and increase the number of individuals needing assistance. Information on unique determinants of household well-being, particularly after experiencing adverse shocks, will allow social assistance programs to better target interventions to address the distinct needs of chronic and temporarily poor households.

2.2 Urban and Rural Poverty and the Role of Agriculture

Historically, most research has concluded poverty levels are higher in rural areas and traditionally aid efforts have focused on rural areas (Garrett and Ruel 1999). However, in Garrett's and Ruel's (1999) research using 1997/98 IAF survey data for Mozambique, food insecurity was found to be higher in urban areas than rural. As urban households are becoming a larger proportion of the total poor and internal migrants overwhelm cities' resources and strain their ability to provide public services, urban poverty is receiving increasing attention. Rapid urbanization in recent years has increased donor and government spending for poverty reduction efforts in urban areas (Garrett and Ruel 1999).

The concept of poverty has grown to encompass a host of criteria defining well-being beyond monetary levels. Access to quality education, health services, information, and transportation are also components of household poverty. This holistic evaluation of well-being often favors urban households as public services are generally more concentrated in urban areas. In Mozambique's most recent poverty assessment, indicators of access to education, measured by net enrollment rates, were higher among urban households[1] (MPD 2010). Health indicators were also better in urban areas. For example, a higher percent of mothers receive pre-natal care and rates of chronic malnutrition and underweight infants are lower in urban areas (MPD 2010; Garrett and Ruel 1999). Further, over 50% of urban households are estimated to have access to a source of potable water compared to approximately 30% of rural households (MPD 2010). An example at the provincial level, is Nampula where 1.6% of rural households have a bathroom or toilet inside of the household, while 18.3% of urban households have these facilities (MPD 2010). Also, the number of goods owned by a household (i.e.: bicycles, televisions, radios, refrigerators) are higher for city dwellers. In conclusion, access to public services is heavily concentrated in urban areas, raising the living standards for cities' residents.

Market infrastructure is also more developed in urban areas and urban households have access to more diverse employment opportunities than rural households. However, when considering self-reported employment figures in the IOF 2008/09 data, 25% of urban households surveyed reported at least one adult member unemployed in the last week while less than 3% of rural households surveyed reported any adult member unemployed[2]. The difference in the statistics likely stems from the urban households' reliance on labor as their most important asset. Steady, well-paying jobs in the formal sector are difficult to come by, particularly for rural migrants, and many rely heavily on employment in the informal sector (Ruel *et al* 1998). Insecure job tenure and variable wages leave urban households struggling to maintain steady consumption levels which meet the household's basic needs (Ruel *et al* 1998).

Dependence upon wage employment for income, rather than agricultural production, underlines a key difference between urban and rural households. Arndt (2008) notes the

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[1] Statistics in Mozambique's Third Poverty Assessment are generated from IOF 2008/09 data.
[2] Unemployment figures are generated from IOF 2008/09 data and do not included seasonal or discouraged workers.

importance of household production in determining the impact of increases in food prices on Mozambique's urban and rural poor. In Mozambique, urban households purchase around 75% of their food while only 19% of food is purchased by rural households. Further, Arndt estimates 73.7% of rural households in the Northern and Central provinces are net sellers, and may therefore benefit from a hike in price of their crop. In contrast, only 14.6% of households in the urban South are net sellers. Households who are net-sellers may be able to increase home consumption or marketable surplus to offset or benefit from higher food prices. Urban households have limited potential to increase own consumption or offset losses through increased sales of home production. Due to their reliance upon purchased food, urban households (net food buyers) were hit hard by these unavoidable and dramatic increases in food expenditures in the last few years.

While the vast majority of rural Mozambican households cultivate some land, farm households are not always able to increase productivity in response to a shock. While global food productivity has significantly increased over the last 40 years, in Sub-Saharan Africa cereal yields have stagnated around one tonne per ha (Jayne *et al* 2010). Current production systems in Mozambique are labor intensive and current farming methods have low levels of productivity (Heltberg 2002). Constraints to small landholders' productivity can include limited or costly inputs, such as water, fertilizer, and livestock for draught power (Jayne *et al* 2010). Further, Jayne *et al* (2002) document declining farm sizes in Sub-Saharan Africa over time, even in land abundant Mozambique. Of the 3.9 million hectares of arable land in Mozambique, only 10% is in use (FAO 2007). However, tracts of available, arable land are often far away from markets and have extremely limited access to services (Jayne *et al* 2010). Thus, even with arable land still unplowed, the productivity of rural households is limited by inadequate access to profitable land and unavailable or costly inputs.

Heltberg and Tarp (2002) note the constraints on small landholders' ability to adjust production during times of high prices. For small farmers who may be able to increase production, market participation is limited by risky environments and high transaction costs. Poor social and physical infrastructure in rural areas has led to widespread market segmentation and removal of a significant portion of the rural poor from major food markets. Even in times of national shortage, small producers may sell produce for minimal prices as demand is met in the local market and traders selling to outside markets come infrequently (Eriksen and Silva 2009). Rural farmers are forced to accept traders' low prices as they do not know when another trader will come or the prevailing prices in larger, unfamiliar markets. In order to capitalize on regional shortfalls in supply, farm households must overcome a limited ability to increase production, underdeveloped markets, and asymmetrical information on prevailing prices and demand in outside markets.

The current structure of small farmer production has long-term consequences as well. Jayne *et al* (2010) conclude agricultural growth is necessary for non-agricultural activities with higher returns to develop. Low levels of productivity can tie labor and capital into the farm and prevent investment in human capital and non-farm activities with higher returns. In the absence of alternative employment opportunities with higher returns, labor productivity stagnates and the benefits of investing in education are minimal. As a result, rural households and communities can become stuck in a state of perpetual poverty, limited in their capacity to diversify income through off-farm employment. Further, without economic diversification in the community, there is little opportunity for households to temporarily smooth consumption though alternative labor employment in the face of external shocks. The next section will expand upon the impact of specific shocks on household poverty in Mozambique.

2.3 Impact of Specific Shocks on Poverty

External shocks to the household can be classified as covariate shocks, shocks whose probability of occurrence is correlated between households. However, the impact on the household after experiencing a climatic shock is likely to vary based upon the individual assets and conditions of the household. Exposure to idiosyncratic shocks, such as illness and theft, are more likely to be related to aspects specific to the household and the probability of exposure is uncorrelated between households. Covariate and idiosyncratic shocks exacerbate the magnitude of existing food insecurity and poverty in Mozambique. Climatic, agricultural, and health related shocks can cause a surge in the numbers of those needing aid as vulnerable populations are pushed into food insecurity and poverty. Continual exposure to shocks strains the ability of poor and vulnerable households to maintain adequate consumption levels and buffer against future shocks. The determinants of exposure, the impact of the shock, and the available coping mechanisms vary by shock. In this section, the major covariate shocks (drought, floods, cyclones, and agricultural pests) and idiosyncratic shocks (illness and death) affecting Mozambicans are discussed.

2.3.1 Droughts, Floods, and Cyclones

Mozambique is frequently exposed to natural disasters and a 2007 FAO report labeled 20 of the 128 districts as “highly prone to drought”, 30 to flooding, and 7 to both (FAO 2007). Recurring climatic shocks prevent households from rising above the poverty line and require annual assistance in order for households to meet their basic needs (FAO and WFP 2010). The number of households affected by natural disasters is persistently high in Mozambique. In 2007, 324,000 ha of crops were lost and 309,000 agricultural families were affected by droughts, floods and cyclones (SETSAN 2008).

Similar to other Sub-Saharan countries, drought is a persistent threat to the livelihood of Mozambicans, especially in the Central and Southern provinces. A 2010 FAO/WFP Crop and Food Supply Assessment Mission cited drought as the most frequently reported shock in Mozambique, affecting three-fourths of the sample communities and 90% of sample households (FAO and WFP 2010). In some cases, the impact of the drought is lessened for households in drought-affect areas with good access to markets and multiple, informal sources of income (VAC 2003). Access to markets and alternative means of employment suggest households have a broader range of potential coping mechanisms. Farm households who are able to increase production can benefit from higher prices resulting from constricted supply. Further, households in diversified markets may be able to shift into additional or alternative income generating-activities to mitigate production losses from the drought. Eriksen and Silva (2009) studied the changes in Mozambican households' coping mechanisms over three years of drought. In the first year, households' time is shifted towards selling firewood, charcoal, and handicrafts in local markets as farm production levels are reduced. However, with subsequent years of low rainfall, local markets dry up and the number of viable coping mechanisms become fewer as households are unable to find buyers for their products. In the second and third year, casual employment for low pay replaced time spent in the farm production, guaranteeing only a subsistence living. Indeed, with repeated years of drought, households often sell the few assets they have, such as livestock, poultry, and farm instruments. By divesting themselves of these productive assets, households limit their ability to increase production in the future. In extreme cases of drought, assets can be completely abandoned as households move to areas with a better water supply (SETSAN 2008).

Floods and cyclones are also recurring annual events. In the 2000 floods, 550,000 people were relocated; in the 2007 floods 140,000 people were displaced; and 120,000 people were left homeless due to Cyclone Favio in Februrary 2007 (WFP 2007, Ericksen and Silva 2009). As a result of floods and cyclones, infrastructure is damaged, crops are destroyed, irrigation systems are swept away, and local food security is disrupted. Further, huge accommodation camps must be constructed for evacuees and poor living conditions in the camps heighten households' vulnerability. Concerns of inadequate shelter and food are in addition to needs of police to maintain camp safety, teachers to conduct classes for the camp's children, and health staff to control the spread of malaria, diarrhea, and fever as well as provide HIV/AID prevention programs (WFP 2007). Flood victims must then be resettled away from fertile flood plains or return to flood-prone areas. Often resettled households are relocated to areas with lower soil fertility, shortening or limiting the number of growing periods and reducing yields. Along with the costs associated with moving homes and farms, resettlement can disrupt social networks which provide informal insurance. However, returning to flood-prone areas increases the likelihood of cyclical exposure and continued asset depletion. Either case can further diminish current and future household asset levels. Many input transfer programs are implemented in response to floods and cyclones seeking to rebuild households' depleted physical assets (Hodges and Pellerano 2010). For government and donor programs, financing the continual evacuation and resettlement is also extremely costly. Due to Mozambique's high degree of exposure to climatic shocks, effective targeting of vulnerable households is necessary to prevent resulting transient poverty and to maximize inclusion of the neediest households.

2.3.2 Agricultural Pests

Agricultural pests affect farm households in all regions and have a direct impact on producer yield. Major pests affecting Mozambique include brown streak disease and mealy bug for cassava, downy mildew for maize, yellowing disease for coconut, and oidium for cashews (FAO and WFP 2005). Red locusts (grasshoppers) are also a major problem in Mozambique, particularly in the Buzi river region (SETSAN 2008). There is a climatic component determining exposure to pests and often pest outbreaks are correlated with rainfall. Chiconela *et al* (2003) analyzed 33 years of red locust outbreaks and rainfall. The author found the lower the dry season rainfall and the longer it persisted, the higher the probability of an outbreak. While rainfall is out of producers' hands, the likelihood of pest outbreaks also depends upon their access to irrigation systems, fertilizers, insecticides, fungicides, and clean storage facilities (FAO and WFP 2010). However, poor households are often unable or unaware of how to implement these preventative measures. The pest management methods which are available to poor households often reduce the yield and quality of the crop. For example, to avoid brown streak disease, cassava is prematurely harvested, resulting in lower yields (FAO and WFP 2005). To avoid rot, tubers may also be harvested earlier. In one case, in areas where premature harvesting practices were implemented, estimated tuber yields fell from an average of 14-18 tonnes per ha to just 6 tonnes per ha (FAO and WFP 2005). For households struggling to meet their basic needs, a one-half to two-thirds reduction in yield is devastating. Wild animals also pose a significant threat to household yields as they invade fields, eating or trampling crops yet to be harvested. Scaring away elephants, wild pigs, monkeys, and birds is a task often assigned to children members and can represent a significant portion of the households' total labor hours (FAO and WFP 2005). After harvest, pest infestation can be a problem. During storage, up to

40% of community food store loses were attributed to rats and weevils in a 2005 Crop and Food Supply Assessment (FAO and WFP 2005). The large grain borer also seriously reduces food stores (FAO and WFP 2005). Enabling small landholder's access to preventative measures against agricultural pests during all stages of production is vital to improve food security conditions in Mozambique.

2.3.3 Health Shocks

Unlike the climatic and agricultural events listed above, illness is not strongly regional specific and is wide-spread throughout Mozambique. Life expectancy at birth for Mozambique is low by international standards. The average Mozambican is expected to live 51 years, but after adjusting for time spent in good health the average healthy life expectancy is just 42 years (WHO 2010). While demand for formal health services is limited by household finances and reliance on traditional healers, inadequate access to health services is generally considered a supply-side issue (Hodges and Pellerano 2010). Health services in Mozambique have too few facilities, staff, and vaccines. Between the 1996/97 and 2002/03 IOF surveys, access to a health post or center in rural areas decreased in five out of ten provinces, access to a physician or health care technician decreased in four provinces, and the average number of residents per health service unit increased in seven provinces (PARPA II, 2006). Limited resource and information availability are particularly detrimental to the poor; especially in remote areas where access to health services and information are generally lower already (PARPA, 2005).

Mozambique's Action Plan for the Reduction of Absolute Poverty for 2006 – 2009 (PARPA II) specifically cites HIV/AIDS, tuberculosis (TB), and malaria as major diseases threatening human capital development in Mozambique (PARPA II 2006). The heavy impact of TB, malaria, and HIV/AIDS is obvious in the latest statistics estimated by the World Health

Organization (WHO 2010). Deaths due to these diseases are high. Per 100,000 people, HIV kills 379 people, malaria 92, and TB 31. Another major health issue is malaria, considered to be endemic to Mozambique. In 2008, there were 4,831,491 reported cases of malaria in Mozambique. In 2002, 9% of total deaths and 19% of children deaths (age five and younger) were ascribed to malaria. Despite malaria's high mortality rate for children, only 7% of children age five and younger under have insecticide-treated bed nets and only 23% of children with a fever received anti-malarial treatment. However, the burden of TB and malaria is far below the heavy cost of HIV and AIDS in the country. HIV and AIDS plague Sub-Saharan Africa and Mozambique is no different. PARPA II (2006) calls HIV and AIDS a "national emergency" affecting all strata of the population. HIV infection rates of persons aged 15 – 49 are up from 8.6% in 2000 to 11.4% in 2008. Similar to other Sub-Saharan countries, HIV is consistently the top cause of death in Mozambique. In 2002, 28% of all deaths and 13% of deaths for children under five are attributable to HIV and AIDS. With such a large percent of the population afflicted with HIV, scarce resources are spread thin and funding for HIV and AIDS is often included as a cross-sectoral issue in other social assistance programs in Mozambique.

In addition to loss of life due to illness, financial costs of lost earnings, treatment, and transportation can be substantial. Unfortunately, the poor suffer larger losses due to illness as medical expenses compose a larger proportion of their income. For example, Nyirenda's (2006) study estimated the total direct costs of TB treatment at US$11 and that one-third of costs arise from transportation and half from fees and drugs. Castillo-Riquelme *et al* (2008) surveyed 828 households in Mozambique (and 827 in South Africa) to estimate the negative effects of malaria on households. In Mozambique, out-of-pocket expenditures cost households $6.50 per episode, or approximately 17% of household income. Reported expenditures for malaria treatment also had a broad range. Some households faced much higher costs with catastrophic losses (costs greater than 10% of monthly household income) occurring in 32.6% of households surveyed. Additional indirect costs can be incurred as labor hours are reduced. The average duration of the illness was less than a week (average of 5.8 days). Further, over half of adults surveyed took time off of work (for an average of 3.4 days) and required an additional 2.7 days of care on average. Needham *et al* (1998) conducted a survey of 202 TB patients in Zambia and reported that 31% of patients stopped work due to TB and the average amount of days off was 48 days. As with the previous shocks discussed, the direct and indirect cost of the disease can be substantial as households reallocate resources towards treatment and decrease working labor hours.

In conclusion, the impact of covariate and idiosyncratic shocks on household well-being is a significant component of poverty analysis in Mozambique. Existing social assistance programs which look to mitigate the impacts of the shocks mentioned above as well as efforts addressing chronic poverty are discussed in the next section.

2.4 Current Poverty Interventions in Mozambique

Poverty reduction interventions in Mozambique are organized under multiple government entities and large and small scale international donors. Within the government's ministries, the Ministry of Women and Social Action run many of the government's large scale programs, such as the Food Subsidy Program. The Ministry of Health and the Ministry of Education and Culture also have large social assistance programs, such as the Nutritional Support Program and the School Feeding Program, respectively. Most of these large national programs are run with financial and technical support from international donors including UNICEF, WFP, the World Bank, the Clinton Foundation, and foreign development aid, such as the United Kingdom's

DFID and the Netherlands' RNE. There is a growing recognition of the need to unite parties seeking the same objectives and to structure efforts within the governmental framework developed in PARPA II (Waterhouse 2007). The Mozambican government is increasingly taking leadership in joint efforts with international donors, and is thus moving social assistance programs closer to the goal of being fully supported by Mozambique's technical and financial resources.

Programs targeting chronic poverty provide assistance to households with the intent to allow them to meet a minimum level of basic needs. The government's largest transfer program, the Food Subsidy Program (PSA), works closely with RNE, DFID, the International Labor Organization and UNICEF. When the PSA began in 1990 its original mission was to assist urban poor households in Mozambique (Low 1999). In 1998, the program expanded to include smaller urban centers and in recent years has begun to include rural areas (Low 1999). While the PSA covers less than 2% of Mozambicans, it has the most beneficiaries of any government program (Pellerano 2010). However, monthly PSA cash transfers account for just 4% of minimum wage rather than the stated goal of 30% (Shendy *et al* 2009). Transfers are targeted towards those unable to work or unable to be self-supporting, such as the elderly and households headed by the disabled or chronically ill. A maximum earned monthly income level is set as an additional criterion for eligibility.

There is also a concern about the categorical targeting methods used by the program. While the elderly receive 92% of all transfers, recent analysis of the PSA program did not find clear evidence that the number of elderly in a household is correlated with low levels of food consumption (Shendy *et al* 2009). An expansion of the PSA program is being considered and there is much debate as to whether the program should continue to target those unable to become self-sustaining or expand to include vulnerable households as well (Pellerano 2010). A recent study by Hodges and Pellerano (2010) suggests improved economic targeting of households and improved categorical targeting methods to support both permanently dependent and vulnerable households most in need. The National Institute of Social Action and foreign partners are examining these concerns along with evaluating potential improvements in monitoring, distribution efficiency, cost reductions, and increasing the value of subsidies (Ellis, 2007).

Reducing chronic poverty through increased educational attainment is a long standing criterion of Mozambique's PARPA and international donors. The World Food Programme (WFP) first began the SFP in 1998 to develop Mozambique's human capital with the dual goals of improving school attendance and vulnerable children's nutritional status. The 2009 WFP's Country Programme Mid-term Evaluation estimates more than 300,000 pupils have been targeted by the SFP (WFP 2009). However, the WFP report also notes interventions are scattered, resulting in increased costs and ineffective targeting of those most in need. Currently, the WFP is aiding in the construction of a national school feeding program to be run within the national policy framework through Mozambique's Strategic Plan for Education and Culture. However, progress has been slow and resistance to developing a national strategy for school feeding is attributed to the inability to develop a simple, cost-effective, replicable model. Nevertheless, gains in other legislation strengthening educational access have been realized. In 2004, Mozambique achieved free public primary education and eliminated textbook fees for primary schools (Hodges and Pellerano 2010). Removing primary level textbook costs and tuition fees is a significant step towards addressing the financial barriers of enrollment. However, educational costs, such as transportation and uniform costs or the opportunity cost of lost labor, are still prohibitive for poor households (Hodges and Pellerano 2010). At the same time, the goals of increased school attendance and improved nutritional status for children, mothers, and orphans and vulnerable children are progressing out of the realm of foreign aid and into an area of governmental responsibility.

Another area of social assistance programs focuses on the short and long term impacts of illness and disease. Programs directly targeting health issues focus heavily on increasing access and availability to health services, particularly for poor and vulnerable households. Reduced health fees for government health care services are provided to poor Mozambicans and free service is provided for some illnesses and groups (Hodges and Pellerano 2010) [3]. In order to receive free treatment based on income, a lengthy process is required to obtain a poverty voucher and often costs more than the health fees (Hodges and Pellerano 2010). However, due to the wide-spread incidence of illness, many parties are urging a removal of all health fees (Hodges and Pellarno 2010).

The Ministry of Health's programs highlight the government's focus on women and children as vulnerable groups. Out of the MOH's nine thematic areas for their health programs, five deal specifically with children and women's health issues. The MOH has also developed large scale programs addressing vulnerability and treatment of specific diseases, such as The Roll Back Malaria in Mozambique program and the National Response to TB (WHO 2010). HIV and AIDS is the most prominent health risk in Mozambique and the National Council for the Fight Against AIDS (CNSC) is officially in charge of HIV and AIDS programs. However, as HIV and AIDS are deeply interwoven with social issues such as poverty, gender inequality, educational attainment, agriculture, etc. and missions of other ministries and initiatives overlap those of the

[3] Specifically: maternal health services, children under five, war veterans, blood donors, disabled persons unable to work, retired persons and pensioners, domestic servants, the unemployed, people with no means of subsistence, and those with tuberculosis, leprosy, trypanosomiasis (sleeping sickness), chronic psychological disorders, and HIV/AIDS (CITE)

CNSC (Waterhouse 2009). Improving access to and quality of public health services is vital to help break the continuation of existing poverty and the prevention of poverty in the future.

Natural disasters and emergency situations can increase the depth and severity of poverty as well as increase the number of poor as vulnerable households fall into a state of poverty. Input transfers and Food-for-Work (FFW) programs are often initiated in response to an emergency to mitigate the long-term impact of natural disasters (Hodges and Pellerano 2010). FFW programs are funded by national and international programs attempting to provide short term employment opportunities, strengthen community infrastructure, and improve access to markets (Hodges and Pellerano 2010). Input transfers aim to stabilize productivity levels for farm households which have lost productive assets. Programs transferring inputs often employ community-based targeting methods in disaster affected areas and for households which have low food reserves and resource levels, but are still able to produce (Hodges and Pellerano 2010). The Vulnerability Analysis Committee of Mozambique analyzed household level survey data to assess the impact of the 2003 drought on food security and nutrition (VAC 2003). While 63% of households lived in areas with drought mitigation programs, only 44% of households surveyed were reached by the programs. FFW was the largest mitigation program, reaching 39% of households surveyed. Input transfers of seeds, tools, livestock, cash, and irrigation equipment were distributed to 5% of affected households. While mitigation programs, such as FFW and input transfers, help alleviate the impact of natural disasters, a large number of affected households are continually left out of these programs (Hodges and Pellerano 2010). Combining the efforts of multiple emergency relief actors could increase the efficiency, and the scale, of disaster mitigation programs.

In emergency situations, Mozambique is increasing its leadership role by bringing government entities and foreign partners together in joint response efforts. The Cluster

Approach supports the Inter-Agency Contingency Plan of Mozambique and delegates individually lead or co-lead responsibilities (such as Logistics, Shelter, Water and Sanitation, etc) between governmental and international organizations (UNICEF 2007). Current cluster members include the government, WHO, WFP, FAO, CARE, World Relief and the Mozambican Red Cross (UNICEF 2007). The collaboration of government and non-government entities can help facilitate timely responses which are organized with the most up-to-date information available. Mozambique is rapidly gaining experience in combining the comparative advantages of each organization to streamline emergency response efforts (Foley 2007).

Mozambique is committed to alleviating chronic and transient poverty through effective targeting and implementation of social assistance programs. But social assistance programs have poor targeting and monitoring procedures, complex registration, and limited budgets (Shendy *et al* 2009). Further, negative incentives and moral hazards increase the leakage and under-coverage in many programs. Without thorough analysis to identify and regulate enrollment requirements, scarce resources can be wasted. Particularly in relation to transient poverty resulting from natural disasters, there is a lack of data analyzing the magnitude and frequency of climatic shocks and their impact on household poverty (Shendy *et al* 2009). Social assistance programs can greatly increase their impact with an accurate, ex-ante identification of who is in need, where they are, and how much assistance is required. While progress is being made, increased efficiency in targeting methods for both governmental and multinational programs is needed to significantly increase food security in Mozambique.

Current research addresses the gap in knowledge for effective targeting methods for SPPs in Mozambique by identifying and developing targeting indicators for chronically poor households and households who become poor with exposure to a shock. The following chapter develops a conceptual framework for the model, based upon recent research on household poverty and vulnerability.

Chapter 3: Theoretical Framework

3.1 Introduction

In this chapter the following questions are discussed. First, how do we define and quantify poverty? Second, how do we identify poor households? Lastly, how can we predict which households are likely to be poor? To answer these questions, this chapter provides a brief review of previous research on identifying poor and vulnerable households. However, the literature reveals gaps in current practices with respect distinguishing between chronic and transient poverty and establishing a method to quantify the impact of specific shocks on household well-being and structurally determine the underlying determinants of exposure. Therefore, this study attempts to directly measure the impact of negative shocks on food expenditures of the chronically poor as well as on households who become poor with exposure to shocks and the conditions which increase the likelihood of exposure. Due the use of cross-sectional data for this analysis, the definition of chronic and transient poverty in this paper diverges from those in the poverty reduction literature. In the analysis, the *chronic poor are defined as households whose food expenditures are expected to fall below the national food poverty line in the absence of a shock*. *Transient poor are defined as households whose food expenditures are expected to fall below the national food poverty line with exposure to a shock or shocks*. Vulnerable households are essentially synonymous with transient poor households by referring to households who have a high risk of falling below the poverty line in the future.

3.2 Estimating Household Poverty Levels

The concept of poverty is strongly related to household well-being. As household well-being is not directly measureable and comparable between households, a proxy for well-being is required. Proxies for household well-being can include food and non-food expenditures, income, or composite indices. In this analysis, non-food items are excluded from household expenditures, as verifying and determining the value of durable items can be an inaccurate, subjective process and may lead to misleading estimates of poverty. The use of composite indices faces similar concerns of subjectivity in selecting key indicators of well-being and difficulty in verifying a broad range of household indicators. Income was rejected as it is difficult to measure and verify, particularly in developing countries, and can vary drastically over a short period of time (Sharif 2009). Further, income fluctuations may not mirror the occurrence and magnitude of changes in household consumption as savings, transfers, and other coping mechanism are employed to smooth household expenditures during periods of minimal income. On the other hand, food expenditures are considered to 1) be a fairly objective measure of well-being, 2) more accurately reflect actual household consumption and 3) be straight-forward to measure with good survey data. In conclusion, food expenditures accurately assess a household's ability to meet their basic needs and are selected over other proxies for household well-being.

3.3 The Components of Poverty: Chronic and Transient Poverty

Poverty is dynamic and households move in and out of poverty due to both internal and external changes. Recent research seeks to understand the relative shares of chronic and transient poverty in composing total poverty. In Ethiopia, Dercon and Krishnan (2000) estimate rural poverty rates with short panel data collected in three surveys from 1994 to 1995[4]. Even with a fairly short amount of time between surveys, there are significant changes in the composition of total poverty. In the first and third round, 75% of total poverty is composed of the chronic poor. However, in the second round, 90% of the poor are chronically poor. The authors conclude that with significant movement of households in and out of poverty, current poverty estimates cannot capture households vulnerable to future poverty. In rural China, Jalan

[4] Dercon and Krishnan use Jalan and Ravaliion's definition of poverty, see below.

and Ravallion (1996) analyze panel data from 1985 to 1990 and see similar fluctuations in poverty rates[5]. Only 6.21% of households are poor at all dates and 33.38% have a mean consumption above the poverty line, but are sometimes poor. Further, transient poverty not only increases the poverty head count, but also accounts for half of the depth of poverty. Thus, in order to predict future fluctuations in poverty rates, a distinction must be made between transient poverty and chronic poverty.

Poor households are a heterogeneous group and the causes and factors of poverty are diverse, particularly between the chronic and transient poor. Jalan and Ravallion's (1996) study in China takes a set of household and community variables and compares their ability to explain transient and chronic poverty. While some factors influence both transient and chronic poverty, such as the life-cycle stage of the household and command over physical capital, the impact of most other variables differ between transient and chronic poverty, such as variability in wealth and household education levels. In fact, the authors note agricultural technologies which are predicted to reduce chronic poverty figures may actually increase exposure to risk for the rural poor. Nega's (2010) study on rural poverty in Ethiopia focuses on the impact of two poverty reduction programs: Food-for-Work (FFW) and Food Security Package (FSP). The authors' findings conclude that the FSP reduces total and chronic poverty. Yet the FFW program has no impact on total, chronic, and transient poverty and in fact benefits better-off households. Chaudhari *et al*'s (2002) results on vulnerability in Indonesia conclude the determinants of vulnerability vary between sub-grouping of the population. For example, vulnerability for rural, uneducated households is influenced by low mean consumption levels. For urban, more educated households, vulnerability is due to consumption volatility. These studies suggest that

[5] It should be noted that Jalan and Ravallion defined the chronic poor as those whose mean consumption over time is below the poverty line. Transient poverty is defined as the households who are poor in at least one observation and whose standard of living varies over time. These definitions diverge from those employed in this paper.

interventions which are based solely upon the characteristics of currently poor households will be inadequate in terms of poverty prevention, as they do not target the unique causes and characteristics of transient poverty.

3.4 Identifying the Chronic Poor

Social assistance programs in developing countries aim to maximize coverage of the neediest households with minimal funding. Thus, governments look for methods which distribute transfers while minimizing leakage (households receiving benefits who are not eligible) and under-coverage (households who are eligible for benefits not receiving a transfer). The targeting method selected depends upon the number of potential beneficiaries, data collection requirements, and the cost of implementation. As national Living Standards Measurement Surveys are more prevalent in developing countries, it is becoming more feasible to utilize assessment targeting methods that primarily rely on household-level data to generate classifications of household well-being. A common example of an individual assessment method is the proxy means testing (PMT). In PMT, a regression is run for select variables on household expenditures (or income) and the estimated coefficients are used to assign weights to each variable. The sum of the weights is used to classify households into poverty levels by comparing predicted household expenditures to established thresholds (Ahmen and Bouis 2002). Attractive features of proxy means tests include 1) a transparent process in guiding transfers; 2) an established, objective criterion in selecting beneficiaries; and 3) a reduction in elite capture (Sharif 2009).

Another individual assessment is means testing, which collects income or expenditure data for households. While mean testing has a high degree of accuracy in targeting desired beneficiaries, it is a costly process requiring the collection and verification of individual household expenditure and or income data (Castaneda 2005). When targeting a large percent of the population, as is often the case with governmental social assistance programs, means testing may not be the most effective and cost efficient targeting method.

However, there are noted drawbacks to the individual targeting methods. Cross-sectional data is frequently used and thus poverty estimates only consider current levels of consumption. As such, they are most accurately used to identify the chronic poor and do not identify vulnerable households (Castaneda 2005). Thus, individual targeting methods, such as PMT and means testing, may be best for estimating expected chronic poverty.

3.5 Identifying the Transient Poor

Future poverty is often the result of exposure to a shock which negatively impacts food expenditures. The nature of the shock can help determine the level of household risk of become poor based upon exposure to a shock. Idiosyncratic shocks, such as illness and death, are thought to be more specific to the household. Covariate shocks are generally regionally and spatially correlated, with natural disasters being the most common examples. The role of natural disasters in maintaining the cycle of poverty or adding to the number of the impoverished in both the long and short term is established in chapter two. However, the determinants of exposure and vulnerability to the consequences of natural disasters remain an area for research. Certainly the occurrence of climatic, covariate shocks cannot be directly controlled by the household. However, neither can vulnerability be solely attributed to ‘technical’ or geographic considerations, such as living in a flood plain or rainfall data. For example, when two households live in a flooded area, we cannot assume the flood will impact the two households equally. Factors such as education levels, employment, the number of working and dependent members, or the amount of physical assets held by the household may cause well-being to vary between the two households exposed to the flood. The same factors may also effect exposure to shocks, particularly when exposure is subjective. Recent studies confirm that household vulnerability is dependent upon factors which increase the likelihood of exposure as well as limit their ability to cope with the consequences (Devereux *et al* 2006, Doward and Kydd 2004, Devereux *et al* 2002).

The empirical measurement of vulnerability often focuses on determining the mean and variance of household consumption (or income) (Chrisiaensen and Subbarao 2005, Jalan and Ravallion 2000, Dercon and Krishnan 2000). This method is best when panel data is available, but numerous studies use cross-sectional data to estimate the probability of exposure and the degree of household vulnerability to shocks. Chaudhuri *et al* (2002) uses cross-sectional data to distinguish between chronically and transiently poor households. Chronically poor households are as those with an expected mean below the poverty lines. Estimates of the variance of consumption are then used to estimate the probability a household will become poor and identify transient poor households. Gunther and Harttgen (2008) also use cross-sectional data to analyze the level and source of vulnerability based upon expected mean and variance. However, Arun *et al* (2010) takes a straight-forward approach to examining vulnerability as the probability of poverty and exposure to shocks for households in Southern India. Using cross-sectional data, the authors developed a probit model to estimate households' exposure to covariate and idiosyncratic shocks dependent upon household and locality factors.

Datt and Hoogeveen (2000) regress the impact of shocks, household assets and characteristics, community characteristics, and social networks on household consumption. The authors account for potential endogeneity of the shocks by using instrumental variables in the model. Additionally, the authors use interaction terms with the shock variables to allow for the impact of shocks on consumption to vary across households with different characteristics and circumstances. In Zambia, del Ninno and Marini (2005) consider the correlations of household endowments and characteristics, community assets, death, unemployment, and drought with household consumption. In order to account for the potential endogeneity of a shock on household well-being, del Ninno and Marini (2005) also use instrumental variables for shock variables in a two stage least squares regression model. However, the authors note the difficulty in finding strong instrumental variables for drought, death, and unemployment at the household and community level. Del Ninno and Marini (2005) separately estimate the probability of a household experiencing a shock based upon household and community characteristics.

3.6 Summary

The above research identifies methods which determine chronic poverty and determine vulnerability. There has been much research determining the factors which influence chronic and transient poverty, as well as the differential poverty interventions needed for the two groups. Additionally, recent research has estimated the likelihood of becoming poor based upon a households' exposure to a shock. However, what is missing in the literature is a model which can bring these two concepts together and incorporate the probability of experiencing a shock in a model identifying the chronic poor and the transient poor. While Datt and Hoogeveen incorporate interaction variables to allow the impact of a shock to vary across households, they do not structurally estimate the probability of a household experiencing a shock. The endogenous treatment effects model presented in Chapter 5 allows household food expenditures to be a function of not only household characteristics, but the probability of a household being exposed to common shocks. To limit concerns of endogeneity, identifying restrictions are included in the treatment equation (discussed in more detail below). Thus, the endogenous treatment effects model can quantify the impact of a shock on household well-being. These results can be compared to an establish poverty threshold to classify households as chronic and transient poor. Based upon these classifications, a smaller set of variables can be selected which accurately predict households into each of these poverty groups. Chapter four next describes the data used in analysis.

Chapter 4: Data

4.1 Description of Data[6]

Specific household and community variables were constructed from Mozambique's Inquérito Sobre Orçamento Familiar (IOF) or Household Budget Survey. The IOF was a nation-wide survey administered by the Republic of Mozambique's Institute of National Statistics between June 2008 and August 2009 (NIS 2009). In the 2008/09 IOF survey, 10,832 household surveys were completed for 1,040 enumeration areas (EAs) in 144 districts in all ten provinces as well as the capital city, Maputo City. The selection of households was conducted in two stages. First, 40 enumeration areas were randomly selected in eight of the provinces. Due to their larger share of Mozambique's population, 80 EAs were selected in Nampula and Zambezia and 50 EAs were selected in Maputo City (Triebkorn *et al* 2010). Second, a systematic sample of households was drawn within the EAs (Triebkorn *et al* 2010). For each rural EA, nine houses were selected (with three additional houses in case an interview could not be conducted with the original nine selected). For urban areas, 12 households were selected with three additional households as reserves. The EAs are particularly important in our study, as they allow us to identify other households in the same local area as the enumerated household. A description of the variables used in the models is given in Table A.1. Table A.2 and Table A.3 provides summary statistics for the included variables.

4.1.1 Expenditure Data

As a proxy for household well-being, food expenditures per pepson per day (pppd) are calculated. Food expenditures are based upon IOF survey data, where households were asked to recall the price and quantity of food expenditures and auto-consumption. Ideally, analyses would also be run using caloric data to serve as a comparison. However, the quantity data on

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[6] The statistics presented in this section are calculated using population weights given in the IOF 08/09 survey data, unless otherwise stated. Stata command: [aweight = popwt].

food purchased suffers from measurement error and significant underreporting. Respondent recall for the amounts spent on food appears to be more accurate and consistent. By using food expenditures rather than calorie estimates, concerns of measurement error from inaccurate quantities reported by households are minimized.

Food expenditures are adjusted by a temporal price index to account for variation in prices between quarters of the survey period, with the fourth quarter equal to one. Six different temporal price indices were calculated for separate regional groupings. Food expenditures pppd average 15.85 meticais (MZN), with expenditures ranging from 0 MZN pppd to 1,215.31 MZN pppd. Converted to international dollars, average expenditures are $1.21 pppd and range from $0 to $93.06 pppd. However, half of the survey population spends 11.75 MZN or less on food pppd. In other words, over 50 percent of households are living on less than a dollar a day for their dietary needs. Food expenditures by percentiles can be reviewed in Table 1.

Food secure, non-poor households are defined as those with food expenditures above the national food poverty line required to meet minimum caloric requirements. The national poverty line was obtained by taking the average of the non-spatially adjusted regional food poverty lines. The average was then multiplied by the average food share (0.5851) to arrive at a national food poverty line, 10.76 MZN.

4.1.2 Data on Covariate and Idiosyncratic Shocks

In the IOF survey, respondents were asked if the household experienced any of 15 listed shocks in the last five years. They were also asked to rank the relevance of the shocks from primary to tertiary as well as how many months ago each shock occurred. Table 2 presents the responses for the 15 shocks in terms of the percentage that 1) reported the shock occurred the last five years, 2) reported the shock as primary, and 3) reported the shock occurred during the previous year. Considering the spike in food prices in 2008, it is not surprising that the high price of food was listed as the most significant shock overall. To focus upon shocks which affect poor households, agricultural epidemics, bankruptcy, death or theft of cattle, and loss of a salaried worker member were not considered in the model as few poor households are in the position to be exposed to these specific events. Shocks involving food prices were also not considered due to the requirement of extensive market and price data.

The focus of this paper is on the remaining shocks which are grouped into six binary variables for exposure: drought; flood and cyclones; agricultural pests; illness; death; and theft. The percent of households reporting exposure for these six shock categories are listed in Table 3. Since food expenditures were collected over a one week interview period, the model only considers shocks which were reported to have occurred in the year previous to the time of interview.

4.1.3 Household Control Variables

Control variables for household characteristics were taken from the IOF 2008/09 survey and summary statistics are given in Table A.2 and Table A.3. Variables are segregated into four groups: household demographics, human capital, physical assets, and interview period. Household demographic variables cover the household's age and gender composition; urban or rural location; and the region of the household. By design, approximately half of households surveyed live in rural areas, half in urban areas, however when applying survey weights, rural households account for 71.2% of the population. The sample is also roughly equally distributed across provinces with 29.26% of households surveyed in the Northern provinces of Niassa, Cabo Delgado, and Nampula; 36.43 % in the Central provinces of Zambézia, Tete, Manica, and Sofala; and 34.3% in the Southern provinces of Inhambane, Gaza, Maputo province and the capital, Maputo City.[7] Table 4 provides the number and of households surveyed in each province and their percent of the total sample. Turning to household demographics, the composition of dependents in a household is predominately children. The average number of children in a household is 2.22 while the average number of elderly members is only 0.22. As the average household size is 4.73 members, this is 1:1 dependency ratio on average.

Human capital consists of education and employment variables. Few adult members of the household (4.4%) consider themselves unemployed in the last week. This stems from the predominately agrarian population, where 84.2% of household heads consider agriculture their primary sector of employment.

The households' physical assets consist of agricultural assets, water quality, and wealth variables. Even though Mozambique is one of the few developing countries not facing strict land constraints, the average household cultivates 2.16 hectares (including landless and urban households). For those who do own land, 2.80 hectares are cultivated on average. Few households use irrigation (4.6%) or own a large number of livestock.[8] In the MNL model, additional binary variables are included for the following household assets: electricity, latrine, and a lusalite roof. A significantly larger proportion of urban households have electricity and a latrine compared to rural households. However, few households in both urban and rural areas have a lusalite roof.

The interview variable is a dummy variable for whether the household was interviewed during the hungry or lean season for the north and south/central regions. Lean seasons were

[7] The statistics for households in the north, central, and south provinces represent the number of households out of total households surveyed and are not calculated with survey weights.
[8] The number of livestock is estimated by Tropical Livestock Units, where livestock of different sizes (ie: cattle and chickens) can be compared and aggregated with common units based upon the animal's body weight and metabolic weight. http://www.fao.org/ag/againfo/programmes/en/lead/toolbox/Mixed1/TLU.htm

determined by Mozambique Food Security Update reports from the Famine and Early Warning Systems Network and are summarized in Figure A.1.

4.1.4 Rainfall Variables

Daily rainfall data was obtained from NASA's Climatology Resource for Agroclimatology for the period between January 1, 1997 and April 31, 2009 (NASA 2009). Point data was collected for 204 cells from 10.5° S to 26.5° S and 30.5° E to 41.5° E, where the point refers to the center of the cell (NASA 2009). Average daily rainfall and the percent deviation from the historical weekly average (in millimeters) are computed for Mozambique's distinct regional rainy and cyclone seasons. The relevant rainfall period for the north and south/central regions are identified through USAID's FEWSNET reports from September 2007 to June 2009. Again, a summary of the FEWSNET reports is provided in Figure A.1. Matching the rainfall data to the district point locations was done by interpolating the point rainfall data using the Inverse Distance Weighted (IDW) method in the ArcGIS Editor program. The IDW method estimates cell values by averaging the values of sample data points near the cell, with closer points given larger weights. As will be discussed later, climatic variables are used as instrumental variables in the drought; flood and cyclone; and agricultural pest models.

4.2 Data Limitations

Recent analysis by the World Bank identifies some concerns in the food expenditures data from the IOF 2008/09 survey which may influence this analysis. Conversations about the IOF 2008/09 analysis conclude there may be significant underreporting of the food expenditure estimates stemming from the collection of quantity data. First, measurement error may enter the data in converting reported units of food purchased or consumed from local units into a standard unit. The conversion into units was left to the enumerator and may not be consistent across observations. Second, 20 own production items and 18 purchased items were specifically listed in the expenditure section and there was a limited amount of space to report additional food items. This may have led to an over-reporting listed items and exclusion of unlisted items. Additionally, items listed were mostly unprocessed, which may have led to under-reporting of food expenditures for urban households specifically.

Another concern is the estimated regional food poverty lines. It is thought the spatial price indices used to develop the regional poverty lines are inaccurate and, as a result, may underestimate rural poverty and overestimate urban poverty. Analysts of the IOF 2008/09 data have suggested a national “fixed price-fixed bundle” poverty line may be more accurate. In order to address these concerns, simulations are run using the national poverty line and are then compared to results based on the regional poverty lines. A comparison of the results using regional food poverty lines, a national food poverty line, and considering qualitative measures of food security are presented in chapter six.

Chapter 5: Model Specification and Empirical Framework

5.1 Specification of the Empirical Model

The regression analysis has five principle goals:

1. Identify variables which are strongly correlated with household food expenditures.
2. Identify variables which are strongly correlated with a household reporting exposure to a shock in the last year.
3. Quantify the impact of exposure to commonly experienced shocks on household food expenditures.
4. Categorize households as the non-poor, transient poor, or chronic poor based upon food expenditure levels based upon estimated food expenditures with and without exposure to shocks.
5. Select targeting indicators to determine poverty status based on household characteristics and exposure to shocks. Good targeting indicators will also need to be easily collected in a household screening questionnaire and readily verifiable.

The first four goals are addressed by the endogenous treatment effects (ETE) model and the last goal is addressed by the multinomial logit regression (MNL) model. The empirical framework for each model is described below.

5.1.1 Endogenous Treatment Effects Model

The endogenous treatment effects model uses a system of two equations to identify the impact of possibly endogenous shocks on household food expenditures.

The food expenditure equation is defined as:

$$C_i = X_i B + S_i \alpha + u_i$$

Where C_i is the food expenditures pppd of household *i* adjusted for temporal differences in prices. X_i is the vector of observed variables, including variables for household demographics, human capital, physical assets, and the interview month. S_i is a binary variable for exposure to a shock, and u_i is a household specific error term (specific variables are listed in Table A.1). Observed S_i is assumed to arise from a latent intensity of exposure:

$$S_i = \begin{cases} 0 \text{ if } S_i^* \leq 0 \\ 1 \text{ if } S_i^* > 0 \end{cases}$$

where S_i^* is the latent propensity for exposure. The latent intensity of then estimated as:

$$S_i^* = Z_i \gamma + v_i$$

Here, γ contains the observed climatic, geographic, and household variables.

Estimates of α are unbiased if household idiosyncratic errors are orthogonal to differences in observed household characteristics and differences in exposure to shocks. However, the later condition may not hold for two reasons. First, reverse causality may be present if expenditures levels influence the likelihood of exposure to the shock. For example, richer households are less likely to get sick. This problem is most likely to occur with idiosyncratic shocks, whose occurrence is likely to be influenced by household well-being. Second, exposure to the shock may not be orthogonal to the error term due to the presence of unobserved heterogeneity. The shock may be truly exogenous to households, in that its occurrence does not depend on observed household characteristics or levels of well-being, but there exist unobserved factors that influence both exposure to shocks and expenditures. For example, more affluent households may possess better soils that are less prone to drought. If soil quality is not observed, the estimated impact of drought on expenditures declines may be upwardly biased. Two assumptions must hold for consistent estimates using the instrumental variable approach. First, that there is a variable that appears in row vector Z_i that does not appear in the expenditures equation. Second, that the unique variable in Z_i influences expenditures only through its impact on household exposure to the shock.[9]

To account for concerns of reverse causality, community exposure ratios are used as instrumental variables in illness, death, and theft regressions. The ratio is generated from households in the same enumeration area, except household *i*, reporting exposure or no exposure to the shock in the past year. A neighbor's exposure to illness is unlikely to affect a household's food expenditures, except through it impact on the probability of exposure to a shock. To determine exposure to climatic shocks, drought, floods, and cyclones, as well as agricultural pests, rainfall variables are included. Rainfall is likely to be highly correlated to exposure but unrelated to household food expenditures except through exposure to these shocks.

An ETE model is run with STATA 11 (treatreg command) in order to correct for the endogeneity of shocks on food expenditures pppd. Here, the treatment is exposure to a negative shock in the last year.

In establishing chronic and transient poverty, three approaches are employed. The first approach considers household expenditures levels as predicted with and without universal exposure to a specific shock. Predicted expenditures are compared to the national food poverty line and households are classified into one of three categories. Those who are below the poverty line with and without exposure to a shock are identified as the chronic poor. Households who are above the poverty line in the absence of a shock, but are estimated to be poor with exposure, are labeled as transient poor households. Lastly, those who are above the poverty line with and without exposure are classified as non-poor. The second and third approaches account for

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[9] Specifically, $\mathrm{Cov}[S,Z] \neq 0$, $\mathrm{Cov}[u,Z] = 0$, $\mathrm{Cov}[u,X] = 0$, $\mathrm{Cov}[v,Z] = 0$.

varying degrees of vulnerability to shocks across households. In the second approach, the probability of exposure to each shock is predicted. The probability of exposure for shock is then multiplied by the shock's coefficient from the food expenditure equation to arrive at the probable impact of the shock on the household's food expenditures. In this case, the products of the probability of shock and food expenditure coefficient are then summed over all shocks.[10] The resulting estimates of food expenditures are compared to the national poverty line. Those who fall below the poverty line once including the aggregate probable impact of exposure to the shock are classified as the transient poor. In the third approach, the same procedure is followed, but the product of the probability of shock and the impact coefficient is considered for each shock individually.

5.1.2 Multinomial Logit Regression

The ETE model allows us to identify the impact of a shock on household food expenditures and classify households as chronically poor, transiently poor, and non-poor. A MNL model is then run to test the ability of a smaller set of selected variables to predict household poverty levels based upon the previous classifications. Variables included in the MNL model are easily collectible and readily verifiable and were selected based upon the results of the ETE model as well as those known to be highly correlated with food expenditures, such as the household's physical assets. The MNL model allows for the parameter estimates to vary across the poverty groupings. As the goal of this analysis is to identify factors correlated with chronic and transient poverty, the non-poor is the base outcome for this analysis.

The multinomial logit regression model is defined as:

For non-base outcomes:

[10] Since coefficients in the expenditure equation differ by shock, the results differ slightly depending on the base shock.

$$\Pr(y_i = j) = \frac{\exp(X_j \beta_j)}{1 + \Sigma^{J}_{j=1} \exp(X_j \beta_j)}$$

For base outcomes:

$$\Pr(y_i = 0) = \frac{1}{1 + \Sigma^{J}_{j=1} \exp(X_j \beta_j)}$$

Where j is the non-base outcomes (chronic or transient) and X_j includes the variables for region, household characteristics, housing quality, employment sector, and exposure to shock.

To categorize households as chronic poor, transient poor, and non-poor, the probability of a household falling into each of the three poverty groups is estimated. Households are considered to fall into a poverty group if their estimated probability is above the group's mean probability estimated by the MLR model. By this method, households can fall into more than one poverty group. In order to ensure a unique group for each household the following definitions are applied. All households estimated to be chronically poor are classified as chronic poor. Transient poor households are those estimated to be transient poor, excluding those estimated to be chronic poor. The non-poor households are those estimated to be non-poor poor and exclude those also estimated to be chronic or transiently poor. Leakage and under-coverage rates are calculated as a goodness of fit test for the model. The leakage rate is the percent are households who are not observed to be poor, but are predicted to be poor by the model. The under-coverage rate is the percent of households who are observed to be poor, but are not predicted to be poor by the model.

One of the fundamental principles for monitoring and evaluating poverty in Mozambique's PARPA II (2005) is the combination of quantitative and qualitative monitoring. Quantitative measures of poverty do not encompass all the factors of household well-being and other measures, such as perceived food security, can provide additional information on the causes and occurrence of poverty. To meet this standard, we compare the poverty rates and parameter estimates obtained with food expenditures as the quantitative dependent variables to results based upon qualitative dependent variables. A logit model is run using the same set of variables as the MNL model regressed upon 1) households whose observed food expenditures are below the national poverty line, 2) self-reported food sufficiency levels and 3) the number of meals eaten in a day. In the logit model, households are classified as non-poor or poor. A comparison of the parameter estimates obtained from the three different measures of food security can be used to determine if the variables that are strongly correlated with low food expenditures are also strongly correlated with qualitative measures of food security. Further, the results will indicate whether the households who have low levels of food expenditures also report food insufficiency and one or no meals a day. These comparisons will allow us to determine the ability of the selected variables to target poor households define by both quantitative and qualitative measures.

5.2 Model Specification

This section provides a brief discussion of the variables included in the ETE and MNL models and their expected impact on the household's food expenditures and poverty level. First, the model specification for the ETE model is presented followed by the model specification for the MNL model.

5.2.1 Endogenous Treatment Effects Model

An endogenous treatment effects (ETE) model is employed to estimate household food expenditures dependence on household characteristics and arguably endogenous shocks. To account for potential endogeneity of the shocks, the probability of exposure to a shock is predicted in a separate treatment equation. The treatment equation is a probit model predicting whether households are exposed to a shock. The treatment outcome is predicted using the two-step method and is then incorporated into the food expenditure equation. The food expenditure equation is then run as an ordinary least squares equation (OLS) where household characteristics, household assets, and exposure to shock are included as regressors. All standard errors are adjusted to account for the outcomes of the treatment equation being a predicted rather than observed variance. The adjustment of the standard errors and the presence of a discrete, binary treatment variable make an ETE model preferred to other models.

5.2.2 Food Expenditure Equation of the ETE Model

For each shock model, a common set of variables is used in the food expenditure equation. To account for regional disparities in poverty levels, binary variables were added for households living in the Northern and Central provinces, as well as in rural areas. Thus, urban households in the Southern provinces are the base group for the model. Characteristics of the household head are also controlled for in the model. We expect households with an unmarried household head to have lower food expenditures than households with married household heads. Also, households headed by a single female are expected to have lower levels of economic well-being on average and an interaction variable for a single, female household head is included in the model. The age composition of the household is also expected to impact per capita food expenditures. Thus, variables for the percent of household members aged 14 and under and the percent of elderly members (age 60 and over) are included in the model.

Human capital variables for education indicate the grade completion levels of adult members by gender. We expect males' educational attainment levels to have a larger impact on food expenditures than females'. Also, it is expected that an increase in adult members who have completed primary schooling will have a stronger impact on food expenditures than an increase in adult members who have completed of post-primary schooling[11]. Employment is also expected to have a large impact on food expenditure levels and the percent of adult members unemployed in the last week is included in the model. In previous studies of developing countries, households with income obtained outside of the agricultural sector generally have higher levels of well-being. A variable for the household head's primary sector of employment being non-agricultural is therefore included in the model.

Households with more agricultural assets are expected to have higher food expenditures due to a higher production capacity. For that reason, variables for the household's cultivated land quintile, total Tropical Livestock Units, and the use of irrigation are included in the model. Also, households which treat their drinking water are expected to have higher food expenditures and the treatment of drinking water is added as an indicator variable in the model. Lastly, we expect a strong correlation between wealth and food expenditures. We account for varying bases of wealth by adding the household's wealth index[12].

5.2.3 Treatment Equation of the ETE Model

For the treatment equation, a probit model is used to estimate exposure to the discrete shock. Model specification differs for each shock examined. Variables employed include agricultural assets; characteristics of the household; community rates of exposure to the same shock; and climatic variables. We assume climatic shocks are more likely to impact farm households than non-farm households. Therefore, variables for rural households and non-agricultural households are included in the specifications for droughts; floods and cyclones; and agricultural pests. The household's cultivated land quintile and use of irrigation are also included in the covariate shock models as they are expected to impact a household's probability

[11] This assumption is made when the base households is one where no adult members have completed any level of education, primary or post-primary.
[12] The household's wealth index is based upon IOF 2008/09 data on assets owned by the household.

of exposure to a shock. As part of the identification strategy, instrumental variables are incorporated in the model. Instrumental variables are assumed to influence food expenditures only through their impact on exposure to shocks. Indicators of community exposure to covariate shocks are expected to be strongly correlated with households' exposure (due to the nature of covariate shocks) but not to otherwise directly impact individual household food expenditures. Thus, community rates of exposure are used as identifying restrictions in the specifications for the covariate shocks. Generally, these rates have fairly low average values. Only 8.33% of households in an EA reported drought as one of the top three negative events in the last year. Floods, cyclones, and agricultural pests were less frequently reported. On average, 1.86% of households in an EA reported flooding, 4.13% reported cyclones, and 6.07% reported agricultural pests in the last year. As expected, these community rates of reported exposure to the covariate shocks are similar to the percentages of reported household exposure.

For drought, the average daily rainfall and percent deviation from the historical weekly rainfall average for the previous rainy season are also used as identifying restrictions. Rainfall during the rainy season has an average of 14 mm per week with a weekly deviation of 6 mm for Mozambique. Low rainfall is assumed to directly impact exposure to a drought, but only affect household food expenditures through its impact on drought.

In modeling exposure to flooding and cyclones, variables for the number of weeks which received over 25 mm of rain during the rainy and cyclone seasons are used as identifying restrictions. These climatic variables account for short periods of time when the household was subject to exceptionally high rainfall. The 75th percentile for weekly rainfall had an average of 22.46 mm of rain from January 1997 to April 2009 for Mozambique. Thus, 25 mm of rain or greater is used as an indicator for periods with heavy rainfall.

Both high and low amounts of rain can influence exposure to agricultural pests. For example, excessive rains are expected to increase the likelihood of crops getting a fungus. However, crops can become stressed during periods with low rainfall and become more susceptible to locusts. For this reason, exposure to agricultural pests is also modeled using daily rainfall averages and deviations for the rainy season.

Several household characteristics are included in the idiosyncratic shocks of illness, death, and theft. To account for regional differences in exposure to the idiosyncratic shocks, variables for households in rural areas and the household's region (north and central) are added in the treatment equations. As we expect the probability of exposure to differ between agricultural and non-agricultural households, the primary sector of employment variable is included in the three idiosyncratic treatment equations as well. With more members in the households, the probability of illness and death necessarily increases and household size is also included in these treatment equations. Further, households interviewed during the lean season may be more likely to be ill or experience a recent death may be more likely to report the shock as one of the three most significant shocks. Therefore, the time of interview is controlled for in the illness and death models. Interviews were spaced evenly throughout the survey year, and about one-third of the surveys occurred during the four month lean season (Figure A.1). The number of children aged four and under is included in the illness model to account for young children being particularly vulnerable to illness and disease. In the death model, the number of adult members is included in the model to account for the varying impact of death on households with more potential working members. Wealth quintiles were added in the theft model as we expect wealthier households to be targeted for theft more often than poorer households.

Community rates of exposure are also used in the idiosyncratic shocks to control for concerns of reverse causality, as described below. Illness is not a commonly reported shock, with an average of only 3.64% of households in an EA reporting illness in the past year. Death and theft are also rare events, with an average of 4.05% and 4.64% of households in an EA reporting the shock in the last year, respectively. The community rates of exposure are identifying restrictions in the idiosyncratic specifications.

5.2.4 Multinomial Logit Regression Model

A multinomial logit regression (MNL) model is developed to predict households' poverty level using the household classifications obtained in the ETE model (chronic poor, transient poor, or non-poor). Fourteen variables, including exposure to a shock in the last year, region, household demographics, housing quality, and employment sector are expected to be highly correlated with poverty status and are included in the MNL model. There are three binary variables controlling for housing quality employed in the MNL which are not included in the ETE model: electricity, toilets, and lusalite roofs. These variables are included because they are easily verifiable and known to be highly correlated with food expenditures. While these variables were excluded from the ETE model due to concerns of endogeneity, potential endogeneity of the variables is not a concern for predicting poverty outcomes in the MNL model. Other variables in the MNL model were drawn from the results of the ETE model, where selected variables had a strong, significant impact on food expenditures. Additionally, the selected variables are also easily identifiable and verifiable and require little or no calculation on the part of future enumerators, ensuring the variables can be realistically employed as targeting criteria for poverty interventions.

We expect the importance of the variables to vary between the poverty groupss when compared to the base group, the non-poor. Household demographics and housing quality are expected to more important in predicting chronic poverty. We also expect exposure to shocks to have a much higher weight in predicting transient poverty than chronic poverty. Variables we expect to have similar weights between the poverty groups include those for region, rural households, and employment in a non-agricultural sector.

5.3 Summary of Chapter

This chapter has presented the ETE and MNL models and their specifications. The foundation for these models is based upon recent analyses of poverty and vulnerability in developing countries described in Chapter 2. Further, as panel data is unavailable for Mozambique, the transient poor are predicted using cross-sectional data. The data used in this analysis are drawn from Mozambique's National Household Survey and is the same dataset used by the Republic of Mozambique for their National Poverty Assessments. By employing the same dataset as that employed in the National Poverty Assessment, the data for this analysis is consistent with the data guiding current policy decisions. This chapter also describes the variables included in the model and the rational for their inclusion. An ETE model structurally estimates the impact of a shock on household's food expenditures. This model accounts for the potential endogeneity of the shocks by estimating exposure to a shock as a function of household characteristics and the identifying restrictions; community response rates and rainfall data. Food expenditures are compared to national poverty lines to categorize households as chronic, transient or non-poor. Based upon the poverty classifications estimated by the ETE model, a MNL model is developed to predict households' poverty level based upon easily identifiable and verifiable characteristics of the household. In the next chapter, the results of the analysis are presented and discussed.

Chapter 6: Results and Discussion

6.1 Impact of Individual Shocks on Food Expenditures

The impact of exposure to a shock on household food expenditures are estimated for the following: 1) droughts; 2) floods and cyclones; 3) agricultural pests; 4) illness; 5) death of the head, worker, or another member of the household; and 6) theft. Parameter estimates for the impact of shocks on food expenditures are provided in Table 5. The coefficients for all binary variables are interpreted as a percentage shift in food expenditures, calculated by taking the exponent of the coefficient and subtracting one. Of the six shocks considered, death has the strongest impact on household food expenditures, reducing them by 54%. It should be noted that death is a relatively rare shock and has few observations in the dataset. Still, household expenditures pppd significantly decrease as income generated by the individual is lost and household responsibilities must be shifted to another member in the household. Funeral expenses may also be substantial.

The next strongest shock is floods and cyclones, which are estimated to reduce food expenditures by 32%. Floods and cyclones effect households as communities are evacuated; agricultural crops or livestock are lost; assets are washed away or ruined; and food stores are destroyed. Following floods and cyclones, exposure to illness is estimated to result in a 25% reduction in food expenditures. Illness can reduce expenditures as time dedicated to home production or work outside of the home is reduced for the individual, as well as for household members caring for them. Medical expenses may also reduce the income available to spend on food.

Agricultural pests and drought are estimated to have the weakest impact. Both reduce food expenditures by approximately 17%, as crops used for auto-consumption or for sale by the household suffer reduced yields and quality. The impact of drought is less than that of floods and cyclones. Droughts may have a lower impact due to a more gradual onset of the shock, and thus increase the ability of households and communities to employ coping mechanisms to deal with drought's effects.

Lastly, theft is the only shock with an insignificant impact on food expenditures in the model. Wealthier households are more often the victims of theft and are therefore less likely to fall below the poverty line based on exposure to the shock. The model may not sufficiently address the endogeneity of theft, but the result does suggest that social programs may not wish to target households exposed to theft.

6.2 Food Expenditure Equation

The other variables specified in the food expenditure equation are common for each shock. As expected, the determinants of food expenditures pppd are fairly consistent across the models. Regional indicators have large impacts on food expenditures. Compared to households in the Southern provinces, households in the Northern and Central provinces have approximately 28.66% and 18.65% higher food expenditures, respectively. Rural households show 3.87% higher food expenditures than urban households. Further, characteristics of the household head also significantly impact food consumption. Households with single, female household heads show 22.26% lower food expenditures than households with married or male household heads. However, single-male headed households have 22.66% higher food expenditures than married household heads. In addition, there is a reduction in food expenditures for households with higher shares of children (aged 14 or younger) and elderly members (60 years and older).

Education levels do not show strong correlations with food expenditures in the models. A minimal impact is estimated for females and males completing the fifth and seventh levels of primary education. However, given the relatively low percentage of females and males in these categories, the overall impact of education levels is minimal. Employment variables have a greater impact on food expenditures pppd. There is a moderate, negative impact of adult unemployment levels on food expenditures. The ability to obtain employment outside of agricultural also improves expenditures, as food expenditures are estimated increase by 23.37% when the household head's primary sector for employment is non-agricultural,

Additionally, physical assets have significant impacts on household food expenditures. A shift into a higher quintile for land in cultivation is positively correlated with an increase in food expenditures. The household's total Tropical Livestock Units also have a significant and positive impact on food expenditures. While few Mozambican households are able to afford irrigation or treat their drinking water, the use of some form of irrigation is associated with 12.86% increase in food expenditures and treating water is associated with an 8.98% increase in expenditures. As expected, there is a significant, positive relationship between the household's wealth index and food expenditures.

6.3 Treatment Equation

Table 6 presents the estimated parameter estimates for the treatment equations. In all models except for theft, lambda estimates are positive, indicating the error terms of the food expenditure equation and the treatment equations are positively correlated. These results suggest that the use of discrete indicators for the shocks without accounting for potential endogeneity would lead to bias estimates of the impact of the shock.

Turning to the impact of independent variables in the individual probability of treatment equations, exposure to drought is discussed first. Surprisingly, drought is less likely to be reported among rural households than urban households. But, households not involved in agriculture have a significantly lower probability of indicating exposure, as expected. The probability of indicating exposure also decreases for households with more cultivated land. Irrigation does not have a significant impact on the probability of reporting exposure in the drought model. Higher community exposure ratios significantly increase the likelihood of an individual household in the community being exposed to a drought. This is expected, given the covariate nature of droughts. While the probability of indicating exposure to drought increases with the district's average daily rainfall during the rainy season, it is not influenced by the average rainfall deviation during rainy season prior to the survey. This suggests that areas with higher average rainfall become more dependent on rainfall.

A similar set of household control variables are employed in the treatment equation for floods and cyclones. No significant difference in the probability of indicating exposure is found between urban and rural households in the model. However, the probability of indicating exposure to floods and cyclones is lower for households whose primary employment sector is not agriculture and those at the higher quintiles of cultivated land. Irrigation is significant and increases the likelihood of reporting exposure. Variables for the number of weeks with 25 mm or more of rain in the rain season and cyclone season are strong predictors of household reported exposure. Community rates of exposure for floods and cyclones are also strong indicators of households reporting exposure to floods and cyclones, which is expected due to the covariate nature of flooding and cyclones.

The treatment equation estimates for agricultural pests are similar to those in the other covariate shock models. As in the drought model, households in rural areas are less likely to report exposure to agricultural pests. Similarly, households which are not engaged primarily in agricultural activities are significantly less likely to report exposure to pests. More cultivated land is also negatively correlated with reported exposure to pests. Damage from pests and disease may impact a smaller percentage of total production when more land is cultivated; reducing the significance of the shock and the likelihood it is reported. Irrigation is not significant in this model. As previously discussed, the incidence of agricultural pests is likely correlated with rainfall. Higher average rainfall for the district increases the likelihood of reporting exposure, while deviations from last year's rainfall decrease the likelihood of reporting exposure to agricultural pests. As in the previous treatment equations, there is a significant positive relationship between community rates of exposure to agricultural pests and household reported exposure.

In order to test the strength of the rainfall variables as instruments in the covariate shock models, the food expenditure equation is run as an OLS model where rainfall variables replaced exposure to a shock in the expenditure equation. Table 7 presents the parameter estimates for the three covariate equations: drought, floods and cyclones, and agricultural pests. The OLS results are quite similar to those obtained using the ETE model (Table 5). Thus, we can conclude that the impact of reported exposure to shocks is reflecting variability in the exogenous difference to rainfall. These results also suggest regional rainfall data can be used in predicting transient poverty.

Variables for the idiosyncratic models are more specific to the individual shock. However, region variables are included in all of the idiosyncratic shocks' treatment equations. For illness, the regional variables are not significant. Further, the probability of reporting illness in the last year does not vary between households in rural and urban areas. Employment in non-agricultural activities also does not influence reported exposure to illness. Household size has a significant, positive correlation with reported illness. However, the number of children under 4 decreases the likelihood of reporting exposure. The time of the interview is also controlled for in the illness treatment equation. If the household is interviewed during the lean season, they are estimated to be more likely to report exposure to illness. The rate of community reported illness is also positive and significant in the model, suggesting clustering of negative health outcomes.

As discussed, death has the largest impact on household food expenditures. Rural households are less likely to have reported a death in the household in the last year. At the same time, households which are employed primarily outside of agriculture have a lower probability of reporting a death. Community rates of reported deaths and if the interview period was during the lean season both positively impact the probability a household reported death in the last year. However, regional indicators, household size, and the number of adult members in the household are not significant within the model.

In the theft treatment equation, rural households are estimated to have a lower probability of reporting theft than urban households. Households in the Northern provinces have a higher probability of reporting theft, but there is no significant difference between households in the central and Southern provinces. Wealth quintiles have a significant, positive influence on reported theft. As in the previous models, there is a significant, positive relationship between community rates of exposure to theft and household reported exposure.

6.4 Poverty Simulations

In the poverty simulations, food expenditures are estimated based upon alternative measures of exposure to shocks and the predicted expenditures are compared to the national food poverty line. As expected, the weighted mean of observed expenditures (log) and predicted expenditures (log) is the same, at 2.38 MZN pppd. Further, 45.24% of households are observed to be below national food poverty lines in the initial data, while 47.66% of households are below food poverty lines based upon predicted food expenditures. In Mozambique's National Well-Being and Poverty Assessments (2004 and 2010), urban and rural regions of Mozambique's ten provinces and capital are grouped into thirteen spatial domains which reflect similar costs of living. Due to the large differences between urban and rural areas within a province, we find poverty estimates presented by spatial domain provide more information than if presented by province. Therefore, we follow the spatial domains given in the well-being and poverty assessments and Table 8 lists the number of survey households and their percent of the total population for each domain.

6.4.1 Chronic Poverty

Estimates of chronic poverty were developed by comparing household food expenditures estimated without exposure to a shock to the national food poverty line. While a common set of variables are used to estimate food expenditures for the different shocks, food expenditure parameter estimates still vary slightly with the different shocks. Thus, there is a small variation in estimates of chronic poverty in the different shock models. Table 9 presents the resulting estimates of chronic poverty rates.

What is clear from Table 9 is that chronic poverty is the driving force in total poverty in Mozambique. National chronic poverty estimates range from 51.20% in the illness model to 48.66% in the death model. Rural areas also have higher chronic poverty rates on average. Chronic poverty rates range from 34.61% to 37.77% in urban areas and 54.34% to 56.94% in rural areas. Chronic poverty estimates are lower in the south (44.40%) and north (46.94%), and higher in the center of the country (57.14%). Urban areas of Maputo province and Maputo City have the lowest levels of chronic poverty, at 32.25% and 18.68%, respectively[13]. The next lowest chronic poverty rates are in the urban areas of Niassa and Cabo Delgado (in the north

[13] Spacial domain estimates are drawn from the drought model as an example. Table 8 presents poverty estimates for all six shock models.

region) and Sofala and Zambézia (in the center region) at approximately 40%. The highest estimated rates of chronic poverty are in the rural areas of Sofala and Zambézia, at 64.86%, and Gaza and Inhambane, at 60.51%.

6.4.2 Comparison to Chronic Poverty Estimates using Regional Food Poverty Lines

Analyses using IOF data from the previous survey rounds have estimated poverty rates based upon regional poverty lines (Simler *et al* 2004). Regional food poverty lines are adjusted by a spatial weight to account for differenes in purchasing power and establish a uniform standard of living across the thirteen spatial domains (Simler *et al* 2004). However, there is concern that the spatial price indices used to construct the regional poverty lines in the 2008/09 IOF survey are inaccurate. To test the sensitivity of our results to the application of a national or regional set of poverty lines, we again estimate chronic poverty using the regional food poverty lines. Chronic poverty estimates derived from regional food poverty lines are significantly higher than those estimated with a national food poverty lines. Approximately 75% of predicted household food expenditures are below regional food poverty lines. The large chronic poverty estimate is due to the tendency of the model to fit predicted values closer to the mean then the ends of the distribution. Therefore, because the mean is below the food poverty line for 12 of the 13 regions (Table 10), the percentage of predicted expenditures which fall below the food poverty line is larger than the percentage using observed expenditures. Applying population weights to observed food expenditures, 66% of households are estimated to be below regional food poverty lines[14].

[14] It should be noted that using food expenditures pppd (compared to regional food poverty lines) produce higher poverty estimates than those using total (food and non-food) expenditures pppd (compared to regional total poverty lines). For example, the national poverty rate is 54.8% when using total expenditures pppd.

In Table 11, estimates of chronic poverty based upon regional food poverty lines are presented. National chronic poverty estimates range from 72.62% in the death model to 74.46% in the agricultural pests model. Urban areas have higher chronic poverty rates on average, particularly for the covariate shocks. Chronic poverty rates range from 74.46% to 76.74% in urban areas and 71.30% to 72.70% in rural areas. The chronic poverty estimates also have a distinctly regional trend, with lower rates in the north and higher rates in the south of the country. Urban areas of Maputo province in the south have the highest levels of chronic poverty for all shocks considered, ranging from 92.64% in the death model to 94.31% in the agricultural pests model. The next highest chronic poverty rates are in Maputo City and rural areas of Maputo province; at 87.74% and 94.03%, respectively. The lowest estimated rates of chronic poverty are in the Northern province, Nampula, with 56.62% for the rural areas and 58.60% for the urban areas. Following Nampula, the urban areas of Sofala and Zambézia and the rural areas of Niassa and Cabo Delgado have next lowest estimated rates of chronic poverty levels. Thus, estimates using regional food poverty lines do not align with chronic poverty estimates using a national food poverty line. Further, chronic poverty estimates based upon regional food poverty lines go against accepted regional poverty trends, where poverty is lowest in urban, Southern areas, particularly in Maputo City. Thus, these estimates are likely to overestimate urban poverty levels and underestimate rural poverty levels. Again, the divergence in poverty estimations may be due to an inaccuracy of the spatial weights used to develop the regional food poverty lines. Therefore, the remaining poverty estimations are compared to the national food poverty line.

6.4.3 Transient Poverty: Approach 1

In the first approach, transient poverty is estimated based upon universal exposure to each shock. As mentioned above, households which fall below the poverty line without exposure to a shock are classified as chronically poor. Transient poor households are those that fall below the national food poverty line only after exposure to a shock. Thus, the results represent the percentage point increase in poverty if all households are exposed to the shock. Table 9 also presents transient poverty estimates under the first approach. Overall, transient poverty is highest in the urban areas of Mozambique for all shocks considered. However, rural and urban differences in transient poverty are generally small (< 5%), except in the death model where transient poverty is 14.55 percentage points higher in urban areas. At the spatial domain level, highest transient poverty rates are estimated for urban areas in the south (Maputo province and Maputo City) and the north (rural and urban areas of Niassa and Cabo Delgado). The lowest rates are estimated for rural areas of Sofala and Zambézia in the central region.

Experiencing a death in the household generates the highest rate of transient poverty. Almost all households are simulated to become poor following a death in the family and the national poverty incidence increases by 49.14 percentage points. Moreover, increased poverty rates in the death model range from 36.00 percentage points in rural areas of Sofala and Zambézia to 73.94 percentage points in Maputo City. This is expected due to the large, negative estimated impact of death on household food expenditures. Flood and cyclones generate intermediate increase in transient poverty rates, with national rates estimated at 34.98 percentage points. Illness is also estimated to be a moderate shock, increasing poverty rates by 27.20 percentage points. The weakest shocks are agricultural pests and drought, estimated to increase the national poverty rate by 19.05 and 19.46 percentage points, respectively. Additionally, the drought and agricultural pest models have the smallest ranges. For drought, the lowest rate is in urban areas of Manica and Tete and rural areas of Sofala and Inhambane at 15.51% and the highest is in rural areas of Niassa and Cabo Delgado at 23.93%. For agricultural pests, the lowest rate is 13.98% (in rural areas of Sofala and Inhambane) and the highest rate is 23.49% (in urban areas of Maputo). As the impact of theft on food expenditures was not significant in the model, the shock is dropped from the simulations.

These figures are particularly interesting for covariate shocks, where an entire region experiences a severe flood, drought, or epidemic. Transient poverty estimates under this approach indicate that when the covariate shocks occurs, there is a large increase in poor households. Ex-ante estimates of transient poverty under crisis conditions can help emergency relief efforts understand and prepare for the increase in the number of poor households resulting from a regional disaster before aid is needed.

6.4.4 Transient Poverty: Approach 2

The first approach for transient poverty estimated poverty rates when all households are exposed to a shock. In the second set of simulations, the impact of each shock is adjusted to account for varying probabilities of exposure to the shock between households. The probability of exposure for each shock is multiplied by the impact of the shock in the food expenditure equation and is summed across all shocks. As the shock parameter estimates in the food expenditure models varied slightly, aggregate transient poverty rates are provided using the food expenditure equation estimates with each shock in Table 12. The aggregate probable impact of shocks results in a national transient poverty rate of approximately 9%. Transient poverty rates are highest in rural areas for all shocks except illness.

Based on parameter estimates across the models, the rural and urban areas of Nampula again show the highest rates of transient poverty, at approximately 12%. Urban areas of Niassa and Cabo Delgado in the Northern region are also estimated to have high rates of transient poverty (11%). Aligning with chronic poverty estimates, the lowest rates of transient poverty are found in Maputo City in the south. Other regions with low transient rates include the urban areas Maputo province and rural and urban areas of Manica and Tete.

6.4.5 Transient Poverty: Approach 3

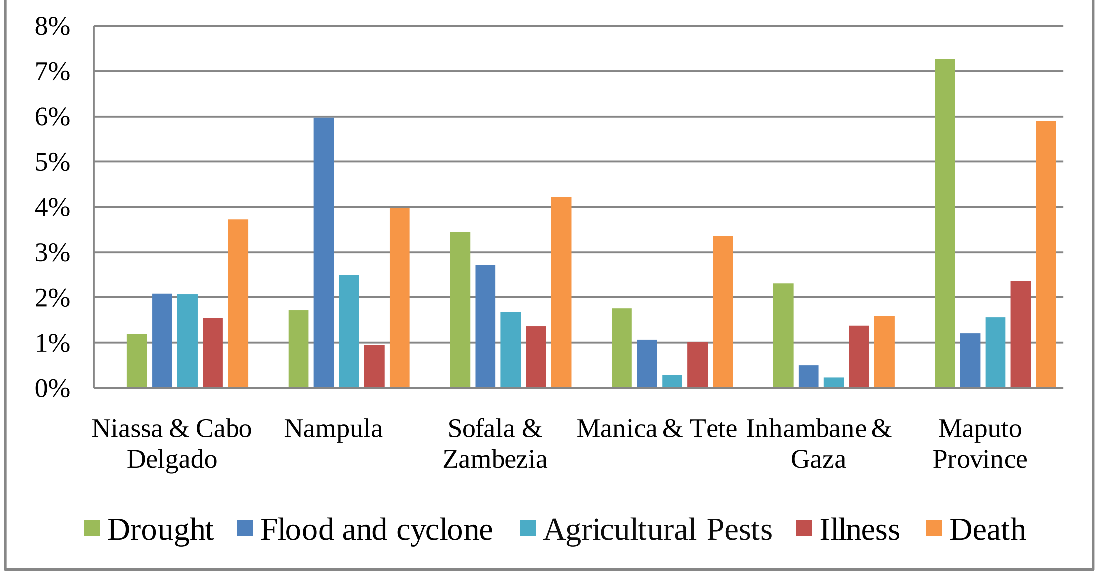
In the third approach (Table 13), the probable impact of the individual shock is estimated based on the probability of a shock occurring and its expected impact coefficient. This approach allows us to identify the contribution of individual shocks to transient poverty estimates generated using the aggregate probable impacts under approach two. Particularly, we can determine if individual shocks are affecting transient poverty in specific regions and areas or if the effects are widespread across Mozambique. On average, death generates the largest impact on transient poverty, with a national transient poverty rate of 3.77%. Floods and cyclones and drought generate moderate national transient poverty rates of 2.32% and 1.96%, respectively. Agricultural pests and illness generate the lowest national transient poverty rate at 1.18% and 1.28%, respectively. Covariate shocks result in higher transient poverty rates in rural areas than urban areas, as we would expect. In contrast, illness and death generate higher transient rates in urban areas. However, low rates do not suggest that these regions not being exposed to the shock or being unaffected, but rather that the shocks are not causing a large share of those who are not already chronically poor to become poor.

Approach three identifies large gaps in transient poverty estimates between urban and rural households, particularly for the climatic shocks. These gaps are highlighted Figures 1 and

2. For drought, rural areas in the Southern and Central provinces have the highest transient poverty rates. Rural areas of Maputo province are by far the most affected by drought, with a transient poverty rate of 7.27%. Urban areas of Gaza and Inhambane and rural areas of Sofala and Zambézia have rates at 3.55% and 3.44%, respectively. For floods and cyclones, Nampula province is most affected, with a 5.96% transient poverty rate in rural areas and a 4.99% rate in urban areas. Rural areas of Sofala and Zambézia and Niassa and Cabo Delgado have transient poverty rates of 2.71% and 2.08%, respectively. For agricultural pests, rural areas in the north and center are most affected. Rural areas of Niassa and Cabo Delgado, Nampula, and Sofala and Zambézia have transient poverty rate estimates of 2.07%, 2.49%, and 1.67%, respectively.

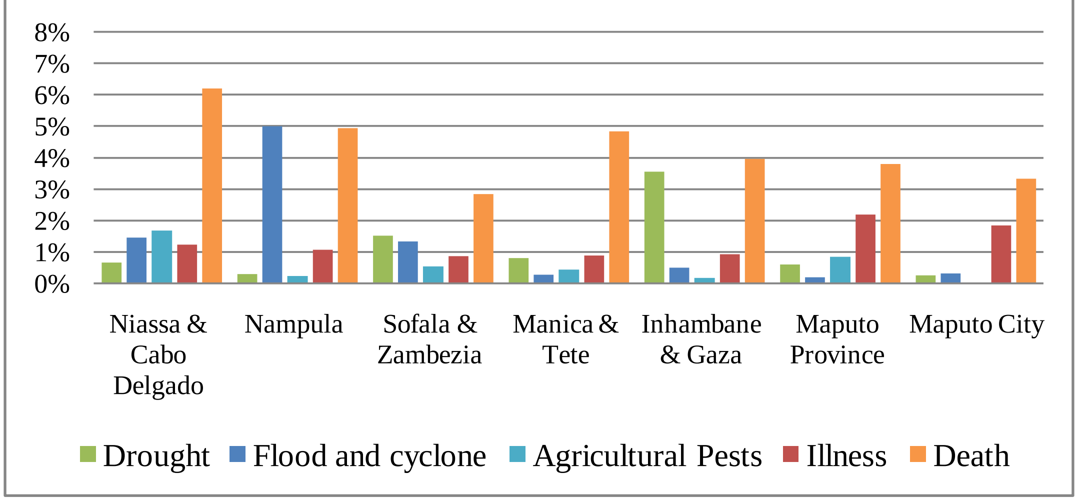
The idiosyncratic shocks of illness and death do not show clear regional trends. Specifically, rates are lowest in the urban areas of Sofala and Zambézia (0.85%), Manica and Tete (0.88%), and Gaza and Inhambane (0.92%). The highest rates are in the rural and urban areas of Maputo and Maputo City. For death, the trend is even less clear. Urban areas of Niassa and Cabo Delgado and rural areas of Maputo province have the highest transient poverty rates at 6.19% and 5.89%, respectively. The lowest rates are estimated at 1.59% in rural areas of Gaza and Inhambane and 2.84% in urban areas of Sofala and Zambézia.

Figure 1: Transient Poverty Estimates for Individual Shocks by Region (Rural)



Estimates obtained using Mozambique's 2008/09 Household Budget Survey (NIS 2009).

Figure 2: Transient Poverty Estimate for Individual Shocks by Region (Urban)



Estimates obtained using Mozambique's 2008/09 Household Budget Survey (NIS 2009).

6.5 Multinomial Logit Regression Model and Poverty Predictions

As mentioned above, the MNL model tests the ability of a smaller set of readily observable variables to predict household poverty levels based upon the poverty classifications from the

ETE model. Since variables for targeting were selected based upon the results of the ETE model and those known to be highly correlated with food expenditures, we expect most, if not all, of the variables to be highly correlated with chronic or transient poverty and to be significant in a MNL model. Indeed, all variables are significant in either the chronic or transient poor outcomes. Table 14 presents the relative risk ratios (RRR) for predicting chronic and transient poor outcomes compared to the base outcome, non-poor, in MLR model. An RRR close to one indicates the risk of being in one group is the same as the risk of being in the base group. RRR greater than (less than) one indicate an increase (decrease) in the probability a household falls into the category compared to the base. For example, with exposure to a shock in the last year, the risk of being in the transient group is 2.43 times the risk of being non-poor when all other variables in the model are held constant.

6.5.1 Indicators for Chronic Poverty

Considering the life cycle of the household, the addition of one child age four and under or one child between 5 and 14 years old significantly increases the risk of being chronically poor compared to non-poor, all other variables held constant. One more child age four or under in the household increases the risk of being chronically poor is 35.54 times that of being non-poor. For another child age five to fourteen, the risk of being chronically poor is 30.97 times that of being non-poor. The large RRRs for the number of children age four and under and the number of children age five to fourteen are a result of poor households having more children in these age groups than non-poor households. The number of elderly members has a significantly smaller impact, moderately increasing the risk of being chronically poor by a factor of 1.39. The relative risk ratio for number of young adults in the household (age 15-19) is fairly close to one (1.12). Thus, it is expected that there is a minimal difference in the risk of being chronically poor compared to non-poor based upon the number of young adults. However, household size decreases the risk of being chronically poor. If household size were to increase by one more member, the relative risk of being chronically poor decreases by 80%. Thus, with more members in the household, particularly those age 20 to 59, some of the risk arising from young children and elderly members is offset. This follows the assumption that lower dependency ratios are correlated with higher household well-being.

As expected, households' physical assets decrease the risk of being chronically poor. The absence of a latrine has the second highest relative risk ratio for chronic poverty, increasing the risk of being chronically poor by 2.45. Irrigation and treating the household's drinking water decrease the relative risk of being chronically poor by 93% and 86%, respectively. Lusalite roofs and electricity decrease the risk of being chronically poor by 74% and 66%, respectively.

Regional variables are moderately correlated with predicting chronic poverty and the relative risk of being chronically poor compared to non-poor is lower for households in the north and center than for households in the south. On average, households in the north have an 82% lower risk of being chronically poor than households in the south. For households in the center, the relative risk of being chronically poor is 69% lower than the risk for households in the south. Rural households have a 57% lower risk of being chronically poor than urban households. Variables accounting for the demographics of the household head have mixed results in predicting chronic poverty. Single headed households decrease the risk of chronic poverty by 47%. Female household heads increase the risk by 74%. Households outside of agricultural also have a 70% lower risk of being chronically poor.

6.5.2 Indicators for Transient Poverty

Table 14 also provides the RRR for the outcome of transient poor compared to non-poor. The largest risk is exposure to a shock in the last year. The relative risk of being transiently poor is 5.06 times higher for household with exposure to a shock than without when all other variables in the model are held constant. Other variables increasing the risk of being transiently poor include children age four and under and the number of children age five to fourteen, by factors of 4.46 and 3.92, respectively. The other life cycle variables (number of young adults and elderly) have similar RRRs for the chronic poverty outcome. For an additional member in the household, the risk of being transiently poor moderately decreases by 42%.

Physical assets decrease the risk of being transiently poor compared to non-poor, but not as much as they decrease the risk of being chronically poor. Electricity and irrigation have the smallest RRR, decreases the risk of a transiently poor outcome by 76% and 73%, respectively. Regional variables moderately decrease the risk of transient poverty. The risk of transient poverty for households in the north is 31% lower than households in the south. For households in the center, the risk of transient poverty is 28% lower than households in the south. Rural households have a risk of transient poverty 48% lower than urban households. Households employed primarily outside of agriculture have a risk of transient poverty 59% lower than agricultural households. Single-headed households have a decreased risk of transient poverty by 49%. Female headed households have an increased risk of transient poverty by 30%.

Thus, when compared to the base outcome or non-poor, we can see there is a decrease in the impact of most variables on a transient poor outcome than a chronic poor outcome. Notable exceptions are exposure to a shock, which has a larger impact for transient poor outcomes, and the number of children four and under and the number of children age five to fourteen, which has a significantly larger impact of chronic poor outcomes.

Turning to the relative risk ratios in Table 15 provides insight for the risk of being transiently poor compared to chronically poor. Comparing Table 14 with Table 15, it is obvious that the strongest predictors for transient poverty vary when compared to alternative base outcomes. In other words, the factors affecting the probability of non-poor household becoming transiently poor are different than those affecting the probability that transient households become chronically poor. Regional variables increase the risk of being transient poor compared to chronic poor. For example, for households in the north, the relative risk of being transiently poor is 3.58 times more likely than being chronically poor. Further, with an additional member in the household, the risk of being transient poor compared to chronically poor increases by a factor of 2.86. Physical assets increase the relative risk of being transiently poor compared to chronically poor. Electricity has a particularly large increase in the risk of transient poor outcome compared to chronic poor outcome, by a factor of 7.15. As we expect, exposure to a shock increases the risk of being transient poor compared to chronically poor by a factor of 2.09.

6.5.3 Poverty Simulations

The household's probability of falling into each poverty group is now compared to the average probability for each group. Since the household's probability can be above the average for more than one poverty group, the following definitions are employed. All households predicted to be chronically poor as considered to be chronically poor, regardless if they are also predicted into another group. Transient poor households are those who are predicted to be transiently poor, excluding those already labeled as chronic poor. The non-poor compose the remaining households.

In the MLR model, national chronic poverty estimates are similar to those in the ETE model at 52.06% (Table 16). Further, estimates of chronic poverty in rural and urban areas are 58.08% and 37.20%, respectively, similar to those reported in the ETE model. Chronic poverty predictions with the MNL model have lower rates in the north (48.68%) and south (45.37%), and higher rates in the center of the country (58.77%). At the spatial domain level, urban areas of Maputo province and Maputo City have the lowest levels of chronic poverty, at 31.55% and 18.48%, respectively. The next lowest chronic poverty rates are in the urban areas of Niassa and Cabo Delgado and Nampula (in the north region) at 35.03% and 42.15%, respectively. The highest estimated rates of chronic poverty are in the rural areas of Sofala and Zambézia (64.62%). Rural areas of Gaza and Inhambane and Manica and Tete have next highest estimated rates of chronic poverty levels, at 64.35% and 58.94% respectively.

Table 16 also provides transient poverty predictions by spacial domains. Predicted transient poverty levels are considerable higher than those estimated in the ETE model at 22.51% nationally. In the MNL model, transient poverty predictions are similar between urban and rural areas. However, there are clear regional trends. The lowest rates of transient poverty predictions are in the Southern provinces and average to 15%. The highest rates of transient poverty predictions are in the Northern provinces and average to 29%. These broad regional trends generally align with the transient poverty estimates obtained under the second approach with the ETE in Table 12. However, the results suggest that verifiable household attributes may be more effective for targeting chronic poverty than transient poverty.

6.6 Leakage and Under-coverage Rates

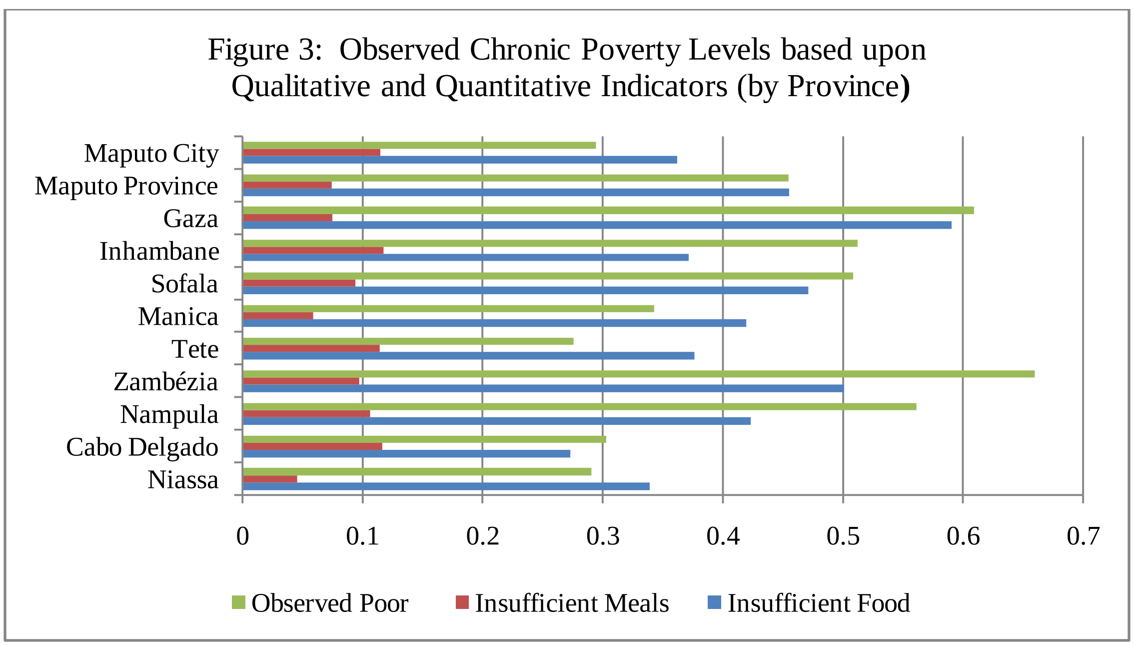
Leakage and under-coverage rates are frequently used as goodness-of-fit tests for models attempting to target transfers to desired beneficiaries. The leakage rate is the percent of those targeted by a poverty reduction program that are not poor. The under-coverage rate is the percent of those not targeted by a poverty reduction program that are poor. Table 17 compares the number of households estimated to be poor (based on the ETE model) to those observed to be poor (based upon reported food expenditures below the national poverty line). The table reveals moderate leakage and under-coverage rates at 39.6% and 38.4%, respectively. Table 18 compares the number of households predicted to be poor (based on the MNL model) to those observed to be poor. When predicting households to be chronically poor, the leakage and under-coverage rates are 42.2% and 39.4%, respectively. This indicates that ETE model and the MNL model are estimating fairly similar rates of chronic poverty. Table 19 confirms that estimated and predicted chronic poverty rates are similar with a fairly low leakage rate of 16.9% and an under-coverage rate of 14.4%. It is important to note, however, that poverty based upon observed food expenditures includes both the chronic and transient poor while the TE model and the MNL model are only looking to identify the chronic poor. As mentioned above, the model is estimating a higher poverty rate than when reported food expenditures are compared to a national food poverty line. Thus, the leakage rates estimated in Table 17 and 18 are not surprising. The under-coverage rates estimated in Table 17 and 18 suggest a somewhat imperfect targeting model, but are within a normal range for individual assessment targeting methods. Finally, Table 20 compares the estimated transient poverty rates (from the ETE model) with predicted transient poverty rates (from the MNL model). It is not surprising that the leakage and under-coverage rates are fairly high, at 80.9% and 51.4%, respectively. Other than exposure to a shock in the last year, the MNL has few strong determinants for transient poverty. Further, as the mean probability of transient poverty is used as the threshold to determine transient poverty, a fairly high number of households are predicted to be transiently poor. As there is no way to observe transiently poor households in cross-sectional data, there is also no way to verify the results obtained in the TE or MNL models. Thus, Tables 17 – Table 20 suggest the MNL may be more adept in predicting chronic poverty rather than transient poverty

6.7 Comparison of Poverty Predictions Based on Quantitative and Qualitative Measures

Included in the IOF 2008/09 survey were questions related to qualitative measures of poverty. Specifically, the household was asked if food in the household was 1) insufficient, 2) sufficient, or 3) more than sufficient in the past month. Also, the household was asked how many meals the household had yesterday; none, one, two, or three. The following section compares the poverty estimates obtained with quantitative food expenditure data to these qualitative measures of poverty. Based upon self-reported, qualitative measures of poverty, poor households are those who reported insufficient food in the past month or those who reported eating one or no meals yesterday.

A fairly low correlation is found between the two observed, qualitative measures of poverty and those identified as chronically poor based upon food expenditures (Table 21). However, the correlation coefficient is higher for observed food expenditures and reported food sufficiency than observed food expenditures and the number of meals. Figure 3 presents the observed poverty estimates for all three poverty indicators at the provincial level. From Figure 3 it is clear that the poverty estimates for the number of meals are substantially different than those of food expenditures and reported food sufficiency. The percent of poor households defined by one or no meals eaten yesterday provides extremely low estimates of poverty, at 9.58% nationally. However, the percent of households with observed food expenditures below the national food poverty line (47.6%) is similar to the percent of households reporting insufficient food in the past month (42.4%)[15]. Even though there is some variation in the poverty estimates by province, there is a general trend across provinces for food expenditures and reported food sufficiency. Inhambane and Zambézia are notable exceptions of poverty estimates varying between food expenditures and reported food sufficiency. However, when comparing poverty estimates based upon the number of meals to estimates obtained from the other two poverty indicators, there is considerable re-ranking of provincial poverty estimates. The regional trends of qualitative and quantitative indicators can be drawn from the provincial chronic poverty estimates in Figure 3.

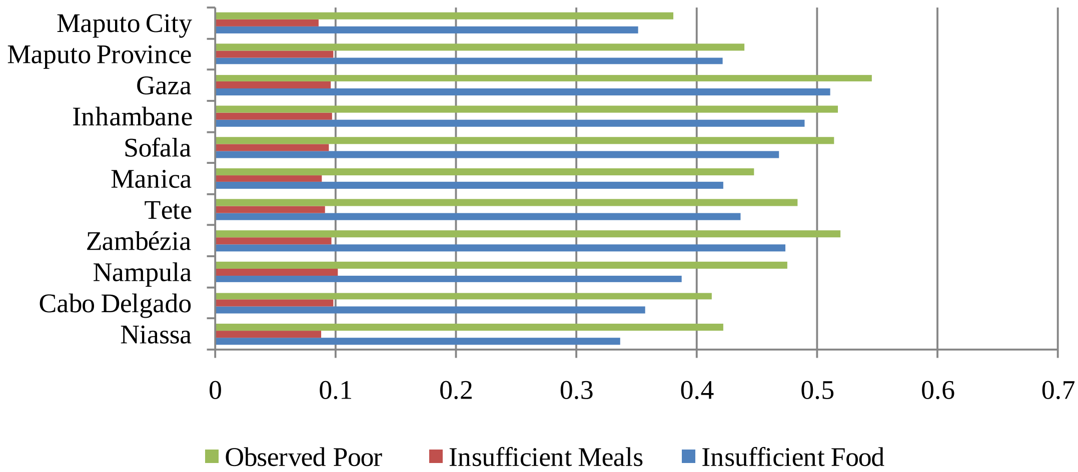
Based upon Figure 4, it appears provincial trends are fairly consistent for predicted poverty rates based upon food expenditures and food sufficiency levels. However, predicted poverty estimates based upon the number of meals do not follow the regional trends of the other two poverty indicators.



Estimates obtained using Mozambique's 2008/09 Household Budget Survey (NIS 2009).

[15] However, while the percentages are similar, 50% of households identified as chronically poor using food expenditures are not identified as chronically poor based upon reported levels of food sufficiency.

Figure 4: Predicted Chronic Poverty Levels based upon Qualitative and Quantitative Indicators (by Province)



Estimates obtained using Mozambique's 2008/09 Household Budget Survey (NIS 2009).

To test the sensitivity of the targeting variables selected to predict poverty levels in the MNL model, the same set of variables were regressed on the three poverty indicators. As the qualitative poverty indicators cannot gauge transient poverty, a logit model was used to compare poverty estimates between each poverty indicator using the same set of variables as the MNL model. Table 22 displays the correlation between the two qualitative, predicted measures of poverty and those predicted poor based upon food expenditures. As expected, there is a higher correlation coefficient for reported food sufficiency and food expenditures when the indicators are predicted rather than observed. Further, there is a negative correlation between food expenditures and the number meals when predicted rather than a positive correlation when observed.

Table 23 presents the marginal effects obtained from the three logit models, based upon 1) food expenditures 2) self—reported levels of food sufficiency and 3) the number of meals eaten yesterday as measures of poverty. The magnitude and significance of targeting variables varies between the two models. However, with the exception of primary employment not in agriculture, the signs of all significant variables are the same between models. Regional variables, physical assets, exposure to a shock, and the number of children four and under decrease the average probability of predicted poverty with food expenditures. The absence of a latrine has the largest impact and increases the average probability of poverty by 13.94%, followed by electricity (-12.70%), drinking water (-11.07%), and irrigation (-9.31%). Exposure to a shock and regional variables decrease the average probability of poverty by approximately 9%. Four variables in the food expenditure model are insignificant, including characteristics of the household head and lusalite roofs.

In the food sufficiency model, six variables are insignificant. Importantly, the life cycle variables, which were significant and moderately correlated in the food expenditure model, are insignificant in the food sufficiency model. Only the number of elderly members has a significant impact. Variables which have large, positive marginal effects associated with food insufficiency include irrigation (12.91%), electricity (11.37%), the presence of a latrine (11.22%), and a female head of household (8.05%). Additionally, exposure to a shock in the last year increases the average probability of poverty by 10.12%.

The model is weakest in predicting food insecurity determined by the number of meals eaten yesterday. Eight variables are insignificant in the model and the marginal effects of the remaining variables are minimal. Again, electricity is a strong variable in the model, decreasing the average probability of food insecurity by 5.47%. After electricity, households in rural areas are the strongest predictor in the model, decreasing the average probability of food insecurity by 3.24%.

Table 23 reveals the factors influencing poverty change based upon the definition employed. The marginal effects for the food expenditures and food sufficiency models are more similar than the marginal effects obtained with the number of meals model. This suggests measures of food insecurity may be used to target households with chronically low levels of food expenditures. However, the number of meals eaten yesterday does not appear to be a good predictor of chronically low levels of food expenditures.

6.8 Discussion

6.8.1. Impact of Shocks on Household Food Expenditures

A unique component of the model is it structurally estimates the impact of exposure to a shock on household food expenditures. The relationship between household food expenditures and shocks common to poor, Mozambican households is estimated for each shock individually. In the food expenditure equation, the magnitude of death is significantly higher than the other shocks. This finding goes against the theory that a decrease in household consumption resulting from the loss of a household member offsets the lost earnings attributed to the deceased member.

The substantial negative impact of a flood and cyclone is also expected, as these events are often sudden. Illness has a substantially lower impact that death, as it takes into account fairly short-duration illnesses, such as malaria, along with long-duration illnesses, such as tuberculosis. Agricultural pests are not likely to completely wipe out a households' entire yield, as the case may be for drought or flooding, and thus we expect to see a lower impact estimated for this model. Droughts are reoccurring events and have a slower onset than the other shocks, possibly leading to their weaker impact on food expenditures. As mentioned earlier, while the theft model may not sufficiently address the endogeneity of theft, the results suggest theft is a weak shock and may be less likely to occur in poor households. Thus, households reporting theft may not be those targeted by poverty interventions.

Approach one for transient poverty estimates the impact on the poverty rate when an entire region is affected by a shock. The results indicate death has the largest percentage point increase in the poverty rate at 49.14% nationally, followed by floods and cyclones at 34.98% nationally. For covariate shocks, the first simulation represents emergency situations, where a geographical area is hit by a catastrophic event. When a major disaster does occur there is a significant jump in the transient poverty estimates compared to estimates in approach two where the impact is adjusted for the household's probability of exposure. The difference in the number of transient poor households with approach one and approach two suggests that interventions during emergency situations may focus on the geographical targeting criteria of regional exposure to covariate shocks.

Calculating the aggregate probable impact of shocks is useful to adjust estimates of households vulnerable to transient poverty and to identifying regions where these households are concentrated. Also, while the impact of each shock is obtained from the ETE model, we also estimate the aggregate probable impact to account for variation in households' probability of exposure to a shock. Table 12 identifies regions with increasing estimates of transient poverty based upon the aggregate probable impact (approach two). From this table, we can conclude Sofala has a significantly larger percentage of households vulnerable to transient poverty and the northern, coastal provinces are also highly vulnerable. This suggests there are regional inequalities which need to be addressed when looking to prevent households becoming poor in the future. However, a 9% overall estimate of households vulnerable to transient poverty aligns with current practice in poverty interventions. Often, chronic poverty estimates are increased by 5% to 10% to account for transient poor households as well.

However, the aggregate probable impact of shocks may not be very useful in guiding interventions addressing the specific components of transient poverty. Identifying the probable impact of individual shocks allows us to identify the contribution each shock makes to overall transient poverty and the regions which are most impacted by particular shocks. For example, while drought is estimated to have one of the lowest parameter estimates in the ETE model, when taking into account a high probability of exposure to drought, it increases transient poverty rates by 2%. Death and floods and cyclones precede drought by increasing transient poverty rates by 3.77% and 2.32%, respectively. Mozambique's Third National Poverty Assessment (2010) notes the susceptibility of the central region to covariate shocks in recent years. However, our research expands upon the broad regional understanding of vulnerability to covariate shocks by identifying specific urban and rural areas within provinces which are most affected. While we can see rural areas of Sofala and Zambézia in the central region are particularly vulnerable to covariate shocks, so too is Nampula in the north and rural areas of Maputo province in the south. These results underscore the need to identify areas vulnerable to specific shocks at an increasingly disaggregated level.

6.8.2 Components of Chronic Poverty

The ETE model also identifies household characteristics which have strong relationships to food expenditures and those with weaker impacts. Strong correlates include marital status and gender of the household head, region, employment outside of the agricultural sector, and wealth. Further, agricultural assets, such as the quintile of cultivated land, irrigation, and livestock, have a moderate impact on food expenditures. Surprisingly, educational attainment levels considered separately for males and females are not strongly correlated with food expenditure levels. We compare these findings to results from Simler *et al* (2004), Fox *et al* (2005), and Mozambique's Third National Poverty Assessment (MPD 2010). Overall, we find our findings align with results presented in these three studies. All of the studies estimate higher food expenditures for households in the north and central provinces as well as rural areas[16]. Fox *et al* (2005) also found married, female headed households had positive impacts on food consumption. Households employed in the agricultural sector also had lower returns overall in the previous studies. Simler *et al* (2004) also have moderate impacts of irrigation and livestock on consumption levels. Further, land area increases consumption for rural households and has a very slight negative impact for urban households (Simler *et al* 2004). One point where the studies' results diverge from our results is the impact of education. Our model estimates almost no impact for and level of educational attainment for either gender, while Fox *et al* (2005) and Simler *et al* (2004) both establish a significant, moderate impact of education on food expenditures. The difference in impact may be due to the variables used to measure education levels of the household. In our model, there are three educational variables for the percent of adult members who have completed each degree of school for each gender. Thus, with a total of six education variables, the individual contribution of each may be minimal. In contrast, Simler *et al* (2004) uses the number of adults completing primary education and Fox *et al* (2005) only considers the education level of the household head.

6.8.3 Poverty Predictions

Looking first at chronic poverty, the ETE model estimates a national poverty rate of 50%. The MNL model predicts a national chronic poverty rate of 52%. This is fairly close to the national poverty rate estimated in Mozambique's Third Poverty Assessment, at 54.7% (MPD

[16] Both models regressed household variables on the log of household consumption

2010). However, a comparison of chronic poverty estimates at the provincial level reveals broader discrepancies (Table 24). The MNL model has poverty estimates closer to those in the National Poverty Assessment, likely due to the inclusion of housing quality and household assets in the MNL model. However, noteworthy differences exist in Niassa, Tete, and Maputo City. The difference is likely due to using the national food poverty line rather than regional poverty lines. The Third Poverty Assessment used total consumption estimates and compared them to regional poverty lines, where our model estimates figures based upon food expenditures compared to a national poverty line. The discrepancy in the results highlights the need to establish reliable regional poverty lines to reflect levels of purchasing power between regions.

While we find the 9% estimate of transient poverty in the TE model reasonable, the MNL model estimates a 22.51% transient poverty rate. The weak impact of the selected variables in the MNL model in predicting transient poverty suggests the model is more adept for determining chronic poverty. This assumption is supported by the relatively high leakage and under-coverage rate estimated in Table 20, suggesting the model is not accurately identifying transient poor households. However, estimates of transient poverty have not been established for Mozambique at the provincial or national level. Thus, we cannot compare our results to previous studies. These results suggest that continued analysis of transient poverty and the impact of common shocks on households are necessary to improve the ability to target households vulnerable to transient poverty separately from chronically poor households.

Chapter 7: Conclusions

7.1 Summary of Methods and Results

The main purpose of the study is to identify household characteristics which can 1) distinguish between the chronic poor and transient poor and 2) be feasibly implemented as targeting criterion in poverty interventions. Data for this study was drawn from Mozambique's 2008/09 Household Budget Survey and consisted of 10,832 observations. As noted in chapter two, previous studies have estimated transient poverty as the expected variance of income (or consumption) or as the household's estimated probability of exposure. This study fills a gap in the literature by structurally determining the impact of common shocks (drought, floods and cyclones, agricultural pests, illness, death, and theft) on 1) food expenditures at the household level and 2) poverty rates at the national level. We account for the potential endogeneity of each shock and the resulting overestimation of the shock parameters by using an endogenous treatment effects (ETE) model. Household food expenditures are then compared to a national food poverty line and classified as chronically poor (poor without exposure to a shock), transiently poor (becoming poor with exposure to a shock), or non-poor. Based upon these classifications, a multinomial logit regression (MNL) model is then used to predict a household's poverty level using a smaller set of selected variables. The independent variables included in the MNL model are restricted to those which can be easily collected and verified in order to be feasibly implemented as targeting criterion for poverty intervention programs.

The results of the ETE model indicate that shocks are one of the key determinants of household food expenditures. Death has the largest negative impact on food expenditures and drought and agricultural pests have the lowest impact. Theft was dropped from the poverty simulations due to its insignificance in the ETE model. When aggregating the probable impact of all shocks, there is a 9% increase in the national poverty rate. The probable impact of each individual shock was then estimated to determine the contribution of each shock in transient poverty. The strongest shock, death, increases the national poverty rate by 3.77%. For the weakest shock, agricultural pests, the poverty rate increases by 1.18% or by approximately 270,800 people. Further, we find the concentration of transient poverty varies greatly across the shocks and across provinces. Turning to chronic poverty, the model estimates a 50% national chronic poverty rate. Again, provincial estimates of chronic poverty vary greatly, with the highest rates estimated in the central provinces. Urban areas, the southern provinces, and the capital city have the lowest estimates of chronic poverty. As discussed in chapter six, the national estimate for chronic poverty and its regional trend reflects findings in previous studies of poverty in Mozambique. A regional food poverty line may obtain more precise estimates of poverty by accounting for regional differences in purchasing power. However, poverty estimates based upon regional food poverty lines do not reflect findings from previous studies and the current regional food poverty lines are generally considered to be inaccurate.

The MNL model works well in predicting chronic poverty, but does not find many indicator variables for predicting transient poverty. However, exposure to a shock was a key variable in distinguishing transient poor households from chronic and non-poor households. The results suggest that identifying the geographical area affected by the shock and households which report exposure to the shock may be used by social assistance programs looking to scale up transfer to vulnerable households during emergency situations. However, finding additional variables that uniquely identify the transient poor may improve the performance of the MNL model in estimating transient poverty as well as improve the efficiency of programs targeting transient poor households. We then compare poverty estimates using quantitative food expenditure data to estimates based upon qualitative measures of food insecurity. The results suggest poverty rates estimated with food expenditures and self-reported food sufficiency levels are fairly similar at the national and provincial level. However, poverty estimates based upon the number of meals per day are much lower and do not have the same regional trend. Therefore, we conclude the number of meals eaten in a day is not a good indicator of low levels of food expenditures.

7.2 Contributions of the Study and Policy Implications

By structurally estimating the impact of shocks on food expenditures, this study concludes exposure to shocks is a significant determinant of low levels of food expenditures. Further, when households are exposed to a shock, poverty estimates increase substantially. These findings have key implications for poverty reduction policy. As total poverty figures are composed of chronic and transient poverty, it is essential to determine their relative weight in poverty estimates. Poverty reduction programs can then be targeted towards social protection, providing the chronically poor the ability to meet a basic level of well-being, as well as social assistance and social insurance, providing safety nets to poor households to prevent or shorten temporary lapses into poverty. Further, each shock has varying affects on regional and provincial transient poverty rates. Thus, short-term poverty interventions need to determine the regions and households that are vulnerable to specific shocks common to Mozambique in order to better target the transient poor.

For transient poverty interventions, such as input fairs and FFW programs, targeting methods which incorporate both geographical and household-level may be more suitable when addressing covariate shocks. For example, interventions looking to reduce transient poverty resulting from exposure to drought should focus on the southern regions. However, agricultural pests have a larger impact on poverty estimates in the north and interventions should emphasize these areas. On the other hand, the idiosyncratic shocks may not benefit from significant geographical targeting beyond urban and rural areas. For illness and death, an emphasis should be placed on determining the household and community characteristics which limit households' access to quality health services and facilities. For chronic poverty, poverty reduction programs should continue to monitor and evaluate their targeting criteria. For example, while the PSA currently focuses heavily on assisting the elderly, the results support a broadening of the targeting criteria to include more single, female headed households and households with a large number of young children. Further, interventions which provide adult training and education or help to create and diversify local employment opportunities to sectors outside of agriculture may be appropriate for addressing chronic poverty. Poverty estimates in Mozambique can continue to decline as households exposed to negative shocks are more rapidly identified and enrolled in poverty interventions and methods targeting the chronic poor continue to be improved.

7.3 Limitations of the Study

While the use of cross-sectional data to estimate transient poverty is a constraint in itself, there are other limitations for our study. The key concern for this study is the use of community rates of exposure as identifying restrictions in the idiosyncratic shocks without additional variables to control for community wealth and health infrastructure. Data on district rates of malaria, tuberculosis, maternal death, or other illnesses and causes of death were desired, however, such information was unavailable for this study. Other potential instrumental variables for illness and death include the distance of the household to a health post or school. Further, while the rainfall variables implemented in the covariate shock models are strong identifying restrictions, GIS data on the location of the household can improve the accuracy of rainfall estimates, currently collected at the district level, and improve the strength of rainfall variables as instrumental variables.

Additionally, we can only be confident in poverty estimates provided at the national, urban and rural, and provincial level. This is a fairly aggregated level and ideally poverty estimates could be obtained at the district level or lower. However, the data quality issues mentioned in chapter four restrict us from providing poverty estimates at a more disaggregated level. Also, regional food poverty lines would likely improve poverty estimates by accounting for differences in purchasing power across regions. The regional food poverty lines included in the data produce highly divergent poverty rates and may not be accurate. Therefore, the non-spatially adjusted national food poverty line is likely the most accurate given the data available.

Lastly, only a very small percentage of households reported exposure to each of the fifteen shocks in the survey, particularly when considering only those occurring in the past year. This has a few implications for the study. First, the time period set to establish exposure to a shock is likely to influence the results. In this model we took all observations occurring in the past year; however, as the number of months since exposure increases, households have more time to employ coping mechanisms and smooth consumption. Thus, the true, unmitigated impact of the shock is less certain than if the time period was shortened. Second, with so many zeros for the exposure to treatment, we had to be parsimonious in the number of variables employed in the ETE model. Thus, only the variables we considered to have the most direct impact on food expenditures and exposure to individual shocks were included in the model. Thirdly, some shocks were grouped together which otherwise would have been kept separate. For example, in the death model, the impact of the death of the household head is likely to be significantly higher than the impact of the death of a young child. With more observations in each death category, we would be able to look at the varying impact of death dependent upon the role of the member in the household.

7.4 Future Research

Research on vulnerability is a growing field within the poverty reduction literature. From this study and previous studies, we see the targeting criteria for chronic poverty cannot be universally applied to programs targeting households vulnerable to transient poverty. Further, this study highlights the need to further investigate the causes and coping mechanisms employed for individual shocks to determine the severity and duration of reduced consumption among households and communities. Additionally, there is a need to determine the degree to which assistance can be geographically targeted in response to covariate and idiosyncratic shocks and when household-level targeting can improve the efficiency and impact of these transfers.

Tables

Table 1: Percentiles and Ranges for Household Food Expenditures pppd (in MZN)

Percentiles		Smallest	
1%	1.005		0.000
5%	2.938		0.002
10%	4.320		0.035
25%	7.114		0.039
50%	11.752	Largest	
75%	19.088		252.511
90%	30.250		259.985
95%	40.223		323.525
99%	77.202		1,215.314

Estimates obtained using Mozambique's 2008/09 Household Budget Survey (NIS 2009).

Table 2: Percent of Households Reporting a Shock within the Last 5 Years, as the Primary Shock, and within the Last Year for All Shocks Listed in the IOF Survey

Description of Shock	Reported within the Last 5 Years	Reported as Primary	Reported within in the Last Year
		%	
Increased prices for food	65.7	28.9	15.1
Drought	**29.6**	**15.6**	**8.3**
Agricultural pests (plague)	**16.4**	**6.0**	**6.1**
Theft, robbery	**11.3**	**3.8**	**4.6**
Illness or accident of household member	**11.3**	**6.5**	**3.6**
Death of another household member	**11.1**	**8.5**	**2.9**
Low producer prices	10.0	3.1	1.9
Cyclone	**9.0**	**3.6**	**4.1**
Epidemic	8.5	2.8	2.8
Flood	**6.4**	**3.3**	**1.9**
Bankruptcy of household business	4.2	1.7	1.4
Death of head of household	**4.1**	**3.9**	**0.7**
Loss of salaried worker	2.2	1.3	0.6
Death or theft of cattle		2.9	1.0
Death of a worker member	**1.8**	**1.4**	**0.5**
# of Observations		10,832	
# of Households represented		4,562,969	

Notes: Data is binary; a no response = 0 and a yes response = 1 if the shock is reported by the household. Percents are the reported exposure to each shock out of all 10,832 observations. Shocks in bold are considered in the models. Data is weighted.

Estimates obtained using Mozambique's 2008/09 Household Budget Survey (NIS 2009).

Table 3: Percent of Households Reporting a Shock within the Last 5 Years, as the Primary Shock, and within the Last Year for Each Shock Model

Description of Shock	Reported within the Last 5 Years	Reported as the Primary Shock	Reported within the Last Year
		%	
Drought	29.6	15.6	8.3
Floods and cyclones	14.6	6.8	5.8
Agricultural pests (plague)	16.4	6.0	6.1
Illness of household member	11.3	6.5	3.6
Death of a household member	16.5	13.8	4.1
Theft, robbery	11.3	3.8	4.6
# of Observations		10,832	
# of Households represented		4,562,969	

Notes: Data is binary; a no response = 0 and a yes response = 1 if the shock is reported by the household. Percents are the reported exposure to each shock out of all 10,832 observations. Data is weighted.

Estimates obtained using Mozambique's 2008/09 Household Budget Survey (NIS 2009).

Table 4: Number and Percent of Household in each Province

	Number of Households	Percent of Observations
Niassa	814	6.06
Cabo Delgado	780	8.80
Nampula	1,575	20.30
Sofala	1,523	18.64
Zambezia	768	8.87
Manica	804	7.07
Tete	851	7.03
Gaza	803	6.14
Inhambane	815	5.67
Maputo Province	900	6.37
Maputo City	1,199	5.05

Note: The percent of observations is calculated using population weights.

Estimates obtained using Mozambique's 2008/09 Household Budget Survey (NIS 2009).

Table 5: Coefficients for the Food Expenditure Equation for Each Shock Model

	Drought		Flood and Cyclone		Agricultural Pests		Illness		Death		Theft	
	Coefficient	Std Dev	Coefficient	Std Dev	Coefficient	Std Dev	Coefficient	Std Dev	Coefficient	Std Dev	Coefficient	Std Dev
rural	0.038*	0.020	0.046**	0.020	0.037*	0.020	0.036*	0.020	0.025	0.021	0.037*	0.020
north	0.252***	0.023	0.302***	0.023	0.285***	0.023	0.275***	0.023	0.277***	0.023	0.275***	0.023
central	0.171***	0.021	0.193***	0.021	0.186***	0.021	0.182***	0.021	0.182***	0.022	0.181***	0.021
hh_single	0.201***	0.035	0.197***	0.035	0.197***	0.035	0.198***	0.035	0.200***	0.035	0.198***	0.035
hh_femsin	- 0.257***	0.040	- 0.255***	0.040	- 0.253***	0.041	- 0.254***	0.040	- 0.256***	0.040	- 0.255***	0.041
p_0114	- 0.010***	0.000	- 0.010***	0.000	- 0.010***	0.000	- 0.010***	0.000	- 0.010***	0.000	- 0.010***	0.000
p_60p	- 0.002***	0.000	- 0.002***	0.000	- 0.002***	0.000	- 0.002***	0.000	- 0.002***	0.000	- 0.002***	0.000
p_edu_pri5f	0.001*	0.000	0.000	0.000	0.001*	0.000	0.000*	0.000	0.000	0.000	0.000*	0.000
p_edu_pri7f	0.001**	0.001	0.001**	0.001	0.001**	0.001	0.001**	0.000	0.001**	0.001	0.001**	0.000
p_edu_postprim_f	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001
p_edu_pri5m	- 0.001***	0.000	- 0.001***	0.000	- 0.001***	0.000	- 0.001***	0.000	- 0.001***	0.000	- 0.002***	0.000
p_edu_pri7m	- 0.001**	0.000	- 0.001**	0.000	- 0.001**	0.000	- 0.001**	0.000	- 0.001**	0.000	- 0.001**	0.000
p_edu_postprim_m	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
p_unemploy	- 0.098**	0.042	- 0.092**	0.042	- 0.101**	0.042	- 0.101**	0.042	- 0.099**	0.042	- 0.099**	0.042
no_ag	0.210***	0.031	0.209***	0.031	0.220***	0.031	0.230***	0.031	0.211***	0.032	0.230***	0.031
farm_quint_lur_cult	0.070***	0.006	0.066***	0.059	0.079***	0.006	0.071***	0.006	0.069***	0.006	0.071***	0.006
irr	0.121***	0.036	0.133***	0.036	0.125***	0.036	0.127***	0.036	0.128***	0.036	0.127***	0.036
TLU_total	0.012**	0.005	0.011**	0.005	0.010**	0.005	0.010**	0.005	0.011**	0.006	0.010**	0.005
treath20	0.086***	0.024	0.083***	0.023	0.085***	0.024	0.088***	0.024	0.085***	0.024	0.082***	0.024
wealth	0.176***	0.012	0.181***	0.011	0.178***	0.012	0.181***	0.012	0.180***	0.011	0.180***	0.012
treatment	- 0.189***	0.047	- 0.389***	0.046	- 0.188***	0.057	- 0.292**	0.116	- 0.771***	0.190	- 0.055	0.127
constant	2.493***	0.037	2.481***	0.036	2.469***	0.0376	2.474***	0.037	2.481***	0.038	2.468***	0.037
# of Observations	10,830											

*** p<0.01, ** p<0.05, * p<0.1 The two-step endogenous treatment effects model cannot be estimated using weights and thus the results are unweighted.

Estimates obtained using Mozambique's 2008/09 Household Budget Survey (NIS 2009).

Table 6: Treatment Equation Coefficients For Each Shock Model

	Drought		Flood and Cyclone		Agricultural Pests		Illness		Death		Theft	
	Coefficient	Std Dev	Coefficient	Std Dev	Coefficient	Std Dev	Coefficient	Std Dev	Coefficient	Std Dev	Coefficient	Std Dev
lambda	0.070**	0.029	0.155***	0.034	0.0825**	0.034	0.113**	0.056	0.336***	0.088	0.0611	0.062
rural	- 0.114**	0.050	- 0.059	0.086	- 0.131**	0.057	- 0.076	0.056	- 0.168***	0.053	- 0.122**	0.054
no_ag	- 0.746***	0.092	- 0.226*	0.133	- 1.280***	0.181	0.034	0.062	- 0.118*	0.062		
farm_quint_lur_cult	- 0.035**	0.016	- 0.064**	0.027	- 0.048***	0.018						
irr	0.084	0.095	0.463***	0.131	0.140	0.11 2						
av_droughtyr	3.636***	0.091										
drought_avgseason	0.045***	0.010										
drought_dev_season	- 0.002	0.002										
av_floodyr			3.081***	0.217								
av_cycloneyr			2.766***	0.163								
flood_season_n25			0.116***	0.007								
cyclone_season_n25			0.103***	0.007								
av_agpestyr					3.489***	0.111						
agpest_avgseason					0.078***	0.010						
agpest_dev_season					- 0.032***	0.003						
north							- 0.017	0.062	0.001	0.061	0.145**	0.060
central							- 0.043	0.058	0.010	0.057	0.032	0.056
hhsize							0.037***	0.011	0.019	0.013		
ch4							- 0.087***	0.032				
av_illnessyr							3.293***	0.163				
int_lean							0.250***	0.047	0.258***	0.046		
numadult									- 0.013	0.024		
av_deathyr									2.523***	0.210		
quint_wealth											0.076***	0.021
av_theftyr											3.026***	0.158
constant	- 1.851***	0.059	- 2.462***	0.093	- 1.855***	0.069	-2.156***	0.080	- 1.955***	0.079	- 2.138***	0.110

Standard errors are given below the coefficients. Instrumental variables used in the treatment equations are in bold. *** p-val <0.01, ** p-val <0.05, * p-val <0.1

Table 7: Coefficients for the Food Expenditure Equation for Covariate Shocks with Rainfall Variables

	Drought		Flood and Cyclone		Agricultural Pests	
	Coefficient	Std Dev	Coefficient	Std Dev	Coefficient	Std Dev
rural	0.040**	0.020	0.043 **	0.020	0.040 **	0.020
north	0.278***	0.025	0.295 ***	0.023	0.260 ***	0.025
central	0.178***	0.023	0.193***	0.021	0.170 ***	0.023
hh_single	0.199 ***	0.035	0.198 ***	0.035	0.201 ***	0.035
hh_femsin	-0.256***	0.041	-0.255 ***	0.040	-0.255 ***	0.040
p_0114	-0.010***	0.000	-0.010 ***	0.000	-0.010 ***	0.000
p_60p	-0.002*	0.000	-0.002 ***	0.000	-0.002 ***	0.000
p_edu_pri5f	0.000*	0.000	0.000	0.000	0.000	0.000
p_edu_pri7f	0.001**	0.000	0.001 **	0.000	0.001 **	0.000
p_edu_postprim_f	-0.000	0.001	-0.000	0.001	-0.000	0.001
p_edu_pri5m	-0.001***	0.000	-0.001 ***	0.000	-0.001 ***	0.000
p_edu_pri7m	-0.001**	0.000	-0.001 **	0.000	-0.001 **	0.000
p_edu_postprim_m	-0.001	0.000	-0.000	0.000	-0.000	0.000
p_unemploy	-0.095**	0.042	-0.094 **	0.042	-0.092 **	0.042
no_ag	0.231 ***	0.031	0.213 ***	0.031	0.226 ***	0.031
farm_quint_lur_cult	0.071 ***	0.006	0.068 ***	0.006	0.071 ***	0.006
Irr	0.122***	0.036	0.124 ***	0.036	0.117 ***	0.036
TLU_total	0.010**	0.005	0.011 **	0.005	0.011 **	0.005
treath20	0.087 ***	0.024	0.082 ***	0.024	0.088 ***	0.024
wealth	0.183 ***	0.012	0.180 ***	0.011	0.182 ***	0.012
drought_av~n	-0.009 **	0.004				
drought_de~n	-0.002 **	0.001				
flood_sea~25			-0.018 ***	0.003		
cyclone_s~25			-0.009 ***	0.003		
agpest_avg~n					-0.012 ***	0.004
agpest_dev~n					-0.003 ***	0.001
Constant	2.493 ***	0.037	2.475 ***	0.036	2.518 ***	0.038
# of Observations	10,830					

*** p<0.01, ** p<0.05, * p<0.1
As the two-step endogenous treatment effects model cannot be estimated using weights, the regression was run unweighted to allow for a better comparison better models.

Estimates obtained using Mozambique's 2008/09 Household Budget Survey (NIS 2009).

Table 8: Number and Percent of Household in each Spatial Domain

	Number of Households	Percent of Observations
Niassa & Cabo Delgado, Rural	970	11.89
Niassa & Cabo Delgado, Urban	624	2.98
Nampula, Rural	1,005	14.74
Nampula, Urban	570	5.56
Sofala & Zambezia, Rural	1,511	20.34
Sofala & Zambezia, Urban	863	5.33
Manica & Tete, Rural	1,044	12.94
Manica & Tete, Urban	528	2.99
Gaza & Inhambane, Rural	899	9.13
Gaza & Inhambane, Urban	719	2.68
Maputo Province, Rural	180	2.13
Maputo Province, Urban	720	4.24
Maputo City	1,199	5.05

Note: The percent of observations is calculated using population weights.

Estimates obtained using Mozambique's 2008/09 Household Budget Survey (NIS 2009).

Table 9: Percent of the Chronic and Transient Poor by Spatial Domain

	Drought			Floods and Cyclones			Agricultural Pests			Illness			Death		
	Chronic	Transient	Non-poor	Chronic	Transient	Non-poor	Chronic	Transient	Non-poor	Chronic	Transient	Non-poor	Chronic	Transient	Non-poor
National	50.59	19.46	29.94	49.94	34.98	15.08	51.11	19.05	29.84	51.20	27.20	21.59	48.66	49.14	2.21
Urban	37.42	19.47	43.11	37.00	38.66	24.39	37.77	19.31	42.91	37.06	29.29	33.64	34.61	59.49	5.89
Rural	55.93	19.46	24.61	55.20	33.49	11.31	56.50	18.94	24.55	56.94	26.35	16.71	54.34	44.94	0.71
Niassa & Cabo Delgado Rural	43.25	23.93	32.82	39.97	41.72	18.31	42.14	23.23	34.64	43.23	32.60	24.16	40.75	58.78	0.46
Niassa & Cabo Delgado Urban	40.54	21.71	37.75	36.53	37.87	25.60	39.17	20.92	39.91	40.04	28.54	31.41	34.59	62.21	3.20
Nampula Rural	52.83	21.17	26.00	48.69	35.74	15.57	50.96	21.86	27.17	52.61	28.10	19.29	49.51	50.03	0.46
Nampula Urban	42.65	17.71	39.64	40.12	37.35	22.53	41.65	17.65	40.70	41.49	28.52	29.99	39.18	54.01	6.81
Sofala & Zambézia Rural	64.86	15.51	19.64	65.39	27.75	6.85	66.67	13.98	19.36	66.90	20.06	13.03	63.76	36.00	0.24
Sofala & Zambézia Urban	39.73	17.16	43.11	40.02	35.08	24.89	40.21	16.87	42.92	39.75	26.49	33.77	38.42	54.11	7.47
Manica & Tete Rural	55.61	19.33	25.06	56.28	33.03	10.70	56.75	19.01	24.25	56.75	27.31	15.94	54.59	43.92	1.48
Manica & Tete Urban	42.26	15.51	42.23	41.66	34.60	23.74	42.24	16.01	41.74	41.84	25.61	32.54	38.36	55.03	6.61
Gaza & Inhambane Rural	60.51	19.51	19.99	62.57	32.56	4.87	62.39	20.01	17.61	61.72	28.05	10.22	61.07	38.73	0.21
Gaza & Inhambane Urban	56.54	19.89	23.57	58.39	32.89	8.72	58.08	19.93	22.00	57.46	27.39	15.16	54.63	44.38	0.99
Maputo Province Rural	45.35	20.93	33.72	49.78	33.64	16.58	51.21	17.57	31.23	48.77	26.42	24.81	43.32	50.80	5.88
Maputo Province Urban	32.25	23.18	44.57	32.83	44.43	22.74	33.57	23.49	42.94	31.95	32.66	35.39	29.91	67.00	3.09
Maputo City	18.68	21.56	59.76	19.75	44.96	35.29	20.18	20.92	58.90	18.20	33.92	47.88	16.71	73.94	9.35

Notes: Transient Poverty is estimated under Approach 1, where households are universally exposed to each shock. Chronic poverty is defined as households below the national food poverty line without exposure to a shock. Based on observed food expenditures, 45.24% of the households in the model fall below the national food poverty line. Data is weighted.

Estimates obtained using Mozambique's 2008/09 Household Budget Survey (NIS 2009).

Table 10: Comparison of Average Household Food Expenditures to Food Poverty Lines by Spatial Domain

	Average household food expenditures (log of)	Food poverty line (log of)
Niassa & Cabo Delgado, Rural	2.656	2.527
Niassa & Cabo Delgado, Urban	2.613	2.635
Nampula, Rural	2.205	2.411
Nampula, Urban	2.355	2.528
Sofala & Zambezia, Rural	2.165	2.429
Sofala & Zambezia, Urban	2.381	2.616
Manica & Tete, Rural	2.603	2.718
Manica & Tete, Urban	2.576	2.746
Gaza & Inhambane, Rural	2.177	2.572
Gaza & Inhambane, Urban	2.313	2.643
Maputo Province, Rural	2.260	2.884
Maputo Province, Urban	2.471	3.030
Maputo City	2.794	3.038

Estimates obtained using Mozambique's 2008/09 Household Budget Survey (NIS 2009).

Table 11: Percent of the Chronic Poor based upon Regional Food Poverty Lines by Spacial Domain

	Drought	Floods and Cyclones	Agricultural Pests	Illness	Death
National	74.28	73.86	74.46	74.28	72.82
Urban	76.39	76.28	76.74	75.97	74.46
Rural	72.31	71.60	72.35	72.70	71.30
Niassa & Cabo Delgado, Rural	62.89	60.31	61.86	62.47	60.62
Niassa & Cabo Delgado, Urban	68.43	66.83	67.63	67.47	66.35
Nampula, Rural	56.62	53.63	55.42	56.62	54.63
Nampula, Urban	58.60	55.79	57.37	57.54	55.09
Sofala & Zambezia, Rural	71.08	71.14	71.54	71.81	70.28
Sofala & Zambezia, Urban	61.65	61.30	61.76	61.41	58.98
Manica & Tete, Rural	87.16	87.16	87.45	87.36	86.59
Manica & Tete, Urban	72.92	73.11	73.86	72.92	70.64
Gaza & Inhambane, Rural	81.87	83.43	83.43	83.43	82.31
Gaza & Inhambane, Urban	81.08	82.89	82.89	81.64	79.97
Maputo Province, Rural	87.22	87.22	87.22	86.67	86.67
Maputo Province, Urban	94.03	94.17	94.31	93.61	92.64
Maputo City	87.74	88.41	88.49	86.99	86.49

Notes: Based on observed food expenditures, 60% of the households in the model fall below the regional food poverty line. Chronic poverty is defined as households below the regional food poverty line with and without exposure to a shock.

Estimates obtained using Mozambique's 2008/09 Household Budget Survey (NIS 2009).

Table 12: Percent of Transient Poor Households under Approach 2 (Aggregate Probable Impact of Shocks)

	Drought	Floods and Cyclones	Agricultural Pests	Illness	Death
National	8.82	9.11	8.76	8.69	9.59
Urban	8.59	8.89	8.69	8.78	8.81
Rural	8.92	9.20	8.78	8.65	9.76
Niassa & Cabo Delgado, Rural	9.24	9.85	9.30	8.92	9.90
Niassa & Cabo Delgado, Urban	11.45	11.45	11.11	11.35	11.83
Nampula, Rural	11.31	12.92	12.16	11.52	12.86
Nampula, Urban	11.68	11.91	11.64	12.59	12.05
Sofala & Zambézia, Rural	9.50	9.26	8.52	8.38	10.28
Sofala & Zambézia, Urban	9.01	9.01	8.76	9.10	7.89
Manica & Tete, Rural	6.52	6.35	6.15	6.63	6.78
Manica & Tete, Urban	6.68	7.61	7.18	7.20	8.99
Gaza & Inhambane, Rural	6.41	6.97	7.69	7.51	7.04
Gaza & Inhambane, Urban	9.52	10.12	10.01	9.50	9.95
Maputo Province, Rural	10.42	6.00	5.77	7.01	12.46
Maputo Province, Urban	6.35	7.41	7.31	6.22	6.83
Maputo City	5.56	5.29	5.30	5.45	5.39

Notes: Transient households are those who are below the national food poverty line when taking the probability of exposure multiplied by the coefficient for the shock and aggregating the impacts for all shocks. The data is weighted.

Estimates obtained using Mozambique's 2008/09 Household Budget Survey (NIS 2009).

Table 13: Percent of Transient Poor Households under Approach 3 (Probable Impact of a Shock)

	Drought	Floods and Cyclones	Agricultural Pests	Illness	Death
National	1.96	2.32	1.18	1.28	3.77
Urban	0.94	1.51	0.50	1.31	4.12
Rural	2.37	2.65	1.46	1.27	3.63
Niassa & Cabo Delgado, Rural	1.19	2.08	2.07	1.54	3.71
Niassa & Cabo Delgado, Urban	0.66	1.45	1.67	1.22	6.19
Nampula, Rural	1.71	5.96	2.49	0.95	3.97
Nampula, Urban	0.28	4.99	0.22	1.07	4.92
Sofala & Zambézia, Rural	3.44	2.71	1.67	1.36	4.21
Sofala & Zambézia, Urban	1.50	1.33	0.54	0.85	2.84
Manica & Tete, Rural	1.76	1.05	0.28	1.00	3.35
Manica & Tete, Urban	0.80	0.27	0.43	0.88	4.82
Gaza & Inhambane, Rural	2.31	0.49	0.22	1.37	1.59
Gaza & Inhambane, Urban	3.55	0.49	0.17	0.92	3.94
Maputo Province, Rural	7.27	1.20	1.55	2.35	5.89
Maputo Province, Urban	0.60	0.18	0.84	2.18	3.79
Maputo City	0.24	0.30	0.00	1.84	3.31

Notes: Transiently poor households are those who are below the food poverty line when taking the probability of exposure multiplied by the coefficient for the shock. Data is weighted.

Estimates obtained using Mozambique's 2008/09 Household Budget Survey (NIS 2009).

Table 14: Average Marginal Effects and Relative Risk Ratios
Base Outcome = Chronic Poor

	Average Marginal Effect			Relative Risk Ratio		
	dy/dx	Std. Err.	P>z	RRR	Std. Err.	P>z
Chronic						
Rural	-0.0669	0.0097	0	0.4287	0.0447	0
North	-0.1713	0.0116	0	0.1752	0.0227	0
Central	-0.1108	0.0123	0	0.3148	0.0416	0
Household size	-0.1494	0.0067	0	0.2037	0.0167	0
# children 0 - 4	0.3249	0.0082	0	35.5399	4.5902	0
# children 5 - 14	0.3150	0.0077	0	30.9662	3.8634	0
# member 15-19	0.0044	0.0092	0.633	1.1160	0.1047	0.242
# of elderly members	0.0215	0.0094	0.022	1.3869	0.1272	0
Household head is female	0.0496	0.0113	0	1.7437	0.2028	0
Household head is single	-0.0420	0.0125	0.001	0.5339	0.0683	0
Primary employment not in agriculture	-0.0971	0.0132	0	0.2956	0.0391	0
Has electricity	-0.3097	0.0169	0	0.0331	0.0064	0
No latrine	0.0779	0.0092	0	2.4494	0.2346	0
Roof made of lusalite	-0.1255	0.0565	0.026	0.2640	0.1348	0.009
Treats drinking water	-0.1817	0.0184	0	0.1443	0.0281	0
Uses irrigation	-0.2299	0.0237	0	0.0737	0.0187	0
Experienced a shock in the last year	0.0351	0.0088	0	2.4252	0.2345	0
Transient						
Rural	-0.0156	0.0078	0.046	0.5297	0.0640	0
North	0.0358	0.0095	0	0.6858	0.1011	0.01
Central	0.0180	0.0097	0.064	0.7195	0.1066	0.026
Household size	0.0185	0.0045	0	0.5833	0.0464	0
# children 0 - 4	-0.0206	0.0068	0.002	4.4637	0.5984	0
# children 5 - 14	-0.0251	0.0055	0	3.9193	0.4471	0
# member 15-19	0.0106	0.0071	0.137	1.2209	0.1271	0.055
# of elderly members	0.0147	0.0071	0.037	1.4402	0.1428	0
Household head is female	-0.0012	0.0101	0.904	1.2974	0.1936	0.081
Household head is single	-0.0266	0.0106	0.012	0.5081	0.0791	0
Primary employment not in agriculture	-0.0205	0.0108	0.058	0.4112	0.0636	0
Has electricity	0.0187	0.0114	0.1	0.2364	0.0400	0
No latrine	0.0021	0.0077	0.79	1.6073	0.1870	0
Roof made of lusalite	0.0163	0.0352	0.643	0.6440	0.2589	0.274
Treats drinking water	0.0223	0.0112	0.047	0.5171	0.0839	0
Uses irrigation	0.0004	0.0143	0.977	0.2744	0.0632	0
Experienced a shock in the last year	0.0862	0.0068	0	5.0653	0.5560	0

Marginal Effects and relative risk ratios are compared to the base outcome, non-poor.
Estimates obtained using Mozambique's 2008/09 Household Budget Survey (NIS 2009).

Table 15: Average Marginal Effects and Relative Risk Ratios
Base Outcome = Chronic Poor

	Average Marginal Effect			Relative Risk Ratio		
	dy/dx	Std. Error	P>z	RRR	Std. Error	P>z
Transient						
Rural	-0.0156	0.0078	0.046	1.2354	0.1491	0.08
North	0.0358	0.0095	0	3.9148	0.5892	0
Central	0.0180	0.0097	0.064	2.2857	0.3438	0
Household size	0.0185	0.0045	0	2.8628	0.2369	0
# children 0 - 4	-0.0206	0.0068	0.002	0.1256	0.0170	0
# children 5 - 14	-0.0251	0.0055	0	0.1266	0.0152	0
# member 15-19	0.0106	0.0071	0.137	1.0941	0.1202	0.413
# of elderly members	0.0147	0.0071	0.037	1.0385	0.1190	0.742
Household head is female	-0.0012	0.0101	0.904	0.7441	0.1114	0.048
Household head is single	-0.0266	0.0106	0.012	0.9517	0.1518	0.756
Primary employment not in agriculture	-0.0205	0.0108	0.058	1.3909	0.2359	0.052
Has electricity	0.0187	0.0114	0.1	7.1455	1.4781	0
No latrine	0.0021	0.0077	0.79	0.6562	0.0767	0
Roof made of lusalite	0.0163	0.0352	0.643	2.4398	1.6040	0.175
Treats drinking water	0.0223	0.0112	0.047	3.5844	0.7255	0
Uses irrigation	0.0004	0.0143	0.977	3.7213	0.9119	0
Experienced a shock in the last year	0.0862	0.0068	0	2.0886	0.2266	0

Marginal Effects and relative risk ratios are compared to the base outcome, chronic poor.
Poverty groups are established using national poverty lines
Estimates obtained using Mozambique's 2008/09 Household Budget Survey (NIS 2009).

Table 16: Estimates of Chronic, Transient, and Non-poor households based upon Multinomial Logit Regression

	Chronic	Transient	Non-poor
	%		
National	52.06	22.51	25.38
Urban	37.2	22.56	40.24
Rural	58.08	22.49	19.36
Niassa & Cabo Delgado, Rural	46.58	27.62	25.80
Niassa & Cabo Delgado, Urban	35.03	34.21	30.76
Nampula, Rural	55.61	27.93	16.46
Nampula, Urban	42.15	30.42	27.43
Sofala & Zambézia, Rural	64.62	19.62	15.76
Sofala & Zambézia, Urban	45.01	25.63	29.36
Manica & Tete, Rural	58.94	21.85	19.13
Manica & Tete, Urban	42.49	22.76	34.75
Gaza & Inhambane, Rural	64.35	15.44	19.99
Gaza & Inhambane, Urban	52.17	21.54	26.29
Maputo Province, Rural	44.94	17.71	36.56
Maputo Province, Urban	31.55	14.33	54.11
Maputo City	18.48	11.13	70.40

Estimates obtained using Mozambique's 2008/09 Household Budget Survey (NIS 2009).

Table 17: Leakage and Under-coverage rates for Chronic Poverty (Observed vs. Estimated)			
Estimated to be Chronically Poor	Observed to be Poor		
	Yes	No	Total
Yes	3,016	1,975	4,991
No	1,884	3,957	5,841
Total	4,900	5,932	10,832
Leakage Rate	39.6%		
Under-coverage	38.4%		

Table 18: Leakage and Under-coverage rates for Chronic Poverty (Observed vs. Predicted)			
Predicted to be Chronically Poor	Observed to be Poor		
	Yes	No	Total
Yes	2,970	2,168	5,138
No	1,930	3,764	5,694
Total	4,900	5,932	10,832
Leakage Rate	42.2%		
Under-coverage	39.4%		

Table 19: Leakage and Under-coverage rates for Chronic Poverty (Estimated vs. Predicted)			
Predicted to be Chronically Poor	Estimated to be Chronically Poor		
	Yes	No	Total
Yes	4,271	867	5,138
No	720	4,974	5,694
Total	4,991	5,841	10,832
Leakage Rate	16.9%		
Under-coverage	14.4%		

Table 20: Leakage and Under-coverage rates for Transient Poverty (Estimated vs. Predicted)			
Predicted to be Transiently Poor	Estimated to be Transiently Poor		
	Yes	No	Total
Yes	458	1,940	2,398
No	484	7,950	8,434
Total	942	9,890	10,832
Leakage Rate	80.9%		
Under-coverage	51.4%		

Table 21: Correlations between Observed Poverty Levels using Qualitative and Quantitative Indicators

	Insufficient Food	Insufficient Meals	Observed Poor
Insufficient Food	1		
Insufficient Meals	0.1423	1	
Observed Poor	0.1562	0.0825	1

Estimates obtained using Mozambique's 2008/09 Household Budget Survey (NIS 2009).

Table 22: Correlations between Predicted Poverty Levels using Qualitative and Quantitative Indicators

	Insufficient Food	Insufficient Meals	Observed Poor
Insufficient Food	1		
Insufficient Meals	0.5469	1	
Observed Poor	0.5585	-0.1252	1

Estimates obtained using Mozambique's 2008/09 Household Budget Survey (NIS 2009).

Table 23: Average Marginal Effects for Quantitative and Qualitative Poverty Measures

	Food expenditures Pseudo R^2 = 0.0968			Insufficient Food Pseudo R^2= 0.0446			Number of Meals Pseudo R^2= 0.0426		
	dy/dx	Std. Error	P>z	dy/dx	Std. Error	P>z	dy/dx	Std. Error	P>z
Rural	-0.0456	0.0148	0.002	-0.0281	0.0148	0.057	-0.0324	0.0092	0
North	-0.0908	0.0159	0	-0.1210	0.0160	0	0.0031	0.0103	0.767
Central	-0.0877	0.0163	0	-0.0614	0.0163	0	0.0006	0.0102	0.955
Household size	0.0169	0.0080	0.035	0.0028	0.0077	0.713	-0.0028	0.0047	0.551
# children 0 - 4	0.0781	0.0115	0	0.0046	0.0118	0.694	-0.0062	0.0074	0.399
# children 5 - 14	0.0489	0.0101	0	0.0066	0.0107	0.539	-0.0116	0.0060	0.055
# member 15-19	0.0350	0.0123	0.004	-0.0042	0.0120	0.726	-0.0134	0.0070	0.057
# of elderly members	0.0252	0.0133	0.058	0.0375	0.0137	0.006	0.0020	0.0072	0.782
Household head is female	0.0131	0.0171	0.446	0.0520	0.0173	0.003	0.0230	0.0107	0.032
Household head is single	0.0259	0.0183	0.157	0.0805	0.0186	0	0.0286	0.0110	0.009
Primary employment not in agriculture	-0.0126	0.0196	0.522	-0.0355	0.0188	0.059	0.0286	0.0125	0.022
Has electricity	-0.1270	0.0184	0	-0.1137	0.0193	0	-0.0547	0.0088	0
No latrine	0.1394	0.0139	0	0.1122	0.0147	0	0.0297	0.0094	0.002
Roof made of lusalite	-0.0556	0.0465	0.232	-0.0397	0.0411	0.334	0.0250	0.0283	0.376
Treats drinking water	-0.1107	0.0194	0	-0.0304	0.0197	0.122	-0.0277	0.0119	0.02
Uses irrigation	-0.0931	0.0276	0.001	-0.1291	0.0258	0	-0.0071	0.0174	0.685
Experienced a shock in the last year	0.0997	0.0144	0	0.1012	0.0152	0	0.0078	0.0087	0.373

Food expenditures are compared to national food poverty lines to determine chronic poverty. Data is weighted.
Estimates obtained using Mozambique's 2008/09 Household Budget Survey (NIS 2009).

Table 24: Comparison of the Models' Estimated Poverty Rates to Mozambique's Poverty Assessment

	Mozambique's Poverty Assessment	Chronic Poverty Rates Estimated by the TE Model	Chronic Poverty Rates Predicted by the MNL Model
		%	
Niassa	31.9	47.5	51.8
Cabo Delgado	37.4	39.4	39.1
Nampula	54.7	50.0	51.9
Zambézia	70.5	64.7	63.0
Tete	42.0	59.5	56.2
Manica	55.1	45.1	55.4
Sofala	58.0	46.2	54.1
Inhambane	57.9	62.6	61.9
Gaza	62.5	56.4	61.3
Maputo Province	67.5	36.6	36.0
Maputo City	36.2	18.7	18.5

Data is weighted.

Estimates obtained using Mozambique’s 2008/09 Household Budget Survey (NIS 2009).

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Appendix A

Table A.1: Variable List	
Name	**Description**
Dependent Variable	
l_food2	log of the temporally adjusted food consumption per capita per day
Endogenous Variables	
Shocks	*binary variables*
agpestyr	Household responded agricultural pests were one of the top 3 negative events in the last year
droughtyr	Household responded a drought was one of the top 3 negative events in the last year
floodcycyr	Household responded a flood or cyclone was one of the top 3 negative events in the last year
illnessyr	Household responded illness was one of the top 3 negative events in the last year
deathyr	Household responded the death of a household member was one of the top 3 negative events in the last year
theftyr	Household responded theft was one of the top 3 negative events in the last year
Independent Variables	
Location	*binary variables*
Rural	Household lives in a rural area
North	Household lives in Niassa, Cabo Delgado, or Nampula
Central	Household lives in Inhambane, Gaza, Maputo Province, or Maputo (capital city)
Demographics	
ch4	Number of members in the household age 4 and under
hh_femsin	Head of household is female and single (*binary variables)*
female	Head of household is female (*binary variable)*
hh_single	Head of household is single (*binary variables)*
hhsize	Number of members in the household
p_0114	% of household between under the age of 14
p_60p	% of household over the age of 60
num514	Number of children age five to fourteen
num1519	Number of members age fifteen to nineteen
numelderly	Number of members age sixty and older
Education	
p_edu_postprim_f	% of household adult females who have completed secondary or higher education
p_edu_postprim_m	% of household adult males who have completed secondary or higher education
p_edu_pri5f	% of household adult females who have completed primary school (grade 5)
p_edu_pri5m	% of household adult males who have completed primary school (grade 5)
p_edu_pri7f	% of household adult females who have completed primary school (grade 7)
p_edu_pri7m	% of household adult males who have completed primary school (grade 7)
Employment	
p_unemploy	% of adults unemployed in the household in the last week
no_ag	Head of household is not engaged in agricultural activity (*binary variable)*

Table A.1 (continued)	
Assets	
farm_quint_lur_cult	Land quintile cultivated including urban and rural landless
irr	Household uses some form of irrigation (*binary variables)*
quint_wealth	Wealth quintile
no_toilet	Household does not have a latrine (*binary variable)*
electricity	Household has electricity (*binary variable)*
roof_lusalite	Household has a lusalite roof (*binary variable)*
Name	**Description**
TLU_total	Tropical Livestock Units for all animals
wealth	wealth index (*asset score*)
Water Variables	*binary variables*
treath20	Household treats water before drinking it
Interview variables	*binary variables*
int_lean	Household was interviewed during the lean season*
Instrumental Variables	
Community Exposure	Enumeration area (EA)
av_agpestyr	% of other households in the same EA who responded yes to agricultural pests as one of the top 3 negative events in the last year
av_deathyr	% of other household in the same EA who responded yes to death as one of the top 3 negative events in the last year
av_droughtyr	% of other households in the same EA who responded yes to drought as a top 3 negative event in the last year
av_floodcycur	% of other households in the same EA who responded to flood or cyclone as one of the top 3 negative events in the last year
av_illnessyr	% of other households in the same EA who responded to illness as one of the top 3 negative events in the last year
av_theftyr	% of other households in the same EA who responded to theft as one of the top 3 negative events in the last year
Rainfall Variables	
agpest_avgseason	average mm of rainfall for the north & south/central rainy seasons
agpest_dev_season	% deviation in rainfall (mm) for the north & south/central rainy season based upon a historical avg. from 1997 to season before shock
cyclone_season_n25	# of weeks when rainfall was over 25 mm during the north & south/central cyclone season
drought_avgseason	average mm of rainfall for the north & south/central rainy season
drought_dev_season	% deviation in mm of rainfall for the north & south/central rainy season based upon a historical avg. from 1997 to season before drought
flood_season_n25	# of weeks when rainfall was over 25 mm during the north & south/central rainy season

Table A. 2: Summary Statistics

Variable	Mean	Std. Dev.	Median	Min	Max
Food expenditures					
l_food	2.430	0.846	2.464	-6.108	7.103
rural	0.503	0.500	1	0	1
North	0.293	0.455	0	0	1
Central	0.364	0.481	0	0	1
hh_single	0.270	0.444	0	0	1
hh_femsin	0.211	0.408	0	0	1
p_0114	39.872	24.696	50	0	100
p_60p	7.465	20.781	0	0	100
p_edu_pri5f	22.817	29.160	0	0	100
p_edu_pri7f	6.830	17.607	0	0	100
p_edu_postprim_f	6.531	17.343	0	0	100
p_edu_pri5m	18.234	24.634	0	0	100
p_edu_pri7m	8.767	18.473	0	0	100
p_edu_postprim_m	9.634	20.208	0	0	100
p_unempl	0.066	0.193	0	0	3
no_ag	0.258	0.438	0	0	1
farm_quint_lur_cult	1.751	2.064	2	-1	5
irr	0.048	0.213	0	0	1
TLU_total	0.364	1.484	0.010	0.000	45.180
treath20	0.132	0.338	0	0	1
Wealth	0.332	1.189	-0.250	-1.377	4.623
Drought					
av_droughtyr	0.081	0.185	0	0	1
drought_avgseason	2.006	2.292	0	0	7.784
drought_dev_season	6.367	9.758	0.000	-20.563	33.816
Flood and Cyclone					
flood_season_n25	0.616	2.756	0	0	21
cyclone_season_n25	0.626	2.751	0	0	22
av_floodyr	0.018	0.083	0	0	1
av_cycloneyr	0.030	0.135	0	0	1
Agricultural Pests					
av_agpestyr	0.054	0.147	0	0	1
agpest_avgseason	2.186	2.295	2.508	0	8.101
agpest_dev_season	7.155	10.452	0	-23.457	33.816
Illness					
Hhsize	4.725	2.512	4	1	34
ch4	0.810	0.899	1	0	8
av_illnessyr	0.043	0.095	0	0	0.875
int_lean	0.394	0.489	0	0	1

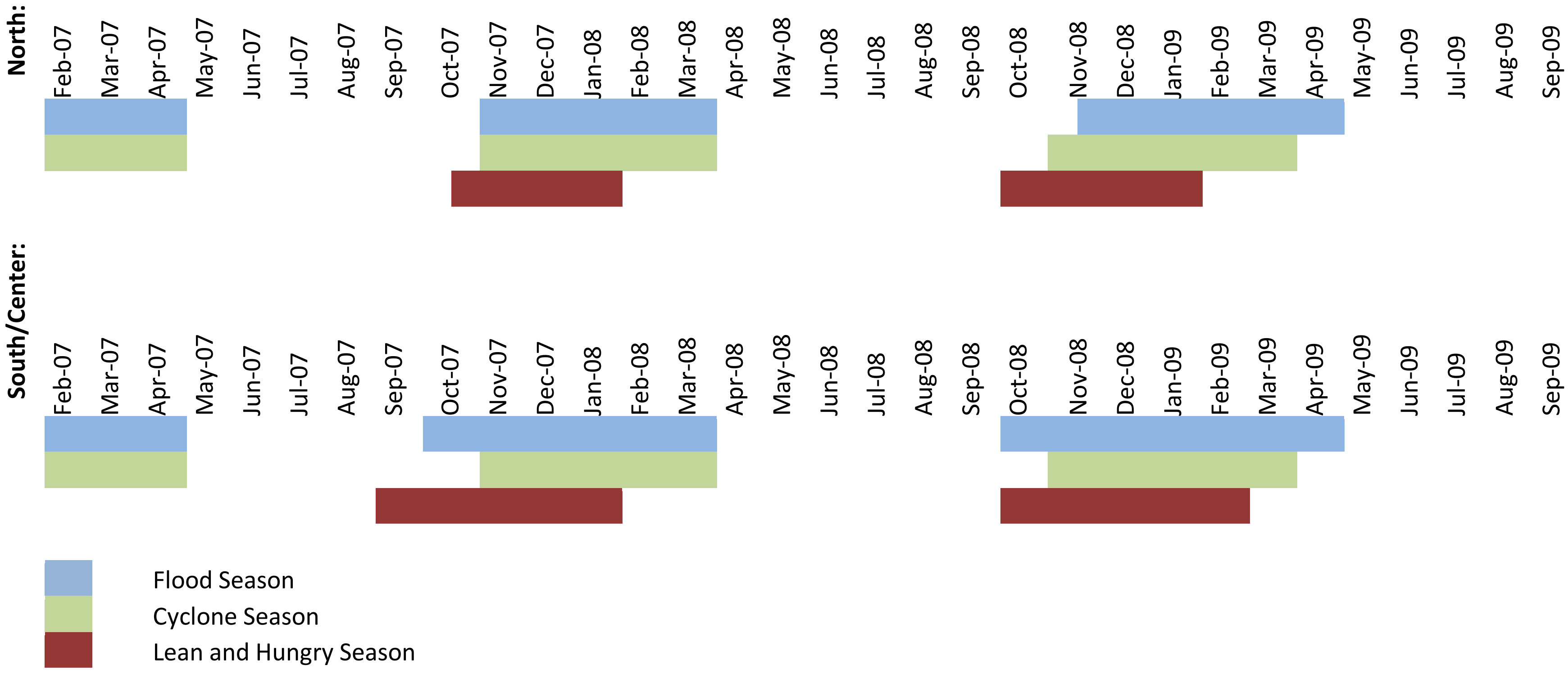
Table A. 2: Summary Statistics (continued)					
Variable	Mean	Std. Dev.	Median	Min	Max
Death					
av_deathyr	0.042	0.081	0	0	0.727
Theft					
quint_wealth	3.342	1.420	4	1	5
av_theftyr	0.053	0.100	0	0	0.667
Multinomial Logit Regression Varibales					
num514	1.424	1.379	1	0	14
num1519	0.431	0.695	0	0	7
numelderly	0.215	0.492	0	0	4
female	0.294	0.456	0	0	1
electricity	0.130	0.336	0	0	1
no_toilet	0.494	0.500	0	0	1
roof_lusalite	0.019	0.137	0	0	1
* Variables are listed as results are reported. Data is weighted.					

Table A. 3: Summary Statistics by Urban and Rural Areas				
	Urban		**Rural**	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Food expenditures				
food_pc_tpi	17.503	25.004	14.307	12.500
rural				
north	0.229	0.420	0.352	0.478
central	0.266	0.442	0.456	0.498
hh_single	0.307	0.461	0.236	0.425
hh_femsin	0.228	0.420	0.195	0.396
p_0114	37.241	24.043	42.323	25.044
p_60p	6.000	18.221	8.830	22.827
p_edu_pri5f	19.805	27.522	25.620	30.342
p_edu_pri7f	10.449	20.831	3.462	13.083
p_edu_postprim_f	12.143	22.141	1.307	8.238
p_edu_pri5m	13.860	22.945	22.305	25.443
p_edu_pri7m	11.264	20.253	6.443	16.308
p_edu_postprim_m	16.115	24.234	3.602	12.901
p_unempl	0.120	0.243	0.016	0.107
no_ag	0.505	0.500	0.028	0.164
farm_quint_lur_cult	0.659	1.984	2.768	1.554
irr	0.042	0.200	0.053	0.225
TLU_total	0.227	1.295	0.491	1.630
treath20	0.193	0.395	0.075	0.263
wealth	1.087	1.248	-0.371	0.505
Drought				
av_droughtyr	0.061	0.154	0.099	0.208
drought_avgseason	1.868	2.084	2.134	2.463
drought_dev_season	8.159	10.416	4.699	8.780
Flood and Cyclone				
flood_season_n25	0.415	2.299	0.802	3.110
cyclone_season_n25	0.412	2.257	0.826	3.129
av_floodyr	0.015	0.065	0.020	0.097
av_cycloneyr	0.017	0.095	0.041	0.164
Agricultural Pests				
av_agpestyr	0.035	0.112	0.071	0.172
agpest_avgseason	1.991	2.096	2.367	2.452
agpest_dev_season	8.769	10.799	5.653	9.884
Illness				
hhsize	4.902	2.645	4.559	2.369
ch4	0.749	0.863	0.866	0.927
av_illnessyr	0.052	0.102	0.034	0.088

Table A. 3: Summary Statistics by Urban and Rural Areas (continued)				
	Urban		**Rural**	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Illness				
int_lean	0.389	0.488	0.399	0.490
Death				
av_deathyr	0.047	0.080	0.037	0.082
Theft				
quint_wealth	4.195	1.140	2.549	1.175
av_theftyr	0.074	0.114	0.035	0.081
Multinomial Logit Regression Varibales				
num514	1.384	0.024	1.440	0.027
num1519	0.5600	0.014	0.379	0.011
numelderly	0.178	0.007	0.230	0.008
female	0.312	0.008	0.287	0.008
electricity	0.419	0.008	0.013	0.002
no_latrine	0.0225	0.008	0.603	0.008
roof_lusalite	0.050	0.004	0.007	0.0014

* Variables are listed as results are reported. Data is weighted.

Figure A.1: Mozambique Seasonal calendar: February 2007 - September 2009



Data is obtained from USAID's Famine and Early Warning Systems Network

Specific Reports include:

Mozambique Food Security Update, September 2007 (FEWSNET, September 2007)

Mozambique Food Security Update, May 2008 (FEWSNET, May 2008)

Mozambique Food Security Update, March 2009 (FEWSNET, March 2009)

Mozambique Food Security Update, June 2009 (FEWSNET, June 2009)