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Vulnerability and the Impact of Climate Change in South Africa's Limpopo River Basin

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Environment and Production Technology Division

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

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Any and all remaining errors are the responsibility of the author.

ABSTRACT

This paper uses farmers' responses to exogenous weather shocks in South Africa's Limpopo River Basin to gauge how farmers are apt to respond to future climate change-induced shocks, in particular drought. Droughts are expected to increase in both frequency and intensity as a result of climate change. This study examines the costs of drought today and who it affects the most, in an effort to guide policy adaptations in the future. A combination of descriptive statistics and econometric analysis is used to approximate the potential impact of droughts on rural South African households. This paper also estimates household vulnerability. After controlling for household heterogeneity using propensity score matching, it is noted that there is no statistically significant impact of droughts on income, thus suggesting households have already adapted to living in a drought-prone environment. The types of households that were more vulnerable to climate shocks are analyzed using two measures of vulnerability: the probability of falling below income of 7,800 South African Rand (R), and the probability of income falling below 16,000 R. Residents of the Limpopo province were the least vulnerable under both metrics. Setswana and SeSwati households were more vulnerable than other ethnic groups. Households that do not own livestock and households that rely on rainfed agriculture were also more vulnerable than other households.

Keywords: vulnerability, climate change, drought, South Africa

ABBREVIATIONS AND ACRONYMS

DFID	Department for International Development of the United Kingdom
IPCC	Intergovernmental Panel on Climate Change
VER	vulnerability as expected poverty
ILRI	International Livestock Research Institute
IFPRI	International Food Policy Research Institute
CEEPA	Center for Environmental Economics and Policy in Africa

1. INTRODUCTION

Climate change is expected to exacerbate Africa's struggles with strained water resources and food security. Rising global temperatures are expected to increase flooding in coastal areas, cause declines in agricultural production, threaten biodiversity and the productivity of natural resources, increase the range of vector-borne and waterborne diseases, and exacerbate desertification; thus, they have a disproportionately adverse impact on Africa's agriculture-based economy (Mendelsohn et al. 2000). To make matters worse, Africa has a low adaptive capacity due to its dependence on rainfed agriculture, low levels of human and physical capital, and poor infrastructure. Of the first wave of studies on the effects of climate change on economic variables, most estimated the predicted loss of income from climate change through crop simulation experiments (see, for example; Rosenzweig and Parry, 1994). The next generation of studies—Ricardian studies (such as by Mendelsohn and Dinar, 1994; 2003) and hedonic studies (such as by Deschenes and Greenstone, 2007)—sought to capture adaptations to climate change by exploiting cross-sectional variance in climate and land prices. However, looking at how land rents change with climate misses an important part of the impact of climate change. Climate change is expected to cause an increase in drastic weather events and this, in combination with households employing costly risk-coping strategies, is likely to increase the probability of income shocks having an even larger impact on the poor. For this reason, studying the impact on expected incomes is not enough: it is important to keep in mind the stochastic nature of poverty to understand how a changing distribution of risk will lead to increased vulnerability, not just decreased expected income.

By analyzing today's responses to natural disaster shocks in Ethiopia and South Africa, this paper which is part of a larger project aimed at studying and characterizing vulnerability seeks to better understand these issues in order to implement policy options for adaptation to climate change. Using data from a 2005 survey of just under 800 households, this paper focuses on South African households' characteristics, farm production, and response to shocks as well as perceptions of climate change in the Limpopo River Basin.

Farmers' responses to droughts of today are used to estimate the impact of climate change-induced droughts and study vulnerability in the region. This paper does not examine the impact of floods, hailstorms or fire outbreaks; the data on these other climate-related shocks were insufficient and therefore could not lead to a meaningful analysis. This paper explored the thesis that an increase in the frequency and severity of droughts (as well as floods, hailstorms and fire outbreaks) will induce a change in behavior to mitigate the risk from this new shock distribution, that this change is measurable and that it can be approximated with the response to shocks today. It is difficult to predict exactly what this behavior will be, and exactly how it will impact welfare, but coping strategies used in response to shocks today do convey information on how rural South Africans will cope in the future. The types of climate-related shocks examined in this study are primarily droughts. This study examines the cost of droughts through propensity score matching, a statistical method that corrects for selection bias. Lastly, the vulnerability of individual households is calculated, and vulnerabilities across groups are compared, in order to gain insights into what the characteristics of households are that lead them to be more vulnerable to shocks of various kinds.

Background

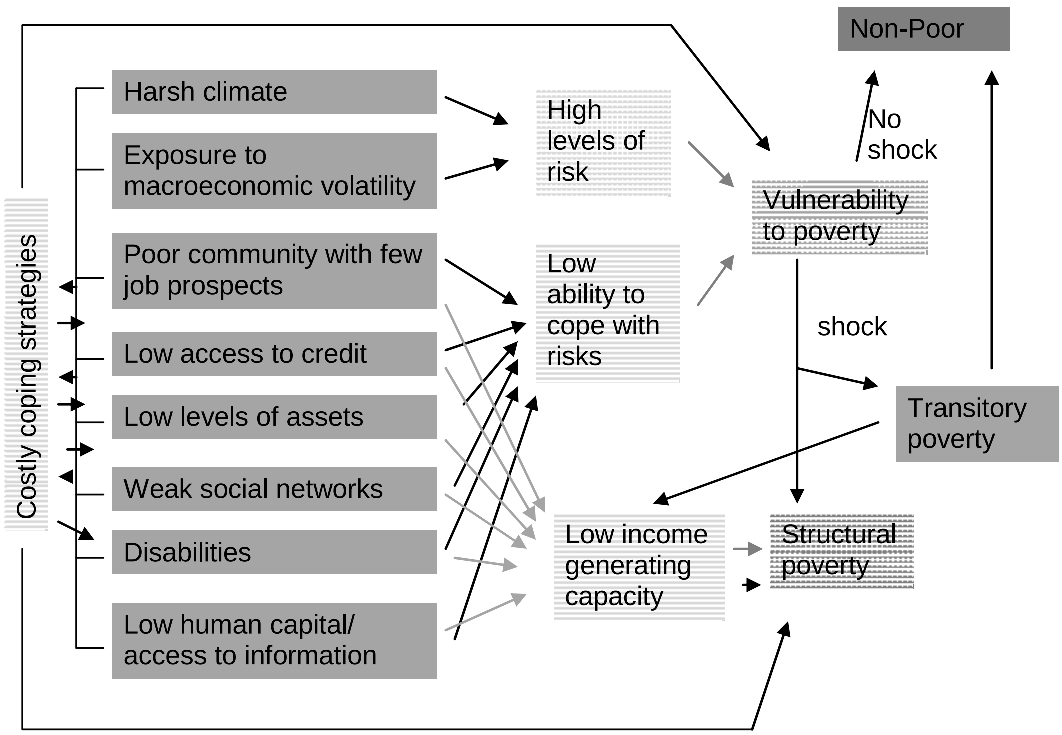
Climate change is expected to bring changing rainfall patterns with resulting changes in agriculture, food security and economic growth; increased temperatures; increases in the prevalence of vector-borne diseases; decreased water security; sea level rise; and increased variability of floods and droughts (DFID, 2004). Increased temperatures will bring potentially faster plant growth, but also shorter growing seasons and increased stress to livestock production. No precise information is available about the future impacts of these changes in terms of the exact changes in the distribution of temperature, floods, droughts or their impacts on crop production, but there is consensus on the qualitative impacts. It is clear, for instance, that increased rainfall variability will bring simultaneously more floods and more droughts (DFID, 2004). Indeed, farmers are aware of many of these impacts (Challinor et al. 2007).

One way to understand the impacts of climate change is to look at land values, since the future productivity of the land as a function of climate, soil, distance to market, and so forth is embodied in the price of the land. Deschenes and Greenstone (2007) adopt this approach in some of their recent work. Their methods were not employed in this paper due to data constraints and the scale and focus of this project, they are not appropriate for studying poverty in rural South Africa. Information on the price of agricultural land does not exist for a hedonic study such as in Deschenes and Greenstone (2007). While estimating production functions may have been useful, the survey did not provide reliable data on production inputs. Neither of these methods also tells us anything about the fluctuations in income that may be particularly important in a developing-country context. Instead, information about wealth, income and climate change-induced shocks is used to estimate future vulnerability to climate change. The analysis will not result in a point estimate of the impact of climate change, but instead will call attention to particularly vulnerable groups and obtain rough approximations of climate change's potential impact.

Vulnerability to climate change means different things to different people. The Intergovernmental Panel on Climate Change describes vulnerability as the degree to which a system is susceptible to, or unable to cope with, adverse effects of climate change, including increased variability and downside risk (IPCC 2001). Geographers refer to vulnerability as what Leichenko and O'Brien have defined as "the extent to which environmental and economic changes impact the capacity of regions, sectors, ecosystems, and social groups to respond to various types of natural and socioeconomic shocks" (Leichenko and O'Brien 2002). Economists, who study the stochastic aspects of poverty, see vulnerability as an ex-ante measure of well-being, reflecting the prospects a household faces in the future (Skoufias and Quisumbing 2008; Gilligan and Hoddinott 2007; Chaudhuri 2003; Heitzmann et al. 2002; Dercon 2001; Holzmann and Jorgensen 2000; and Moser 1998). All of these definitions convey vulnerability as having two components: i) an exposure to risk; and ii) a low capacity to cope with adverse outcomes. In many ways, it is impossible to separate either risk or adaptive capacity as cause or effect because the presence of risk may induce costly risk-averse behavior, whereas the absence of a safety net may induce greater exposure to risk.

In general, economists have found that vulnerable households tend to be those with low levels of human capital and poor access to information, limited access to credit and risk-management instruments, and few productive and financial assets. Vulnerable households tend to suffer from physical and psychological disabilities, social exclusion and inadequate social support networks. They tend to live in harsh agroclimatic environments with limited natural resources, and as part of communities with little entrepreneurial activity. Their work tends to be in sectors that are particularly sensitive to macroeconomic volatility and sectoral shocks (Chaudhuri 2003). Figure 1 was adapted from Chaudhuri (2003) and presents these linkages schematically. A vulnerability assessment will determine which of these linkages are most important in a particular setting. With the kind of large, uncertain shocks to food and water security that climate change is likely to bring, being able to address vulnerability becomes a useful tool in poverty reduction.

Figure 1. Linkages between risk, poverty and vulnerability



Vulnerability is important because an efficient social policy seeks to go beyond poverty alleviation in the present, and examine poverty prevention in the future. A poverty reduction strategy that ignores the transient nature of poverty misses households that have a high probability of being poor and may instead devote scarce resources to households that are only transiently poor and would have found a way out of poverty without government assistance.

This paper uses vulnerability as expected poverty (VER), the probability of falling below some welfare threshold (becoming poor), conditional on the occurrence of an exogenous shock, $P(z_i < \bar{z} \mid X_i)$ where z_i is expected welfare; $\bar{z}$ is a welfare threshold level; and X_i is a vector of household characteristics and shocks. This definition takes into account the risk a household may face, as well as the capacity of the household to adapt to adverse outcomes. VER is flawed in that it is not always consistent with ideas about risk aversion and does not differentiate between poverty and extreme poverty. Other economic definitions of vulnerability overcome these issues, such as vulnerability as expected low utility, and vulnerability as uninsured exposure to risk (Hoddinott and Quisumbing, 2003a). These are refinements of VER, but they are more complicated to use and less intuitive for policymakers.

Poverty is defined as a low level of income, because it is an intuitive definition, and because we believe income is more accurately measured in the data than consumption is. Vulnerability can also be defined as the probability of losing the means of production, the probability of poor nutrition in the future, or the probability of children dropping out of school; hence, sustaining gaps in human capital formation, but none of these measures was available in the data. While income, in contrast to consumption, is a flawed measure of current welfare, it is the best measure of welfare in this dataset.

Vulnerability to climate change is defined as "expected poverty;" that is, the probability of falling below an income threshold as a result of climate change. The type of vulnerability of interest in this paper is vulnerability to the increased number of droughts and floods climate change is expected to bring. Estimating vulnerability to climate change is difficult since it requires making predictions about the physical and economic impacts of climate change, both of which vary greatly. Different assumptions about the future path of carbon dioxide ($CO_{2)}$ and different physics models create very different predictions about what will happen to physical properties of the atmosphere. In addition, the scale of climate change models is not always appropriate for study of economic effects. Scaling down to predict local conditions compounds this uncertainty and faces computing power limitations (Challinor et al. 2007, ILRI 2006, Coppola and Giorgi, 2005, and Arnell et al. 2003).

The measurement of vulnerability should give a static picture of the costs of climate change. There will be short-run adaptations to individual shocks, but also long-run adaptations to a changing distribution of shocks. The data only allow us to measure the short-run adaptations, but are nonetheless an important analytical tool used to identify risks and vulnerable groups, assess the outcome and impact of shocks, and identify households that face a high risk of falling into poverty due to climate change.

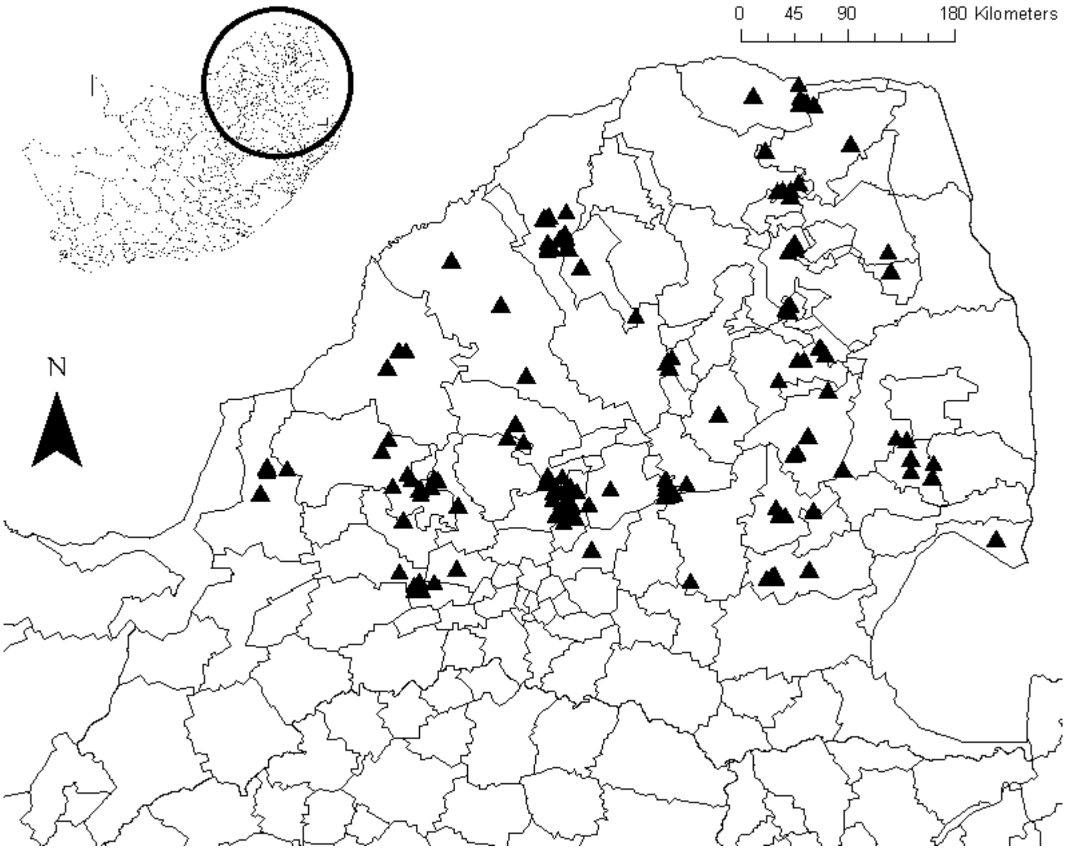
2. DESCRIPTION OF THE DATA

The data come from a survey of approximately 800 farmers in 20 districts of South Africa's Limpopo River Basin, which was part of a project jointly sponsored by the International Food Policy Research Institute (IFPRI) and the Center for Environmental Economics & Policy in Africa (CEEPA). The project is entitled "Food and Water Security under Global Change: Developing Adaptive Capacity with a Focus on Rural Africa." The distribution of observations by village and by farm type is reported in Table 1. The location of farms can be seen in Figure 2. The questionnaire had nine sections: i) a household roster with demographic information (Figure 2); ii) a household assets section which included information about basic services, diseases and shocks; iii) a section on land tenure and farm value; iv) a section on farm machinery, farm buildings, wells, pumps, and wage rates; v) a section on crop production for both annual and perennial crops; vi) a section on livestock production; vii) a section on access to extension, markets and credit; viii) a section on food expenditures and income; and ix) a section on climate change perceptions and adaptation options.

Table 1. Sampled households by village and farm type

District	Frequency	Percentage of sample
Bronkhorstspruit	29	3.9
Cullinan	5	0.7
Krugersdorp	13	1.7
Carolina	31	4.1
Lydenburg	36	4.8
Middelburg	49	6.5
Nkomazi	25	3.3
Witrivier	43	5.7
Brits	25	3.3
Marico	49	6.5
Rustenburg	26	3.5
Lephalale (Ellisras)	61	8.1
Tzaneen (Letaba)	45	6.0
Messina	48	6.4
Nebo	39	5.2
Makpopane (Potgietersrus)	55	7.3
Soutpansberg	65	8.7
Thabazimbi	30	4.0
Thohoyandou	49	6.5
Warmbad (Bela-Bela)	28	3.7
Total	**751**	**100**
Type of farm		
Small-scale	689	92.5
Large-scale	56	7.5
Total	**745**	**100**
pe		

Figure 2. The Limpopo River Basin with district boundaries and household locations



Source: Created by Author using data from Food and Water Security under Global Change:

Table 2. Household demographic information

Variable	Mean	Min	Max	Standard Deviation	Obs
Household size	6.2	1	24	2.9	727
Years of education*	9.5	0	34	5.1	746
Ethnic Group		***Number of households***		***Percentage of sample***	
Zulu		15		2	
Xhosa		18		2	
Tshivenda		125		17	
Southern Sotho		11		1	
Shangaan/Tsonga		70		9	
SeTswana		146		20	
SeSwati		73		10	
Sepedi/ N Sotho		194		26	
Ndebele		59		8	

Table 2. Continued

Ethnic Group	*Number of households*	*Percentage of sample*
English	4	0.5
Afrikaans	25	3
Other	2	0.3
Households with access to landline	709	95
Households with access to electricity	143	19
Households that obtained a loan	166	22
Households that did not obtain a loan because they did not have access to or information about credit	203	41
Households that did not want a loan	160	32
Households that own livestock, poultry, fish or other farm animals	324	58.8

Note: It was not clear from the survey who was the household head. "Years of education" refers to the educational level of the most educated household member as is typically done.

Households reported having from 1 to 24 individuals, but the household roster only had information for 15 members. Information was gathered on the age, gender, and educational level of all household members as well as about the jobs and salaries of each individual, as discussed below. Wealth is measured by household assets and farm value. Households were asked if they owned various assets, such as a television, radio, flush toilet, cell phone, house made of stone/concrete or brick, refrigerator, irrigation system or a car (Table 3). If they did not own any of these, they were also asked if they owned a bicycle, hand-drawn cart or a set of iron cooking pans. Households were also asked how many of each item they owned as well as either the replacement cost or year purchased and original price. To calculate farm value, households were asked about the area, use, soil type, fertility, slope, erosion, water source, title status, and value (when known) of the land they owned or rented.

Table 3. Household asset information used to create a wealth factor score

Percent of people owning a:	
Television	75.0
Radio	87.0
Flush Toilet	27.6
Cell Phone	77.8
House made of stone/concrete or bricks	77.6
Refrigerator	21.9
Car	36.6
Sprinkler	16.0
Pump	65.0

Source: Author's Calculations from Food and Water Security under Global Change: Developing Adaptive Capacity with a Focus on Rural Africa

Questions about income were asked multiple times in the survey. In various parts of the survey modules, there are questions about the derivation of income from specific sources, such as whether the income is from employment, crop sales or livestock sales. Section 8 of the survey had a separate income module where questions about income from employment, crops, and livestock as well as gifts and remittances were asked (Table 4). The data on income from crop and livestock sales were unusable; thus, only information on crops and livestock from the final module was used. Data on income sources from work were more reliable as they were broken down by person and job. Many observations on the quantity of income received from each job were missing. Because ignoring missing data can lead to biased results, income by job source was imputed using information on gender, education and type of job, using the multiple imputation algorithm known as "Amelia," which was developed by Gary King and described in Honaker et al. (1999). This figure was then aggregated by person and by household to calculate a figure on total household income from employment. These results are reported as imputed labor income in Table 4. Note that the totals in Table 4 are not necessarily consistent with the columns and number of households reporting income from a source. While some households reported receiving income from a source, they did not list the amount of income received. In this case, the household was counted as a missing observation in calculating the mean and standard deviation of income from that source, but still listed as a household reporting income from that source. In calculating total income, the unreported income was included as a zero. This is why three households report receiving income from selling nonfarm assets, but there is only one observation for the amount of income from selling non-farm assets.

Table 4. Sources of income (April 2004–2005)

Type of income	Households reporting income from this source	Income obtained (in S.A. Rand)			
		Mean	Std. Dev.	Min	Max
Total nonfarm net income (labor and selling items)	245	42,649	82,653	150	979,200
Gifts	20	11,929	42,869	100	178,000
Remittances	30	4,050	9,005	150	43,000
Net crop sale	413	99,009	709,300	30	10,200,000
Net livestock and livestock Product sale	247	146,032	1,420,288	100	21,400,000
Pension	266	12,350	8,175	1,000	66,000
Savings	26	13,626	12,792	750	40,000
Sale of assets for farming	6	29,400	35,423	2,000	90,000
Sale of nonfarming assets	3	2,000	---	---	---
Government or other grants (child grant, disability)	39	5,403	3,488	130	18,000
Total from above sources	674	128,200	1,116,143	51	25,100,00
Imputed labor income	749	1,133	2,768	6.6	41,990
Total income*	749	116,090	1,060,024	10	25,000,000
Total income)	749	9.627	1.879	2.3	17.0

Source: Author's Calculations from Food and Water Security under Global Change: Developing Adaptive Capacity with a Focus on Rural Africa

Note: *Total income was computed adding totals from "Gifts" through "Grants" to either "Total nonfarm net income" (which had many missing observations) or "Imputed labor income," depending on which one was larger and, hence, deemed more complete.

The variable farm value was often missing. The Amelia logarithm was again used to impute missing values for farm value, using information on plot size, use of plot (crops, livestock, garden), type of soil, slope, erosion status, type of irrigation, and land tenure. The results are summarized in Table 5. Rainfall information was constructed from a set of climate grids called CRU TS 2.1, as described in Mitchell and Jones (2005). The mean and coefficient of variation (CV) of rainfall were first calculated for half degree latitude/longitude grid cells, and then interpolated to household sites based on their locations.

Table 5. Farm characteristics

Variable	Mean	Min*	Max**	Standard Deviation	Obs.***
Years in farming	12.5	1	60	11.7	741
Value of farm land (in S.A. Rand)	64,7179	540	15,000,000	1,088,400	727
Rainfall (October 2004-April 2005) (mm)	370.2	265.7	463.5	54.1	749
Seasonal (October – April) mean of rainfall 1951-2000 (mm)	561.4	260.1	813.8	94.3	749
Seasonal (October-April) coefficient of variation of rainfall 1951-2000	0.244	.0176	0.451	0.0393	749
Distance of household to market (km)	51.19	0	600	72.89	749
Distance of household to primary school (km)	3.05	0.01	50	4.96	716

Note: The abbreviations stand for the following, respectively: * Min = minimum; **Max=maximum; and Obs. =observations.

While the data are cross-sectional and, ideally, questions about vulnerability could be answered with panel data (Dercon et al. 2005, Hoddinott and Quisumbing 2003), the assumption is that cross-sectional variation mimics intertemporal variation, thus mirroring the approach of Tesliuc and Lindert (2002). Certain types of assets and farm value are used as predetermined variables to examine the effect on income of droughts in 2005. This is further discussed in the next section on the impact of shocks.

Description and Structure of Shocks

Data were gathered on 27 types of shocks, with an additional category for reporting "other." The shocks were pre-coded as one of the following: drought, flood, hailstorm, fire outbreak, landslide, pests of crops before harvest, crop loss during storage, animal disease, large increase in input prices, large decline in output prices, inability to sell agricultural products, inability to sell nonagricultural products, land distribution by government, forced migration, discrimination for political reasons, discrimination for social reasons, forced contributions or arbitrary taxation, destruction or theft of tools or inputs for production, theft of crops, theft of livestock, other theft, loss of job by family member, death of family member, illness of family member, separation of family member(s), dispute with extended family, dispute with others in village and other. The percentage of households reporting the various shocks can be seen in Table 6. Shocks were reported as far back as 1977, but the question specifically asked for shocks from the last five years, so all shocks occurring before 2001 were deemed unreliable and highly subject to recall bias.

Table 6. Description of self-reported shocks

Variable	Percentage of households reporting shock in 2005	Percentage of households reporting shock in 2004	Percentage of households reporting shock between 2001 and 2005
Drought	16.8	28.8	99.3

Flood	0.9	1.3	7.9
Hailstorm	0.5	3.6	8.9
Landslide	4.4	3.3	10.5
Pests of crops before harvest	0	0	0.0
Crop loss during storage	1.9	2.7	7.7
Animal disease	0.3	0.3	0.9
Large increase in input prices	1.5	1.1	5.7
Large decline in output prices	0.1	0.9	1.6
Inability to sell agricultural products	0.1	1.1	1.7
Inability to sell nonagricultural products	0.5	1.3	7.3
Land distribution by government	0.1	0	0.5
Forced migration	0	0.1	0.1
Discrimination for political reasons	0	0	0
Discrimination for social reasons	0.3	0.1	0.8
Forced contributions or arbitrary taxation	0.1	0	0.3
Destruction or theft of tools or inputs for production	0	0.3	0.4
Theft of crops	0.8	0.9	3.6
Theft of livestock	1.6	1.6	4.7
Other theft	1.2	0.7	3.6
Loss of job by family member	0.4	1.2	2.0
Death of family member	0	0.1	0.8
Illness of family member	1.2	1.2	6.1
Separation of family member	0.1	0.1	0.5
Dispute with extended family	0	0	0.1
Dispute with others in village	0.3	0	0.4
Other	0	0.4	0.4

To examine the potential for recall bias in self-reported shocks, two variables—mean and coefficient of variation (CV) —were used to measure the historical intensity and frequency of drought events over the time range of 1951-2000, and information about the October 2004 to April 2005 growing season was also considered. The coefficient of variation is the standard deviation of rainfall divided by mean. As can be seen in Table 5, 2004-05 was a drier year than the 1951-2000 average. Mean of rainfall and CV were first calculated for half degree latitude/longitude grid cells, and then interpolated to household sites based on their locations (latitudes and longitudes). In addition to this information about the distribution of historical rainfall, information specifically for the 2004-2005 growing season from October to April was used. As can be seen in Table 7, the relationship between self-reported droughts and floods and rainfall data is weak. Even after standardizing rainfall data and examining deviations from the mean, the correlations are very low.

Table 7. Correlation between self-reported and hydrological data

Variable	Self-reported drought 2005	Self-reported flood 2005	Rainfall (October 2004- April 2005) (mm)	Seasonal (October-April) coefficient of variation of rainfall 1951-2000	Seasonal (October-April) coefficient of variation of rainfall 1951-2000	Standard deviations from historical mean
Self-reported drought 2005	1					
Self-reported flood 2005	0.1047	1				
Rainfall (October 2004-April 2005) (mm)	0.0737	-0.0451	1			
Seasonal (October – April) mean of rainfall 1951 – 2000 (mm)	-0.0022	-0.0312	0.4472	1		
Seasonal (October-April) coefficient of variation of rainfall 1951-2000	-0.0941	0.0347	-0.5649	-0.4367	1	
Standard deviations of October 2004– April 2005 (Rainfall from Historical Mean)	0.0125	0.0119	0.1224	-0.7665	0.401	1

Self-reported droughts and floods were reported as zero-one variables, while rainfall was reported in millimeters, and the coefficient of variation was unit-less. Standard deviations of rainfall from historical mean ranged from -2.54 to 1.25 mm.

Figure 33a and 3b presents kernel densities of households reporting shocks and households not reporting shocks. No apparent relationship appears between those who reported droughts and those who would have been expected to report droughts from the rainfall data. The relationship on floods is more difficult to see since only seven floods were reported in 2005. One reason for this is that the hydrological data is an average over the entire growing season; hence, it may not capture a run of rainless days. In addition, because the rainfall data were extrapolated from rainfall data stations, it is by construction spatially correlated and may be missing important microclimate dynamics. Faced with the choice of using potentially biased self-reported shocks and potentially unrelated climate data, the potentially biased self-reported shocks are used since they more accurately capture the variation. Using shocks from the past year should limit the extent of recall bias problems and provide more valuable information about microclimates within the Limpopo River Basin.

Figure 3a. Kernel densities of rainfall with drought and flood status

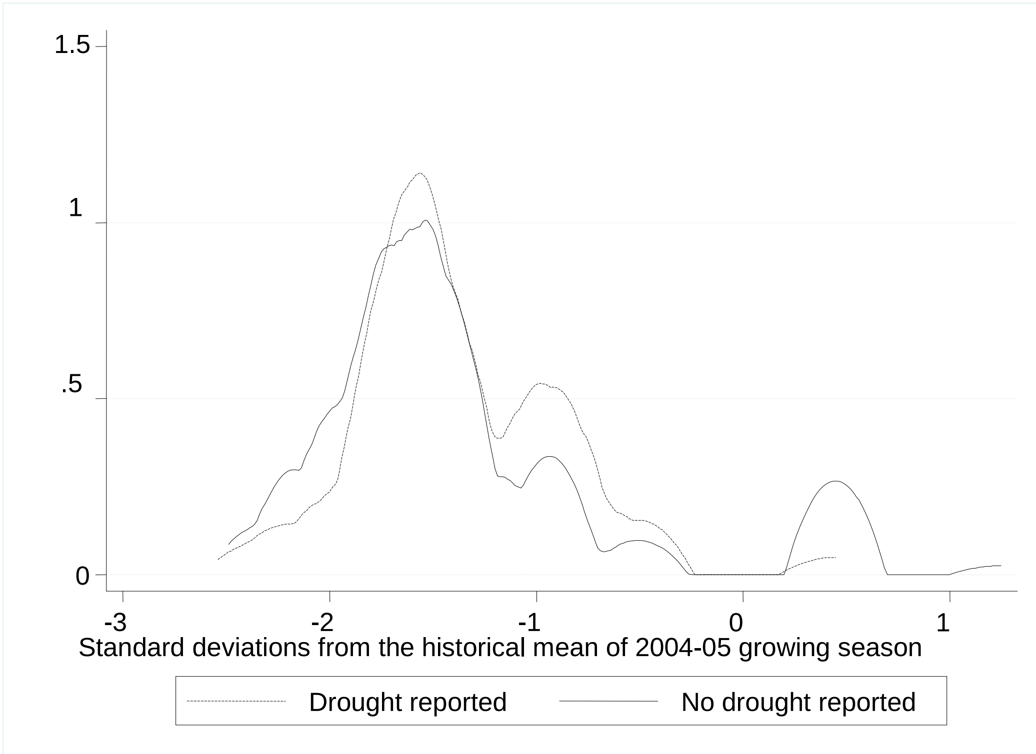


Figure 3b. Kernel densities of rainfall with flood status

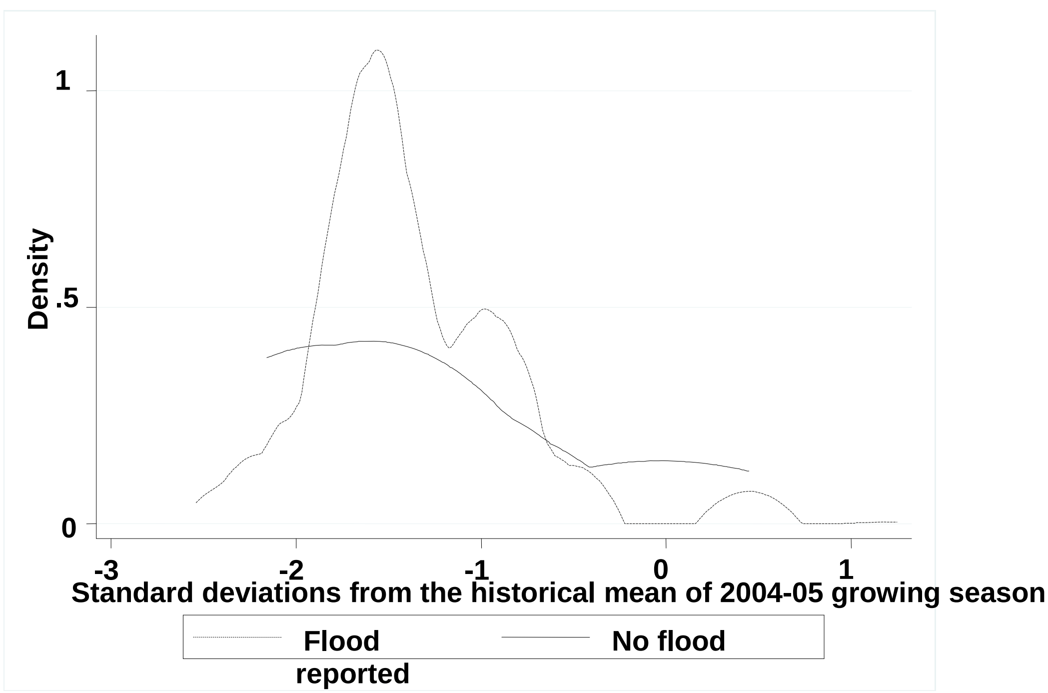
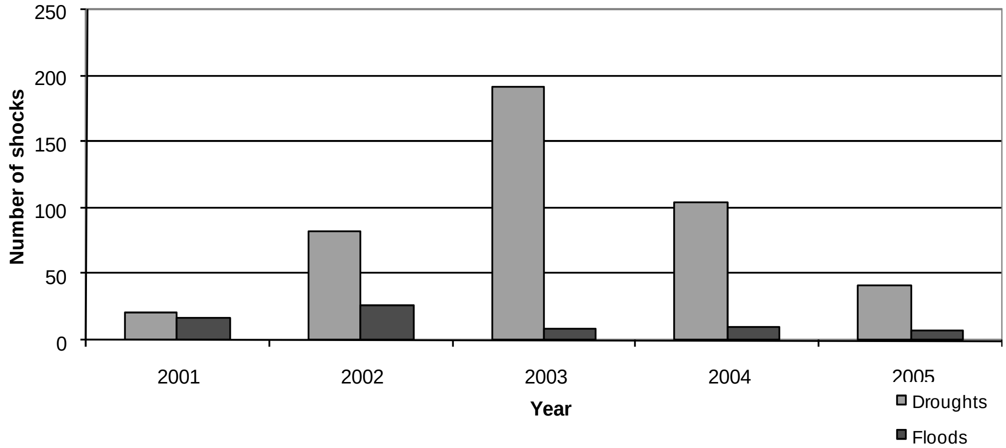


Figure 4. Shocks reported by year



The frequency over the last five years of the most relevant climate change shocks, as well as their outcomes, is reported in Figures 3a and 3b. The figure shows that droughts were the most prevalent type of shock. Forty-one instances of drought and seven floods were reported in 2005. The year of the survey, 2005, was a relatively normal year for South Africa: The currency crisis of 2001 had faded, and the South African currency—the Rand—was holding steady at a little over 6 Rand to the dollar. There were some minor labor strikes, and there were some earthquakes west of Johannesburg, but 2005 was not otherwise an abnormal year for macroeconomic volatility or natural disasters.

Coping Strategies

When a household is hit by a shock, its coping strategies are an important indication of adaptation and vulnerability. The vast majority, 75 percent of respondents, said that they did nothing in response to the shock. Other responses included coping strategies such as selling livestock, borrowing from relatives or the bank, receiving aid, migrating to another rural or an urban area, seeking off-farm employment or eating less. That there were so many respondents reporting they “did nothing” is puzzling: At the very least, a household is likely to have dug into its assets or reduced consumption. It may be that households are reporting many types of droughts, and not just the ones having the most impact. This means that the results will be biased towards thinking there is less of an impact from droughts and floods than more. This could also reflect that households have already adapted to living in a drought-prone environment. Households may be using drought-resistant varieties or other coping mechanisms that minimize the cost of droughts.

Table 8. Actions resulting from shocks that occurred from 2001 to 2005

Action	Frequency of actions resulting from a:			
	Drought		Flood	
	2005	2001-05	2005	2001-05
Did nothing	34	366	6	43
Sold livestock	1	19	0	1
Borrowed from relatives	1	3	0	2
Borrowed from bank	1	7	0	0
Received food aid	0	1	0	0
Migrated	1	4	0	0
Ate less	0	2	0	0
Other	9	30	2	5
Not specified	0	20	0	6
Total	47	452	8	57

Source: Author's Calculation from Food and Water Security under Global Change: Developing Adaptive Capacity with a Focus on Rural Africa
Note: The total may be more than the number of shocks reported because more than one response could be given for the same shock.

3. IMPACT OF SHOCKS

Propensity score matching provides a way to estimate the impact of a drought, despite droughts not being randomized across groups. Simply comparing the income between shocked and un-shocked households would lead to a biased estimate of the impact of droughts because of covariates correlated with both the probability of receiving a drought and income. Ideally, households with the same set of covariates could be compared across drought and no-drought status to estimate the impact. Implementing this would be next to impossible because of dimensionality problems, so propensity score matching is used. Households' characteristics are used to estimate the probability of receiving a drought (the propensity score). Next, income of households with similar probabilities is compared to estimate the impact of droughts. (Caliendo and Kopeinig 2008; Dehejia and Wahba 2002). Here a logistic regression is run to estimate the probability of a drought, given household characteristics. Since only cross-sectional data are available, it is essential that the propensity score reflects only pre-determined variables, those that have not been impacted by the drought. Therefore, droughts that occurred in the last four months are used, and assets that are difficult to sell and time-invariant characteristics are used.

In the income section of the survey, households were asked if they sold farming or nonfarming equipment from 2004 to 2005. These results can be seen in Table 4. Only three households reported selling nonfarming equipment, and none of those households reported a drought in 2005. Six households reported selling farming equipment; none of these reported a shock either. This evidence, combined with the conservative choice of assets, means that the control variables are pre-determined and unaffected by a drought from the last four months. Even with the assurance that the covariates are all pre-shock variables, propensity score matching is only reliable if all the important covariates are captured in the propensity score and the same approach is used as in Tesliuc and Lindert (2002).

Logistic Descriptions of Shocks

To understand the impact of droughts on income, the first step is estimating the probability of experiencing a shock, given household characteristics. For this reason, a logistic regression is run to estimate the probability of experiencing a drought as a function of household characteristics:

$$P(shock) = f(X) \tag{1}$$

Here *f* is the exponential probability density function; *X* is a vector of household variables listed in Table 9 and shock refers only to droughts, because drought was the only shock with enough variation to study. The type of farm refers to small-scale farming versus large-scale farming, with a 0 for a small-scale farm, and a 1 indicating a large-scale farm. Since it was not clear in the survey which member of the household was the household head, the educational variables—"Years of education" and "Years of education squared"—refer to the number of years of education of the most educated member of the family. Three variables related to rainfall were included to capture important aspects of the quantity and distribution of rainfall. The coefficient of variation (CV) for 2004-2005 annual rainfall was included to capture the intra-year rainfall variation, while the CV for 1951-2000 was included to capture inter-year variation. The mean of historical rainfall (1951-2000) was included to capture whether the area was on average relatively dry or wet. Distance to a primary or secondary school, and distance to market were included to pick up variation in distance to village center, and variables on assets and district dummies were also included.

Table 9. Logistic regression on drought

Variable	Coefficient	Std. Err.	P-value
Years in farming	0.00823	0.0111	0.457
Type of farm (0= small-scale, 1= large-scale)	0.626	0.419	0.135
Years of education	0.338***	0.0977	0.001
Years of education squared	-0.0176***	0.00523	0.001
Value of farm land	1.5E-07	1.27E-07	0.236
CV of 2004-05 annual rainfall	68.1**	31	0.028
CV of 1951-2000 growing season rainfall	-58.8**	24.8	0.018
Mean of 1951-00 growing season rainfall	-0.00367	0.00444	0.409
Distance to school (km)	-0.0478**	0.0238	0.044
Distance to market (km)	0.00103	0.00175	0.556
Does the household own a car?	-0.0109	0.278	0.969
Does the household own a pump?	0.0344	0.111	0.757
Does the household own a sprinkler system?	0.259	0.344	0.452
Does the household own a flush toilet?	-0.109	0.344	0.752
Does the household own a concrete house?	0.526	0.331	0.112
Does the household own a refrigerator?	0.0121	0.187	0.948
Does the household have formal title to its land?	-2.5E-05	0.000328	0.939
Does the household have access to electricity?	0.0776	0.33	0.814
District dummies			
Cullinan	-0.602	1.29	0.64
Carolina	-0.225	1.09	0.836
Lydenburg	2.1**	1.04	0.042
Middelburg	0.766	0.727	0.292
Nkomazi	-0.701	1.25	0.576
Witrivier	-1.17	1.23	0.341
Brits	-1.41	0.862	0.102
Marico	-2.11**	0.879	0.017
Rustenburg	-0.191	0.739	0.797
Lephalale (Ellisras)	-3.41***	0.969	0.000
Tzaneen (Letaba)	-0.151	1.05	0.886
Messina	-1.14	0.938	0.222
Nebo	0.0199	0.661	0.976
Makpopane (Potgietersrus)	-2.35**	0.917	0.010
Soutpansberg	-2.32**	0.944	0.014
Thabazimbi	-3.46***	1.22	0.005
Thohoyandou	-1.88	1.16	0.104
Warmbad (Bela-Bela)	-2**	0.84	0.018
Constant	-1.33	-1.23	4.39
Pseudo R^2	0.1659		
Number of observations	647		

Note: * Indicates significance at a 10% level; ** indicates significance at a 5% level; and *** indicates significance at a 1% level. “Std. error” is short for “standard error,” and P-value refers to

Rainfall variability as measured by CV was an important predictor of drought. Intra-year variability increased the probability of a drought, while inter-year variability decreased the probability that a drought was reported. The coefficients on these variables and the coefficient on historical means of rainfall were unstable; when one was excluded, the others were not significant. Both inter- and intra-variability should increase the probability of a drought, since a larger variance increases the probability of being in the tails of a distribution. However, the negative coefficient on inter-year variability indicates that the perception of drought occurrence decreases if a farmer is used to large inter-year variability. While using three variables on rainfall may seem excessive, the three values capture different aspects of the distribution of rainfall. The loss of precision due to multi-co linearity is made up for by the reduction in bias by omitting one of the three variables. Three of the district dummies were significant, indicating that droughts are a spatially correlated, covariate risk.

Years of education, and years of education squared are significant predictors of the probability of a drought. Since these logistic regressions are later used in estimating the impact of droughts on income, understanding the importance of education in relation to the probability of experiencing a drought is important. There are three possible explanations for why this relationship matters. First, more educated people may simply report more droughts. Second, education could be picking up spatial clustering within districts. Third, people may invest more in education in response to droughts, which could yield higher returns in nonfarm activities. If educated people are reporting more droughts, it would help explain the relatively low correlation between reported droughts and actual rainfall behavior noted in Table 7 and Figure 33a and 3b, but also lead to a problem of self-reporting bias. Self-reporting bias would lead to reporting of the most noteworthy and harmful droughts, exaggerating the impact of droughts on income. Because the results end up being insignificant, self-reporting bias is not a problem in this analysis. The second explanation, that education is accounting for spatial clustering, is also not a problem for the analysis.

If education is acting as a proxy for other exogenous, unobserved characteristics such as spatial clustering, it only makes the propensity score estimates in the following section more robust. However, if the third explanation alluded to is correct, and people are responding to droughts by acquiring more education, then there is an endogenous problem that must be examined. One way to test for this is to see whether or not education is correlated with rainfall variables other than self-reported droughts. As can be seen in Table, this is clearly not the case. The correlation between rainfall levels is positive and the correlation between CV and education is negative, suggesting that the population is more educated in less drought-prone environments. This suggests reasons 1 and 2 above do a better job explaining the relationship than does reason 3. Furthermore, it suggests that individuals in households are not acquiring more education in response to droughts.

Table 10. Correlation between education and rainfall data

	Education	October–April rainfall 1951–2000 (mm)	Coefficient of Variation (CV) for October–April rainfall 1951-2000	Rainfall October 2004–April 2005 (mm)	Coefficient of Variation (CV) for October 2004–April 2005
Education	1.0000				
October–April rainfall 1951–2000 (mm)	0.1911	1.0000			
Coefficient of Variation for October–April rainfall 1951–2000	-0.1407	-0.4370	1.0000		
Rainfall October 2004–April 2005 (mm)	0.1787	0.9919	-0.3683	1.0000	
Coefficient of Variation October 2004–April 2005	-0.1472	-0.5698	0.9543	-0.5136	1.0000

Propensity Score Matching Results

The logistic regression presented in Table 9 is used to obtain the probability of experiencing a drought; that is to say, the propensity score. Observations that have a propensity score within a bandwidth of 0.001 are compared using an Epanechnikov kernel to estimate the difference between current and counterfactual income. Standard errors are derived by bootstrapping 1,000 times to obtain the standard errors and p-values that are reported in Table 11. Neither of the impacts is significant; in fact, they are both positive. This could be because of problems with the data; the income variable, in particular, may not be capturing enough variation after all the imputations were performed. Another explanation could be that the propensity score did not accurately capture the probability of experiencing a drought (the R^2 from the logistic regressions was 0.17). Lastly, the impact of shocks may be insignificant because households have adapted to droughts. This last explanation is especially compelling in light of the responses shown in Table 8 in which 34 out of 47 respondents said they “did nothing” to cope with a drought. Droughts are common in South Africa, and households may already have coping mechanisms (such as off-farm labor sources, drought-tolerant farming practices, informal sharing of resources, and so on) in place to deal with their occurrence. While individual droughts do not appear to have a significant impact on income, this does not mean the presence of droughts does not impact income. Frequent droughts would be reflected in lower land values, which could be analyzed through a hedonic analysis.

Table 11. Effect of drought on income within the last 16 and last 4 months

	Sample mean unmatched	**Sample mean matched**	**Number of observations off-support**	**Number of observations on-support**
Propensity score matching on drought in last 16 months				
Households that received a shock in last 16 months	447,805	94,376	0	112
Households that received no shock in last 16 months	60,294	52,153	24	534
Difference		42,223	P-value	0.713
Propensity score matching on drought in last 4 months				
Households that received shock in last 4 months	797,582	69,606	11	23
Households that received no shock in last 4 months	88,713	48,954	0	636
Difference		20,652	P-value	0.936

4. ESTIMATION OF VULNERABILITY

Thus far this paper has described the sources of vulnerability in the Limpopo Basin, and provided an estimate of the loss to income from the droughts reported in 2005. The final goal is to quantify who is likely to be vulnerable in the future and to identify household characteristics that indicate vulnerability. Recall that vulnerability is the probability of becoming poor or falling below some income threshold during some future time span. The threshold in this case is defined as those with an income of less than 7,800 Rand, which corresponds to being in the bottom 25 percent of household income in the sample. A second threshold of median household income of 16,000 Rand is also used. Vulnerability is the probability that the household will fall below this threshold in the next time period.

Vulnerability is estimated following Tesliuc and Lindert's application of Chaudhuri (2000). First, income is written as a function of household characteristics and shocks, X_h, and a disturbance term, e_h:

$$\ln(I_h) = X_h\beta + e_h \tag{2}$$

The error term, e_h has a variance of $\sigma^2_{e,h} = X_h\theta$. Only shocks from 2005 are used. The estimation of θ and β follows a three-stage least squares framework. First, $\ln(I_h) = X_h\beta + e_h$ is estimated and the residuals are saved in order to obtain θ from $\sigma^2_{e,h} = X_h\theta$. Then the income equation is transformed to:

$$\frac{\ln(I_h)}{\sqrt{X_h\theta}} = \frac{X_h\beta}{\sqrt{X_h\theta}} + u_h \tag{3}$$

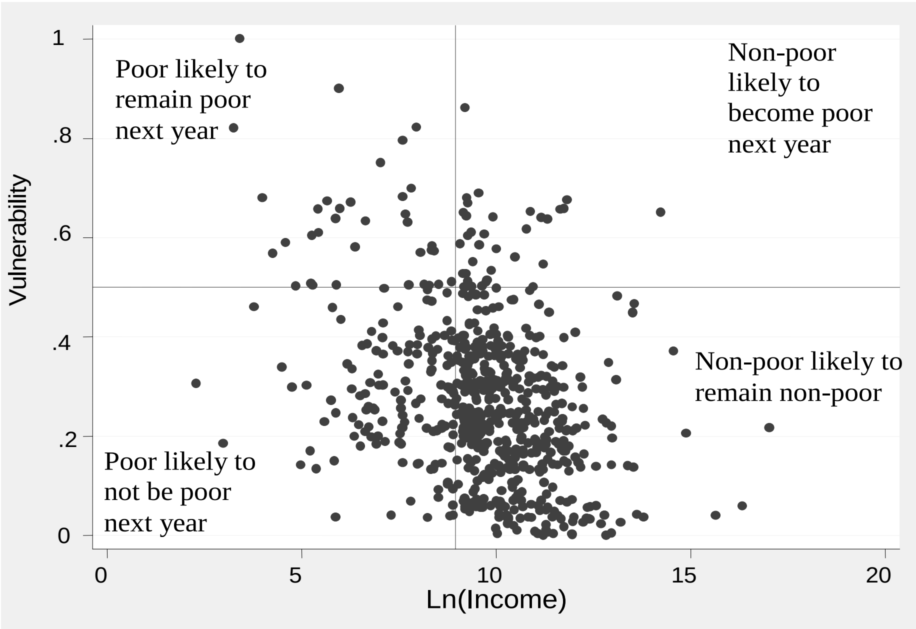
where $u_h = {e_h}/{\sqrt{X_h\theta}}$, a standard N(0,1) error term. Thus, vulnerability can be calculated as:

$$v_h = P(\ln(I_h) < \ln z \mid X_h) = \Phi\left(\frac{\ln z - X_h\beta}{\sqrt{X_h\theta}}\right) \tag{4}$$

where Φ is the standard normal cumulative distribution function, and *z* is the income threshold.

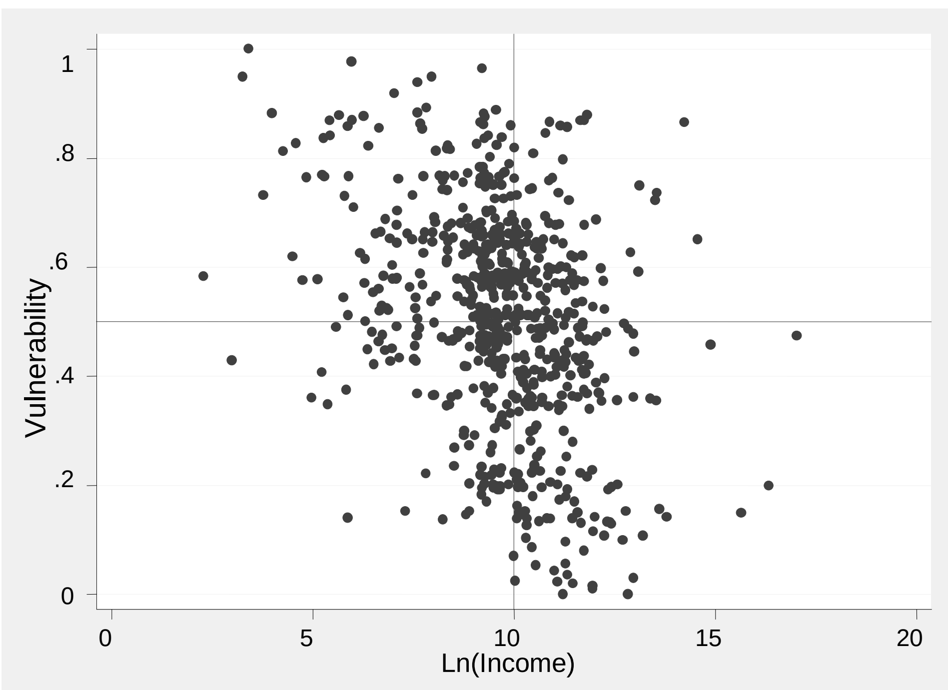
The results are plotted in Figure 5 and Figure 6. The x-axis shows the observed and imputed values for the natural log of income, while the y-axis shows the computed estimates of vulnerability. The graph is broken up into four sections. Those in the upper left are poor today and likely to be poor tomorrow, and those in the bottom left are poor today, but have characteristics suggesting they have a less than 50 percent chance of being poor in the future. Those in the upper right corner are not below the income threshold at present, but are likely to become so in the future, while those in the bottom left are above the income threshold and are likely to remain above it in the future. In Figure 5 the results show that most households are not vulnerable to having their income fall below 7,800 Rand. However, if the poverty line is increased to 16,000 Rand (the second income quartile), vulnerability increases, as is shown in Figure 6. This analysis can be used to explore other dimensions of poverty. These results are summarized in Table 12 and in the figures shown in the Appendix. Figures 1-7 in the Appendix were made by dividing up those in various groups and plotting against the whole, examining those that have and do not have access to credit, those households that own animals and those that do not, those households that use irrigation and those that are only use rainfed agriculture, as well as households by size and income.

Figure 5. Vulnerability (income < 7,800 R) plotted against Ln (income)



Note: Vulnerability is defined here as the probability of household income falling to less than 7,800 Rand.

Figure 6. Vulnerability (income < 16,000 R) plotted against Ln (income)



Note: Vulnerability is defined here as the probability of household income falling to less than 16,000 Rand.

Table 12 can be used to identify household characteristics that signal vulnerability. Many of the associations in Table 12 are not surprising; households that have characteristics associated with being poor are also households that are generally vulnerable. Households that have obtained loans are more vulnerable than households that did not obtain a loan because they did not want one or those households that could not obtain a loan. Households that do not own farm animals are more vulnerable, as were households that rely on rainfed agriculture. Larger households and households with lower income are also more vulnerable. Gauteng is the most vulnerable province when it comes to the lowest threshold level (7,800 Rand) but not when it comes to falling below 16,000 Rand. For the second vulnerability measure, residents of North West province are most vulnerable, but it should be noted the differences are minimal and not statistically significant. Residents of Limpopo are the least vulnerable. Members of the SeSwati and Setswana ethnic groups are the most and second most vulnerable groups to poverty no matter the threshold level. This method of examining vulnerability by household characteristics was done by Ligon and Schechter (2003) and Tesliuc and Lindert (2002).

Table 12. Vulnerability by household characteristic at income levels below 7,800 R and below 16,000 R

Vulnerability by household characteristics		Mean Vulnerability	Std. Dev.	Mean Vulnerability	Std. Dev.	Obs.
		<7,800 R		<16,000 R		
Residents of Gauteng		0.361	0.211	0.573	0.282	37
Residents of Mpumalanga		0.310	0.191	0.542	0.220	167
Residents of North West		0.336	0.223	0.577	0.210	90
Residents of Limpopo		0.231	0.144	0.467	0.173	377
Ethnicity:	Zulu	0.177	0.108	0.393	0.167	12
	Xhosa	0.252	0.132	0.489	0.198	18
	Tshivenda	0.218	0.162	0.428	0.227	114
	Southern Sotho	0.250	0.137	0.488	0.193	11
	Tsonga	0.223	0.131	0.458	0.154	67
	Setswana	0.286	0.164	0.526	0.197	129
	SeSwati	0.429	0.207	0.663	0.215	67
	SePedi	0.259	0.110	0.511	0.138	177
	Ndebele	0.279	0.219	0.489	0.262	46
	English	0.383	0.199	0.638	0.167	4
	Afrikaans	0.288	0.144	0.533	0.194	19
	Other	0.047	--	0.170	--	1
Households that obtained a loan		0.297	0.196	0.526	0.221	148
Households that did not obtain a loan because they did not have access to credit or knowledge about credit		0.259	0.143	0.497	0.188	185
Households that did not want a loan		0.266	0.155	0.501	0.198	167
Households that own livestock, poultry, fish or other farm animals		0.258	0.151	0.495	0.188	284
Households that do not own livestock, poultry, fish or other farm animals		0.327	0.197	0.560	0.225	204
Households that use irrigation		0.272	0.174	0.503	0.209	461
Households that use only rainfed agriculture		0.277	0.145	0.522	0.172	191
Small households (≤5 members)		0.275	0.166	0.511	0.198	290
Medium households (5<members≤10)		0.263	0.162	0.497	0.199	309
Large households (>10 members)		0.299	0.195	0.527	0.233	72
All households		0.272	0.167	0.506	0.202	671

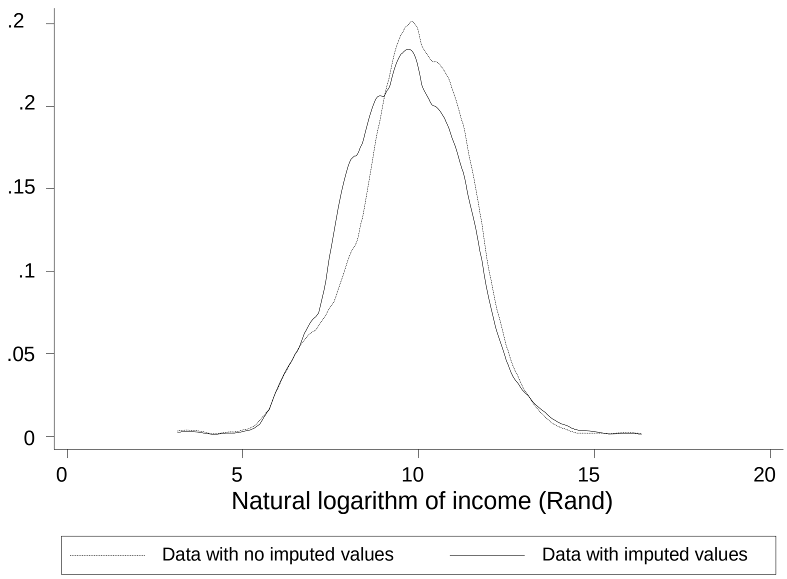
5. CONCLUSION

The estimates of the impact of shocks on income were not statistically significant; one of the reasons for this could have been the quality of the data. A more compelling explanation is that households have already adjusted to living in a drought-prone environment and developed income smoothing methods. A major piece of evidence pointing in this direction is that so many households said they “did nothing” in response to droughts. This does not necessarily mean that households are prepared for climate change. Climate change is expected to bring a different distribution of shocks, as well as adaptive behavior to mitigate against the shocks, both of which could be costly to those least able to bear the cost. The impact of a changing distribution of droughts and, hence, more costly risk coping devices, remains to be studied. The different distributions of rainfall were partially addressed with the inclusion of mean and CV rainfall data, but could be further studied with better data and higher order moments of rainfall distribution. If South Africa had a vibrant land market such that land prices could be observed, a hedonic study such as that by Deschenes and Greenstone (2007) could be done with enough data and enough attention paid to higher order moments of rainfall distribution. While first and second moments may be appropriate for studying agriculture in economies with irrigation and risk mitigation strategies, they are not appropriate for developing economies. Predicting the actual effects of climate change is fraught with difficulties due to the high levels of uncertainty, but that does not mean information about behavior today cannot be used to guide predictions of what will happen tomorrow.

The vulnerability breakdowns can help policymakers identify households that are not poor currently, but have a high probability of becoming poor in the future. Households that do not own livestock are typically vulnerable, as are large households. Residents of Limpopo Province were least vulnerable, while members of the SeSwati ethnic group were most vulnerable. While panel data would be preferred for vulnerability analysis, cross-sectional data were used. Given that climate change will involve a redistribution and intensification of risk, attention to vulnerability is important to policymakers’ decisions.

APPENDIX. SUPPLEMENTARY FIGURES

Figure A.1. Distribution of Ln (income) with and without imputed values



Note: This graph describes how imputing values of income changes the overall distribution of the natural logarithm of income.

Figure A.2. Plot of vulnerability (income below 7,800 Rand); Gauteng Province

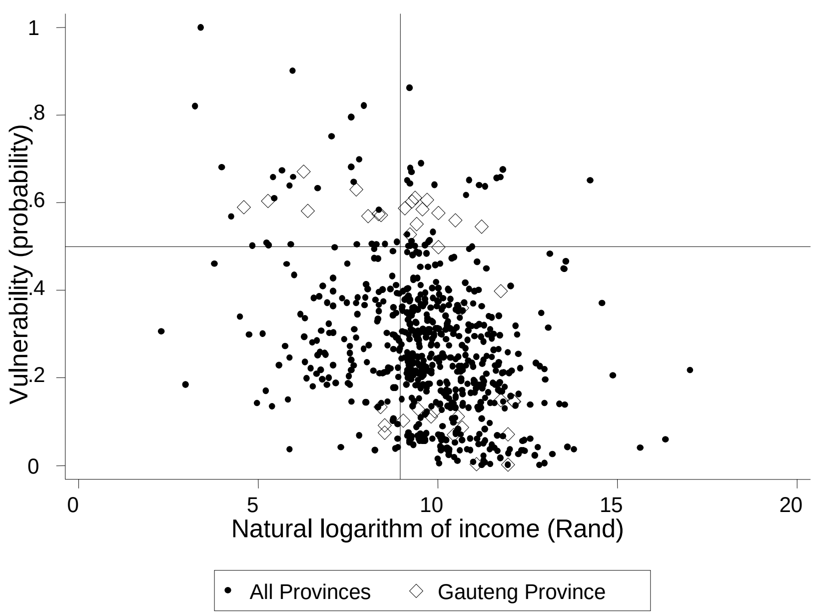


Figure A.3. Plot of vulnerability (income below 7,800 Rand); Limpopo Province

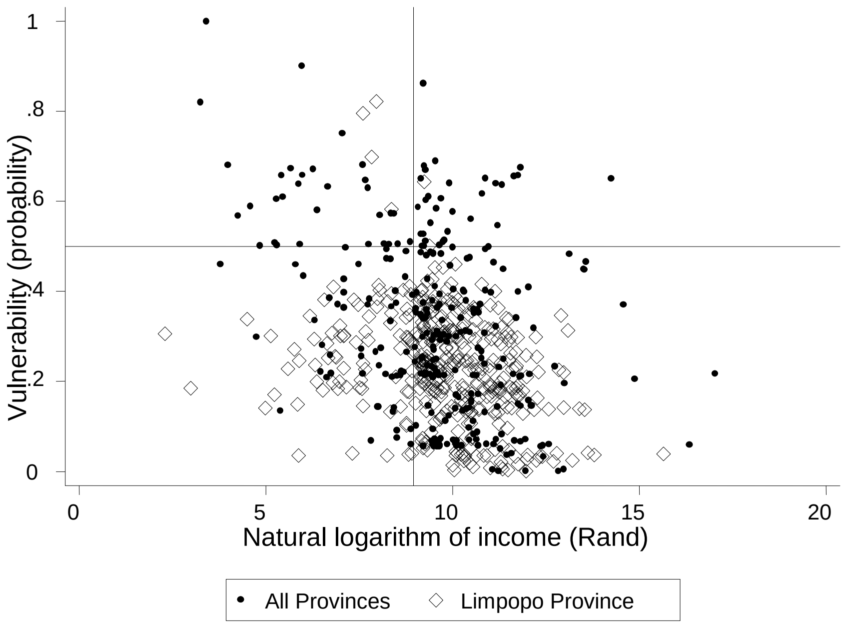


Figure A.4. Plot of vulnerability (income below 7,800 Rand) by province; Mpulamanga Province

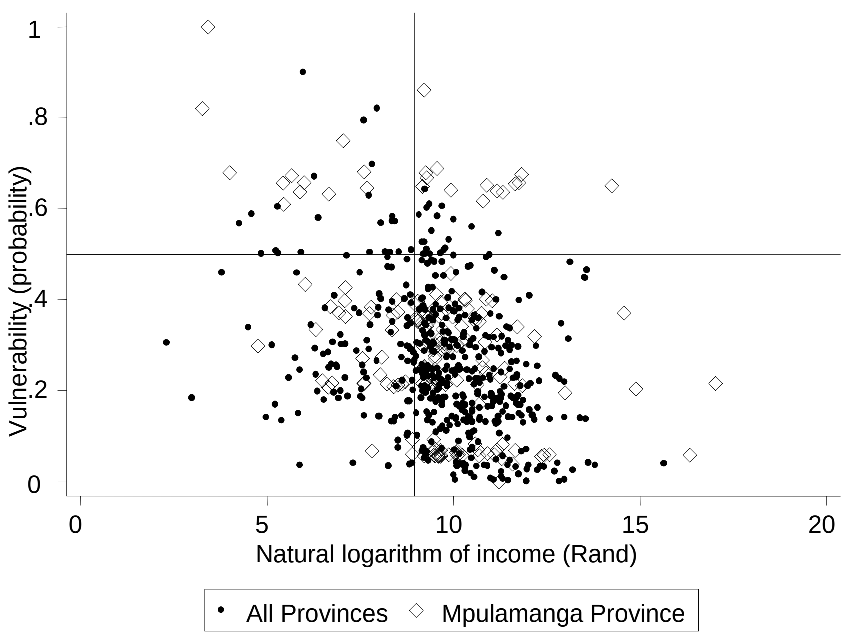


Figure A.5. Plot of vulnerability (income below 7,800 Rand) by province; North West Province

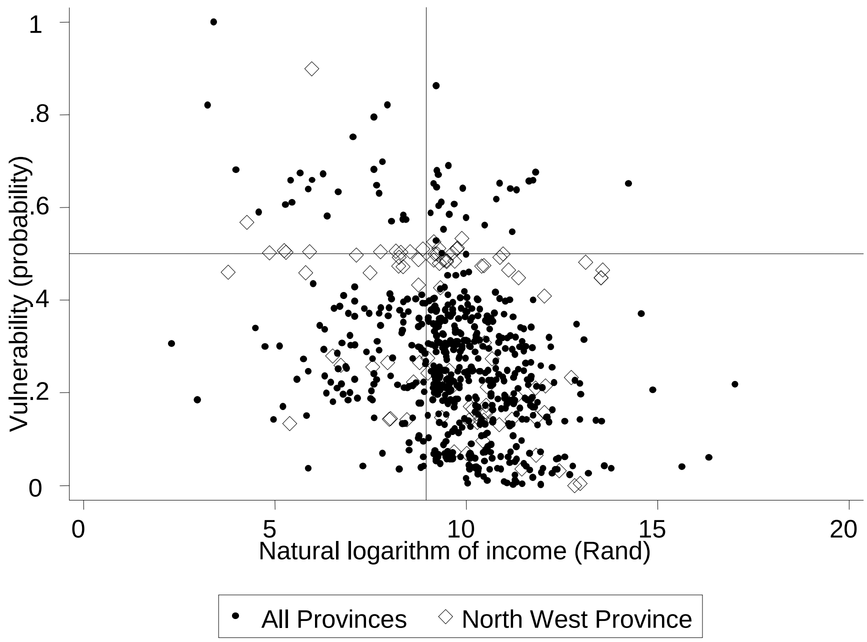


Figure A.6. Plot of vulnerability (income below 16,000 Rand) by province; Gauteng Province

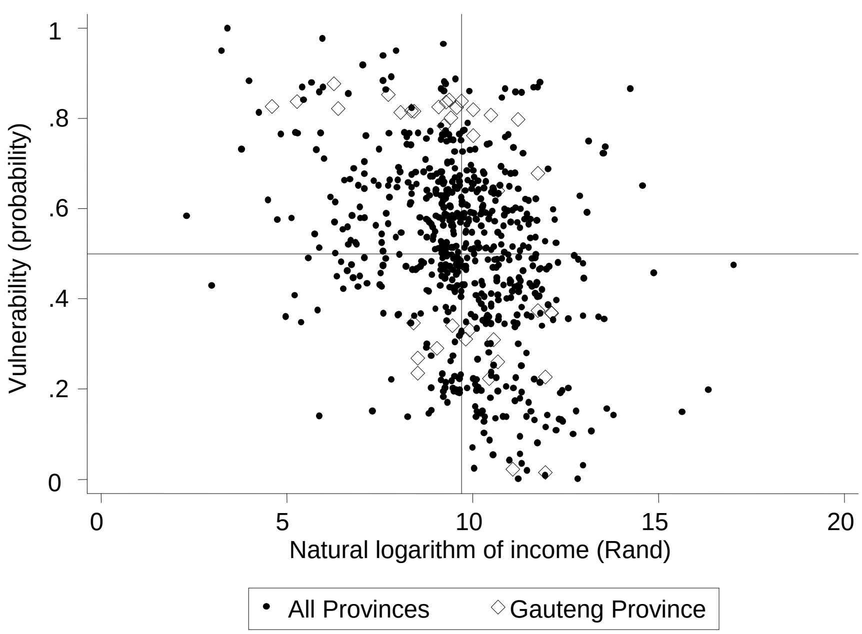


Figure A.7. Plot of vulnerability (income below 16,000 Rand) by province; Limpopo Province

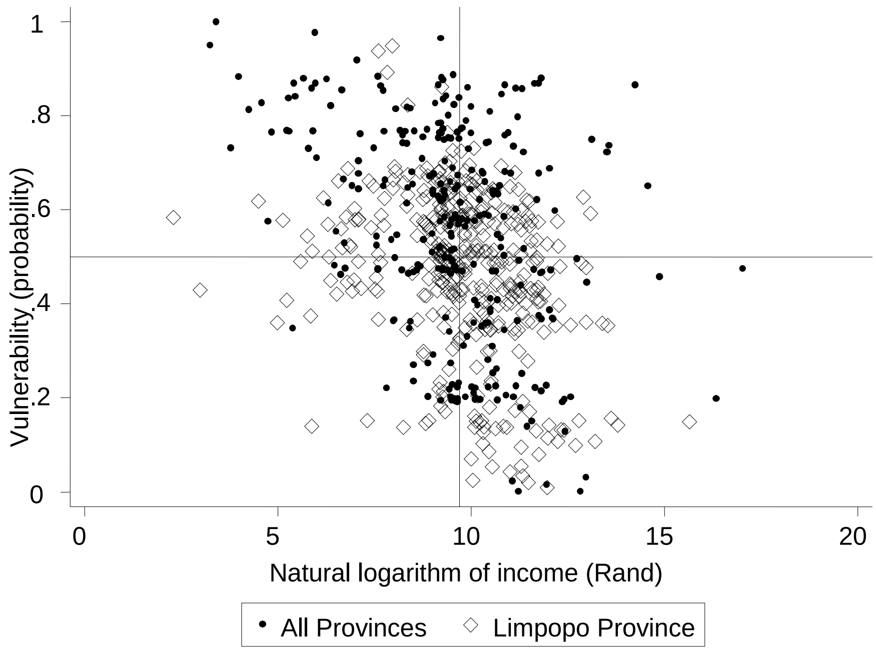


Figure A.8. Plot of vulnerability (income below 16,000 Rand) by province; Mpulamanga Province

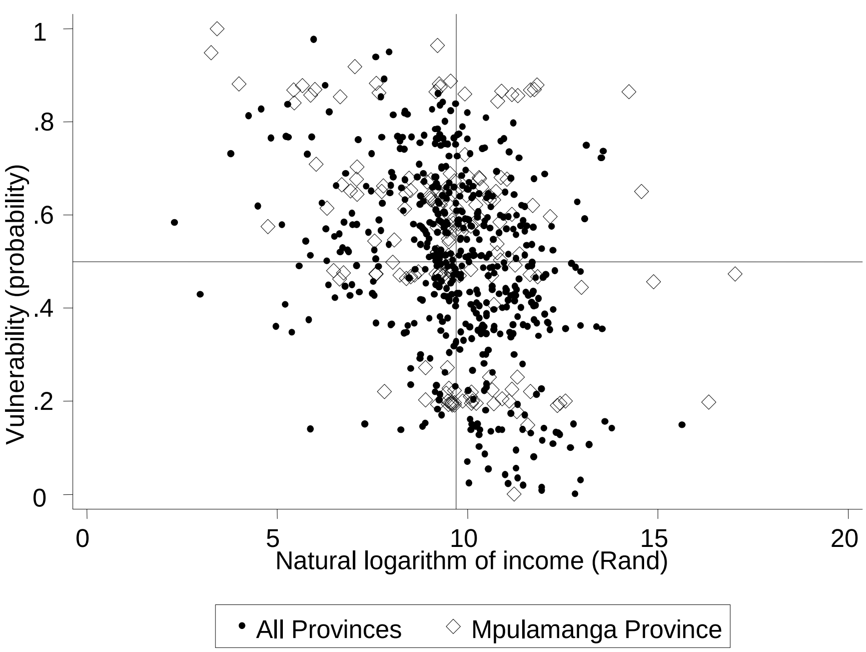


Figure A.9. Plot of vulnerability (income below 16,000 Rand) by province; North West Province

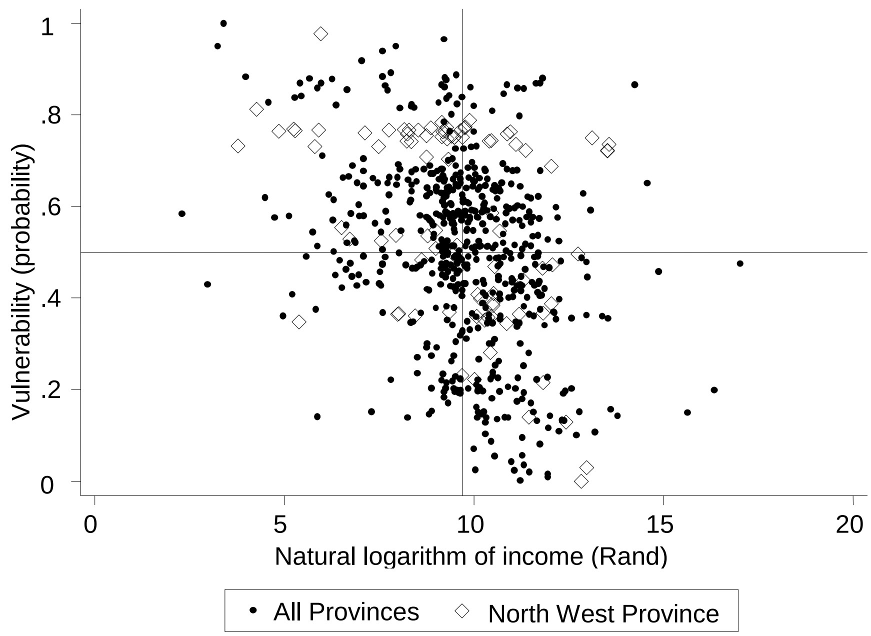


Figure A.10. Plot of vulnerability (income below 7,800 Rand) animal ownership

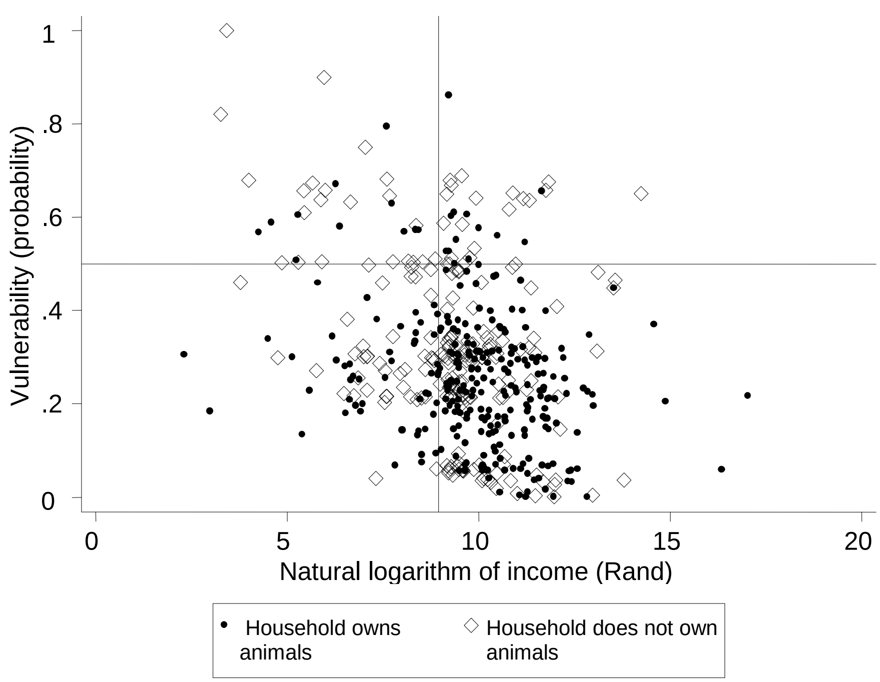


Figure A.11. Plot of vulnerability (income below 7,800 Rand) access to credit

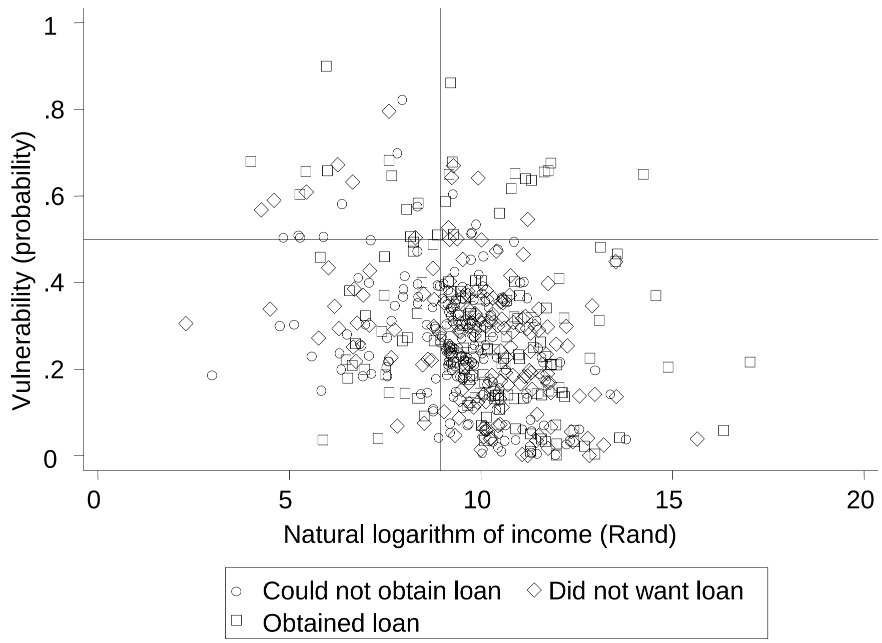


Figure A.12. Plot of vulnerability (income below 7,800 Rand) by irrigation

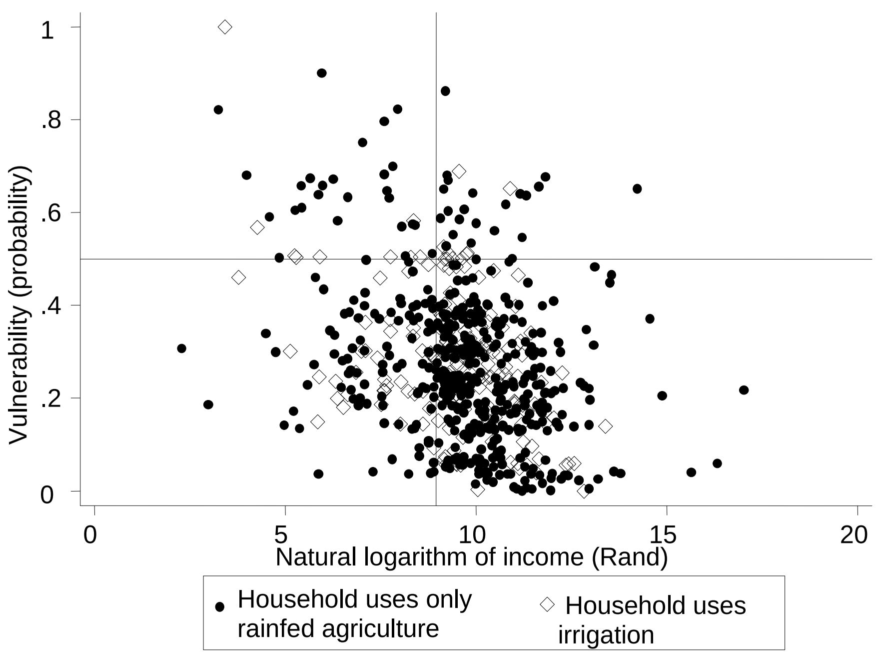


Figure A.13. Plot of vulnerability (income below 7,800 Rand) by household size

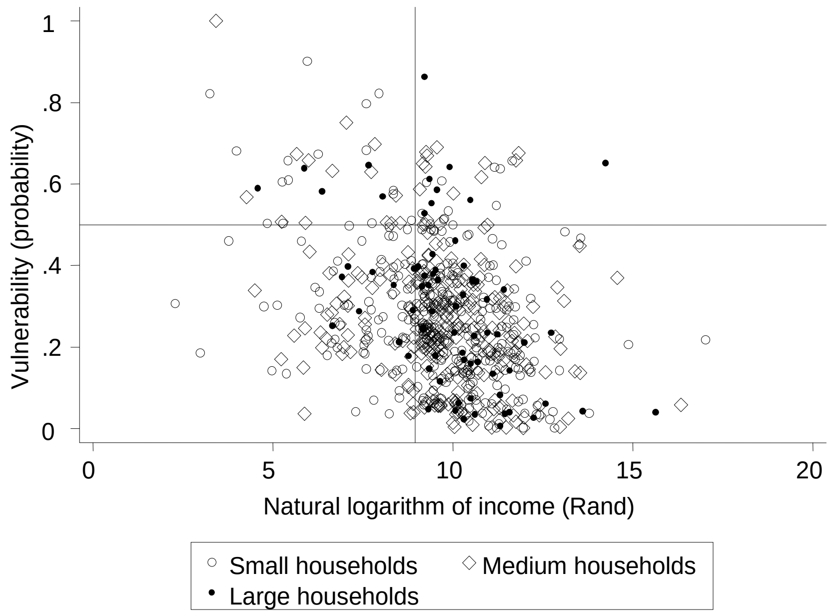


Figure A.14. Plot of vulnerability (income below 16,000 Rand) by animal ownership

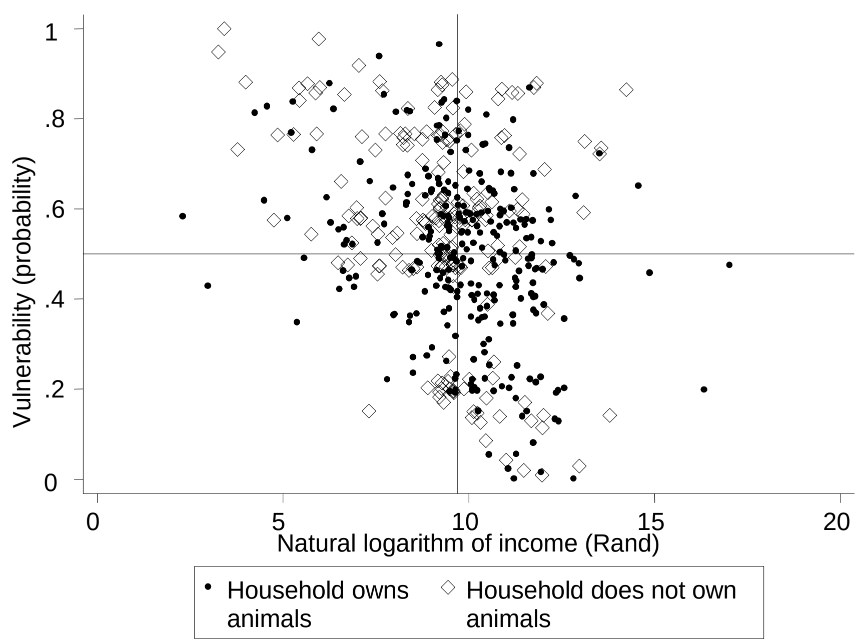


Figure A.15. Plot of vulnerability (income below 16,000 Rand) by access to credit

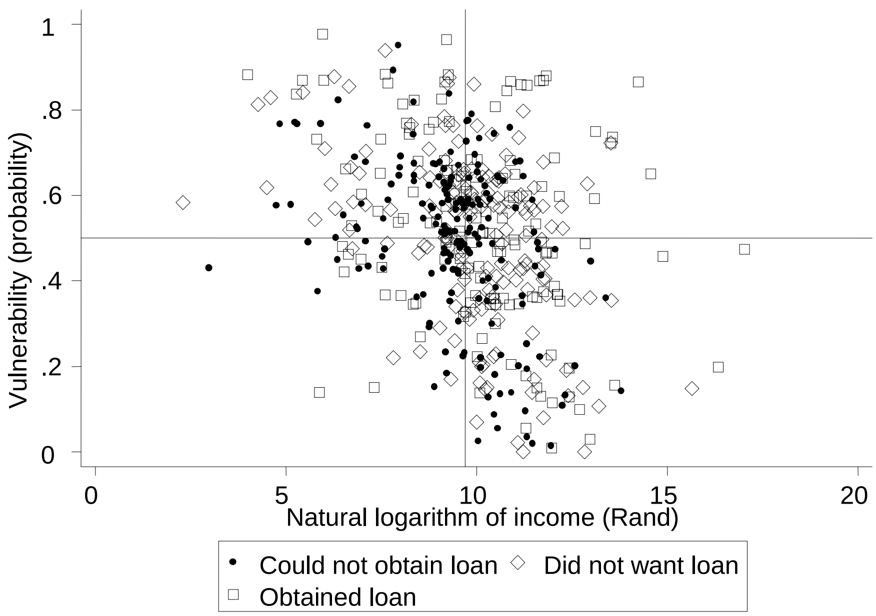


Figure A.16. Plot of vulnerability (for those with income below 16,000 Rand) by irrigation and household size

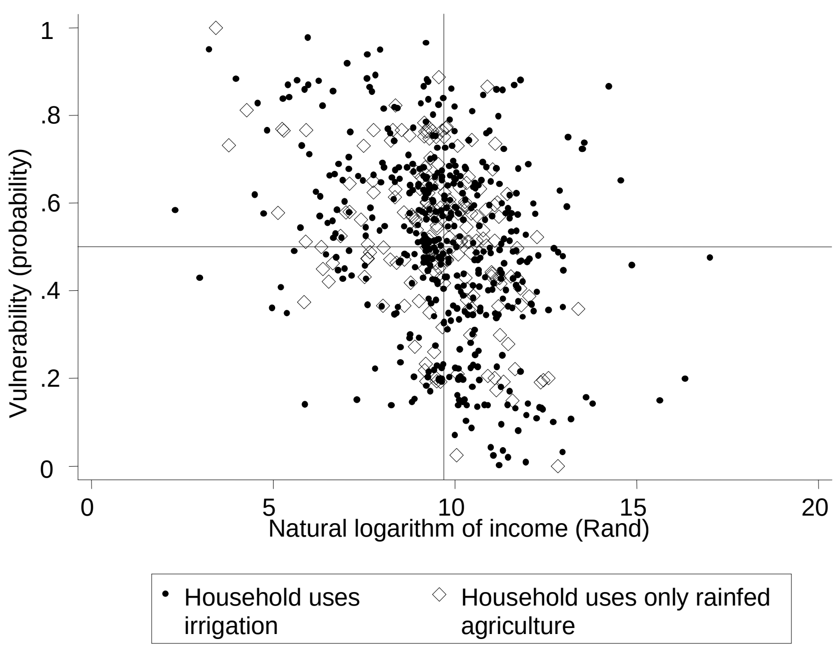
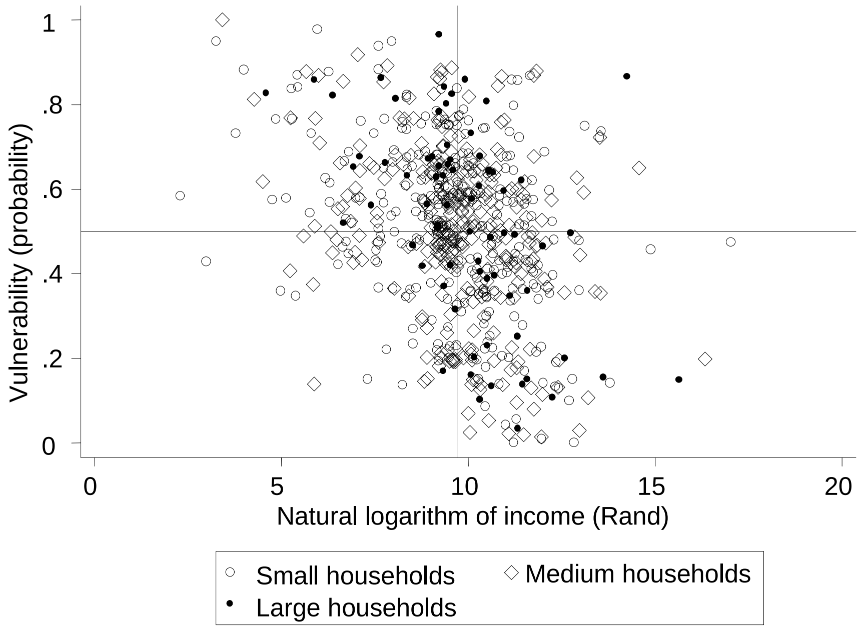


Figure A.17. Plot of vulnerability (for those with income below 16,000 Rand) by household size



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