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Abstract

Considerations of risk and vulnerability are key to understanding the dynamics of poverty in rural Malawi. This study measures vulnerability to consumption shortfalls and analyzes its sources using a two-period panel of 2,789 households, drawn from the 2010 Third Integrated Household Survey and the 2013 Integrated Household Panel Survey. The results show that in 2010 two-fifths of all households had a chance of at least 40 percent of falling below the poverty line in the future. The results show that many households in rural Malawi are vulnerable to poverty, although, as with many other studies of rural areas in other countries, much of the vulnerability is caused by chronic poverty. Nonetheless, risks, particularly rainfall and loss of off-farm employment, are also important in explaining why poor households remain poor, and why some non-poor households are more likely to fall into poverty in the next period. Household wealth and agricultural assets can protect households from falling into poverty and reduce the severity of the fall when shocks occur. However, there is little evidence to suggest that other strategies to reduce vulnerability are effective.

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Vulnerability to Poverty in Rural Malawi*

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1. Introduction

One of the most pervasive features of poverty across rural households in developing countries is their exposure to risk. Ex ante, households typically adopt actions to reduce their exposure to risk, which can translate into choosing strategies that provide low, but relatively more stable, incomes. Such choices can lead to persistent poverty. Similarly, since the poor tend to lack adequate access to financial and insurance mechanisms, they often cope with risk ex post by reducing consumption or selling productive assets, which plunges them further into long-term poverty (Hoddinot et al. 2008; Carter & Lybbert, 2012; Hansen et al., 2004). A better comprehension of the dynamics of poverty in risky environments would be helpful for several reasons. Assessing the likelihood of households falling into poverty in any given place or territory can help us understand the processes underpinning this likelihood. This would facilitate the design of forward-looking anti-poverty interventions, including the implementation of preventive measures to reduce damages from risk events. Understanding such processes that may lead to future poverty can also improve our knowledge of how to best provide support and relief to people when they are faced with risk events, so that they can retain assets and avoid irreversible damage while simultaneously protecting their consumption and incomes against sudden drops.

The concept of vulnerability is suitable for approaching the above task. Distinguished from *risk*, which refers to the probability of events that can damage welfare (Dercon, 2001), vulnerability can be understood as the capacity to manage the realization of such damages.[1] This capacity, in turn, determines how vulnerable individuals or households are to remaining in, or falling into, poverty. In addition to risk, the likelihood of experiencing poverty may result from more permanent disadvantages within households or the villages where those concerned reside. Thus, some currently non-poor households can be vulnerable if they are exposed to relatively high risk but have only a modest asset base, have limited access to informal and formal insurance, and are located in isolated areas with limited opportunities to diversify income sources. Similarly, many currently poor households will also be vulnerable, where they too face relatively high risks but have very low asset holdings, many dependents, limited to no education, and are located in isolated communities with little infrastructure and availability of basic services. More formally, we will follow much of the literature by defining a household as vulnerable to poverty when the given probability that it will suffer a future welfare loss is below some socially accepted norm(s) or specified benchmark of wellbeing (i.e., a poverty line) (Chaudhuri et al., 2002; Holzmann, 2001; Christiaensen and Subbarao, 2004; Christiaensen and Boisvert, 2000; Pritchett et al., 2000; Kamanou and Morduch, 2002; Ravallion, 1988).

In rural Malawi, there are good reasons to approach the link between poverty and risk using the concept of vulnerability to poverty. An overwhelming majority of rural households are still poor, and they accounted for about 90 percent of the total population in poverty in the country in 2013 (NSO, 2014). But this type of poverty, as we know from other studies (World Bank, 2007), derives not only from poorly-endowed households and communities, but also from large fluctuations in incomes due to reliance on risk-prone activities like rain-fed agriculture. Smallholders in rural Malawi are particularly vulnerable to exogenous shocks that reduce harvests, income and consumption levels, primarily due to very small landholdings and limited availability of insurance mechanisms to help households cope with shocks. Harvested quantities of crops, livestock and fish are primarily affected by weather shocks. Given that

[1] Risk is often differentiated from shocks (risk realizations) to emphasise that risk can negatively impact on welfare through the 'lack of peace of mind' that being exposed to risk entails and through the adoption of (sub-optimal) activities to avoid or limit its impact in case it occurs). Shocks, for their part, can affect welfare given the imperfections of the available mechanisms to cope with them. Most of the time, this paper will use the terms *risks* and *shocks* interchangeably to refer to realized risks. This decision is driven by data constraints which limit the availability of information to realized hazards and responses to them.

households' incomes in rural Malawi are still dominated by agricultural income, shocks that affect crop production also impact on incomes, as does price volatility. And, consumption is highly correlated with agricultural income, though informal insurance mechanisms within a community or extended household may help to smooth consumption in the face of agricultural production and income shocks. In addition, given imperfect labor and credit markets, household labor shocks including illness or death, can affect production and off-farm income earnings, and subsequently consumption. A priori, we expect harvested quantities to exhibit the greatest variability, followed by income and then consumption. In light of this consideration, this paper is motivated by two key questions: *(1) To what extent is the phenomenon of vulnerability to consumption and income poverty and low crop production per capita present across rural households in Malawi?* and *(2) What are the determinants of this vulnerability, e.g. the risks they face, assets endowments, and household socio-demographic characteristics, particularly those expected to proxy for risk management and risk coping capacity?*

To answer these questions, we construct measures of vulnerability to poor realizations of maize harvest per capita, income per capita, and consumption per capita, following the vulnerability measures developed in Christiaensen and Subbarao (2005) and Chauduri et al. (2002). This measure is categorized as a "vulnerability to expected poverty" (VEP) measure, which is comprised of the probability of falling below the poverty line multiplied by a Foster-Greer-Thorbecke (FGT) measure of the severity of the expected shortfall below the poverty line. We explicitly consider a number of different shocks that may affect rural households, including rainfall, maize price, health and off-farm income employment shocks. We use the poverty line developed by the National Statistical Office (NSO, 2012), which is based on minimum subsistence requirements for consumption (see forthcoming Malawi Poverty Assessment), and household level panel data collected by the NSO, in conjunction with the World Bank, covering two time periods, 2010 and 2013. We augmented this data set with measures of current period rainfall shocks and measures of long-term rainfall variability obtained from the National Oceanic and Atmospheric Administration (NOAA), and data on variance of maize prices obtained from Malawi Agriculture Statistics Bulletin, of the National Statistical Office. These additional data sources enable us to rely on objective measures of shocks, such as for rainfall, to capture the temporal variation in rainfall.

Results show that many households in Malawi are vulnerable to poverty, though as with many other studies of rural areas in other countries, much of vulnerability is due to chronic poverty. Nonetheless, risks – particularly rainfall and employment shocks – are also important in explaining why poor households remain poor, and why some non-poor households are more likely to fall into poverty in the next period. The results also underscore the importance of having access to long-term measures of variability, as opposed to relying on spatial variation as a proxy for temporal risks. In particular, rainfall patterns in 2013 were relatively better than generally observed over the period 1983-2012. Using the information from the longer-term rainfall data to generate expected shocks better captures the number of households vulnerable to falling into poverty. Of the additional explanatory variables included in the vulnerability analysis, both household wealth and agricultural asset indices are the most important in protecting households from falling into poverty and reducing the severity of the fall when shocks occur.

The paper contributes to the literature in two main ways. First, the data set includes explicit information on a number of shocks hypothesized to affect vulnerability, including longer-term, objective measures of rainfall variability and current period rainfall shocks. Many previous analyses have limited information on actual shocks faced, and as we shall see below, the standard vulnerability analyses without such information makes it difficult to disentangle which shocks are more important for explaining vulnerability using various welfare measures. Second, the paper uses a two-period data set covering households in rural Malawi; contributing to very sparse evidence on vulnerability in Southern Africa using this particular econometric approach and rich data set. We also look at four different welfare measures, to distinguish whether different shocks have different impacts on vulnerability to different welfare outcomes.

The rest of the paper is organized as follows. Section 2 outlines the working definition of vulnerability to poverty and its main desirable properties. It then sets out the measure and methods employed in this paper to assess this concept. Section 3 describes the available panel data set to assess this concept in Malawi and sets the context in which this study takes place. Section 4 presents the empirical strategy followed to establish the extent to which the phenomenon of vulnerability is present across rural households in rural Malawi. Section 5 presents the incidence and correlates of vulnerability to poverty obtained for our sample. Section 6 concludes.

2. Literature Review

Various approaches have been proposed to define and obtain explicit measures of vulnerability. Thus far these efforts have followed different paths – showing that there is still no definitive agreement on how to do so. There is however a consensus around the fact that, at the minimum, the concept should be able to capture that 'something bad can happen and spell ruin for the household' (Calvo and Dercon, 2008), at least for some period of time. Hoddinott and Quisumbing (2003) define vulnerability as "the likelihood that at a given time in the future, an individual will have a level of welfare below some norm or benchmark" (Hoddinott & Quisumbing, 2003, p. 8). The likelihood of falling below a benchmark is a function of both the external risks faced by the household, as well as the ability of the household to manage risks ex ante or mitigate negative impacts ex post (Dercon, 2001; Alwang, Siegel, & Jørgensen, 2001; de la Fuente, Ortiz-Juárez, & Rodriguez-Castelán, 2015; López-Calva & Ortiz-Juarez, 2014). Hoddinot and Quisumbing (2003) also review the three main approaches to operationalizing this definition in empirical settings, including (i) models predict the probability of becoming poor in the future, mainly based on the Foster-Greer-Thorbecke family of poverty measures (P_α)[2]and then estimating its expected value, known as "vulnerability to expected poverty" **(VEP)** measures; (ii) prediction models that define vulnerability as low expected utility **(VEU)**; and (iii) models that assess ex post the extent to which negative shocks cause a welfare drop **(VER)**.

The VER approach focuses on the ex post ability of the household to absorb shocks, and is thus a backward-looking measure that attempts to explain how well households fared in the face of shocks, such as the ability to smooth consumption (Tesliuc & Lindert, 2002). As various authors have noted defining vulnerability solely in terms of a household's consumption-smoothing ability ignores its initial and ending position in the welfare distribution (Dercon, 2002, 2006; Chaudhuri, 2003; Christiaensen and Subbarao, 2004). This can have deleterious consequences for analysis. For instance, even if income shocks led to identical consumption losses, poor families may be less able to tolerate the occasioned damage than are the better-off, particularly if they are forced well below the poverty line. This differentiated effect would not be captured.

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[2] $P_\alpha = 1/N\sum_{i=1,G}\left[\left(z-y_i\right)/z\right]^\alpha$ where *z* is the poverty line, *y* is the welfare indicator for household i, *N* is the total population size, and the sum is taken only on poor households ordered from bottom to top: $y_1, y_2, \ldots y_G$. Here if α = 0 then *P* is equal to the share of the population which is poor, if α = 1 then *P* is equal to the mean distance that separates the poor population from the poverty line or in other words the depth of poverty, and if α = 2 then *P* is a measure that describes the severity of poverty, meaning that weights are higher as the depth of poverty increases.

The VEU measures are based on expected utility. Ligon & Schecter (2003) develop a model that decomposes vulnerability into expected poverty, observed aggregate (or co-variate) risk, observed idiosyncratic risk and unexplained risk captured by the random error term. This approach has strong theoretical foundations and, within the expected utility framework, is consistent with the Risk Aversion axioms, which state that increased risk would necessarily increase expected poverty. However, it is not exempt from some conceptual problems. Given that vulnerability depends on expected welfare, the VEU measure will be sensitive to the likelihood and magnitude of the "good" outcomes as well as "bad" outcomes (i.e. high consumption). Thus, the measure is bound to violate the Focus axiom property, which requires concentrating only on those outcomes that are likely to capture threats to future poverty (Günther & Maier, 2014).

For the above reasons, in the remainder of this section, we focus on the literature associated with VEP, which is the model on which our empirical work is drawn. First, the VEP measure does not require information on households' risk-aversion, which is almost never available empirically. Second, the benefits to applying a utility weight, as in the VEU approach, to the consumption shortfall is unclear in terms of policy implications, particularly where people are ill-informed regarding how today's behavior may affect future outcomes (Christiaensen & Subbarao, 2005). And finally, Ligon & Shechter (2004) performed an extensive analysis on both cross-section and panel data sets to evaluate a range of VER and VEP measures, and determined that they performed quite similarly, particularly where consumption is stationary. Where the data are collected at relatively short intervals and the prediction concerns a short time horizon, this assumption does not seem too extreme; however, the assumption of stationarity is more likely to be violated when predictions of vulnerability are made further into the future. In our analysis, we focus on predicting vulnerability of falling into poverty in the next period.

The simplest measure of vulnerability under the VEP approach is the probability that household consumption (or any other welfare indicator of interest) falls below some benchmark, e.g. the poverty line. A more sophisticated measure proposed by Christiaensen & Subbarao (2005) also takes into account the expected depth of poverty, as follows:

$$V_{it} = F(z)\int_{\underline{c_{t+1}}}^{z} p_{i,t+1}(z, c_{i,t+1}) \frac{f(\mathrm{c}_{i,t+1})}{F(z)} dc_{i,t+1}$$

Where V_{it} is the measure of vulnerability in the current period, $F(z)$ is the probability that the household will fall, or remain, below the poverty line, z, $p_{i,t+1}(z, c_{i,t+1})$ is a measure of the depth of poverty, and $f(\mathrm{c}_{i,t+1})$ is the probability density function. Most authors adopt the Foster-Greer-Thorbecke family of poverty indices (Pα) widely used in poverty assessments, and then estimate their expected value, setting $p_{i,t+1}(z, c_{i,t+1}) = \max\left[0, \frac{z - c_{it}}{z}\right]^{\gamma}$, where γ scales the depth of a proportionate shortfall. For $\gamma > 1$, greater deviations from the poverty line are weighted more heavily. Thus, a household's vulnerability is equal to the probability of falling below the poverty line, times the expected value of the shortfall raised to the power γ.

Because the goal of vulnerability analysis is to predict which households are not only poor currently, but who are susceptible to staying or falling into poverty in the future, the optimal data set would be a panel with at least three periods, which are generally quite rare, particularly for developing countries. In the absence of panel data, some researchers have simply relied on cross-sectional estimates alone, though Ligon & Schecter (2004) caution that such results can be quite biased. In other cases, researchers have used “pseudo-panel” techniques, where repeated rounds of cross-sectional survey data are collapsed at a supra-household level where there are repeated observations (Christiaensen & Subbarao, 2005).

A recurring theme in the literature is the choice of the poverty line, and the choice of a probability threshold on which to categorize household vulnerability. Due to data constraints, few studies have been able to empirically test how these two choices affect the ability of estimated vulnerability to capture realized poverty in future periods. Zhang & Wan (2008), using three-period panel data from China, estimate poverty and vulnerability using different poverty lines for the first two periods of the panel to get an estimate of vulnerability with which they then compare to observed poverty in the third period. The authors find that a relatively high poverty line closer to the mean observed income per capita does a better job at predicting the percent of households that stay in poverty and transition into poverty than a lower poverty line, as does setting the probability threshold at .5.[3]

Cruces et al. (2010) also discuss the sensitivity of vulnerability classification depending on the threshold probability. They use two different threshold probabilities, the common “more likely than not” .5 probability, and the proportion of the population currently classified as poor. It is difficult to understand why the authors’ use the proportion currently classified as poor, but it does highlight difference in results, especially when comparing across countries. For countries with high poverty rates, a relatively large fraction of non-poor households will be considered vulnerable, while in countries with relatively low poverty rates, relatively few non-poor households will be classified as vulnerable. While these results are to be expected given the log-normal distribution, as with the results in Zhang & Wan (2008), the ability of predicted vulnerability to actually capture vulnerable households may be more difficult in countries with very high or low poverty rates. Finally, Jha et al. (2010) have two periods of household data for Tajikistan, though they calculate the VEP vulnerability measure using cross-sectional data in the earlier period and assess how well it predicts actual vulnerability in the second period. In their case, about 60% of households were below the poverty line in the first period, so that the poverty line is neither very high nor very low. And, the predicted vulnerable in the first period, 65%, was close to the observed poor in the second period, 62%.

Another point of interest from the extant empirical literature is the fact that, in most applications, the explanatory power of the variance equation estimates tends to be quite low. For instance, in Jha et al. (2010), estimated equations for different variance measures have an R^2 of around .05. This is similar to results found in Christiaensen & Subbarao (2005), Imai et al. (2011), and Bronfman (2014). Of the papers reviewed, the greatest explanatory power for the variance equation is found in Bogale (2012), with an R^2 of .20. Limited capacity to explain the variance would indicate either limited heteroskedasticity or omitted relevant variables, which gives some cause for concern about the use of this method to generate predicted variance and using this as a measure of risks households face.

In terms of empirical evidence, most studies find that poverty is the most important component of vulnerability, then followed by risk (Chaudhuri, Jalan, & Suryahadi, 2002; Ligon & Schechter, 2003; Christiaensen & Subbarao, 2005). Of the factors associated with vulnerability, almost all studies find that

[3] From the paper, it appears that the authors only looked at aggregate percentages falling into different categories. Given that vulnerability is a probabilistic measure, it would have been instructive to note the proportion of poor households predicted to remain poor who actually did so, the proportion of non-poor households predicted to be vulnerable who actually fell below the poverty line.

household size has a negative impact on per capita consumption or income (Christiaensen & Subbarao, 2005; Jha, Dang, & Tashrifov, 2010; Bronfman, 2014; Klasen, Lechtenfeld, & Povel, 2015; Imai, Gaiha, & Thapa, 2015). Studies that include measures of health shocks also generally find that these do increase vulnerability, as expected (Abimbola, Yusuf, Omonona, & Okunmadewa, 2011). Various measures of wealth and education, on the other hand, often reduce vulnerability, though this is generally through higher expected consumption or income per capita rather than reduced variance (Ligon & Schechter, 2003; Christiaensen & Subbarao, 2005; Makoka & Kaplan, 2005; Jadotte, 2010; Jha, Dang, & Tashrifov, 2010; Klasen, Lechtenfeld, & Povel, 2015). Interestingly, education increased vulnerability in a small-sample study undertaken in Ethiopia by Bogale (2012), and post-secondary education also led to higher consumption variance in Vietnam (Imai, Gaiha, & Kang, 2011). Another interesting finding is that most studies that have included a dummy for gender of household head do not find that female-headed households are more vulnerable (Christiaensen & Boisvert, 2000; Ribas & Machado, 2007), and in some cases, are less vulnerable (Bronfman, 2014; Imai, Gaiha, & Thapa, 2015). An exception is Klasen, Lechtenberg & Povel (2015), who exploit a two-year panel data set from Thailand and Vietnam to show that *de facto* female-headed households are more vulnerable to consumption poverty than male-headed households.

3. Data and Descriptive Statistics

This paper exploits the rural sample of Malawi's nationally representative panel data set, which became available in 2013 via the Integrated Household Panel Survey (IHPS). The Malawi National Statistical Office conducted the surveys on which our data set is based, with support from the World Bank Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA) project. The baseline round is from a subsample of 3,247 households interviewed between March and November 2010 as part of the Third Integrated Household Survey (IHS3) 2010/11 survey, which is a nationally representative survey of 12,271 households fielded over 12 months (March 2010–March 2011). The follow-up round is from the Integrated Household Panel Survey (IHPS) 2013 survey. The IHPS tracked households and individuals to new locations when necessary. Hence, the IHS3 panel sample grew from 3,247 households in 2010 to 4,007 households in 2013 mostly because households split and formed new households. The IHPS utilized a complex household sample design allowing for 6 key domains of inference: the combination of urban and rural areas with the 3 main regions in the country (North, Central, and South). The data set contains detailed information on a rich variety of topics including demographics, education, health, employment, housing, assets, and agricultural production, as well as self-reported shocks, their impact and coping responses to them.

This paper uses an unbalanced panel on rural households only. This unbalanced panel consists of 2283 households in 2010, which had split into 2789 households in 2013. This characteristic of the data set is viewed as strengthening the results since it more accurately captures outcomes for all 2010 household members, as compared with simply choosing which 2013 household matches the 2010 household and ignoring members who have joined different households.

Welfare Measures

This study employs household total consumption per capita, food consumption per capita, income per capita, and maize harvest per capita as the main outcome measures for detecting vulnerability. Consumption and income capture two different measurements of households' economic security. Maize harvest is a particularly critical welfare measure in Malawi because of the importance of maize as a staple crop in Malawi (Smale, 1995; Ecker & Qaim, Analyzing Nutritional Impacts of Policies: An Empirical Study for Malawi, 2010; Oyekale & Gedio, 2012), and the strong link between maize production and food security (World Bank, 2007). Households' mean consumption per capita in 2013 was approximately USD 396 while mean income per capita was USD 188.[4] As has been amply noted elsewhere, income per capita figures are often lower than consumption per capita figures, largely thought due to under-reporting of some income sources. Consumption is traditionally considered to be a good indicator of the individuals' capability to achieve a certain living standard and is usually better captured than income in household surveys, but we include income to evaluate whether different explanatory factors are associated with vulnerability to income poverty. The three variables are related primarily through crop production, since part of income is comprised of the value of crop production, and part of consumption is comprised of consumption from own production. The correlation amongst the three ranges from .48 and .57, with the highest correlation between maize harvest and income per capita.

Well-being threshold

To identify the poor, we use the 2010 MWK 37,002 consumption per capita per year threshold identified by the National Statistical Office as the poverty line (NSO, 2012). Their calculation is based on the cost of a basket of food that provides sufficient daily calorie intake plus an allowance for basic non-food needs (NSO, 2012). Corrected for 132% inflation between 2010 and 2013, the poverty threshold then becomes 2013 MWK 85,845. We apply this same poverty line for both consumption and income. Because income per capita is much lower than consumption per capita, this results in far more households being below the poverty line when using the income per capita figures at the consumption poverty line. Thus, we generate an income poverty line that results in the same proportion of poor households as under consumption per capita. For maize harvest, we take the median level of maize harvest across both 2010 and 2013 (100 kg per capita per year) as the "poverty" line.

Table 1 below gives the poverty transitions for rural households between 2010 and 2013. The percent of rural households that escaped poverty over the period was greater than households who fell into poverty for overall consumption, food consumption and income per capita. The maize harvest per capita transition matrix shows that a relatively similar proportion of households transitioned from above to below median maize harvests as those who transitioned from below to above median values, as expected.

Table 1. Poverty transitions between 2010 and 2013 for selected welfare indicators

Welfare Indicator	Stay non-poor	Become non-poor	Become poor	Stay poor	Total
Consumption	47.3	19.7	13.2	19.8	100
Food Consumption	43.3	23.4	14.4	18.9	100
Income	48.7	21.5	13.0	16.8	100
Maize Harvest	33.5	17.0	16.4	33.1	100

Source: Authors estimations

[4] Because the analysis performed in the paper is at the household, we report descriptive statistics on household-level variables, including poverty and vulnerability rates, at the household level. The poverty and vulnerability rates would be higher if calculated at the individual level, since households with more members have lower per capita consumption, income and maize harvests.

Note: Table compares types of observed poverty in 2010 and 2013. Estimates account for complex survey design, and are expressed in percentage terms.

Table 2 provides descriptive statistics for our variables of interest for Malawi as a whole, as well as the Northern, Central and Southern regions. The ranking of regions in terms of poverty differs if we use consumption versus income per capita. In terms of consumption per capita, Central has the highest consumption figures, followed by Southern, with Northern quite a bit lower. Income per capita is also highest in Central, but then followed by Northern and then Southern. The pattern for maize harvest per capita follows income per capita, with the highest amounts in Central followed by Northern. Households in Southern obtain approximately half the amount of maize harvest per capita as Central. Households' cropland holdings dedicated to maize production are also much lower in Southern, at .69 hectares on average, versus 1.34 and 1.38 in Northern and Central, respectively.

Shocks

The precarious material conditions of most rural households in Malawi are compounded by their high exposure to rainfall, price, health and off-farm employment shocks. To capture the effect of rainfall shocks, we use the absolute value of the percent difference between flowering season[5] rainfall in 2012/2013 and the long-term mean during the flowering season. Historical rainfall data were obtained from the ARC2 database of the National Oceanic and Atmospheric Administration (NOAA). The absolute value is used since values far from the mean in either direction are expected to correlate with worse welfare outcomes. For maize price shocks, we had to rely on a shorter time period, 2005 – 2013, using administrative data on monthly maize prices observed in 72 markets across the country. We use deviations in 2012 from the mean price during the lean season January-March, since this is the period prior to the harvest when households are most likely to need to purchase maize. We consider 2012 price shocks since we expect previous season prices to have an effect on producer decision-making and well-being outcomes in 2013 without being caused by the weather shocks observed for 2013. Unlike rainfall, where very high and very low realizations are of interest due to their negative effects on well-being, we construct the price shock as the difference in maize prices from the 9-year average where those prices are higher, and set the shock to zero otherwise. Thus, we are capturing the consumer price shock in the lean season of 2012, which we expect to reduce consumption, and possibly income (Ecker & Qaim, 2011; Kaminski, Christiaensen, & Gilbert, 2014).

For health and off-farm employment shocks, we relied on the spatial variation found in the IHPS survey responses. We proxy for illness shocks in the household by including a dummy for whether a household member had malaria in the two weeks prior to the interview. Perennial malaria transmission is intense in Malawi (Roca-Feltrer, et al., 2012; WHO, 2014), and can have substantial effects on productivity and income (Gollin & Zimmermann, 2007; Asenso-Okyere, Asante, Tarekegn, & Andam, 2009). The household economic impact we consider is whether the household received income from any off-farm formal or informal employment (wages, ganyu, or self-employment) in 2010 and lost access to that income in 2013. This loss of access to off-farm income is included as a shock since off-farm employment represents diversification of income, which is expected to contribute to a households' ability to smooth consumption in periods when other sources of income are constrained (Morduch, 1995).

[5] Flowering season refers to December and the following January. Although the start and end of the rainy season and thus the flowering season vary from year to year, December and January are traditionally the months when maize and other crops have been established.

From Table 2, we see that malaria and loss of off-farm income were the most prevalent shocks. While households faced a relatively similar probability for experiencing the malaria shock across regions, they experienced different probabilities for experiencing the off-farm income shock, as well as rainfall and price shocks. Northern and Central faced 8-10% deviations from long-term mean rainfall, whereas Southern faced 15% deviations. Price deviations were smallest in Northern at around 7%, and higher in Southern and Central at 10% and 11% respectively. The probability of an off-farm employment income loss shock was similar in Central and Southern at 13% and 15% respectively, and highest in Northern at 19%.

Table 2 also includes long-term measures of riskiness that are hypothesized to shape peoples' expectations ex ante, which may in turn affect their choices of risk management and risk coping strategies. The coefficient of variation for malaria and employment shocks are spatial variations, whereas those for maize prices and rainfall are generated from the time series data. Consistent with information on actual rainfall shocks realized, households in Southern face higher rainfall variability than households in Central and Northern. On the other hand, maize price variability is highest in Northern, followed by Southern, and lowest in Central. The differences in rainfall and price variability between regions are all statistically significant. Households in Northern face greater variability of malaria incidence, followed by Southern and then Central. Households in Central face the greatest risks in terms of off-farm employment income loss, followed by Northern and Southern with relatively similar and lower levels of risk.

Table 2. Descriptive Statistics

	Malawi		**Northern**		**Central**		**Southern**	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Welfare Measures (2013 values)								
HH Consumption (2013 USD/person)	396	316	352	225	403	331	400	321
HH Food Consumption (2013 USD/person)	241	176	228	138	243	174	241	186
HH Gross Income (2013 USD/person)	188	491	174	250	194	376	170	421
HH Maize Harvest (kg/person)	187	562	188	250	254	830	127	159
Shocks (2013 values)								
Rainfall shock	0.119	0.080	0.079	0.050	0.096	0.063	0.150	0.087
Maize price shock	0.096	0.097	0.070	0.088	0.107	0.092	0.091	0.101
Malaria shock	0.271	0.445	0.274	0.446	0.277	0.448	0.266	0.442
Employment loss shock	0.145	0.352	0.189	0.392	0.132	0.338	0.147	0.354
Risk Exposure								
CoV - Dec-Jan Rainfall, 1983/84-2014/15	0.258	0.046	0.239	0.025	0.222	0.024	0.296	0.035
CoV - Jan-Mar Real Maize Price, 2005-2013	1.918	0.291	2.423	0.292	1.759	0.188	1.940	0.208
CoV - HH Incidence of Malaria	1.665	0.546	1.845	0.546	1.562	0.407	1.715	0.633
CoV - HH Incidence of off-farm employment	3.173	1.734	3.161	1.771	3.592	1.562	2.792	1.787
HH characteristics (2010 values)								
Adult equivalents in HH	4.28	1.97	4.56	2.26	4.60	2.01	3.92	1.79
HH dependency ratio	1.330	1.022	1.299	1.022	1.346	0.995	1.323	1.046
Age of HH Head	44.1	16.4	45.7	16.4	44.3	16.3	43.6	16.5
HH Head is Female	0.252	0.434	0.189	0.392	0.224	0.417	0.294	0.456
HH Head is Chewa	0.583	0.493	0.034	0.181	0.830	0.376	0.492	0.500
HH Head is Tumbuka	0.070	0.255	0.586	0.493	0.008	0.090	0.001	0.024
HH Head is Muslim	0.160	0.367	0.007	0.086	0.090	0.286	0.261	0.439

HH Head is Married	0.678	0.467	0.712	0.453	0.702	0.458	0.647	0.478
HH Wealth and Education Index[a]	0.375	0.234	0.456	0.224	0.363	0.223	0.367	0.243
HH Ag Assets and Land Holdings Index[b]	0.388	0.204	0.484	0.207	0.431	0.224	0.325	0.161
Community Characteristics (2010 values)								
Community infrastructure index	-0.099	1.078	-0.609	1.006	0.226	1.049	-0.271	1.034
Community median slope (%)	4.564	3.761	5.142	3.915	4.009	2.674	4.931	4.446
ln(Access Index)	4.519	1.434	2.439	1.827	5.455	0.957	4.171	0.900
District AEDOs per 1000 farming families	0.433	0.135	0.538	0.173	0.472	0.113	0.372	0.112
Total N. Projects in District	4.385	3.567	4.298	1.148	6.294	4.457	2.663	1.640
Community Land Ownership Gap	1.233	0.640	1.339	0.579	1.489	0.628	0.973	0.557

Notes:

a. Calculations account for complex survey design.

b. The following variables were used to create a household wealth index with principal component analysis: Furniture dummy capturing whether the household had any of (bed, table, chair, chair/couch, coffee table, drawers, or desk), radio dummy, electronic dummy capturing whether the household had any of (fan, air conditioner, stereo, clock, or solar panel), laundry dummy capturing whether the household had any of (sewing machine, washing machine, clothes iron), kitchen dummy capturing whether the household had any of (kerosene stove, electric/gas stove, refrigerator), a dummy capturing whether the household had any of (TV, VCR, computer, satellite dish, or generator), cell phone dummy, improved walls of dwelling dummy, improved roof of dwelling dummy, improved floor of dwelling dummy, number of rooms per capita in household dwelling, improved lighting fuel usage dummy, improved cooking fuel usage dummy, electrification of dwelling dummy, access to an improved water source dummy, access to an improved latrine dummy, improved rubbish removal usage dummy, use of insecticide treated mosquito nets dummy. The index was then normalized, that is, norm_index = ((index - min(index)) / (max(index)-min(index))). Household average years of education is the numbers of years of education completed by each individual collapsed to the household mean number of years of education. This variable also was normalized. The wealth and education index displayed in Table 1.4 is the sum of the normalized wealth index and the normalized average number of years of education.

c. The following variables were used to create an agricultural asset index with principal component analysis: Hand hoe dummy, watering can dummy, hand tool dummy capturing whether the household had any of (slasher, axe, sprayer, panga, or sickle), a dummy capturing whether the household had any of (tractor, tractor plough, ridger, cultivator, treadle pump, motorized pump, ox cart, or ox plough), livestock facility dummy capturing whether the household had any of (chicken house, livestock kraal, poultry kraal, or pig sty), and grain storage dummy capturing whether the household had any of (storage house, granary, or barn). The index was then normalized, that is, norm_index = ((index - min(index)) / (max(index)-min(index))). Land holdings are the number of hectares (ha) that the household "holds." Plots that the household farmed on and had acquired through being granted by local leaders, inheritance, bride price, purchase, or leasehold (about 5% of all plots were acquired by means other than these) are said to be "held." Any plots that the household did not farm but received rent for also were counted as being held. This variable then was normalized. The agricultural and land index displayed in Table 1.4 was the sum of the normalized agricultural asset index and the normalized household land holdings.

Overall households in Southern faced the greatest rainfall shocks in 2013. They also face relatively high coefficients of variation in rainfall shocks, indicating greater exposure to future rain shocks. Households in Central faced the greatest maize price and malaria shocks in 2013. But, Central has relatively low coefficients of variation for rainfall, maize price, and malaria shocks, though they also face the highest variability in off-farm employment. Households in Northern faced the lowest weather and price shocks in 2013, but also had the highest employment loss shocks and relatively high incidence of malaria. They do face relatively high risks of price and malaria shocks in the future compared to the other regions. To summarize, different regions face different risks, with Southern being particularly susceptible to rainfall shocks, Central being relatively susceptible to employment loss shocks, and Northern being historically most susceptible to price shocks.

Household and community characteristics

In the face of all the perils described above, even if most of our sample households could be regarded as poor, there are varying degrees of deprivation between them and over time. As captured in the literature review above, the scope and severity of shocks faced by households, together with the available resources at home and in communities, determine the extent of each household's success in responding to such shocks.

Table 2 also includes descriptive statistics for the main explanatory variables employed in the analyses. Both the IHS3 and IHPS rounds contain information on household socio-demographic characteristics that can be used to proxy the consumption smoothing capacity of households, including the size and life-cycle of the family according to the age and gender composition of its members; as well as the age, gender, civil status and ethnicity of the household head. We have also created two indices of wealth, as detailed in footnotes a and b, Table 2. The first index includes measures of household wealth and education levels, and the second index includes measures of agricultural specific assets and landholdings. Higher levels of wealth, education, agricultural assets and landholdings are all expected to be associated with higher welfare outcomes per capita. The impact on variance measures, however, is ambiguous. Greater wealth levels may enable households to pursue production and income strategies that are more lucrative but also more risky. On the other hand, wealthier households may be more able to finance adoption of risk-reducing activities, such as pursuing income diversification strategies or adopting relatively costly sustainable land management activities (Arslan et al., 2015; Asfaw et al., 2015).

We also control for the availability of socioeconomic infrastructure that exists in the community and the degree of accessibility and slope as proxies for the structures of opportunity that rural households face at the village level. These variables are included to capture a measure of the community conditions relevant to households' economic and social decisions. Higher infrastructure and accessibility scores are expected to correlate with greater ease of conducting economic and social activities, and thus lead to higher, and potentially more stable, welfare outcomes. Higher slope levels are included to capture agricultural land that is more susceptible to erosion and flood damage, and which may lead lower and more variable harvests, and potentially, lower and more variable incomes and consumption levels. We also gather information on economic heterogeneity by looking at the difference in landholding size between the poorest and the wealthiest. On the one hand, heterogeneity can make it more difficult to provide public goods and cooperation that can shield farmers from poor outcomes (McCarthy and Kilic, 2015; Asfaw et al., 2014). On the other hand, relatively large landholders are also more likely to be in a position to offer informal insurance, credit or wage labor in the event of idiosyncratic risk realized by poorer households. We also include the number of AEDOs per farming family as a measure of the degree of government presence in the district beyond the infrastructure and accessibility characteristics captured elsewhere. Finally, we obtained information on the number of donor-led projects operating within each district, from the EPIC team based at the FAO.[6] Such projects may increase welfare outcomes as well as increase stability of those outcomes.

4. Empirical Strategy

In conventional poverty analysis, the first thing to do is choose a welfare indicator. Then one computes a poverty threshold to distinguish the poor from the non-poor. Classifying a person or household as vulnerable under the expected poverty approach requires extra steps that are not usually taken in poverty analysis. The first relates to the estimation of the ex-ante probability distribution of ex-post welfare outcomes of interest. Once the distribution of future welfare has been established, one then needs to establish the vulnerability threshold.

[6] More information on the EPIC project can be found at: http://www.fao.org/climatechange/epic/home/en/

The distribution of future welfare outcomes

In our analysis, we will consider four different measures of welfare, total consumption, food consumption, income, and maize harvest, all in per capita figures. These measures are highly, but not perfectly, correlated, as discussed above. We are particularly interested in evaluating whether the four shock variables have different impacts across these welfare outcomes.

To generate expected welfare levels under VEP, we employ the three-stage feasible generalized least-squares (FGLS) estimator proposed by Amemiya (1978) to estimate a production function where inputs can be risk increasing, neutral or decreasing, as developed in Just & Pope (1978). In terms of consumption, income and maize harvest per capita, this type of estimation procedure can test the hypothesis of whether household characteristics, particularly wealth levels, can mitigate risks and lead to lower variance.

Where two time periods of data are available as in our case, the first stage of the estimation is simply the log of welfare outcome per capita in the current period, regressed on previous period household characteristics, current period shocks, and a potentially heteroskedastic error term, as follows:

$$\ln c_{ijt} = \alpha + \beta_1 X_{ijt-1} + \beta_2 W_{ijt-1} + \beta_3 S_{ijt} + \beta_5 V_{jt} + e_{ijt} \qquad [5]$$

Where $\ln c_{ijt}$ is the logged welfare variable of interest, *j*, for the *i*-th household at time *t*; X_{ijt-1} is a vector of household characteristics not including wealth indices observed in the preceding period; W_{ijt-1} is a vector of wealth indices observed in the preceding period; S_{ijt} is a vector of idiosyncratic and co-variate shocks observed in the current period; and V_{jt} is a vector of community and district level characteristics. The error term, e_{ijt}, is distributed with mean zero and variance of σ_{ijt}^2 , which, following the FGLS procedure, is estimated using the error terms from the logged welfare equation to obtain weights to apply in the third stage as follows:

$$\hat{e}_{ijt}^2 = \delta + \gamma_1 X_{ijt} + \gamma_2 W_{ijt} + \gamma_3 V_{jt} + u_{ijt} \qquad [6]$$

Letting $\aleph$ represent the vector of all included explanatory variables, we can write the estimates of expected consumption and the variance of consumption as follows:

$$E\left(\ln c_{ijt} \mid \aleph\right) = \hat{\alpha} + \hat{\beta}_1 X_{ijt-1} + \hat{\beta}_2 W_{ijt-1} + \hat{\beta}_3 E\left(S_{ijt}\right) + \hat{\beta}_5 V_{jt} \qquad [7]$$

$$Var\left(\ln c_{ijt} \mid \aleph\right) = \hat{\partial} + \hat{\gamma}_1 X_{ijt-1} + \hat{\gamma}_2 W_{ijt-1} + \hat{\gamma}_3 V_{jt} \qquad [8]$$

Note that the expected values of consumption in equation [7] are a function of expected shock variables. While it was unclear to us how the impacts of included shocks were handled in generating expected consumption levels in previous studies, given the terminology used ("predicted" outcomes), it would appear that many studies actually presented results based on predicted results that included the impacts of observed shocks themselves. Had such shocks been unobserved, and thus presumed to be captured in the error term, the expectation would likely be zero. The expected rainfall and maize price deviation is clearly zero by construction using long-term data. Off-farm employment and health shocks are a bit different. Expected off-farm employment and health shocks would be zero if one assumes that there is the possibility of both positive and negative employment and health shocks, with an expected value of zero. We make this assumption in order to treat the shock variables similarly. Setting expected shocks equal to zero, gives the following:

$$E\left(\ln c_{ijt} \mid \aleph\right) = \hat{\alpha} + \hat{\beta}_1 X_{ijt-1} + \hat{\beta}_2 W_{ijt-1} + \hat{\beta}_5 V_{jt} \quad [9]$$

Vulnerability threshold (value above which a household is considered vulnerable)

A recurring theme in the VEP literature is the choice of a probability threshold on which to categorize household vulnerability. The choice of the cut-off probability above which a person or household will be considered vulnerable) has still some degree of arbitrariness in its selection and does carry implications for the results in the analysis. The literature on the choice of the vulnerability thresholds is limited (Bigman 1996). This selection has been done in two main ways. The most common has been to choose a threshold at 50% which indicates that a household above this threshold has a higher probability to end up poor in the next period than not (Chaudhuri et al. 2002; Tesliuc and Lindert 2002; Cruces et al. 2010). A second approach sets the threshold at the poverty rate in the population. To justify this approach Chaudhuri et al. (2002) argued that the poverty rate in a population equals the mean vulnerability level in the community.

Neither of the two arguments is compelling, but we find the 50% threshold to be particularly odd. At the threshold of 50%, whether a household is vulnerable or not is completely driven by expected consumption per capita, and is unaffected by the standard deviation – and thus the variability – a household faces. In other words, the 50% probability occurs when the numerator in the normal probability density function equals zero, which occurs when the expected consumption equals the poverty line. But, we believe that vulnerability should also capture those who are a bit above the poverty line but still subject to high variability. For probabilities less than 50%, an increase in risk increases the probability that a household will be classified as vulnerable. However, setting the threshold above 50% means that as risk increases, fewer households will be classified as vulnerable. As noted by Ligon and Schecter (2004), this would mean that in countries with very high poverty rates, using the Chaudhuri et al. (2002) approach would mean that greater riskiness would actually lead to fewer households being classified as poor, which is also problematic.

While the 50% threshold and mean poverty rate threshold are ad hoc, we can do no better than to propose another ad hoc threshold, though one that at least captures the impact of greater riskiness on vulnerability. For this analysis, we chose a poverty threshold of 40%. To illustrate the different predictions, we compare the vulnerability predictions using both thresholds, given in Table 5 below.

5. Results

5.1 Outcome and Variance FGLS Results

Table 3 presents the results for second and third stages of the FGLS regressions for each of the four outcome variables of interest.[7] First, we note that we have reasonable explanatory power for our

[7] For space reasons, we only include key explanatory variables of interest in the text; full results can be found in Appendix 1.

outcome variables, but in line with most applications in the literature discussed above, we also have very low explanatory power for our variance estimates. What this means in practice is that our predicted variance is going to be lower than the overall variance term, and may well underestimate idiosyncratic variance due to real risks faced by households. Given our data we can test this in a number of ways. First, we ran an alternative specification where we included the shock variables only in the variance equation, particularly since these variables are presumed to be captured in the error term in studies with no or limited information on actual shocks. The four shocks included here were not statistically significant in this alternative specification for any of the variance estimations. Furthermore, we also included a number of other subjective shocks reported by the household, such as losing a member who speaks English, death in the household, ganyu wage shock (deviations of ea-level mean wages from district means), as well as many others and covering many permutations. None of these variables were statistically significant in explaining the variance for any of the outcome variables. To summarize, the actual variance is much greater than our estimate, and is not well explained either by observed objective shocks or household-level subjective shocks. Some of this is likely measurement error, but we need to be careful in interpreting the contribution of the predicted idiosyncratic error to overall variance.[8]

Returning to the estimated equations, we see that the rainfall shock has a significant and negative impact on both food consumption and total consumption per capita. Though the coefficient on the rainfall shock is negative for maize harvest it is not significant. Instead, the coefficient of variation of rainfall is negative and significant. The latter is consistent with numerous studies which have documented the negative impacts of rainfall risks on incentives to adopt improved practices and make investments in cropland (Horowitz and Lichtenberg, 1993; Dercon, 1996; Morduch 1990; Rosenzweig and Binswanger, 1993; Kurosaki and Fafchamps, 2000; Lamb, 2003; and Dercon and Christiaensen, 2011). Because most of the farms received relatively modest deviations from expected rainfall in the 2012-2013 season, results suggest that a strategy to pursue lower but more stable crop output successfully avoided lower maize harvest per capita. The impact on consumption and food consumption could be related to non-staple crop production losses or fewer opportunities to engage as wage labor on others' farms, particularly since 44% of households engaged in ganyu wage labor in 2010, and 45% did so in 2013.

The maize price and malaria/health shocks have the expected sign (i.e., negative impact), but no statistically significant impacts on any of the outcome variables in this sample. However, households subjected to high expected incidence of malaria, captured by the spatial coefficient of variation, do have a lower variance of total and food consumption as well as income. These results suggest that higher malaria risk induces households to seek less risky income and maintain more stable consumption, but with no subsequent impact on consumption and income levels. In other words, households are apparently effective at managing those risks without compromising income and consumption levels.

The off-farm income loss shock has a significant and negative impact on overall consumption and income, but has a positive impact on maize harvest per capita. The latter suggests that loss of off-farm employment was productively re-directed on-farm, though not productive enough to offset all of the lost income. Households facing higher risks of losing employment also have lower total and food consumption. Such households may try to save more rather than consume, as the impact on income is not significant.

Wealth levels are particularly important in enabling households to absorb shocks and increase production, income and consumption. Here we note that we did include interaction terms between the two wealth

[8] We also ran the FGLS regressions for each region, and also controlled for district fixed-effects; and again, shocks were not significant in the variance equations.

variables and the shocks, but because none of the interaction terms were significant and explanatory power dropped, we dropped these from the analysis. Household wealth, which includes both consumer durables and average education of household adults, has a significant and positive coefficient on all of our outcome variables. Additionally, it has a significant and negative impact on the variance of food consumption. The agricultural asset index has a significant and positive impact on maize harvest, income and food consumption, and a negative impact on the variance of maize harvest, income and total consumption. Thus, measures of wealth allow households to enjoy both higher and more stable production, income and consumption.

Table 3. Estimation of well-being controlling for shocks and interactions

		Consumption		Food Consumption		Income		Maize harvest	
		Variance	Level	Variance	Level	Variance	Level	Variance	Level
Shock (2013 values)	Rainfall shock		-0.459 **		-0.603 ***		-0.275		-0.476
			(.014)		(.003)		(.358)		(.257)
	Maize price shock		-0.204		-0.275		0.065		-0.149
			(.237)		(.155)		(.812)		(.604)
	Malaria shock		-0.013		-0.005		-0.017		-0.062
			(.568)		(.831)		(.727)		(.164)
	Off-farm employment loss shock		-0.077 **		-0.046		-0.642 ***		0.114 **
			(.011)		(.150)		(.000)		(.019)
Risk Exposure	CoV - Dec-Jan Rainfall, 1983/84 - 2014/15	0.379	-0.239	0.726	-0.829	-2.020	-0.550	1.466	-2.558 **
		(.366)	(.673)	(.215)	(.221)	(.286)	(.539)	(.314)	(.047)
	CoV - Jan-Mar Real Maize Price, 2005-2013	0.021	-0.060	0.040	-0.076	0.043	0.156	-0.116	0.202
		(.668)	(.300)	(.470)	(.254)	(.845)	(.227)	(.442)	(.128)
	CoV - HH Incidence of Malaria	-0.036 **	0.018	-0.053 ***	-0.004	-0.193 ***	0.061	-0.070	0.031
		(.020)	(.430)	(.009)	(.881)	(.005)	(.107)	(.226)	(.577)
	CoV - HH Incidence of off-farm employment	0.004	-0.015 *	0.006	-0.018 *	-0.017	0.000	0.058 **	0.018
		(.447)	(.095)	(.466)	(.078)	(.487)	(.999)	(.017)	(.337)
Wealth (2010 values)	HH Wealth + Education Index	-0.031	1.085 ***	-0.143 ***	0.918 ***	-0.243	1.646 ***	-0.006	1.359 ***
		(.418)	(.000)	(.003)	(.000)	(.140)	(.000)	(.970)	(.000)
	HH Ag Assets + Land Holdings Index	-0.100 *	0.097	-0.089	0.116 *	-0.899 ***	0.440 ***	-0.386 *	1.055 ***
		(.057)	(.131)	(.119)	(.087)	(.000)	(.000)	(.058)	(.000)
	Number of observations	2789	2789	2789	2789	2770	2770	2432	2432
	R-squared	0.019	0.277	0.025	0.219	0.02	0.223	0.022	0.226

Note: Table reports coefficients and p-values in parentheses. Asterisks denote significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Other co-variates of interest are captured in the full regression results reported in Annex 1, Table 1. They capture the lower per capita consumption and income levels for larger households with more dependents mirrored in most other vulnerability studies. Female-headed households do not have lower total or food consumption per capita, but do have lower income per capita. Finally, outside of the wealth variables, very few explanatory variables reduce the variance of outcome measures.

5.2 Levels of Vulnerability

Given the above regressions, our next step is to calculate the probability that a household will fall below the poverty threshold. Because impacts of shocks on total consumption are similar to food consumption and income, and because shocks had no or a positive impact on maize harvest per capita, for the remainder of the paper, we will focus on shocks and total consumption per capita.

Table 4 displays the matrices for observed poverty in 2013 versus expected poverty in 2013 at the national level. The first scenario (upper matrix) assumes that expected shocks for households are all equal to zero. Rows give the observed number of households at or above the poverty line in 2013 (non-poor), and those falling below the poverty line (poor). Columns contain the number of households who are expected to be at or above the poverty line (not vulnerable), and those expected to fall into poverty in 2013 (vulnerable), given characteristics prevailing in 2010. To the extent that households expect no deviations from long-term averages in terms of the shock variables, just 22.3% of households would be vulnerable, down from the 33.6% who are actually poor in 2013. Just 9.4% of the non-poor are vulnerable, whereas 20.6% of the poor would expect to transition out of poverty.[9]

But while each individual household may expect shocks to be zero when looking just one period ahead, risk averse households would still care about their probability of falling into poverty, and national-level policymakers are also more interested in the likely incidence of poverty one year ahead. For instance, spatially, the rainfall deviation historically averaged about 21% nationally, ranging from 20% in Northern, 18% in Central, and 24% in Southern. We also note here the difference between average historical rainfall deviations versus the observed cross-section deviations, which averaged about 12% nationally, to 8% in Northern, 10% in Central, and 16% in Southern. If we had been restricted to using the spatial variation observed for the 2012/2013 growing season, we would significantly underestimate the number of vulnerable households, since the 2012/2013 season exhibited lower deviations than the historical average in all regions.

[9] The vulnerability ranking at the regional level in our sample switches depending on the shocks scenario used. Under the no shocks scenario, non-poor households in Northern and Central are particularly vulnerable to becoming poor driven mainly by the possibility of future employment shocks. Though Southern does have relatively high exposure to future rainfall variability, households there expect to be the least vulnerable. When using regional-level expected shocks, vulnerability is still highest in Northern, mirroring the results for households' expectations, but Southern is now more vulnerable than Central. This is primarily due to the fact that rainfall variability is higher in Southern than Central, and households there are more exposed to such shocks than those in Central.

Table 4. Consumption Poverty Matrix under No Shocks

		National Expected Poverty in 2013: Expected Shocks=0		
		Non-Vulnerable	*Vulnerable*	*Totals*
Observed 2013	*Non-poor*	57.1	9.4	66.4
	Poor	20.6	12.9	33.6
	Totals	77.7	22.3	100

Table 4a. Consumption Poverty Matrix under Expected Shocks

		National Expected Poverty in 2013: Regional Mean Shocks		
		Non-Vulnerable	*Vulnerable*	*Totals*
Observed 2013	*Non-poor*	45.8	20.6	66.4
	Poor	10.5	23.0	33.6
	Totals	56.4	43.6	100

Table 4b. Northern Region Consumption Poverty Matrix under Expected Shocks

		Northern Region Expected Poverty in 2013: Regional Mean Shocks		
		Non-Vulnerable	*Vulnerable*	*Totals*
Observed 2013	*Non-poor*	35.1	28.3	63.4
	Poor	6.4	30.2	36.6
	Totals	41.5	58.5	100

Table 4c. Central Region Consumption Poverty Matrix under Expected Shocks

		Central Region Expected Poverty in 2013: Regional Mean Shocks		
		Non-Vulnerable	*Vulnerable*	*Totals*
Observed 2013	*Non-poor*	59.1	9.9	68.9
	Poor	19.3	11.7	31.1
	Totals	78.4	21.6	100

Table 4d. Southern Region Consumption Poverty Matrix under Expected Shocks

		Southern Region Expected Poverty in 2013: Regional Mean Shocks		
		Non-Vulnerable	*Vulnerable*	*Totals*
Observed 2013	*Non-poor*	44.6	21.1	65.6
	Poor	9.9	24.5	34.4
	Totals	54.5	45.6	100

Note: Tables compare observed poverty in 2013 with predicted vulnerability. Estimates are expressed in percentage terms.

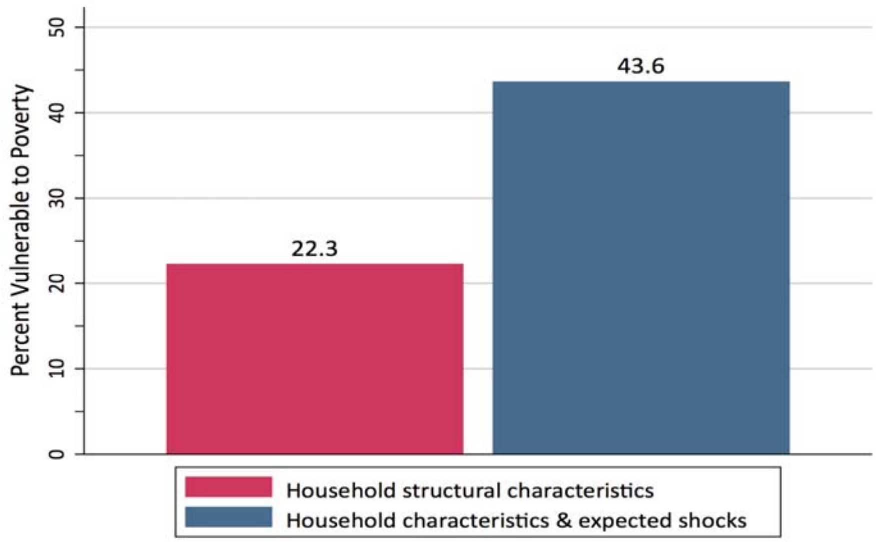
Tables 4a-4d present the national and regional transition matrices where we set the average annual rainfall and price shocks observed in the region historically, and the malaria and formal employment shocks to the average observed within the region in 2013,[10] which of course results in much higher predicted vulnerable households than estimates based on expected shocks. At the national level, the observed poverty rate in 2013 was ~34 percent, whereas the proportion of vulnerable people within the population was estimated to be ~44 percent, almost evenly split between poor households expected to

[10] This produces conservative estimates of vulnerability since it assumes that all households, irrespective of wealth, landholdings, etc., would be equally likely to be affected by a shock next year. In most cases, however, shocks are more likely to occur for poorer households due to more precarious job opportunities, access to preventative health care, etc.

remain poor, and non-poor households that are expected to fall into poverty. Just 10.5% of households are expected to transition from poverty into non-poor status.[11]

Looking at the regions, we see that percent of vulnerable households is highest in Northern at 58.5%, followed by Southern at 45.6% and then quite a bit lower in Central, at 21.6%. In part this is due to the fact that households have the lowest per capita consumption, but are exposed to both relatively high rainfall and job loss risks. Households in Southern are also quite vulnerable, mainly due to high rainfall risks.

Figure 1: Household Vulnerability to Poverty



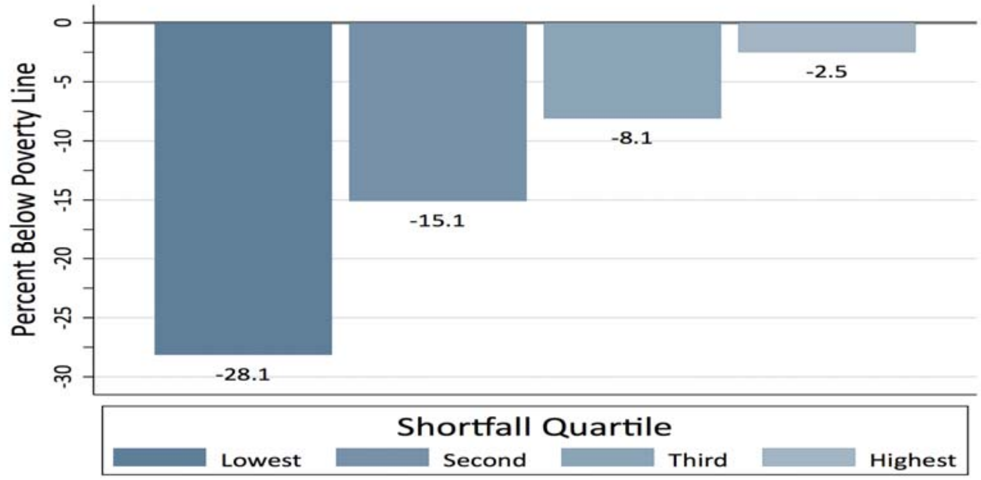
Source: Authors calculations

We illustrate the impact that shocks have on vulnerability at the national level in Figure 1. Figure 1 shows the change in percentage of households who are vulnerable to consumption poverty when considering only structural household characteristics versus including probability of experiencing the historical average shocks. In terms of vulnerability to consumption poverty, 22 percent of households in Malawi were expected to be vulnerable when considering only structural household characteristics such as low wealth and education levels, small land holdings, and large family sizes. When accounting for the effect of expected shocks, 44 percent of households were expected to be vulnerable to consumption poverty.

To highlight the distribution of expected shortfalls with shocks, Figure 2 summarizes the percentage shortfall experienced by households whose consumption would fall below the poverty line under expected shocks. While the average shortfall is just under 14%, the distribution ranges from 2.5% to over 30%, with an average loss of 28.1% for the quartile facing the largest losses.

[11] Using income per capita, and to a lesser extent maize per capita, the results suggest that the percent of vulnerable households is greater than those currently poor. The discrepancy is mainly due to the fact that the chosen poverty line is quite a bit below average consumption per capita, whereas it is much higher than observed income per capita. In the case of income per capita, very few poor households are predicted to move below the poverty line, whereas many non-poor households are predicted to fall into poverty, and vice-versa for consumption. Thus, the choice of a poverty line can be quite critical in determining vulnerable vs. currently poor households.

Figure 2: Consumption Shortfall for Households below the Poverty Line by Wealth Quartile



Source: Authors calculations

The expected shortfall is only negative for those households with a probability of remaining or falling into poverty of 50% or greater. Households with a probability of falling into poverty in the range [40,50), of course have expected consumption levels just above the poverty line. In particular, households with a probability of falling into poverty in that range, the average consumption per capita is just 7.1% above the poverty line. These figures highlight the difference between using a 50% probability threshold versus a 40% vulnerability threshold. Table 5 below highlights the difference between the different probability thresholds.

Table 5. Consumption Shortfall by Probability of Poverty and Region

	Median % difference from poverty line	Mean % difference from poverty line	Number of HH
A. Households with ≥ 50% probability of being poor			
Northern	-15.4	-16.6	237
Central	-8.7	-10.5	167
Southern	-11.0	-12.5	286
Malawi	-11.8	-13.4	690
B. Households with ≥ 40% and <50% probability of being poor			
Northern	5.0	5.5	98
Central	8.1	8.1	230
Southern	7.1	7.3	199
Malawi	7.1	7.3	527
C. Households with ≥ 40% probability of being poor			
Northern	-7.8	-10.1	335
Central	2.5	0.3	397
Southern	-3.1	-4.4	485
Malawi	-2.4	-4.4	1217

Source: Authors calculations

Section A of Table 5 describes consumption shortfall for households who are vulnerable with a 50% threshold, Section B describes the additional households that are vulnerable when we lower the threshold to 40%, and Section C describes consumption shortfall for all households that are vulnerable with a 40% threshold. Using the 50% threshold, we by definition restrict to households whose expected level of consumption is below the poverty line. Thus, all households included in Section A experience a consumption shortfall, and the levels of shortfall are relatively large. The households in Section B all have expected consumption above the poverty line, and thus do not experience 'shortfall.' However, the percent above the poverty line in Section B is modest compared to the percent below the poverty line in Section A, except for households in Central where the difference between Section A and Section B is relatively small. When we combine the households from Sections A and B to create Section C, we see that the average shortfall is much smaller under the 40% threshold, and that the average gap is even positive.

6. Conclusions

Considerations of risk and vulnerability are critical to understanding the dynamics of poverty in Malawi, where the majority of rural households are poor rain-fed farmers. This study assessed the vulnerability to consumption shortfalls of rural households in Malawi using a two-period panel, drawn from the 2010 IHS3 and 2013 IHPS.

The results show that many households in Malawi are vulnerable to poverty, though as with many other studies of rural areas in other countries, much of vulnerability is due to chronic poverty. In terms of empirical evidence, most studies find that poverty is the most important component of vulnerability. Nonetheless, risks – particularly rainfall and loss of off-farm employment shocks – are also important in explaining why poor households remain poor, and why some non-poor households are more likely to fall into poverty in the next period.

The calculation of expected shocks matters quite a bit in the assessment of vulnerability. Setting all shocks equal to zero results in much lower vulnerability rates. But this is unrealistic. In any given year, across the country or each region, the expected value of a shock is not zero, since some households will indeed face a shock while others do not. Thus, we constructed expected welfare outcomes by setting the shocks equal to the regional annual average rainfall and price shocks observed from historical rainfall data, and to regional level average malaria and employment shocks. While fewer households expect to be vulnerable next period than were poor in 2013, overall the government should expect more households to be vulnerable than observed poor in 2013. The empirical analysis confirmed that a sizable number of rural households were vulnerable to poverty in Malawi in 2010 due to the potential realization of risks (the occurrence of shocks) between 2012 and 2013. The latter results primarily because both rainfall and price shocks were relatively low in 2013 versus their long-term historical average, as well as the importance of off-farm employment shocks on consumption per capita.

Of the variables included in the welfare outcome and variance equations, both household wealth and agricultural asset indices are the most important in protecting households from falling into poverty and reducing the severity of the fall when shocks occur. However, in country contexts similar to Malawi's where risk mitigation mechanisms are limited, shocks can force many households into poverty. In short, we found broad similarities between vulnerable and poor households in terms of explanatory characteristics. In both cases, vulnerable households are characterized by large families with high dependency ratios, and limited household wealth and agricultural assets, and located in more isolated communities with poorly developed socioeconomic infrastructure. While household wealth can be used to hedge against risk and thus help to avoid falling into poverty when external conditions deteriorate, there are apparently few other mechanisms for households to rely on when shocks occur.

Most of the variance we observe in the error terms is due to unobserved idiosyncratic risk and unexplained error. A main concern with the analysis is the limited predictive power in the variance equation, and thus drawing conclusions about the contribution of unobserved risks households face in our sample. Unlike many other studies, we do have a fair amount of information on shocks actually faced by households, both from objective data and subjective assessments. The aggregate impact of observed risks has a substantial impact on vulnerability, nearly doubling the number of households considered vulnerable versus those expected to be poor based on structural household characteristics.

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Annex 1 Table 1. Estimation of well-being controlling for shocks

		Consumption		Food Consumption		Income		Maize harvest	
		Variance	Level	Variance	Level	Variance	Level	Variance	Level
Shock (2013 values)	Rainfall shock		-0.459 **		-0.60 ***		-0.275		-0.476
			(.014)		(.003)		(.358)		(.257)
	Maize price shock		-0.204		-0.275		0.065		-0.149
			(.237)		(.155)		(.812)		(.604)
	Health shock (malaria)		-0.013		-0.005		-0.017		-0.062
			(.568)		(.831)		(.727)		(.164)
	Employment shock		-0.077 **		-0.046		-0.642 ***		0.114 **
			(.011)		(.150)		(.000)		(.019)
Risk (time-invariant)	CoV, Historical Rainfall Shock	0.379	-0.239	0.726	-0.829	-2.020	-0.550	1.466	-2.558 **
		(.366)	(.673)	(.215)	(.221)	(.286)	(.539)	(.314)	(.047)
	CoV, Historical Maize Price Shock	0.021	-0.060	0.040	-0.076	0.043	0.156	-0.116	0.202
		(.668)	(.300)	(.470)	(.254)	(.845)	(.227)	(.442)	(.128)
	CoV, Health Shock (malaria)	-0.036 **	0.018	-0.053 ***	-0.004	-0.193 ***	0.061	-0.070	0.031
		(.020)	(.430)	(.009)	(.881)	(.005)	(.107)	(.226)	(.577)
	CoV, Employment Shock	0.004	-0.015 *	0.006	-0.018 *	-0.017	0.000	0.058 **	0.018
		(.447)	(.095)	(.466)	(.078)	(.487)	(.999)	(.017)	(.337)
Demographics (2010 values)	Adult equivalents in household	0.011 **	-0.061 ***	0.008	-0.059 ***	0.035	-0.054 ***	-0.014	-0.134 ***
		(.045)	(.000)	(.188)	(.000)	(.185)	(.000)	(.482)	(.000)
	Dependency ratio	-0.002	-0.057 ***	-0.010	-0.050 ***	-0.084 *	-0.034	-0.011	0.009
	(age < 15 or > 60) : (age 15-60)	(.813)	(.000)	(.414)	(.000)	(.069)	(.170)	(.746)	(.637)
	ln(Head of Household Age)	0.045	0.211 ***	0.042	0.223 ***	-0.149	-0.008	-0.011	0.283 ***
		(.156)	(.000)	(.245)	(.000)	(.321)	(.901)	(.931)	(.000)
	Head of Household: Female	0.029	-0.018	0.035	-0.034	0.013	-0.248 ***	0.105	-0.085
		(.321)	(.620)	(.332)	(.361)	(.940)	(.002)	(.408)	(.231)
	Head of Household: Chewa	-0.049 *	0.038	-0.082 **	0.059	0.020	-0.025	-0.078	-0.067
		(.062)	(.261)	(.015)	(.111)	(.834)	(.659)	(.404)	(.291)
	Head of Household: Tumbuka	0.011	0.197 ***	0.008	0.181 ***	-0.023	0.261 **	0.099	0.189
		(.731)	(.001)	(.853)	(.002)	(.890)	(.014)	(.388)	(.187)
	Head of Household: Muslim	-0.008	-0.151 ***	0.011	-0.182 ***	0.410 **	-0.312 ***	0.152	-0.199 **
		(.821)	(.001)	(.794)	(.001)	(.010)	(.000)	(.249)	(.042)
	Head of Household: Married	-0.028	0.004	-0.011	-0.005	-0.239	-0.035	-0.154 *	0.065
		(.260)	(.914)	(.734)	(.881)	(.103)	(.640)	(.096)	(.274)

Annex 1 Table 1. Estimation of well-being controlling for shocks (continued)

		Consumption				Food Consumption				Income				Maize harvest			
		Variance		Level		Variance		Level		Variance		Level		Variance		Level	
Wealth (2010 values)	Normalized HH Wealth Index	-0.031		1.085	***	-0.143	***	0.918	***	-0.243		1.646	***	-0.006		1.359	***
		(.418)		(.000)		(.003)		(.000)		(.140)		(.000)		(.970)		(.000)	
	Normalized Ag Wealth Index	-0.100	*	0.097		-0.089		0.116	*	-0.899	***	0.440	***	-0.386	*	1.055	***
		(.057)		(.131)		(.119)		(.087)		(.000)		(.000)		(.058)		(.000)	
Community Characteristics	Community Infrastructure Index	-0.012		-0.006		-0.004		-0.006		0.008		-0.053	**	0.040		-0.051	*
		(.187)		(.678)		(.751)		(.733)		(.868)		(.026)		(.267)		(.084)	
	Community median slope (%)	-0.001		-0.001		-0.002		0.000		-0.002		0.001		-0.002		0.017	**
		(.657)		(.776)		(.473)		(.994)		(.882)		(.860)		(.799)		(.012)	
	ln(Access Index)	0.006		0.035	***	0.014	**	0.033	***	0.088	***	0.065	***	0.026		0.013	
		(.292)		(.000)		(.043)		(.000)		(.001)		(.000)		(.258)		(.707)	
	District Ag Extension Development Officers / 1000 farming families	0.132		0.105		0.197	*	0.135		0.201		0.687	***	0.271		0.065	
		(.102)		(.455)		(.054)		(.394)		(.556)		(.004)		(.423)		(.828)	
	Total N. Projects in District	0.002		0.001		0.002		0.001		0.006		-0.016	**	-0.010		0.005	
		(.541)		(.755)		(.712)		(.843)		(.775)		(.027)		(.433)		(.626)	
	Community Difference Between 10th & 90th Land Owned	0.023		0.031		0.023		0.014		-0.009		-0.001		0.098	*	0.060	
		(.218)		(.184)		(.221)		(.575)		(.903)		(.980)		(.057)		(.238)	
	Northern region	-0.097	**	-0.290	***	-0.127	**	-0.209	***	0.346		-0.384	***	0.332	*	-0.562	***
		(.030)		(.000)		(.027)		(.010)		(.162)		(.008)		(.082)		(.002)	
	Central region	0.028		-0.089		0.039		-0.124	*	-0.042		0.064		0.359	**	0.158	
		(.479)		(.146)		(.425)		(.087)		(.820)		(.537)		(.050)		(.234)	
	Constant	-0.030		10.868	***	-0.062		10.634	***	2.502	***	9.333	***	0.544		3.174	***
		(.861)		(.000)		(.794)		(.000)		(.004)		(.000)		(.371)		(.000)	
	Observations	2789		2789		2789		2789		2770		2770		2432		2432	
	R-squared	0.019		0.277		0.025		0.219		0.02		0.223		0.022		0.226	

Note: Table reports coefficients and p-values in parentheses. Asterisks denote significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Annex 1 Table 2. Estimation of Consumption controlling for shocks at the regional level

		Northern				Central				Southern			
		Variance		Level		Variance		Level		Variance		Level	
Shock (2013 values)	Rainfall shock			-0.967				0.44				-0.855	***
				(.218)				(.192)				(.006)	
	Maize price shock			-0.319				-0.232				0.079	
				(.627)				(.405)				(.804)	
	Health shock (malaria)			-0.042				-0.028				0.012	
				(.354)				(.495)				(.723)	
	Employment shock			-0.006				-0.151	***			-0.039	
				(.886)				(.001)				(.436)	
Risk (time-invariant)	CoV, Historical Rainfall Shock	2.577	*	0.293		-1.669	*	-0.168		0.656		1.108	
		(.055)		(.917)		(.055)		(.845)		(.440)		(.214)	
	CoV, Historical Maize Price Shock	0.039		-0.005		0.105		0.110		-0.066		-0.022	
		(.560)		(.986)		(.243)		(.141)		(.496)		(.843)	
	CoV, Health Shock (malaria)	-0.019		-0.076		-0.062		0.065		-0.023		0.062	**
		(.395)		(.168)		(.148)		(.103)		(.317)		(.039)	
	CoV, Employment Shock	-0.005		-0.021		0.01		0.012		-0.002		-0.041	***
		(.494)		(.191)		(.390)		(.370)		(.862)		(.002)	
Demographics (2010 values)	Adult equivalents in household	0.010		-0.070	***	0.017	**	-0.046	***	0.011		-0.066	***
		(.232)		(.000)		(.045)		(.000)		(.349)		(.000)	
	Dependency ratio	-0.031	**	-0.040	**	0.034	*	-0.052	**	-0.020		-0.059	***
	(age < 15 or > 60) : (age 15-60)	(.018)		(.013)		(.081)		(.022)		(.237)		(.000)	
	ln(Head of Household Age)	0.022		0.255	***	-0.021		0.134	**	0.109	**	0.174	***
		(.541)		(.001)		(.734)		(.041)		(.018)		(.000)	
	Head of Household: Female	0.022		0.005		0.113	**	-0.002		-0.017		-0.011	
		(.534)		(.941)		(.048)		(.980)		(.710)		(.843)	
	Head of Household: Chewa	0.122		-0.024		0.000		0.036		-0.082	**	0.011	
		(.205)		(.891)		(1.000)		(.475)		(.023)		(.794)	
	Head of Household: Tumbuka	-0.002		0.068		-0.043		-0.101		-0.243	***	0.213	**
		(.974)		(.402)		(.668)		(.563)		(.000)		(.029)	
	Head of Household: Muslim	-0.381	***	-0.021		0.066		-0.118		-0.028		-0.090	
		(.002)		(.901)		(.373)		(.205)		(.597)		(.114)	
	Head of Household: Married	-0.017		0.010		-0.036		-0.064		-0.010		0.070	
		(.584)		(.871)		(.366)		(.232)		(.834)		(.172)	

Annex 1 Table 2. Estimation of Consumption controlling for shocks at the regional level (continued)

		Northern				Central				Southern			
		Variance		Level		Variance		Level		Variance		Level	
Wealth (2010 values)	Normalized HH Wealth Index	-0.077		1.103	***	0.026		1.173	***	-0.101		0.979	***
		(.161)		(.000)		(.654)		(.000)		(.143)		(.000)	
	Normalized Ag Wealth Index	-0.026		0.103		-0.144	*	0.108		-0.051		0.048	
		(.720)		(.414)		(.074)		(.230)		(.621)		(.721)	
Community Characteristics	Community Infrastructure Index	0.031	**	0.075	**	-0.029	*	-0.020		0.007		-0.005	
		(.048)		(.032)		(.083)		(.307)		(.653)		(.814)	
	Community median slope (%)	-0.006	*	-0.018	**	-0.016	**	0.011	*	0.001		0.003	
		(.063)		(.012)		(.015)		(.070)		(.803)		(.601)	
	ln(Access Index)	0.001		0.027	*	-0.029		0.033		0.023		0.014	
		(.821)		(.053)		(.241)		(.285)		(.224)		(.621)	
	District Ag Extension Development Officers / 1000 farming families	-0.269		-0.265		-0.026		0.522	*	0.056		0.110	
		(.110)		(.284)		(.887)		(.066)		(.776)		(.588)	
	Total N. Projects in District	0.007		0.052		0.010		-0.003		0.006		-0.013	
		(.705)		(.184)		(.110)		(.627)		(.580)		(.272)	
	Community Difference Between 10th & 90th Land Owned	0.024		0.046		0.035		0.031		0.015		-0.017	
		(.371)		(.328)		(.289)		(.388)		(.639)		(.675)	
	Constant	-0.343		10.600	***	0.689	*	10.241	***	-0.187		10.738	***
		(.295)		(.000)		(.075)		(.000)		(.563)		(.000)	
	Observations	626		626		1065		1065		1091		1091	
	R-squared	0.04		0.392		0.043		0.258		0.025		0.315	

Note: Table reports coefficients and p-values in parentheses. Asterisks denote significance levels: * p<0.10, ** p<0.05, *** p<0.01.