International Labour Office

Geneva

THE IMPACT OF MICROINSURANCE ON ASSET ACCUMULATION AND HUMAN CAPITAL INVESTMENTS: EVIDENCE FROM A DROUGHT IN KENYA

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RESEARCH
PAPER No.31

MARCH 2013

THE IMPACT OF MICROINSURANCE ON ASSET ACCUMULATION AND HUMAN CAPITAL INVESTMENTS: EVIDENCE FROM A DROUGHT IN KENYA[1]

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ABSTRACT

When natural disasters strike in developing countries, households are often forced to choose between preserving assets or destabilizing consumption: either can result in permanent consequences. In this paper we ask: can insurance transfer risk in a way that reduces the need for households to rely on costly coping strategies that undermine their future productivity? Since 2010, pastoralists in northern Kenya have had access to a novel index-based drought insurance product. We take advantage of an insurance payout induced by a drought in 2011 to analyze the immediate impacts of this microinsurance pilot on expected asset accumulation and human capital investments. Our results show that insured households are on average 22-36 percentage points less likely to anticipate drawing down assets, improving their ability to recover after the drought. This effect is larger for livestock-rich households who are most likely to compromise assets in response to a negative shock. We also show that insured households are on average 27-36 percentage points less likely to anticipate reducing meals than their uninsured counterpart. This second impact is stronger for livestock-poor households who are most likely to destabilize consumption. By improving food security during a drought, we also find that insured households are less dependent on food aid and other forms of assistance.

1. INTRODUCTION

Whenever extreme drought strikes northern Kenya, the effects can be devastating. Live- stock, the primary asset and source of livelihood, weaken and often die. Distressed sales of livestock flood the market, causing downward pressure on livestock prices. The combination of livestock loss and destocking herds debilitates the household's main productive resource, making recovery after the drought all the more challenging. In an effort to maintain assets, households may instead choose to cut back on meals. Yet by reducing consumption, households undercut critical investments in human capital, inhibiting both current and future productivity. In these ways a single negative shock can lead to chronic poverty by restricting the ability of households to generate current and future income. In this paper we assess whether insurance offers an effective alternative to these costly coping strategies which make recovery so difficult.

Insurance has been widely heralded in the past decade as a market-based risk transfer mechanism that has the potential to act as a safety net, preventing against catastrophic collapse. Although development of insurance pilot projects have been widespread, little is known about their impact. In this paper we ask: Can insurance transfer risk in such a way that it reduces the need for households to rely on costly coping strategies that undermine future productivity? That is, are insured households less likely to sell livestock or reduce consumption? In addition, are insured households more self-sufficient, relying less on food aid or assistance from others?

Our analysis offers one of the first empirical assessments of the impact of a marketed index-based insurance contract on households ability to cope with shocks in developing countries. We report the impact results from the index-based livestock insurance (IBLI) pilot in Marsabit district of northern Kenya. Since 2010, pastoralists in northern Kenya have had the opportunity to purchase a novel index-based insurance contract to protect against livestock mortality losses due to drought. A harsh drought swept the Horn of Africa in 2011 activating the first IBLI payout. We use household expectations at the time of the payout to empirically study the impact of the index-based livestock insurance on pastoralist households' asset accumulation and human capital investment decisions.

Our results reveal that, relative to uninsured households, insured households expect to radically reduce their dependence on costly coping strategies. Our major findings are three- fold: 1) Insuring against losses results in an 22-36 percentage point average reduction in the number of households who anticipated selling further livestock to cope with the wake of the 2011 drought (overall a 50% reduction),

[1] This publication was made possible using data collected by a collaborative project of the International Livestock Research Institute, Cornell University, Syracuse University and the BASIS Research Program at the University of California at Davis. This project was made possible by the generous funding of the UK Department for International Development through FSD Trust Grant SWD/Weather/43/2009, the United States Agency for International Development grants No: EDH-A- 00-06-0003-00 and the World Bank's Trust Fund for Environmentally and Socially Sustainable Development Grant No: 7156906. The authors wish to thank the following individuals for the critical contributions they made to this research project: Chris Barrett, Sommarat Chantarat, Munenobu Ikegami, John McPeak and Andrew Mude. All errors are our own.

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improving their ability to recover after the drought. 2) Insured households are 27-36 percentage points less likely to reduce meals on average than their uninsured counterpart (an overall reduction of about one third). This behavioral change implies a reduction in the number of undernourished and malnourished individuals, including women and children, in this food insecure region. 3) As food security improves, insured households are 42-50 percentage points less dependent on food aid and 0-26 percentage points less reliant on other forms of assistance. Together, these results suggest that insurance can help households to protect assets during crises, without having a deleterious effect on human capital investments.

This paper also makes a critical contribution to the literature of poverty traps. This literature suggests that in certain environments, there exists a critical asset threshold at which we observe a bifurcation in optimal behavior. Households with asset stocks safely above the threshold will be willing to forfeit assets in order to smooth consumption when an adverse shock hits. Alternatively, households with small asset stocks will optimally choose to destabilize consumption in order to smooth assets. In this paper we use Hansen's (2000) threshold estimation method, and provide evidence that a critical behavioral threshold does indeed exist in this setting: consumption smoothing is more common above an estimated threshold, and asset smoothing is more common below an estimated threshold. Our results suggest that the impact of insurance on consumption destabilization is larger for asset smoothers below the estimated threshold, whereas the insurance impact on asset destabliization is larger for consumption smoothers above the estimated threshold. In this way, insurance helps stop the households most likely to give up productive assets from damaging their asset base, and it helps prevent those households most likely to reduce consumption from doing so, thereby protecting households from engaging in behaviors with harmful long-term consequences.

The rest of the paper is organized as follows: We begin with a discussion of the relevant literature. Section 1.1 reviews some of the relevant literature on risk in developing countries and its permanent consequences. Section 1.2 then provides an overview of the literature studying how insurance might help households to cope with uninsured risk and vulnerability, particularly in developing countries. In Section 2, we provide background on the research setting, discuss some of the limitations of our data, and then present our estimation strategy. We employ a number of different techniques to control for selection bias in the decision to insure: instrumental variables, Heckman correction, matching methods, and difference-in-differences. In Section 4, we present and discuss our main finding: that insurance dramatically reduces the need for a household to depend on costly coping strategies which undermine its future productivity. In Section 5 we expand on these findings by taking a threshold-based approach to understanding the impacts of insurance. Section 6 follows with some robustness checks in which we plainly reflect on some of the limitations of the available data, but discuss why we believe the results remain informative. We conclude in Section 7, and also make some suggestions for future research.

2. BACKGROUND LITERATURE

2.1 SHOCKS AND THEIR PERMANENT CONSEQUENCES

Uninsured risk and vulnerability can be an unavoidable part of daily life for households in developing countries. Not only can shocks give rise to temporary consequences, but there is growing evidence to suggest that shocks can result in permanent consequences. This finding has developed into a wide literature of poverty traps. A poverty trap has been defined as "any self-reinforcing mechanism which causes poverty to persist." (Azariadis and Stachurski, 2005). This literature has often focused on multiple equilibrium poverty traps, which are characterized by at least one equilibrium associated with a poor standard of living, and another associated with a high standard of living. The existence of multiple equilibria also implies the existence of a "threshold" or "tipping point" at the boundary between the two regions.

If a threshold exists, at which we observe a bifurcation of equilibrium outcomes, then a shock will result in permanent consequences whenever it propels a household across the threshold. Building on this concept, Carter and Barrett (2006) develop an asset-based approach in which they distinguish transitory poverty from chronic structural poverty by using a dynamic asset poverty line. In this framework, if assets fall below a critical threshold in any period, then households will find it difficult to accumulate assets; they become trapped in poverty.

The asset-based approach to understanding persistent poverty suggests an important behavioral response to critical thresholds. Zimmerman and Carter (2003) use stochastic dynamic programming techniques to show that households above the threshold will optimally choose to smooth consumption, whereas poorer households around the threshold will choose to smooth assets instead, because asset preservation is crucial to future consumption. Hoddinott (2006) provides evidence that in the wake of the 1994-1995 drought in Zimbabwe, richer households sold livestock in order to maintain consumption. In contrast, poor households with one or two oxen or cows were much less likely to sell livestock, massively destabilizing consumption instead. In Ethiopia, Carter et al. (2007) also find evidence of asset smoothing by the poor, as households coping with a drought attempted to hold onto their livestock at the cost of consumption. Carter and Lybbert (2012) find similar evidence in Burkina Faso. They empirically estimate an asset threshold, and show that households above the estimated dynamic asset threshold almost completely insulate their consumption from weather shocks by drawing down assets, whereas households below the threshold do not.

The dilemma, as Hoddinott (2006) points out, is that even though asset smoothing is an attempt to preserve assets, consumption is an input into the formation and maintenance of human capital. Hoddinott poignantly argues that, "The true distinction lies in households' choices regarding what type of capital - physical, financial, social or human (and which human) - that they should draw down given an income shock." While asset protection strategies are designed to avoid a poverty trap, they likely come at a very high cost of immediately reduced consumption, with potentially irreversible losses in child health and nutrition (Carter et al., 2007).

The outcomes of undernutrition and malnutrition are widely known. In children, these conditions can lead to muscle wastage, stunting, increased susceptibility to illness, lower motor and cognitive skills, slowed behavioral development, and increased morbidity and mortality (Ray, 1998; Martorell, 1999). Those that do survive suffer functional disadvantages as adults, including diminished intellectual performance, work capacity and strength. In women, undernourishment during childhood can be the cause of lower adult body mass, which means increased risk of delivery complications and lower birthweights for the next generation (Martorell, 1999). These outcomes set the stage for a pernicious intergenerational cycle of undernutrition and its destructive effects. Moreover, undernourishment during adulthood further diminishes muscular strength and increases susceptibility to disease. Such undernourishment in adults can also lead to a nutrition-based poverty trap if it decreases the capacity to do productive work (Dasgupta and Ray, 1986)

This dilemma points to a need for a productive safety net that protects vulnerable house- holds from 1) losing productive assets, and 2) engaging in costly coping strategies which impair the human capital of current and future generations. Insurance is a market-based product which has the potential to act as a safety net (Barrett et al., 2007; Skees and Collier, 2008). It offers an alternative means of coping with negative shocks, allowing smoothing of consumption and nutrition, as well as avoidance of costly asset depletion (Dercon et al., 2008).

2.2 THE POTENTIAL IMPACTS OF MICROINSURANCE

A growing literature has been devoted to studying the benefits of insurance for poor households in low income countries. This type of insurance (targeted to poor households, and available at low cost) has become known as microinsurance. Barnett, Barrett, and Skees (2008), Dercon et al. (2008) and Cole et al. (2012) provide summaries of the literature. The literature highlights two primary avenues through which insurance might bring about positive impacts. These avenues reflect the fact that households make both ex ante risk management decisions and ex post risk coping decisions.

Section 1.1 suggests that poor households are limited in their ability to cope with risk ex post. Often such households are forced to choose between destabilizing critical consumption and depleting productive asset shocks, and either decision can result in permanent conse- quences. In the absence of insurance, there are several potential avenues for ex ante risk management, though all similarly involve tradeoffs. One option is to simply allocate resources toward activities with lower risk. However, these lower-risk activities generally produce a lower return. Another option is to build up precautionary savings, but such savings must come at the cost of (often critical) investment or consumption today. Households may also choose to reduce their risk exposure by diversifying crop choice, assets or activities, but such diversification is not always possible, and can only be beneficial if the risk involved is not perfectly correlated across the various activities (Dercon et al., 2008).

Insurance provides an alternative risk management tool that may reduce the use of these and other ex ante risk management strategies. By altering the ability of households to cope with risk ex post, insurance may change optimal behavior before a shock is actually observed. To demonstrate this effect, de Nicola (2011) estimates a dynamic stochastic model of weather insurance. The model predicts that insurance will increase the adoption of riskier but more productive seeds, and also stimulate decreased investment, as households shift towards higher levels of consumption. This may reflect the idea that investment is a form of precautionary savings in her model. Janzen, Carter, and Ikegami (2012) use similar methods to show that when you account for a critical asset threshold, around which optimal behavior and equilibrium outcomes bifurcate, increased investment occurs around the threshold as households assume greater risk in order to attain higher productivity and a higher equilibrium. The same model shows that households above the threshold follow de Nicola's prescription: decreased investment and increased consumption as households move away from holding assets as precautionary savings.

Cole et al. (2012) conduct a systematic review of the effectiveness of microinsurance, and specifically index-based insurance, in helping smallholders manage weather-related risks. Their review identifies a substantial evidence gap in the literature on the impact of index- based microinsurance. Several papers have attempted to bridge this gap empirically, but all papers known to the authors focus on the impact of insurance on household's ex ante risk management strategies. These papers all show that insurance encourages investment in higher risk activities with higher expected profits. Mobarak and Rosenzweig (2012) provide evidence that farmers in India with access to insurance shift into riskier, but higher-yielding rice production. Cai et al. (2012) find that insurance for sows significantly increases farmers' tendency to raise sows in southwestern China, where sow production is considered a risky production activity with potentially large returns. Karlan et al. (2012) show that farmers who purchase rainfall index insurance in Ghana increase agricultural investment. Cai (2012) demonstrates that tobacco insurance increases the land tobacco farmers devoted to risky tobacco production by 20% in China. This last finding implies reduced diversification among tobacco farmers. The same paper also finds that insurance causes households to decrease savings by more than 30%, suggesting that households were building up extra savings in order to better smooth consumption in the case of a shock. Hill and Viceisza (2010) use experimental methods to show that in a game setting, insurance induces farmers in rural Ethiopia to take greater, yet profitable risks, by increasing (theoretical) purchase of fertilizer.

While the impacts of insurance on ex ante risk management decisions are important, none of these papers is able to assess how an insurance payout directly influences the ability of poor households to recover after a shock. This paper represents one of the first attempts to fill this gap by studying the impact of insurance on ex post risk coping decisions. We do so by empirically analyzing whether the index-based livestock insurance contract in northern Kenya successfully functioned as a safety net by preventing costly coping strategies which might otherwise have crippled future productivity.

3. RESEARCH SETTING AND DATA

3.1 RESEARCH SETTING

More than 3 million pastoralist households live in northern Kenya's arid and semi arid lands. The vast majority of these households rely on livestock for their primary livelihood. This setting is particularly interesting because previous analyses of this livestock-dependent economy have provided strong empirical evidence of a poverty trap. Lybbert et al. (2004) and Barrett et al. (2006) use different data and methods to demonstrate nonlinear asset dynamics, such that when livestock herds fall below a critical threshold, recovery becomes difficult, and herds tend to move toward a low level equilibrium. Toth (2012) hypothesizes that these nonlinear asset dynamics are due to a critical herd size necessary to support mobility. Small herds are restricted to degraded rangelands near the town centers, where growth becomes challenging. This problem is compounded by an absence of formal credit markets: households can't take out a loan to reach the dynamic asset threshold, thereby moving onto a higher welfare path. Furthermore, Santos and Barrett (2011) show that access to informal credit is concentrated at the observed critical threshold. Thus, the persistently poor are consistently excluded from informal credit arrangements, further exacerbating the poverty trap mechanism.

When drought hits this region, households dependent on livestock must cope with large livestock losses. According to the data used for this paper, in the recent drought that devastated the Horn of Africa in 2011, families lost on average more than one third of their animals. During and after a drought, cash-strapped food-insecure households often face a difficult choice: sell off remaining livestock or reduce consumption. Both asset and consumption destabilization strategies undercut future productivity, often reinforcing the poverty impacts of uninsured risk. The literature on poverty traps suggests that poor households near and below the threshold will strive to protect their main productive assets (livestock), forgoing critical consumption. Richer households should instead smooth consumption, destabilizing assets. Sometimes both strategies are necessary for survival.

In January 2010 the index-based livestock insurance (IBLI) pilot project was launched in Marsabit District of northern Kenya as a collaborative project of the International Livestock Research Institute, Cornell University, Syracuse University and the BASIS Research Program at the University of California at Davis in an effort to help pastoralists manage drought risk. The IBLI index insurance contract uses satellite-based NDVI (normalized difference vegetation index) measures of available vegetative cover to predict average livestock mortality experienced by local communities. The IBLI index has been shown to be highly correlated with actual livestock mortality losses experienced by pastoralists in the region (see Chantarat et al., 2010, 2012 for details). Households choose the number of livestock they wish to insure, with the contract expressed in tropical livestock units (TLU), so that a single annual contract accommodates the various livestock species common in the region: goats, sheep, cattle, and camels.[3] The premium households pay depends on the risk associated with the geographic region in which they live (Upper Marsabit is more susceptible to extreme drought, so households insuring in this region are required to pay a higher premium). Insured households receive a payout at the end of each dry season (at the beginning of October and again early in March) if the predicted average livestock mortality rate reaches 15%, with the payout equal to the value of all predicted losses greater than 15%. In October-November 2011, a harsh drought swept across the Horn of Africa, and the first IBLI payouts were made to households who had purchased insurance earlier in the year. Households in our study received an average payout of about 10,000 Kenyan Shillings (or roughly $150).

3.2 DATA

The IBLI pilot was implemented in connection with a rigorous impact evaluation. As part of the evaluation, households in both of the following geographic regimes were randomly selected to participate in a panel household survey: 1) control locations (no access to IBLI), and 2) IBLI-access locations. This long-term research design will allow researchers to explore the long term intention to treat (ITT) impacts of insurance on both ex ante risk management and ex post coping strategies. For this paper, we would ideally compare the IBLI-access group to the control group. However, the nature and timing of surveys differ between the two regimes. This difference limits our ability to use the control group to assess the immediate impacts of the 2011 insurance payout on the ability of households to cope with the shock ex post. Instead, for this analysis we are limited to IBLI-access locations, in which all households had the opportunity to insure their livestock, but not all households chose to do so. Since households must self-select into purchasing insurance, we are forced to account for selection bias in the analysis.

The data available includes household-level information collected annually (beginning in 2009) for 924 randomly selected households living in various sublocations across Marsabit district, all with access to IBLI. In each round of the survey, households were asked to answer questions about health, education, livestock holdings, herd migration, livelihood activities, income, consumption, assets, and access to credit. Each household also participated in an experiment to elicit their risk preferences. In the surveys following the baseline, households were also asked questions about insurance purchases, access to information about insurance, and tested on their level of insurance understanding.

Two levels of randomization occurred at the household-level. First, as part of an en- couragement design, in each period 60% of surveyed households were randomly selected to receive coupons offering a 10-60% discount on the first 15 TLU insured. Second, some households were randomly selected to participate in experimental games, which were used as a means of communicating the complex concepts of index insurance. The games were designed to demonstrate the inter-temporal benefits of insurance by simulating herd dynamics over multiple seasons. They demonstrated that insurance would have to be purchased before the season began, and for each subsequent season that coverage was desired. In addition, the games conveyed that indemnity payments were triggered by droughts, that IBLI would not cover non-drought-induced losses, and that if a drought did not trigger payments, the premium would not be returned (see McPeak, Chantarat, and Mude, 2010 for details). Non-participants heard about IBLI from other participants, through village assemblies, by word of mouth or through local village insurance promoters.

Most of the data used for this analysis comes from the third round of the panel survey, completed in October-November 2011. The only exception is the non-livestock asset index, which uses information collected in the previous year. This index was constructed from the first principle component using factor analysis. Variables used to generate the asset index include housing characteristics (such as materials used in the wall or for flooring in the house), cooking appliances, access to water, and possession of large assets such as a motorbike, boat, sewing machine, grinding mill or television.

Table 1 reports summary statistics on key variables by treatment and control. The treated group refers to the population which chose to purchase insurance. All households had the opportunity to insure, but only 24% actually purchased insurance. Variables reported include the level of education of the household head, a dummy variable for whether a household is risk-taking or risk-moderate (as determined from an experiment eliciting risk preferences), a non-livestock asset index, the number of livestock owned, livestock losses in the past year, expected livestock losses in the next year and whether households indicated that it is difficult to acquire a loan. In addition, we show summary information on IBLI-specific variables of interest: dummy variables indicating that they learned about IBLI from the game, a village insurance promoter, or from the survey, whether or not they

[3] In the IBLI contract, a goat or sheep is equal to .1 TLU, cattle are equal to a single TLU, and a camel is equal to 1.4 TLU.

received a discount coupon and its value, the number of ways they heard about IBLI (to control for their awareness of IBLI) and a final variable capturing their level of knowledge and understanding about IBLI. This knowledge/understanding variable was constructed by counting the number of correct responses provided in a short test about IBLI.

As we can see, the insured population appears relatively similar to the uninsured population with few observable statistically significant differences between the treatment and control. The encouragement design appears to have been effective, with the treated population being more likely to have received a coupon (and one of larger size). The game, on the contrary, is not strongly correlated with insurance adoption.

Table 1: Summary Statistics for Variables of Interest

Variable	Insured Qtr 3	Uninsured Qtr 3	Difference in Means Qtr 3
Years of education, household head	.76	1.18	.416
	(.20)	(.15)	(.294)
Risk-taking	.24	.29	.049
(dummy=1 if risk-taking)	(.03)	(.15)	(.041)
Risk-moderate	.50	.45	-.054
(dummy=1 if risk-moderate)	(.04)	(.02)	(.046)
Non-livestock asset index	.15	.00	-.150
(from factor analysis)	(.10)	(.05)	(.098)
Number of TLU Owned	16.22	18.86	2.646
	(1.40)	(1.29)	(2.423)
Number of TLU losses in past year	7.67	7.53	-.137
	(.89)	(.49)	(1.001)
Number of Expected TLU losses in next year	6.98	7.56	.579
	(.62)	(.37)	(.748)
Credit Constrained	.42	.37	-.043
(dummy=1 if say it's difficult to acquire a loan)	(.04)	(.02)	(.045)
Participated in IBLI game	.28	.25	-.030
(dummy=1 if true)	(.04)	(.02)	(.040)
Received IBLI discount coupon	.87	.55	-.320***
(dummy=1 if true)	(.03)	(.02)	(.043)
Value of IBLI discount coupon	23.85	16.53	-7.32***
(possibilities include 0, 10, 20, 30, 40, 50, 60)	(1.85)	(.97)	(2.01)
Heard about IBLI from Village Insurance Promoter	.71	.47	-.238***
(dummy=1 if true)	(.04)	(.02)	(.045)
Number of IBLI information sources	2.16	1.89	-.269
	(.07)	(.05)	(.092)

Standard errors, including the standard errors of the difference in means, are reported in parentheses. For the difference in means tests: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

The third round of the panel survey occurred around the same time as the October- November 2011 IBLI payout. At that time every household was asked about the ways in which they had been coping with the drought over the prior three months. Households were asked if they had engaged in specific behaviors, including selling livestock, reducing meals, relying on food aid or assistance from others, pulling children out of school, increasing non- livestock activities, or migrating to look for work outside the community. They were then asked how they anticipated coping with the drought in the upcoming three months. Insured households were asked this second question after being told exactly how much they should expect to receive as an insurance payment if they hadn't already received one. Most payouts were received within days or weeks of the survey, but a few households had already received the payout.

Our results are based on these anticipated behavioral changes after receipt of the October 2011 insurance payouts. By comparing the immediately anticipated behavioral changes made by insured households with those of their uninsured peers, we can measure the immediate impact of drought insurance on household well-being. Table 2 shows a list of actions that both insured and uninsured households could have taken to cope with the drought. Column 2 shows the proportion of insured households reporting that they engaged in a particular behavior in the prior 3 months. For ease of exposition, we describe this period as the 3rd Quarter of 2011. Column 3 shows the proportion of insured households who expected to do so in the next 3 months (during what we refer to as Quarter 4) after receiving their insurance payout. Columns 4 and 5 do the same for uninsured households who were expecting no insurance payout. As can be seen, substantial majorities of both insured and uninsured households cut back on meals and use more food aid to deal with the drought. Roughly a third in each group sold livestock from their already diminished herds.

Table 2: Summary of Behavior to Cope with 2011 Drought in Marsabit

	Insured		Uninsured		Difference in	Difference in
Action	Qtr 3	Qtr 4	Qtr 3	Qtr 4	Means Qtr 3	Means Qtr 4
Sell livestock	.33	.12	.28	.32	-.042	.208***
	(.04)	(.03)	(.02)	(.02)	(.04)	(.04)
Reduce the number of meals eaten each day	.64	.33	.74	.70	.102**	.374***
	(.04)	(.04)	(.02)	(.02)	(.04)	(.04)
Rely more on food aid	.92	.43	.92	.92	.005	.494***
	(.02)	(.04)	(.01)	(.01)	(.02)	(.03)
Rely on assistance from others	.35	.15	.44	.45	.096**	.305***
	(.04)	(.03)	(.02)	(.02)	(.05)	(.04)
Pull children otherwise in school, out of school	.11	.08	.11	09	.006	.006
	(.03)	(.02)	(.01)	(.01)	(.03)	(.03)
Increase non-livestock activities like petty trade	.26	.22	.20	.26	-.061	.041
	(.04)	(.03)	(.02)	(.02)	(.04)	(.04)
Send family members to look for work elsewhere	.04	.04	.05	.07	.010	.026***
	(.02)	(.02)	(.01)	(.01)	(.02)	(.02)

Standard errors, including the standard errors of the difference in means, are reported in parentheses.
For the difference in means tests: *** p<0.01, ** p<0.05, * p<0.1.

The second to last column of Table 2 reports the difference between the percentage of the insured population who answered yes to using a given coping strategy in the 3rd quarter of 2011, prior to receiving an insurance payout, to the uninsured population. A difference between the two implies one of two things: 1) insured households are coping differently in anticipation of a payout (which we would expect if insurance stimulates ex ante behavioral changes), or 2) insured households are intrinsically different from uninsured households. If the former is true, then we will have difficulty distinguishing the impact of insurance due to ex ante risk management decisions from the impact caused by ex post risk coping behavioral changes. If the latter is true (as we might expect), then we need to control for selection bias in our estimation strategy. We find that there are some statistically significant differences. In particular, insured households are less likely to have reduced the number of meals eaten each day and less likely to have relied on assistance from others in the 3rd quarter of 2011. Rather than focus on the differences between insured and uninsured households after insured households received the payout (presented in the last column of Table 2), these differences force us to think critically about selection bias.

4. ESTIMATION STRATEGY

Ideally, we would like to compare a cohort of households randomly assigned to an insurance "treatment" with a control group without access to insurance. Although IBLI was implemented in connection with an integrated impact evaluation which includes a treatment and control region (with and without access to IBLI, respectively), the nature and timing of surveys varies across these two different regimes. This difference limits our ability to use the pure control group to assess the immediate impacts of the 2011 insurance payout on the ability of households to cope with the shock ex post. Instead, for this analysis we are limited only to a population in which all households had the opportunity to insure their livestock, though not all households chose to do so. Since households must self-select into purchasing insurance, we must account for selection bias in the analysis.

In the absence of randomized treatment assignment, a variety of techniques exist to control for selection bias. These methods vary according to the underlying assumptions that must be made to use them. Empiricists often begin with a Heckman selection model, which controls for selection bias and can also inform our beliefs about the importance of the selection bias. If we believe the selection bias is only based on observed characteristics, then matching methods are also appropriate. Of course, we might have reason to believe that insurance uptake depends on unobservables. For this reason, our preferred estimates are based on an instrumental variables approach. Using IV, selection bias on unobservable characteristics is corrected by using an appropriate instrument. This method can only be employed if an appropriate instrument exists. Each of these approaches are outlined in Section 3.1 below.

The aforementioned approaches require only cross section data. We also have panel data of coping strategies covering the periods directly before and after the insurance payouts. This suggests a difference-in-differences (DD) approach which takes into account variation over time. However, theory predicts that insured households will actually manage risk differently in anticipation of a payout, a potential violation of the parallel trends assumption necessary to employ DD methods. We discuss these issues in Section 3.2.

4.1 CROSS SECTION METHODS FOR INSURANCE IMPACT EVALUATION

A first step to test (and control) for selection bias is to use Heckman's correction. Using this method we estimate a probit model, in which we regress the insurance decision, insuredi, (a dummy variable equal to one if the household insured any livestock) on a number of exogenous variables affecting treatment (Zi), including at least one variable which belongs in the selection equation but does not appear in the equation of interest. In its basic form, this first stage equation can be written:

$$insured_i = Z_i \delta + v_i \qquad (1)$$

The estimated parameters are then used to calculate an inverse Mills ratio, defined as $IMR = \frac{\phi(Z)}{\Phi(Z)}$, which captures the part of the unexplained variation vi that is correlated with sample selectivity. For this reason, it is informative to include the inverse Mills ratio as an additional explanatory variable in a second stage regression estimating the impact of insurance on various coping strategies:

$$action_i = \beta_0 + \beta_1 insured_i + \gamma(IMR) + \varepsilon_i \qquad (2)$$

If the estimated coefficient for the inverse Mills ratio is different from zero, then we should be concerned about selection bias.

Another potentially useful approach is to use matching methods. This approach requires an assumption that unobserved factors do not affect participation. If we can control for all the factors that affect participation, then matching provides consistent estimates of the impact of insurance. Matching estimates are obtained by finding a pair of households who appear similar (based on observed characteristics), with one household purchasing insurance while the other did not. The estimated impact of insurance is obtained by taking the average difference in outcomes between pairs.

A number of matching methods exist. In this paper we present the results for nearest neighbor matching. We try two different approaches. First, we match on the initial value of the outcome of interest (a given behavior in the 3rd quarter). This method is an obvious choice in our case since the primary differences between insured and uninsured households are observed across the various outcomes of interest, rather than through other channels. As an alternative, we also present the results in which we match based on wealth and other household characteristics including ethnicity and location. This is also a practical approach since ethnicity and location are important in defining a household's identity in this region.

Even if the Heckman selection model suggests that selection bias is not a problem, we may still have reason to believe that unobserved factors, such as motivation or entrepreneurship, affect a household's decision to insure their livestock. If so, matching methods are not appropriate. In this case, an instrumental variables (IV) approach is a preferable alternative because it allows for endogenous insurance participation. IV estimation requires a carefully selected instrument that is highly correlated with insurance participation, but not correlated with unobserved characteristics affecting outcomes.

The encouragement design implemented with IBLI provides three potentially suitable instruments: participation in an insurance game, receipt of an insurance coupon and the subsequent value of the discount coupon. All are the result of randomization, so none should be correlated with coping strategies (actioni), but we expect all to be highly correlated with insurance uptake. Table 1 suggests that the coupon (both receipt of and value) is a good instrument. Unfortunately, participation in the insurance game is not as highly correlated with insurance uptake as we might expect, and turns out to be a weak instrument.

Using IV we obtain the local average treatment effect of insurance on coping strategies. To obtain this effect, we first estimate a first stage equation similar to equation 1, where Zi includes at least one appropriate instrument. We then estimate the second stage regression using predicted insurance uptake (insuredi) as obtained from the first stage equation. This second stage regression can be written as:

$$action_i = \beta_0 + \beta_1\, insured_i + \varepsilon_i \qquad (3)$$

Because the assumptions necessary for IV are minimal given the available data, this is our preferred approach.

4.2 PANEL METHODS FOR INSURANCE IMPACT EVALUATION

In addition to households' expectations about their coping strategies in the 4th quarter of 2011, the data available contains information on how households had been dealing with the drought in the prior 3 months. This suggests a difference-in-differences approach to control for pre-existing differences. Let actioni,t be the coping strategy in period t, insuredi is the non-random treatment variable, postt is a dummy variable that takes on a value of 1 after insurance payouts have been made, and $insured_i * post_t$ is the interaction between being insured and the postt indicator variable. In our case, this interaction term is equal to 1 if a household receives a payout. The DD estimator, controlling for household baseline characteristics Xi, is obtained by estimating the following specification:

$$action_{i,t} = \beta_0 + \beta_1\, insured_i + \beta_2\, post_t + \beta_3\,(insured_i * post_t) + X_i\,\delta + \varepsilon_{i,t} \qquad (4)$$

The coefficient of interest is β3, and the estimate can be interpreted as a percentage point difference.

The DD approach controls for pre-existing differences only if we can assume a common trend. That is, after controlling for level differences between insured and uninsured households, we assume all households would have exhibited the same trends in how they cope with drought in the absence of insurance. This means the unobserved characteristics which distinguish insured households from uninsured households must not vary over time. Unfortunately, our data provides little opportunity to test that assumption, and there are theoretical reasons to believe that the assumption is invalid. Recall that the microinsurance literature, both theoretical and empirical, suggests that insured households will alter their risk management strategies, even before an adverse shock occurs. If households in Marsabit are making these ex ante adjustments, then difference-in-differences is not appropriate for estimating the impact of insurance on strictly ex post coping strategies.

For this reason, we report the DD estimates only as a robustness check. However, as long as insurance causes ex ante and ex post behavioral changes that move in the same direction (which seems likely), the DD impacts are still informative. The measured impact may pick up part of an ex ante effect, but this is still part of the effect of insurance, so the estimate is useful.

5. RESULTS

In this section we present the results of the impact analysis using IV, Heckman correction, DD and matching methods across various outcomes. Here, we focus on population average impacts. In the next section we take a threshold-based approach, and consider heterogeneous impacts based on a critical asset threshold.

The details of the first stage probit selection equation used to obtain IV and Heckman correction estimates are provided in Table 3. Because we use probit for the first stage regression, we report the Wald test for joint significance of the two instruments: receipt and value of the IBLI discount coupon. Although participation in the IBLI game was a potential instrument, it is not statistically significant from zero, and is not jointly significant with the other two instruments so it was excluded.

Table 3: Demand for Insurance - First Stage Probit Selection Regression

	(1)
Received IBLI discount coupon *(instrument #1)*	1.476***
	(0.202)
Value of IBLI discount coupon *(instrument #2)*	-0.004
	(0.005)
Years of education (head)	-0.047
	(0.029)
Risk-taking	0.126
	(0.170)
Risk-moderate	0.148
	(0.114)
Non-livestock asset index	0.259***
	(0.091)
TLU Owned	-0.007***
	(0.002)
TLU losses in past year	0.012***
	(0.005)
Expected TLU losses	-0.010
	(0.008)
Credit Constrained	0.040
	(0.152)
Ethnicity fixed effects	yes
Location fixed effects	yes
Observations	634
Pseudo R^2	0.263
Wald test for joint significance of instruments	75.47

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

We focus on the impact of insurance on four primary outcomes of interest: *expected* livestock sales, reduction in the number of daily meals consumed, reliance on food aid, and dependence on assistance from others. The results are presented for each outcome in Tables 4-7 respectively. In each of these tables, the first column shows the estimation results using instrumental variable techniques (our preferred method), in which participation in an insurance game, receipt of an insurance coupon and the subsequent value of the discount coupon all serve as instruments. Each of these were the result of randomization, so we can be reasonably certain that they do not influence a household's response to the drought, except through the purchase of insurance. In the second column we use a Heckman correction technique, in which we include the inverse Mills ratio of the insurance selection equation to correct for selection bias. The third column of each table shows the estimation results of equation 4, where the difference-in-differences coefficient of interest is $\beta 3$, corresponding to the interaction term $insured_i * post_t$. It is helpful to note that the coefficient of interest under each specification is the first number reported in each column. Under all three of these approaches we control for ethnicity and location fixed effects, and cluster the standard errors based on location. Columns (4) and (5) show the average treatment effect of insurance using matching methods. The former column matches households who have been coping with the drought in similar ways during the past 3 months. The latter column matches households with similar herd sizes and wealth, who also share a similar ethnic background and live in a similar location.

5.1 IMPACT ON LIVESTOCK SALES

One way households often deal with large negative shocks is to sell their assets in order to purchase food and other necessities. In Marsabit, assets are primarily held as livestock. By the time the drought is severe enough to necessitate such sales, livestock are often weak and of little value. In addition, since drought generally affects a large geographic area, the massive sell-off of livestock throughout the region further reduces the market price of livestock so that income earned from livestock sales generally provides little purchasing power. When the rains return and the drought lifts, the lack of productive assets further increases the difficulty of coping with a drought's aftermath.

Table 4: Impact on Insurance #1, Sell Livestock

	(1) IV	(2) $Heckman$	(3) DD	(4) $Match_a$	(5) $Match_b$
$\widehat{insured}$	-0.363*				
	(0.198)				
insured*post			-0.252***		
			(0.059)		
insured		-0.259***	-0.005		
		(0.076)	(0.044)		
post (time dummy)			0.035		
			(0.022)		
Inverse Mills Ratio		0.255			
		(0.356)			
Years of education (head)	0.002	0.002	0.003		
	(0.006)	(0.006)	(0.004)		
Risk-taking	0.047	0.047	0.026		
	(0.044)	(0.042)	(0.041)		
Risk-moderate	-0.006	-0.006	-0.026		
	(0.025)	(0.026)	(0.026)		
Non-livestock asset index	0.002	0.004	0.012		
	(0.020)	(0.019)	(0.021)		
TLU Owned	0.000	0.000	-0.000		
	(0.001)	(0.001)	(0.001)		
TLU losses in past year	0.004**	0.005**	0.003*		
	(0.002)	(0.002)	(0.002)		
Expected TLU losses	-0.006**	-0.006**	-0.005*		
	(0.002)	(0.002)	(0.003)		
Credit Constrained	0.024	0.026	-0.019		
	(0.078)	(0.078)	(0.084)		
ATE (Matching)				-.217***	-.291***
				(.035)	(.058)
Ethnicity fixed effects	yes	yes	yes		
Location fixed effects	yes	yes	yes		
Observations	634	634	1,268	651	651
R^2	0.153	0.200	0.184	-	-

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results presented in Table 4 suggest that insurance substantially reduces the probability that a household expects to sell livestock. This improves the post-drought income-generating potential of insured households. The IV results imply a 36 percentage point average reduction in the number of households who anticipated selling further livestock to cope with the 2011 drought. This represents an overall reduction of about one half, relative to previous behavior. The estimates obtained using the alternative methods are highly statistically significant, although slightly smaller, suggesting a 22-29 percentage point decrease in a household's tendency to sell livestock. Overall, the results suggest that insured house- holds are much less likely to sell livestock during a drought, improving the possibility of a successful recovery.

5.2 IMPACT ON CONSUMPTION

When poor households endeavor to maintain finite productive assets during a shock, it often imposes a high cost on consumption. Undernutrition and malnutrition not only impose temporary hunger, but are likely to result in irreversible consequences to long run welfare. Table 5 considers the impact of an IBLI payout on daily household consumption. Using IV, insurance (and receiving an insurance payout) results in a 27 percentage point drop in the number of households that anticipate decreasing the number of meals eaten each day when under stress from a drought. Overall, this is a reduction of about one third. This result suggests that insurance improves food security; insured households are much less likely to be malnourished or undernourished during a drought. This result is robust across the different specifications. In fact, the alternative specifications suggest an even larger effect: insured households are 28-36 percentage points less likely to reduce the number of meals eaten each day. These results, coupled with the results of Section 4.1, suggest that insurance can promote asset smoothing without having a deleterious effect on consumption.

Table 5: Impact of Insurance #2, Reduce Daily Meals

	(1) *IV*	(2) *Heckman*	(3) *DD*	(4) $Match_a$	(5) $Match_b$
$\widehat{insured}$	-0.268** (0.092)				
insured*post			-0.277*** (0.062)		
insured		-0.359*** (0.056)	-0.080 (0.057)		
post (time dummy)			-0.046*** (0.014)		
Inverse Mills Ratio		-0.134 (0.154)			
Years of education (head)	-0.002 (0.006)	-0.002 (0.007)	-0.003 (0.006)		
Risk-taking	-0.081* (0.042)	-0.082** (0.036)	-0.068* (0.035)		
Risk-moderate	-0.019 (0.057)	-0.020 (0.054)	-0.015 (0.046)		
Non-livestock asset index	-0.061* (0.029)	-0.060* (0.029)	-0.033 (0.029)		
TLU Owned	0.001** (0.000)	0.001** (0.000)	0.001*** (0.000)		
TLU losses in past year	-0.003* (0.002)	-0.003* (0.001)	-0.004** (0.001)		
Expected TLU losses	0.003 (0.004)	0.003 (0.003)	0.004 (0.004)		
Credit Constrained	0.058 (0.068)	0.060 (0.063)	0.094 (0.068)		
ATE (Matching)				-.349*** (.042)	-.310*** (.069)
Ethnicity fixed effects	yes	yes	yes		
Location fixed effects	yes	yes	yes		
Observations	634	634	1,268	651	651
R^2	0.164	0.236	0.210	-	-

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.3 IMPACT ON SELF-RELIANCE

To assess whether insured households have greater food security during a drought, we also consider whether insurance increases self-reliance. That is, do insured households expect to depend less on food aid or assistance from others? Table 6 considers the impact of insurance on food aid dependence. The results suggest that insurance causes a 42-50 percentage point drop in the probability that a household expects to depend on food aid (more than normal) during a drought. These estimates are highly statistically significant across each specification. Similarly, Table 7 suggests that insured households may be less likely to rely on assistance from others. Although the IV estimate is not statistically significant, the other estimates predict a (statistically significant) 21-26 percentage point anticipated reduction in reliance on others. The results presented in Tables 6 and 7 combined imply that insured households may be more self-reliant during a drought, reducing their reliance on handouts by more than half.

Table 6: Impact of Insurance #3, Rely More on Food Aid

	(1) *IV*	(2) *Heckman*	(3) *DD*	(4) $Match_a$	(5) $Match_b$
$\widehat{insured}$	-0.436***				
	(0.107)				
insured*post			-0.502***		
			(0.073)		
insured		-0.485***	0.018		
		(0.077)	(0.026)		
post (time dummy)			0.002		
			(0.009)		
Inverse Mills Ratio		-0.040			
		(0.075)			
Years of education (head)	-0.008*	-0.008*	-0.010**		
	(0.004)	(0.005)	(0.004)		
Risk-taking	0.027	0.026	0.005		
	(0.029)	(0.026)	(0.027)		
Risk-moderate	0.057	0.056	0.038		
	(0.044)	(0.041)	(0.031)		
Non-livestock asset index	-0.064**	-0.063**	-0.054**		
	(0.027)	(0.024)	(0.023)		
TLU Owned	-0.000	-0.000	-0.000		
	(0.001)	(0.001)	(0.000)		
TLU losses in past year	-0.000	-0.000	0.000		
	(0.002)	(0.002)	(0.001)		
Expected TLU losses	-0.001	-0.001	-0.002		
	(0.002)	(0.002)	(0.002)		
Credit Constrained	0.009	0.012	0.024		
	(0.035)	(0.040)	(0.025)		
ATE (Matching)				-.495***	.415***
				(.038)	(.064)
Ethnicity fixed effects	yes	yes	yes		
Location fixed effects	yes	yes	yes		
Observations	634	634	1,268	651	651
R^2	0.150	0.350	0.291	-	-

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Impact of Insurance #4, Rely on Assistance of the Others

	(1) *IV*	(2) *Heckman*	(3) *DD*	(4) $Match_a$	(5) $Match_b$
$\widehat{insured}$	-0.080				
	(0.082)				
insured*post			-0.208***		
			(0.032)		
insured		-0.264***	-0.043		
		(0.058)	(0.054)		
post (time dummy)			0.010		
			(0.013)		
Inverse Mills Ratio		-0.312			
		(0.231)			
Years of education (head)	-0.008	-0.008	-0.010		
	(0.008)	(0.008)	(0.006)		
Risk-taking	-0.059	-0.060	-0.071		
	(0.053)	(0.056)	(0.053)		
Risk-moderate	-0.019	-0.020	-0.015		
	(0.043)	(0.043)	(0.039)		
Non-livestock asset index	-0.002	-0.002	0.007		
	(0.023)	(0.022)	(0.019)		
TLU Owned	0.000	0.000	-0.000		
	(0.001)	(0.001)	(0.001)		
TLU losses in past year	-0.002	-0.002	-0.001		
	(0.003)	(0.003)	(0.003)		
Expected TLU losses	0.003	0.002	0.003		
	(0.007)	(0.007)	(0.007)		
Credit Constrained	-0.079*	-0.078*	-0.046		
	(0.040)	(0.043)	(0.056)		
ATE (Matching)				-.262***	-.256***
				(.038)	(.064)
Ethnicity fixed effects	yes	yes	yes		
Location fixed effects	yes	yes	yes		
Observations	634	634	1,268	651	651
R^2	0.137	0.177	0.140	-	-

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

5.4 ADDITIONAL IMPACTS

Table 2 shows that selling livestock, reducing meals, and relying on food aid or assistance from others are the major coping strategies employed during a drought. In addition to these options, we might expect that more households would have removed children from school, so that children could instead engage in productive labor to improve the household's consumption options. We do not show that to be the case; 11% of the total population (including both insured and uninsured households) pulled children out of school in the 3rd quarter of 2011 as a way of coping with the drought, and insurance appears to have no impact on this decision. This coping strategy is probably not often utilized because supplemental school feeding programs exist to keep food-insecure children in school. In fact, it seems likely that households are in fact more likely to send previously unenrolled children to school in order to receive supplemental feedings during times of heightened food insecurity.

Approximately one quarter of the population attempted to diversify into non-livestock activities during the drought. However, insurance appears to have no impact on the choice to diversify. Another seldom-used option available to households is to send household members to look for work outside their community. Insurance appears to have no impact on whether households choose to migrate.

6. THRESHOLD-BASED IMPACT ANALYSIS

The literature on poverty traps suggests that poor households near and below a critical asset threshold will hold onto their main productive assets (livestock), forgoing critical consumption. Richer households should instead smooth consumption, destabilizing assets. Using actual behavior in the 3rd quarter of 2011, we can test whether we observe differential consumption and asset smoothing based on a threshold in our sample. Following Carter and Lybbert (2012), we use Hansen's threshold estimation technique (Hansen, 2000) to test for the presence of a threshold that splits our sample into two meaningfully different behavioral regimes based on household's recent coping strategies. This method then estimates the location of the critical threshold in asset space. We calculate the estimated threshold using the same controls included in previous regressions as well as ethnicity and location fixed effects. The behavioral threshold is estimated using our indicators for asset smoothing (livestock sales) and consumption smoothing (reduce daily meals).

Hansen's threshold estimator applied to actual livestock sales and meal reduction prior to the survey yields a threshold estimate near the median herd size (which is 10.2 TLU) of 11.8 TLU using livestock sales or 11.7 TLU using daily meal reduction. Both of these threshold estimates are significant at the 1% level, so we are very confident that households above and below this threshold responded differently to the drought experienced in 2011. Using this threshold, we divide households into asset poor households with livestock holdings below the threshold, and asset rich households with livestock holdings greater than the threshold. We can then compare the proportion of poor and rich households who are asset smoothers (refusing to sell livestock) or consumption smoothers (refusing to cut back on meals).

We make these comparisons in Table 8, which shows that asset rich households were 15 percentage points less likely to cut back on consumption, and 17 percentage points more likely to have sold livestock in Qtr 3. Asset poor households, on the other hand, were less likely to have sold livestock and much more likely to have reduced the number of meals eaten each day. Together these findings provide strong evidence of asset smoothing by those with small livestock holdings, and consumption smoothing by those with large herds.

Table 8: Threshold-Disaggregated Summary of Quarter 3 Coping Behavior

Action	Asset Poor Households (Less than 11.75 TLU)	Asset Rich Households (Greater than 11.75 TLU)	Difference in Means
Sell livestock	.21 (.02)	.39 (.03)	-.17*** (.04)
Reduce the number of meals eaten each day	.79 (.02)	.64 (.03)	.15*** (.03)
Rely more on food aid	.92 (.01)	.92 (.02)	.00 (.02)
Rely on assistance from others	.40 (.03)	.44 (.03)	-.04 (.04)
Pull children otherwise in school, out of school	.10 (.02)	.12 (.02)	-.02 (.03)
Increase non-livestock activities like petty trade	.22 (.02)	.22 (.02)	.-.00 (.03)
Send family members to look for work elsewhere	.05 (.01)	.04 (.01)	.01 (.02)

Theory predicts heterogeneous consumption and asset smoothing behaviors which depend on a critical threshold, but makes no clear prediction on threshold-based behavioral responses regarding self-reliance or the other actions listed in Table 8. These other behaviors thus provide a validity test that the threshold-based differences between consumption and asset smoothing is meaningful. Because we observe no statistical difference in these alternative actions between rich and poor households, the difference in means for consumption and asset smoothing behaviors is even more credible.[4]

Because a household's response to the drought depends on a critical threshold, it seems likely that the impact of insurance, at least for livestock sales and consumption, will also vary depending on whether a household is above or below the threshold. We explore this differential impact of insurance on behavior by using Hansen's (2000) threshold estimation technique again, this time using anticipated behavior. Conditional on finding a threshold and again estimating its location in herd size space, we are then able to run the previous regressions of the impact of insurance separately for the subsamples of poor and rich households.

Hansen's threshold estimator applied to anticipated behaviors yields a critical threshold of $A^* = 10.5$ with respect to asset smoothing, and $A^* = 9.3$ with respect to consumption smoothing. The estimated thresholds are again significant at the 1% level, and are relatively similar to the estimated thresholds obtained using actual behavior in the previous three months. Table 9 shows the results of the subsequent disaggregated impact analysis using IV, in which we compare the differential impact of insurance on both expected livestock sales and consumption for asset poor and asset rich households, as defined by the estimated thresholds.

The magnitude of the insurance impact is larger for poor households when we consider anticipated consumption destabilization, and larger for livestock-rich households when we consider expected livestock sales. That is, poor households, who are most likely to destabilize critical consumption, are 39 percentage points (using the IV estimates) less likely to reduce the meals eaten in their household when an insurance payout is received. The impact of insurance on expected consumption destabilization for richer households is smaller, and not statistically significantly different from zero according to the IV estimates. But that's in part because richer households are less likely to cut back on meals in the first place. The big impact of insurance for the more well-off households stems from an improved ability to protect their assets. According to the IV results, these households are 62 percentage points less likely to plan on selling livestock. The same impact is much smaller for poor households who are already smoothing assets to the best of their ability. These threshold-disaggregated impact estimates are robust across a variety of specifications.

These results suggest that insurance acts as a flexible safety net, protecting heterogeneous households in unique ways. First, insurance helps stop the households most likely to give up productive assets from engaging in that costly coping strategy which would otherwise damage their productive asset base, harming the household's future income-earning potential. Second, insurance helps prevent those households most likely to reduce consumption from doing so, thereby protecting vulnerable household members from undernutrition and malnutrition, and their harmful long-term consequences. In this way it seems that insurance does indeed provide a valuable alternative to coping with negative shocks, allowing smoothing of consumption and nutrition, while preserving productive assets.

7. ROBUSTNESS CHECKS

Because we have presented our findings using a variety of techniques, we have already provided a number of robustness checks. Indeed, our results appear quite robust to a number of specifications. However, the primary limitation of our study is that it relies on household expectations about the future. There is no way we can improve upon this limitation in the data. Nonetheless, there are a few techniques we can use to test whether our results, based on expectations, will reflect reality.

[4] Santos and Barrett (2011) do show that the supply of informal assistance to poor households in this environment is limited, suggesting that few poor households should be able to rely on assistance from others. However, we might also expect the demand for informal assistance to be low among better-off households, such that it is unclear whether poor or rich households should be more likely to rely on assistance from others.

Table 9: Threshold-Disaggregated Impact of Insurance Using IV

	Impact #1 Sell Livestock		Impact #2 Reduce Meals	
	(1) Asset Poor < 10.5 TLU	(2) Asset Rich > 10.5 TLU	(3) Asset Poor < 9.3 TLU	(4) Asset Rich < 9.35 TLU
$\widehat{insured}$	-0.143	-0.616***	-0.393***	-0.137
	(0.142)	(.188)	(0.161)	(0.184)
Years of education (head)	-0.00366	.0106	0.00286	-0.0111
	(0.006)	(0.009)	(0.010)	(0.010)
Risk-taking	0.0333	0.0517	-0.536	-0.102
	(0.060)	(0.070)	(0.070)	(0.068)
Risk-moderate	-0.0304	0.00688	0.0209	-0.0321
	(0.054)	(0.062)	(0.068)	(0.064)
Non-livestock asset index	0.0113	-0.0169	-0.0488	-0.0786***
	(0.029)	(0.035)	(0.038)	(0.034)
TLU Owned	0.0157	0.000755	0.0121	0.00107
	(.008)	(0.001)	(0.010)	(0.001)
TLU losses in past year	0.0113	0.00356	-0.0131	-0.00158
	(0.006)	(0.002)	(0.007)	(0.003)
Expected TLU losses	0.00196	-0.00842***	-0.00885	0.00818***
	(0.004)	(0.003)	(0.004)	(0.003)
Credit Constrained	0.0967***	-0.0415	-0.00840	0.111
	(0.045)	(0.0567)	(0.051)	(0.056)
Ethnicity fixed effects	yes	yes	yes	yes
Location fixed effects	yes	yes	yes	yes
Observations	323	311	304	330
R^2	0.165	0.219	0.198	0.233

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

For the first test, we recognize that 28% of insured households had already received the payout, whereas the rest of insured households were due to receive the payout within days or (at most) a few weeks. We might think that households' expectations of those who had already received the payout will more accurately reflect their true behavior, compared to those who hadn't yet received the payout. Although the sample size of insured households becomes very small, we can run all the previous regressions using only the subsample of insured households who had actually received the insurance payout. These results are reported in Tables 10-13 in the Appendix. We find that excluding insured households who have yet to receive a payout does not substantially alter our main findings. In fact, the magnitude of the effect is stronger when restricted to the subpopulation who has already received their insurance payout, though the IV estimate of the insurance impact on livestock sales becomes insignificant even though the magnitude of the coefficient remains the similar.

Another thing we might worry about is enumerator effects. In many instances, the enumerator was the person who informed the insured household that a payout was to be made, and the amount the household should expect to receive. For this reason we might be particularly concerned about framing effects. Did some enumerators ask the questions about coping strategies in a way that encouraged a dramatic response by insured households? One way to manage this potential problem is to control for enumerator fixed effects. However, there is a strong correlation between the enumerator and the household's location and ethnicity, mainly due to language and cultural barriers.[5] For this reason, we run the same earlier

[5] Enumerators, who could usually speak only 1 or 2 local dialects, were divided into 5 teams for the survey implementation. Each team was sent to a different region with certain cultural and language characteristics.

regressions using enumerator fixed effects in place of location and ethnic fixed effects. These estimates are reported in Tables 14-17 in the Appendix. We find that including enumerator fixed effects does not substantially alter our primary results, but it does substantially increase the explanatory power of each estimated regression. The only estimate which is considerably different is the IV estimate of the insurance impact on household consumption (Impact #2), which is much smaller and becomes insignificant when enumerator fixed effects replace location and ethnicity fixed effects.

The results presented in Section 5 offer the strongest robustness check. If we are worried that the expectations are in some way invalid because they are driven by framing effects, then we would not expect to observe threshold-disaggregated behavioral responses. Because the results match our expectations from theory, we are even more confident that the anticipated behaviors are informative even if they are imperfect.

8. CONCLUSION

When adverse shocks strike in developing countries, poor households are often forced to choose between drawing down productive assets or human capital. Either way, uninsured risk can result in permanent consequences if the household's choice undermines its future pro- ductivity. In this paper we assess whether insurance can function as a safety net, preventing household asset depletion and improving the human capital of future generations.

Our findings suggest that IBLI payouts in Marsabit district of northern Kenya during the drought of 2011 provided substantial immediate benefits to insured households. Insured households were much less likely to sell livestock, improving their chances of recovery. Rather than sell livestock, these same households appear to shift from net sellers to net buyers of livestock. Insured households also intend to use a portion of their anticipated payouts to purchase food. By using part of the payout to purchase food, most insured households expect to maintain their current food consumption, rather than reduce meals like their uninsured neighbors. This makes insured households more self-reliant (less likely to rely on food aid or assistance from others) and more food secure. Moreover, our results suggest that insurance can promote asset smoothing without having the deleterious long term consequences of destabilized consumption.

Our results also contribute to the literature of poverty traps. We show that households in our sample do indeed behave differently depending on their asset holdings and a critical asset threshold. Livestock-poor households were more likely to smooth assets, whereas livestock- rich households were more likely to smooth consumption during the drought experienced in 2011. Recognizing that a household's response to drought depends on the threshold, we show that the impact of insurance will also depend on the critical behavioral threshold. Our results suggest that insurance helps stop the households most likely to give up productive assets from reducing their asset base, otherwise harming the household's future income-earning potential. In addition, insurance helps prevent those households most likely to reduce consumption from doing so, thereby protecting vulnerable household members from undernutrition and malnutrition, and improving the human capital of future generations. In this way we show that insurance can act as a safety net, allowing smoothing of consumption and nutrition, while preserving productive assets.

These results come at a critical time for policymakers. There has recently been a grand push from development agencies to scale up microinsurance pilots with the goal of reaching a larger number of households. This push has transpired in spite of an incomplete understanding of microinsurance impacts. This paper provides some empirical evidence that insurance can improve outcomes when negative strikes occur, but the results are not definitive. The findings are based in part on immediate expectations regarding a specific insurance pilot project. If these expectations closely follow true behavior, then the highly anticipated long term positive welfare impacts of IBLI are likely to be observed in the near future. Regardless, further impact analyses are necessary in order to generalize the results more broadly. While we wait to observe long run impacts of a variety of insurance pilots, the results presented here seem a strong indicator that microinsurance can be a helpful strategy for households coping with risk in developing countries.

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APPENDIX

Table 10: Impact of Insurance #1, Sell Livestock

(Using Insured Subpopulation: Already Received Payout)

	(1) *IV*	(2) *Heckman*	(3) *DD*	(4) $Match_a$	(5) $Match_b$
$\widehat{insured}$	-0.386				
	(0.221)				
insured*post			-0.379***		
			(0.088)		
insured		-0.336***	0.040		
		(0.096)	(0.053)		
post (time dummy)			0.035		
			(0.022)		
Inverse Mills Ratio		0.286			
		(0.389)			
Years of education (head)	0.002	-0.000	0.002		
	(0.007)	(0.007)	(0.005)		
Risk-taking	0.042	0.027	0.010		
	(0.042)	(0.040)	(0.037)		
Risk-moderate	0.019	-0.000	-0.017		
	(0.028)	(0.034)	(0.029)		
Non-livestock asset index	0.007	0.012	0.017		
	(0.022)	(0.019)	(0.023)		
TLU Owned	0.000	0.000	0.000		
	(0.001)	(0.001)	(0.001)		
TLU losses in past year	0.004**	0.004**	0.003*		
	(0.002)	(0.002)	(0.002)		
Expected TLU losses	-0.005*	-0.005**	-0.004		
	(0.002)	(0.002)	(0.003)		
Credit Constrained	0.013	0.015	-0.034		
	(0.077)	(0.077)	(0.085)		
ATE (Matching)				-.309***	-.346***
				(.041)	(.061)
Ethnicity fixed effects	yes	yes	yes		
Location fixed effects	yes	yes	yes		
Observations	578	578	1,156	593	593
R^2	0.163	0.226	0.204	-	-

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 11: Impact of Insurance #2, Reduce Daily Meals

(Using Insured Subpopulation: Already Received Payout)

	(1)	(2)	(3)	(4)	(5)
	IV	*Heckman*	*DD*	$Match_a$	$Match_b$
$\widehat{insured}$	-0.345**				
	(0.114)				
insured*post			-0.486***		
			(0.121)		
insured		-0.507***	-0.028		
		(0.063)	(0.082)		
post (time dummy)			-0.046***		
			(0.014)		
Inverse Mills Ratio		-0.069			
		(0.185)			
Years of education (head)	-0.002	-0.004	-0.004		
	(0.007)	(0.008)	(0.006)		
Risk-taking	-0.071	-0.095**	-0.077*		
	(0.043)	(0.035)	(0.036)		
Risk-moderate	-0.023	-0.053	-0.029		
	(0.057)	(0.052)	(0.046)		
Non-livestock asset index	-0.065*	-0.060*	-0.035		
	(0.030)	(0.030)	(0.030)		
TLU Owned	0.001*	0.001**	0.001***		
	(0.000)	(0.000)	(0.000)		
TLU losses in past year	-0.003	-0.003*	-0.004**		
	(0.002)	(0.001)	(0.001)		
Expected TLU losses	0.003	0.002	0.003		
	(0.003)	(0.003)	(0.003)		
Credit Constrained	0.063	0.064	0.103		
	(0.068)	(0.060)	(0.067)		
ATE (Matching)				-.538***	-.529***
				(.046)	(.077)
Ethnicity fixed effects	yes	yes	yes		
Location fixed effects	yes	yes	yes		
Observations	578	578	1,156	593	593
R^2	0.185	0.301	0.253	-	-

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 12: Impact of Insurance #3, Rely More on Food Aid

(Using Insured Subpopulation: Already Received Payout)

	(1)	(2)	(3)	(4)	(5)
	IV	$Heckman$	DD	$Match_a$	$Match_b$
$\widehat{insured}$	-0.567***				
	(0.129)				
insured*post			-0.762***		
			(0.106)		
insured		-0.741***	0.013		
		(0.108)	(0.034)		
post (time dummy)			0.002		
			(0.009)		
Inverse Mills Ratio		0.029			
		(0.084)			
Years of education (head)	-0.009**	-0.012**	-0.012**		
	(0.004)	(0.004)	(0.004)		
Risk-taking	0.010	-0.025	-0.026		
	(0.030)	(0.030)	(0.029)		
Risk-moderate	0.029	-0.013	-0.006		
	(0.033)	(0.020)	(0.019)		
Non-livestock asset index	-0.064*	-0.056**	-0.052*		
	(0.030)	(0.025)	(0.025)		
TLU Owned	-0.000	-0.000	-0.000		
	(0.001)	(0.001)	(0.000)		
TLU losses in past year	-0.001	-0.000	0.000		
	(0.002)	(0.001)	(0.001)		
Expected TLU losses	-0.001	-0.002	-0.003		
	(0.002)	(0.001)	(0.002)		
Credit Constrained	0.009	0.011	0.026		
	(0.034)	(0.027)	(0.017)		
ATE (Matching)				-.766***	-.751***
				(.037)	(.062)
Ethnicity fixed effects	yes	yes	yes		
Location fixed effects	yes	yes	yes		
Observations	578	578	1,156	593	593
R^2	0.196	0.561	0.436	-	-

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 13: Impact of Insurance #4, Rely on Assistance from Others

(Using Insured Subpopulation: Already Received Payout)

	(1) *IV*	(2) *Heckman*	(3) *DD*	(4) $Match_a$	(5) $Match_b$
$\widehat{insured}$	-0.081				
	(0.109)				
insured*post			-0.292***		
			(0.074)		
insured		-0.392***	-0.084		
		(0.049)	(0.077)		
post (time dummy)			0.010		
			(0.013)		
Inverse Mills Ratio		-0.377			
		(0.260)			
Years of education (head)	-0.010	-0.012	-0.012		
	(0.008)	(0.009)	(0.007)		
Risk-taking	-0.045	-0.064	-0.065		
	(0.048)	(0.055)	(0.052)		
Risk-moderate	-0.025	-0.048	-0.038		
	(0.040)	(0.039)	(0.037)		
Non-livestock asset index	-0.003	0.001	0.008		
	(0.023)	(0.023)	(0.021)		
TLU Owned	0.000	0.000	-0.001		
	(0.001)	(0.001)	(0.001)		
TLU losses in past year	-0.003	-0.003	-0.001		
	(0.003)	(0.003)	(0.002)		
Expected TLU losses	0.003	0.003	0.003		
	(0.006)	(0.006)	(0.006)		
Credit Constrained	-0.091*	-0.091*	-0.050		
	(0.044)	(0.045)	(0.055)		
ATE (Matching)				-.413***	-.395***
				(.046)	(.068)
Ethnicity fixed effects	yes	yes	yes		
Location fixed effects	yes	yes	yes		
Observations	578	578	1,156	593	593
R^2	0.147	0.217	0.161	-	-

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: Impact of Insurance #1, Sell Livestock

(Using Enumerator Fixed Effects)

	(1)	(2)	(3)
	IV	*Heckman*	*DD*
$\widehat{insured}$	-0.395***		
	(0.137)		
insured*post			-0.252***
			(0.066)
insured		-0.225***	0.051
		(0.060)	(0.036)
post (time dummy)			0.035
			(0.031)
Inverse Mills Ratio		-0.216	
		(0.171)	
Years of education (head)	0.001	0.005	0.003
	(0.007)	(0.006)	(0.005)
Risk-taking	0.055*	0.060**	0.045*
	(0.031)	(0.025)	(0.022)
Risk-moderate	0.007	0.010	0.002
	(0.037)	(0.039)	(0.026)
Non-livestock asset index	0.004	-0.002	0.017
	(0.018)	(0.020)	(0.016)
TLU Owned	0.002	0.001	0.000
	(0.001)	(0.001)	(0.001)
TLU losses in past year	0.004	0.004	0.004**
	(0.003)	(0.002)	(0.002)
Expected TLU losses	0.001	0.003	0.000
	(0.003)	(0.003)	(0.002)
Credit Constrained	-0.005	-0.012	-0.031
	(0.043)	(0.036)	(0.030)
Enumerator fixed effects	yes	yes	yes
Observations	588	634	1,268
R^2	0.363	0.392	0.403

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 15: Impact of Insurance #2, Reduce Meals

(Using Enumerator Fixed Effects)

	(1)	(2)	(3)
	IV	*Heckman*	*DD*
$\widehat{insured}$	-0.093		
	(0.101)		
insured*post			-0.277***
			(0.068)
insured		-0.323***	-0.038
		(0.050)	(0.032)
post (time dummy)			-0.046***
			(0.016)
Inverse Mills Ratio		-0.030	
		(0.134)	
Years of education (head)	0.008	0.004	0.005
	(0.007)	(0.006)	(0.005)
Risk-taking	-0.042	-0.053	-0.035
	(0.045)	(0.039)	(0.029)
Risk-moderate	-0.030	-0.021	-0.023
	(0.057)	(0.050)	(0.035)
Non-livestock asset index	-0.072**	-0.069**	-0.058**
	(0.032)	(0.030)	(0.025)
TLU Owned	0.000	0.001	0.001*
	(0.001)	(0.000)	(0.001)
TLU losses in past year	-0.003*	-0.003*	-0.004**
	(0.002)	(0.002)	(0.001)
Expected TLU losses	0.001	0.000	0.001
	(0.004)	(0.004)	(0.003)
Credit Constrained	0.004	0.012	0.031
	(0.054)	(0.049)	(0.047)
Enumerator fixed effects	yes	yes	yes
Observations	588	634	1,268
R^2	0.377	0.427	0.457

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 16: Impact of Insurance #3, Rely More on Food Aid

(Using Enumerator Fixed Effects)

	(1)	(2)	(3)
	IV	*Heckman*	*DD*
$\widehat{insured}$	-0.267**		
	(0.124)		
insured*post			-0.502***
			(0.049)
insured		-0.475***	0.032
		(0.055)	(0.019)
post (time dummy)			0.002
			(0.012)
Inverse Mills Ratio		-0.063	
		(0.174)	
Years of education (head)	-0.006	-0.008	-0.010*
	(0.007)	(0.006)	(0.005)
Risk-taking	0.011	0.001	-0.011
	(0.040)	(0.028)	(0.021)
Risk-moderate	0.032	0.031	0.017
	(0.033)	(0.025)	(0.022)
Non-livestock asset index	-0.048*	-0.044*	-0.036**
	(0.027)	(0.025)	(0.016)
TLU Owned	-0.001	-0.000	-0.000
	(0.001)	(0.000)	(0.000)
TLU losses in past year	-0.000	-0.000	0.000
	(0.002)	(0.001)	(0.001)
Expected TLU losses	0.003	0.002	-0.000
	(0.003)	(0.002)	(0.002)
Credit Constrained	-0.017	-0.009	0.016
	(0.059)	(0.045)	(0.027)
Enumerator fixed effects	yes	yes	yes
Observations	588	634	1,268
R^2	0.211	0.436	0.383

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 17: Impact of Insurance #4, Rely on Assistance from Others

(Using Enumerator Fixed Effects)

	(1)	(2)	(3)
	IV	*Heckman*	*DD*
$\widehat{insured}$	-0.072		
	(0.092)		
insured*post			-0.208***
			(0.063)
insured		-0.269***	-0.097*
		(0.068)	(0.050)
post (time dummy)			0.010
			(0.019)
Inverse Mills Ratio		0.294	
		(0.237)	
Years of education (head)	-0.005	-0.011**	-0.010**
	(0.005)	(0.005)	(0.005)
Risk-taking	-0.058	-0.057	-0.072*
	(0.042)	(0.039)	(0.038)
Risk-moderate	-0.033	-0.025	-0.036
	(0.040)	(0.033)	(0.035)
Non-livestock asset index	-0.016	-0.005	-0.009
	(0.021)	(0.020)	(0.014)
TLU Owned	0.000	0.001	0.000
	(0.001)	(0.001)	(0.001)
TLU losses in past year	-0.000	-0.001	0.000
	(0.001)	(0.002)	(0.001)
Expected TLU losses	0.001	0.001	0.001
	(0.004)	(0.003)	(0.003)
Credit Constrained	-0.017	-0.011	0.005
	(0.048)	(0.037)	(0.032)
Enumerator fixed effects	yes	yes	yes
Observations	588	634	1,268
R^2	0.292	0.407	0.391

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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