Asset Insurance Markets and Chronic Poverty

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Abstract

This paper incorporates asset insurance into a theoretical poverty trap model to assess the aggregate impact of insurance access on chronic poverty. We use dynamic stochastic programming methods to decompose two mechanisms through which a competitive asset insurance market might alter long-term poverty dynamics: first, by breaking the descent into chronic poverty of vulnerable households (the *vulnerability reduction* effect) and, second, by incentivizing poor households to prudentially take on additional investment and craft a pathway from poverty (the *investment incentive* effect). In a stylized economy that begins with a uniform asset distribution, the existence of an asset insurance market cuts the long-term poverty headcount in half (from 50% to 25%), operating primarily through the *vulnerability reduction* effect. If insurance is partially subsidized, the headcount measure drops by another 10 percentage points, with the additional gains driven largely by the *investment incentive* effect.

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Keywords: *insurance; risk; vulnerability; chronic poverty, poverty traps; dynamic stochastic programming.*

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Asset Insurance Markets and Chronic Poverty

In developing countries, governments increasingly address the indigence associated with chronic poverty using cash transfer programs. While there is evidence that such programs may diminish poverty inter-generationally through the human capital development of children (see reviews by Rawlings and Rubio, 2005, Baird et al., 2013 and Fiszbein et al., 2009), there is much less evidence that cash transfers offer a pathway out of poverty in the medium term.[1] Indeed, the eligibility requirements of these programs may, if anything, discourage efforts by beneficiaries to build assets and boost income. In addition, as an *ex post* palliative for those who have already fallen into indigence, cash transfer programs do not address the underlying dynamics that generate indigence in the first place. As noted by Barrientos, Hulme, and Moore (2006), to be effective, social protection must address poverty dynamics and the factors that make and keep people poor. In this paper, we explore whether and how an asset insurance market might alter the forces that both drive and sustain chronic poverty.

To explore these ideas, we incorporate insurance into a theoretical poverty trap model and then utilize dynamic stochastic programming methods to decompose two mechanisms through which a competitive asset insurance market might alter long-term poverty dynamics: first, by breaking the descent into chronic poverty of vulnerable households (the *vulnerability reduction* effect) and, second, by incentivizing

[1] Gertler, Martinez, and Rubio-Codina (2012) provide an exception, showing that beneficiaries of the Opportunidades program in Mexico invested some of their cash transfers in productive assets, leading to sustained increases in consumption through investment, even after transitioning out the program.

poor households to prudentially take on additional investment and craft a pathway from poverty (the *investment incentive* effect). The magnitude of either effect will depend on the initial asset distribution of the population. In a stylized economy that begins with a uniform asset distribution, the existence of an asset insurance market cuts the long-term poverty headcount in half (from 50% to 25%), operating primarily through the *vulnerability reduction* effect. If insurance is partially subsidized, the headcount measure drops by another 10 percentage points, with the additional gains driven largely by the *investment incentive* effect.

At the heart of our analysis is an intertemporal model of asset accumulation in which individuals face a non-convex production set and are periodically buffeted by potentially severe negative shocks. This particular model is motivated by the risk-prone pastoral regions of the horn of Africa. Pastoralist households living in the arid and semi arid regions of northern Kenya are highly vulnerable to drought risk. In 2009, a targeted unconditional cash transfer program was introduced by the government to improve the capacity of targeted households to meet immediate, essential needs, and to make productive investments. At the same time, an index-based livestock insurance program was also developed to help pastoralist households protect against livestock losses caused by drought (McPeak, Little, and Doss, 2012; Hurrell and Sabates-Wheeler, 2013; Chantarat et al., 2007, 2012; Mude et al., 2009). While this particular rural region motivates our analysis, our findings speak in principal to the many rural areas of the developing world where risk looms large.[2]

[2]Krishna (2006), for example, documents the role of weather shocks in driving long-term descents into poverty in Andhra Pradesh, while Centre (2008) has a more general discussion of climatic and other shocks as drivers of chronic poverty at a global scale.

This paper is organized as follows. Section 1 briefly situates our work in the literature on poverty traps, social protection and insurance. In Section 2, we develop a dynamic model of investment and consumption in the presence of a structural poverty trap. Section 3 incorporates insurance and presents our decomposition of the the *vulnerability reduction* and *investment incentive* effects of insurance. The aggregate impact of these effects are evaluated for a stylized economy in Section 4. Section 5 closes with some concluding remarks.

1 The Social Protection Paradox

Azariadis and Stachurski (2005) define a poverty trap as a "self-reinforcing mechanism which causes poverty to persist." A robust theoretical literature has identified a variety of such mechanisms that may operate at either the macro level–meaning that an entire country or region is trapped in poverty–or at the micro level–meaning that a subset of individuals become trapped in chronic poverty even as others escape (see the recent review papers by Barrett and Carter, 2013, Kraay and McKenzie, 2014, and Ghatak, 2015). Although broad-based empirical evidence of poverty traps has been mixed (Subramanian and Deaton, 1996; Kraay and McKenzie, 2014), Kraay and McKenzie (2014) conclude that the evidence for the existence of structural poverty traps is strongest in rural remote regions like the arid and semi-arid lands of East Africa that motivate our work.

In this setting, McPeak and Barrett (2001) report differential risk exposure experienced by pastoralists, while Santos and Barrett (2011) reveal differential access to credit markets indicative of poverty traps. More direct evidence of a poverty trap is provided by Lybbert et al. (2004) and Barrett et al. (2006) who demonstrate nonlinear asset dynamics in the livestock-based economy of Eash Africa's arid and semi-arid lands, such that when livestock herds become too small (i.e. they fall below an empirically estimated critical threshold), recovery becomes challenging, and herds transition to a low level equilibrium. Toth (2015) argues that these nonlinear asset dynamics stem from a requisite minimum herd size that enables herd mobility and the traditional pastoral semi-nomadic lifestyle.

Motivated by recent policy developments in these remote regions of northern Kenya, our goal here is not to further test this poverty trap model, but to instead explore the challenges that this model presents to the design of social protection programs. To do so, we employ a variant of what Barrett and Carter (2013) call the "multiple financial market failure" poverty trap model. As developed in the next section, this model assumes that individuals lack access to credit and insurance contracts and therefore must autarkically manage risk and fund asset accumulation by forgoing current consumption. As in other similar models (for examples - Ghatak, 2015, Dercon, 1998, and Dercon and Christiaensen, 2011), the model here generates multiple equilibria: one at a low asset and income level and another at a high asset level. Between the two equilibria stands a critical asset threshold, which we denote as the Micawber threshold.[3] Individuals who find themselves at or below that thresh-

[3]The label 'Micawber' stems from Charles Dickens's character Wilkens Micawber (in *David Copperfield*), who extolled the virtues of savings with his statement, "Annual income twenty pounds, annual expenditure nineteen nineteen and six, result happiness. Annual income twenty pounds, annual expenditure twenty pounds ought and six, result misery." Lipton (1993) first used the label to distinguish those who are wealthy enough to engage in virtuous cycles of savings and accumulation from those who are not. Zimmerman and Carter (2003) went on to apply the label to

old will with probability one end up at the low level, "poverty trap," equilibrium. Above that threshold, individuals will attempt to accumulate assets and move to the high equilibrium, although they face some probability that shocks will thwart their accumulation plan and they will subsequently fall below the Micawber threshold ultimately arriving at the low level equilibrium. The probability that an individual at any asset position above the Micawber threshold ends up at the low level equilibrium is a well-defined measure of vulnerability, and we will refer to the "vulnerable" as those individuals who face a non-trivial probability of collapse.

The starting point for this exploration is the social protection paradox that emerges in the analysis of Ikegami et al. (2016), comparing conventional needs-based social protection (transfers go to the neediest first) with "vulnerability-targeted social protection". Under the latter policy, resources flow to the current poor only after transfers are made to the vulnerable non-poor. The authors find that under finite aid budgets the welfare of the poorest will be higher in the medium term under a policy that counterintuitively prioritizes state-contingent transfers to the vulnerable and only secondarily transfers resources to the chronically poor. They obtain this paradoxical result because vulnerability-targeted aid stems the downward slide of the vulnerable who may otherwise join the ranks of the poor. Vulnerability-targeted aid also offers a behavioral impact that effectively reduces the Micawber threshold to a lower asset level, crowding in accumulation by those who would otherwise stay in the poverty trap.

describe the dynamic asset threshold for the type of poverty trap model we analyze here. Thus, the Micawber threshold divides those able to engage in a virtuous cycle of savings and accumulation, from those who cannot.

The vulnerability-targeted policy considered by Ikegami et al. (2016) operates like a socially provisioned insurance scheme that makes contingent payouts to the vulnerable, lending them aid only when they are hit by negative shocks. Their results depend on three very strong informational assumptions, namely that shocks, asset levels and the location of the Micawber threshold are all known and used to trigger precisely targeted insurance-like payments.[4] The question we ask here is whether formation of an insurance market would obviate the need for this precise information and allow individuals to self-select into the contingent payment scheme by purchasing insurance in a way that favorably alters poverty dynamics as in the omniscient Barrett, Carter and Ikegami analysis. Moreover, if at least some of the cost of asset insurance is born by the vulnerable, the inter-temporal tradeoff in the well-being of the poor, identified by Ikegami et al. (2016), might be avoided.

Two related papers, Chantarat et al. (2010) and Kovacevic and Pflug (2011), have also analyzed the workings of insurance in the presence of poverty traps. Unlike this paper, Chantarat et al. (2010) and Kovacevic and Pflug (2011) ask what happens if households (are forced to) buy insurance at cost. Both find that this involuntary purchase will increase the probability that households around a critical asset threshold will collapse to the low level, poverty trap equilibrium because the insurance premium payments reduce the ability to create growth. The difference with our analysis–where individuals optimally select into and out of an insurance market–is subtle, but important. In contrast to these other papers, we find that

[4]Unlike the model in this paper, Ikegami et al. (2016) assume that individuals enjoy heterogeneous ability or skill to productively utilize productive assets. They show that the Micawber Threshold is a function of ability and assume that ability is observable such that social welfare payments can be perfectly targeted according to ability.

allowing individuals to optimally adjust their consumption and investment decisions in response to the availability of asset insurance positively and unambiguously alters poverty dynamics akin to the findings of Ikegami et al. (2016).

2 Chronic Poverty in the Absence of Insurance Markets

This section establishes a baseline, single asset model of poverty dynamics in the presence of risk, but in the absence of insurance or other access to financial markets. At the heart of our model is an assumed poverty trap. This allows us to build on previous theoretical work by de Nicola (2015), who evaluates the impact of weather insurance on consumption and investment in the absence of a poverty trap.

Analytically, we obtain insights on the working of the model by examining it in Bellman equation form. Numerical dynamic programming analysis allows further insight into the model's implications. As we will show, under the assumptions of the baseline poverty trap model, vulnerability to chronic poverty is not inconsequential. Both the analytical and numerical findings lay the groundwork for Section 3's analysis introducing asset insurance.

2.1 Baseline Autarky Model

Consider the following dynamic household model. Each household has an initial endowment of assets, A_0, where the subscript denotes time. Households maximize intertemporal utility by choosing consumption (c_t) in every period. The problem can be written as follows:

$$\max_{c_t} \qquad \mathbb{E}_{\theta,\varepsilon} \sum_{t=0}^{\infty} u(c_t)$$

subject to:

$$\begin{aligned}
& c_t \leq A_t + f(A_t) \\
& f(A_t) = \max[F^H(A_t), F^L(A_t)] \\
& A_{t+1} = (A_t + f(A_t) - c_t)\,(1 - \theta_{t+1} - \varepsilon_{t+1}) \\
& A_t \geq 0
\end{aligned} \tag{1}$$

The first constraint restricts current consumption to cash on hand (current assets plus income). As shown in the second constraint, the model assumes that assets are productive ($f(A_t)$) and households have access to both a high and low productivity technology, $F^H(A_t)$ and $F^L(A_t)$, respectively. The technological choice is endogenized such that fixed costs associated with the high technology make it preferred only by households above a minimal asset threshold, denoted $\tilde{A}$. Thus, households with assets greater than $\tilde{A}$ choose the high technology, and households below $\tilde{A}$ choose the low productivity technology.

The third constraint is the equation of motion for asset dynamics: period t cash on hand that is not consumed by the household or destroyed by nature is carried forward as period $t + 1$ assets. This intertemporal budget constraint expresses liquidity in assets. Assets are subject to stochastic shocks (or depreciation), where $\theta_{t+1} \geq 0$ is a covariate shock and $\varepsilon_{t+1} \geq 0$ is an idiosyncratic shock. The covariate shock θ_{t+1} is the same for all households in a given period, but idiosyncratic shock ε_{t+1} is specific to the household and is uncorrelated across households. The distinction between these two types of stochastic shocks is important only for considering practically feasible insurance mechanisms in the next section. Both shocks are exogenous, and realized for all households after decision-making in the current period (t), and before decision-making in the next period ($t+1$) occurs. We consider the simple case where both types of shocks are distributed *i.i.d.*, so that the most recent shock, either covariate or idiosyncratic, does not give any information about the next period's shock.[5]

Finally, the non-negativity restriction on assets reflects the model's assumption that households cannot borrow. This assumption implies that consumption cannot be greater than current production and assets, but it does not preclude saving for the future.

In this model, there is only one state variable, A_t. Under these assumptions, the Bellman Equation is:

$$V_N(A_t) = \max_{c_t} \quad u(c_t) + \beta\, \mathbb{E}_{\theta,\varepsilon}[V_N(A_{t+1}|c_t, A_t)] \tag{2}$$

The N subscript on the value function distinguishes this autarky (or no insurance) problem from the insurance problem presented in the next section.

The intertemporal tradeoff between consumption and investment faced by the

[5]If instead the shocks are serially correlated, the agent would use the most recent shock to forecast future asset levels. The state space would then include current and/or past realizations of θ and ε in addition to A_t. This extension is considered in the absence of a poverty trap in Ikegami, Barrett, and Chantarat (2012).

consumer is captured by the first order condition:

$$u'(c_t) = \beta\, \mathbb{E}_{\theta,\varepsilon}[V_N'(A_{t+1})] \tag{3}$$

A household will consume until the marginal benefit of consumption today is equal to the discounted expected value of assets carried forward to the future.

As has been analyzed by others in similar models (*e.g.*, Buera, 2009), the non-convexity in the production set can, but need not, generate a bifurcation in optimal consumption and investment strategies (or what Barrett and Carter (2013) call a multiple equilibrium poverty trap). This bifurcation happens only if steady states exist both below and above $\tilde{A}$. If they do, there will exist a critical asset threshold separating those (below the threshold) deaccumulating assets and moving towards the low steady state from those (above the threshold) investing in an effort to reach the high steady state. The former group are often said to be caught in a poverty trap.

Following Zimmerman and Carter (2003), we label the critical asset level where behavior bifurcates as the Micawber threshold, and denote it as A_N^M, where the M superscript denotes "Micawber" and the subscript N again indicates that no insurance market is present. Intuitively, small changes in assets around A_N^M will have strategy- and path-altering implications. For example, giving an additional asset to a household just below the threshold will incentivize them to invest in an effort to escape the poverty trap. Taking a single asset away from a household just above A_N^M will push them below the threshold and put them on a path toward the low steady state. This implies that in the neighborhood of A_N^M, incremental assets carry a strategic value. That is, they not only create an income flow, they also give the option of advancing to the high steady state in the long-run.

2.2 Numerical Analysis of Chronic Poverty

To further develop the intuition driving optimal choice in the context of a multiple equilibrium poverty trap, we employ numerical analysis. The model does not guarantee multiple steady states, and if A_N^M exists, its location depends on parameters of the model, including the severity of risk (for example, Carter and Ikegami (2009) show how A_N^M shifts with risk).

We purposefully selected parameters to reflect the observed asset dynamics of the northern Kenyan arid and semi arid lands (ASALs), where empirical evidence of a poverty trap exists and a drought index-based livestock insurance (IBLI) contract was recently introduced. Specifically, parameters were chosen and evaluated based on their ability to generate equilibrium stochastic time paths for multiple steady-states (as well as transitions) that are consistent with the stochastic properties of observed data (Lybbert et al., 2004; Santos and Barrett, 2011; Chantarat et al., 2012) from this region. While parameters were selected with this setting in mind, the exercise is intended as a theoretical one, and empirical analysis will be necessary to draw conclusions specific to this setting or any other context.

For simplicity, we consider a population with identical preferences and access to a single asset-based production technology.[6] To establish a vector of covariate shocks

[6]In northern Kenya, livestock are considered the primary, and often the only, productive asset held by households, (for example, the median household in a 2009 survey reported that 100% of productive assets are held in livestock) so that ignorance of other assets is thought to be acceptable

(such as drought), we roughly discretize the estimated empirical distribution of livestock mortality in northern Kenya reported in Chantarat et al. (2012). Mortality rates have been shown by the same study to be highly correlated within the geographical clusters upon which the index is based, so we assume small idiosyncratic shocks.[7] Using the empirically-derived discretization the assumed mutual shocks allow expected mortality to be 9.2% with the frequency of events exceeding 10% mortality an approximately one in three year event. These two features both reflect observed mortality characteristics in the region.

We then impose equilibrium outcomes based on the findings of Lybbert et al. (2004) and Santos and Barrett (2011) in this setting to obtain parameters for the production technology. Here, equilibrium outcomes refer to two stable steady states (the high and low equilibriums) and a single unstable equilibrium (the Micawber threshold). This identifying restriction allows us to search for numerical values of the production parameters which generate a stable result.[8]

The specific functional forms and parameters used to solve the dynamic programming problem are reported in Table 1. Crucially, the chosen parameterization admits both a low ($A \approx 4$) and high ($A \approx 30$) long-term stochastic steady state in accordance with the baseline poverty trap model. For convenience, any agent who

in this setting. In Carter and Janzen (2015) we extend this analysis to consider a productive technology based on two evolving assets (physical capital and human capital).

[7]This largely reflects the risky environment that pastoralists find themselves in, where the vast majority of households report drought to be their primary risk. Although, more recent evidence suggests basis risk in this setting may be larger than originally thought. Jensen, Barrett, and Mude (2016) estimate that IBLI policyholders are left with an average of 69% of their original risk due to high loss events. We will discuss the implications of this assumption when we discuss the policy implications.

[8]While structurally estimating the parameters of the production function based on empirical data would have been preferred, it was deemed not possible at this time.

ends up at the low steady state will be described as chronically poor, or caught in a poverty trap.

Given these parameter values, we use dynamic programming techniques to find a policy function for each behavior as it depends on asset levels. Specifically, we use value function iteration, by which it follows that the Bellman equation has a unique fixed point as long as Blackwell's Sufficient Conditions (monotonicity and discounting) are satisfied.[9]

Once we have identified the policy function, it is insightful to visualize the first order condition. The solid line in Figure 1 graphs the right hand side of Equation 3 as a function of current asset holdings. As can be seen, this term–which represents the future value of holding an additional asset–is non-monotonic. Ignoring the lower tail, assets are strategically most valuable for agents with 11 assets. It will later be shown that this peak correlates perfectly with a point of bifurcating optimal behavioral stategies and thereby identifies the Micawber threshold. In other words, $A_N^M = 11$. As discussed by Carter and Lybbert (2012), it is the high value of assets

[9]To solve the problem numerically, we assume the following timeline of events:

1. In period t households choose optimal c_t and (implicitly) i_t (where i_t denotes investment) based on state variable A_t (asset holdings) and the probability distribution of future asset losses. In the dynamic model extension presented in Section 3, households also choose to purchase insurance I_t given the probability structure of insurance payouts.
2. Households observe exogenous asset shocks θ_{t+1} and ε_{t+1} which determine asset losses (and insurance payout $\delta(\theta_{t+1})$ in the model extension).
3. These shocks, together with the optimal choices from period t determine A_{t+1} through the equation of motion for asset dynamics.
4. In the next period steps 1-3 are repeated based on the newly updated state variable A_{t+1} and knowledge about the probability of future asset losses (and indemnity payments).

The primary timing assumption is that the shocks happen post-decision and determine A_{t+1} given the household's choices of c_t and i_t (and later I_t), and then once again all the information needed to make the next period's optimal decision is contained in A_{t+1}.

just above the Micawber Threshold that leads households in this asset neighborhood to smooth assets and destabilize consumption when hit with a shock.

To characterize poverty dynamics and assess vulnerability, we next run 1000 simulations of 50-year asset paths. One way to characterize the results of these simulations is to calculate the probability that agents starting with any given asset level are found to be at the low level steady state after 50 years of simulation. The solid line in Figure 2 graphs these probabilities for the baseline autarky model. As can be seen, for all initial asset positions below $A_N^M = 11$, agents approach the low steady state with probability 1. All agents with assets below that level do not find it worthwhile to even attempt to approach the high steady state (if they did, at least some small fraction of them would escape). They are, in essence, trapped.

Beyond A_N^M, agents find it dynamically optimal to try to reach the high steady state. But, as can be seen in Figure 2, they are far from assured of reaching that destination. The probability of chronic poverty for those that begin with asset endowments just above A_N^M is around 45%, and only slowly declines as initial endowment increases. These chronic poverty vulnerability rates are precisely why the strategic value of assets is highest for those in the neighborhood of A_N^M, and reflect the fact that severe shocks, or even minor shocks, can have permanent consequences in this model.

3 Introducing Asset Insurance

The numerical simulation of the baseline model reveals the fundamental role

Figure 1: Opportunity Cost of Assets

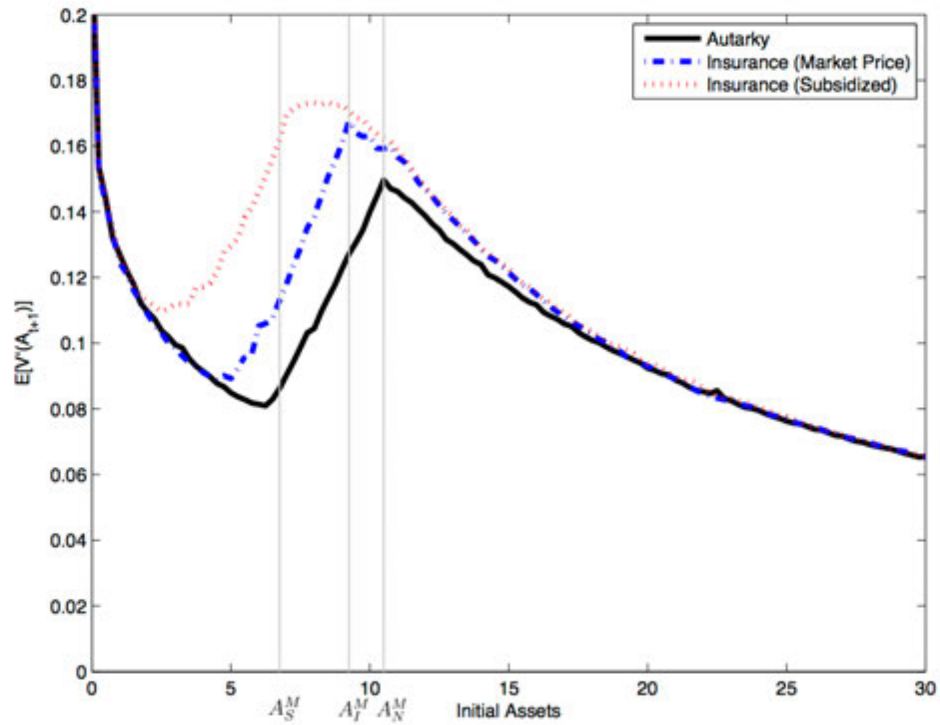
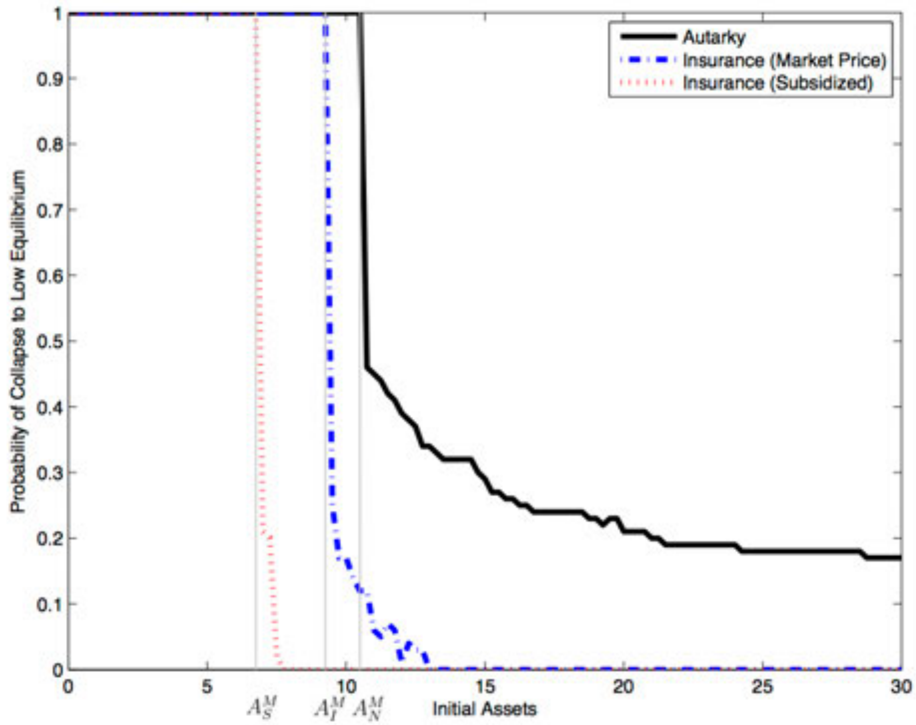


Figure 2: Probability of Collapse to a Low Welfare Steady State



that risk plays in driving chronic poverty. With these issues in mind, a growing literature has been devoted to studying the benefits of insurance, and especially index insurance, for poor households in low income countries (Miranda and Farrin, 2012; Alderman and Haque, 2007; Barrett et al., 2007; Barnett, Barrett, and Skees, 2008; Chantarat et al., 2007; de Nicola, 2015; Hazell, 2006; Skees and Collier, 2008; Smith and Watts, 2009). In contexts where risk looms large, as in the baseline model, it would seem that asset insurance could play an important role in altering long-term poverty dynamics.

In this section, we explore the impact of insurance markets on chronic poverty. We will consider insurance as both a privately provisioned "social protection" scheme, in which the insured household pays the full cost of the insurance, as well as public-private co-funding of asset insurance. In an effort to make our exploration of insurance meaningful, we will consider a type of partial or "index insurance" that at least in principal can be implemented amongst a dispersed, low-wealth population without the problems of moral hazard and adverse selection that historically have crippled efforts to introduce insurance to such populations. The advantage of index insurance is that it requires only a single measurement for a given region (*e.g.*, drought conditions), and the index itself is designed to be beyond the influence of any individual and independent of the characteristics of those who choose to purchase insurance. In most cases, our results will be similar if a traditional insurance contract were instead implemented.

3.1 Extending the Baseline Model to Include Asset Insurance

This section modifies the model of Section 2.1 by giving households the option to purchase asset insurance. If a household wants insurance, it must pay a premium equal to the price of insurance, p, times the number of assets insured at time t, I_t. We assume that the units of assets insured cannot exceed current asset holdings.[10]

We assume an index contract designed to issue payouts based on the realization of the covariant, but not the idiosyncratic shock to assets.[11] To simplify notation, we assume that the covariant shock is observed directly without error so that the shock itself functions as the index that triggers payments.[12] We denote $s \quad 0$ as the strike point or index level at which insurance payments begin. In other words, s is the deductible since it denotes the level of stochastic asset losses not covered by the insurance. Assuming a linear payout function, indemnities, δ, are given by:

$$\delta(\theta_t) \quad = \quad \max((\theta_t) \quad s),\ 0). \tag{4}$$

Under this specification, the insurance fully indemnifies all losses (driven by covariant

[10]This constraint can matter if insurance subsidies lower the price of the insurance below its actuarially fair value.

[11]For the livestock economy that motivates the numerical specification, the covariant shock can be thought of as livestock mortality driven by a drought or other common event, while the idiosyncratic shock could be losses driven by disease or theft uncorrelated across households. In practice, the covariant asset shock is not directly observed, but is instead predicted by some measure of common stress conditions (such as rainfall or forage availability).

[12]If the covariant shock was not measured directly, but was instead predicted by a correlate of covariant losses, then the insurance would cover even fewer loss events (and potentially some non-loss events). While this source of contract failure is important in practice, in our model it is indistinguishable from an increase in the magnitude or frequency of idiosyncratic shocks.

events) beyond the deductible level.

With a market for index insurance, the household now chooses consumption and a level of insurance that maximizes intertemporal utility. The household dynamic optimization problem becomes:

$$\max_{c_t,\, 0 \leq I_t \leq A_t} \quad \mathbb{E}_{\theta,\varepsilon} \sum_{t=0}^{\infty} u(c_t)$$

subject to:

$$\begin{aligned}
& c_t + pI_t \leq A_t + f(A_t) \\
& f(A_t) = \max[F^H(A_t), F^L(A_t)] \\
& A_{t+1} = (A_t + f(A_t) - c_t)\,(1 - \theta_{t+1} - \varepsilon_{t+1}) + (\delta(\theta_{t+1}) - p)I_t \\
& \delta(\theta_{t+1}) = max\ ((\theta_{t+1} - s),\ 0) \\
& A_t \geq 0
\end{aligned} \tag{5}$$

This problem can also be expressed using the following Bellman equation:

$$V_I(A_t) = \max_{c_t,\, 0 \leq I_t \leq A_t} \; u(c_t) + \beta\, \mathbb{E}_{\theta,\varepsilon}[V_I(A_{t+1}|c_t, I_t, A_t)] \tag{6}$$

with two corresponding first order conditions:

$$u'(c_t) = \beta\, \mathbb{E}_{\theta,\varepsilon}[V_I'(A_{t+1})] \tag{7}$$

$$\mathbb{E}_{\theta,\varepsilon}[V_I'(A_{t+1})(\delta(\theta) - p)] = 0 \tag{8}$$

First order condition 7 differs from the analogue autarky condition 3 as long as the availability of insurance increases the expected future value of assets. In general, we would expect this to be the case, as an insured asset is more likely to be around to contribute to future well-being than an uninsured asset.

Noting that the insurance price is non-stochastic and $\delta(\theta) = 0, \forall\theta < s$, i.e. the insurance only pays out in bad states of the world, the second first order condition can be rewritten as:

$$\Pr(\theta \;\; > \;\; s)\, \mathbb{E}_{\theta,\varepsilon}\left[V_I'(A_{t+1})(\delta(\theta))|\, \theta > s\right] = p\lambda(A_{t+1}) \tag{9}$$

where $\lambda(A_{t+1}) \equiv \beta\, \mathbb{E}_{\theta,\varepsilon}[V_I'(A_{t+1})]$ is the opportunity cost or shadow price of liquidity[13] under the credit constraints that define this model. The right hand side of equation 9 is thus the effective cost of insurance, the premium marked up by the shadow price of liquidity. The expression on the left hand side of the same equation is the expected benefit of the insurance, which in bad covariant states of the world adds to the household's asset stock.

Notice that both insurance benefits and costs are valued by the derivative of the value function V_I. In bad states of the world ($\theta > s$), this derivative will tend to be relatively large, especially in the wake of a shock that leaves the household's asset stock in the neighborhood of the Micawber threshold. Of course, if idiosyncratic shocks, which are not covered by the insurance, are important, then the right hand

[13]Each unit of insurance purchased directly implies a reduction in future assets, whose value is given by the derivative of the value function V_I.

side of 9 can also be large, since large asset losses can occur without triggering a compensatory insurance payment. This highlights the importance of basis risk in the household's decision problem - basis risk increases the opportunity cost of liquidity.[14]

In summary, first order condition 9 simply says that the expected marginal dynamic benefits of insurance are set equal to its effective marginal cost, and both depend on the shadow price of liquidy. Combining first order conditions, dynamically optimal choice by the household will fulfill the following condition:

$$u'(c_t) = \beta \frac{\mathbb{E}_{\theta,\varepsilon}\left[V_I'(A_{t+1})\delta(\theta)\right]}{p} = \lambda(A_{t+1}). \tag{10}$$

In other words, the per-dollar marginal values of both consumption and insurance are set equal to the opportunity cost of foregone asset accumulation.

The impact of an asset shock on insurance demand is not transparent since the shadow price of liquidity is highly nonlinear. Where an asset shock raises the shadow price of liquidity, it may also increase or decrease the benefit-cost ratio of the insurance. Analytically, there is no way to disentangle these countervailing forces that influence insurance demand, and we thus return to numerical methods.

3.2 The Vulnerability Reduction Effect of Insurance

To answer the question of whether market-based social protection can reach vulnerable households, we return to numerical methods. In order to parameterize the

[14]This explains the proposition presented in Clarke (2016) that optimal insurance coverage will be decreasing in basis risk

model, the actuarially fair premium (p =.0148) is calculated using the assumed distribution of covariate shocks and the strike point found in the actual IBLI contract available to pastoralists in the region (s = 15%). We assume the market price of insurance is 120% of the actuarially fair value. We additionally assume a subsidy of 50% off the market price. Note also that our assumptions about the structure of risk are relatively favorable for index insurance - we assume small idiosyncratic shocks and an index that perfectly predicts covariate losses so that basis risk (defined as $[(i(\theta_t) \quad \theta_t) + \varepsilon_t])$ is quite small.[15]

To illustrate how insurance changes the consumer's problem, we return to Figure 1. In Figure 1, the dark dash-dot line shows the opportunity cost of assets with a market for insurance. The figure shows the availability of unsubsidized insurance enhances the security, and hence future value of assets, for vulnerable non-poor households (from 11-18 assets) as well as for households below A_N^M destined for chronic poverty (from 5-11 assets). The second dashed line in Figure 1 graphs the increase in the future value of assets when insurance is subsidized (50% off the market price) and optimally purchased by the household. As can be seen, the introduction of subsidized insurance enhances the future value of assets even further, particularly for households holding assets below A_N^M.

Figure 3 demonstrates how this change in the shadow price of liquidity affects the optimal insurance decision. The figure reveals a u-shaped insurance policy function for the percent of assets insured. Focussing first on demand when insurance is unsubsidized, we see that individuals at or below the low level steady state insure 80%

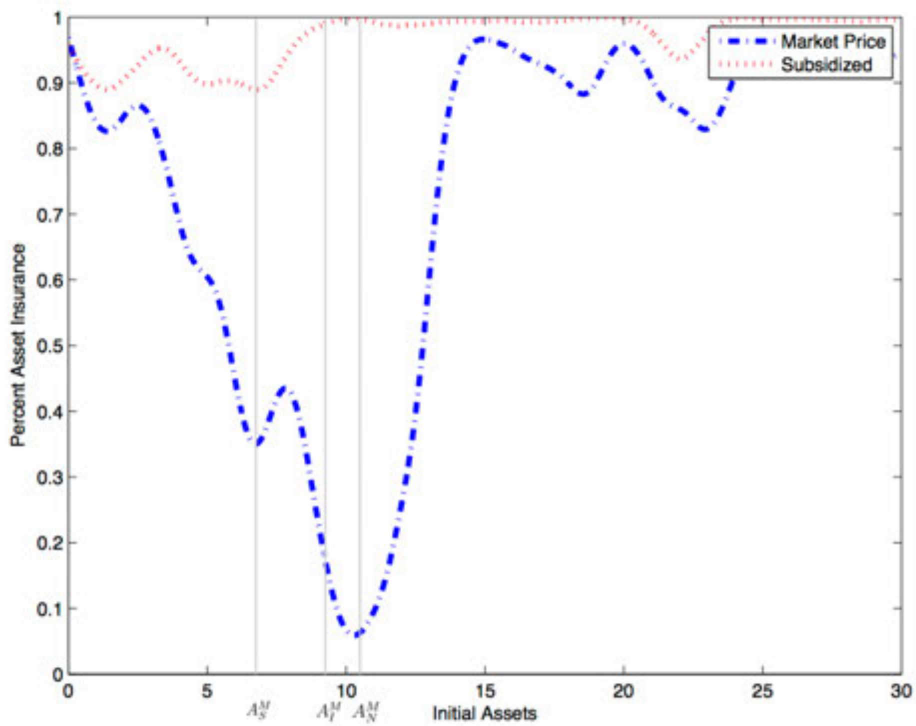
[15] As basis risk increases, rational demand for insurance (across the asset spectrum) will decrease, as explained in Clarke (2016).

to 90% of their assets, a level that is similar to that of individuals with more than about 15 units of assets. In between these levels, demand drops precipitously, bottoming out at less than 10% of assets insured at A_N^M. Notice that there are two types of people in this low demand zone, in parallel to the households with an observed increase in the shadow price of liquidity: households destined to become chronically poor and vulnerable non-poor households.

It is this latter group, the vulnerable non-poor, for whom low insurance demand may seem counterintuitive; the most vulnerable households surely have much to gain from protection against negative shocks. A return to Figure 2 corroborates this intuition. In this figure, the dark dash-dot line shows the probability a household collapses to the low steady state. The figure shows access to insurance decreases chronic poverty vulnerability of currently non-poor vulnerable households. For example, in the absence of an insurance market, a household with 15 assets has an approximately 30% chance of becoming chronically poor in the future, whereas that probability falls to zero when the household has access to insurance. We call this the *ex post vulnerability reduction* effect of insurance.

Yet, many of these same vulnerable households who benefit from a reduction in vulnerability (specifically, households with 11-18 assets), do not immediately insure. While these households clearly have a high marginal benefit of insurance, this intuition on its own overlooks the fact that the effective cost of insurance, $p\lambda(A_{t+1})$, is also highest for the vulnerable. We thus see an irony of asset insurance. The benefit of insurance is highest for the most vulnerable households in the neighborhood of A_N^M, but the opportunity cost of insurance is also highest for these same vulnerable

Figure 3: Insurance Policy Function



households who face a binding liquidity constraint. In other words, those with the most to gain are least able to afford it.[16]

To highlight this tradeoff, notice how insurance demand by the vulnerable population is highly price elastic, as can be seen by comparing the shift in the insurance policy function that takes place when insurance is subsidized. With the 50% insurance subsidy, these households shift from purchasing minimal insurance at market prices, to fully insuring their assets. This suggests the low demand by these households does not reflect a low insurance value, but instead the high shadow price of insurance. In fact, this strong theoretical result has empirical support: A willingness to pay experiment in the region that inspired this work showed that "Households most vulnerable to falling into poverty trap were also shown to have the highest price elasticity of demand, despite their potentially highest dynamic welfare gain from the insurance. This is in contrast to the high and relatively low elasticity of demand found among the poorest, whose dynamic welfare benefits from insurance were minimal."(Chantarat, Mude, and Barrett, 2009)

Without purchase of insurance, how then, does insurance so dramatically alter poverty dynamics of uninsured non-poor yet vulnerable households (and others, as we will explore more fully below)? The critical intuition is that an asset carried into the future is more valuable if it can also be insured in the future, even if it isn't insured today. The impact is subtle, but important. First, the demand pattern

[16]The cost of basis risk is also particularly stark for threshold households. If the covariate shock alone doesn't push the household below the threshold, and it doesn't trigger a payout, but the combination of the idiosyncratic and covariate shocks do push the household over the threshold, then the cost of basis risk is high (because they aren't protected against collapse). Thus, as basis risk increases, insurance demand will decrease, especially for these vulnerable households.

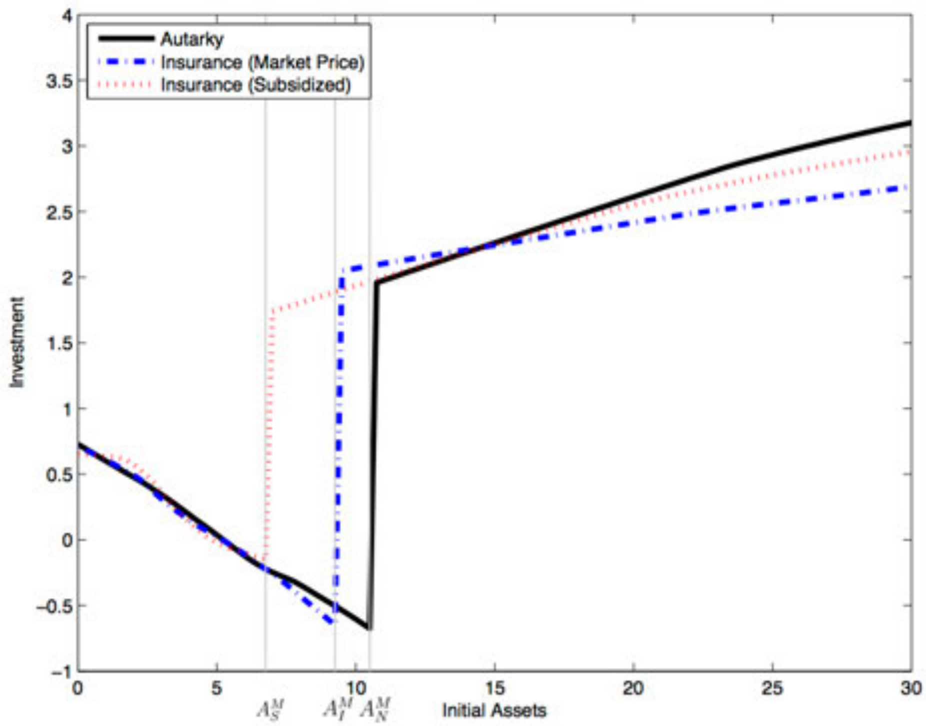
displayed in Figure 3 implies a time-varying insurance strategy; a highly vulnerable household will shift its behavior and fully insure its assets if it is able to increase its asset base. Second, the first order conditions (Equation 10) imply that an increase in the shadow price of liquidity will reduce immediate household consumption. If the household consumes less, but does not buy insurance, then it follows that they are investing more. To fully understand the impact of an insurance market, we need to carefully investigate its implications for household investment behavior.

3.3 The Investment Incentive Effect of Insurance

To explore the effects of an insurance market on investment, Figure 4 shows the optimal investment policy function with and without an insurance market. Here, the baseline Micawber threshold, defined by a behavioral switchpoint, is clearly and intuitively visible at the sharp discontinuity around 11 assets. Absent an insurance market, households below the estimated A_N^M divest assets, instead enjoying greater consumption today, and move toward the low welfare steady state. Alternatively, households above A_N^M invest substantially, giving up contemporaneous consumption in the hopes of reaching the high welfare steady state.

Comparing now the investment policy function with and without an insurance market, we observe two important changes regarding investment behavior. Most important, the policy function demonstrates how the introduction of the insurance market (especially a subsidized insurance market) shifts the behavioral bifurcation point, or Micawber threshold, to the left. That is, $A_I^M < A_N^M$ where subscript I

Figure 4: Investment Policy Function with and without an Insurance Market



denotes a market for insurance.[17] The behavior of households with asset stocks between A_I^M and A_N^M are fundamentally influenced by the introduction of an insurance market. Without an insurance market, they will disinvest. The prospect of insuring (today or in the future) increases the opportunity cost of future assets for households in this zone,[18] inducing these households to take on additional risk by investing sharply. We call this the *ex ante investment incentive* effect of insurance.

The importance of this *investment incentive* effect is perhaps more clear if we return to Figure 2. For households holding assets between A_I^M and A_N^M, an insurance market dramatically alters poverty dynamics. Without access to insurance these households are chronically poor. It is not dynamically rational for these households to reduce consumption, invest, and attempt to move to the high steady state. But with access to insurance these households are able to reach the high asset steady state with positive probability. Note that this fundamental shift in investment behavior does not guarantee that these newly investing households will ultimately achieve the high steady state, but even so their outlook for the future changes fundamentally. Interestingly, given the high shadow price of assets, these households find it optimal to only utilize the insurance markets once they have increased their asset base, shifting from no insurance to nearly full insurance.

With subsidized insurance the range of response to improved investment incentives expands and households between A_N^M and A_S^M that were originally on a path toward destitution are able to reach the high steady state with near certainty. Note

[17]More completely, $A_S^M < A_I^M < A_N^M$ where subscript S denotes the availability of subsidized insurance. For households holding assets between A_N^M and A_S^M, an insurance subsidy dramatically alters poverty dynamics.

[18]In fact, the opportunity cost of assets peaks at the Micawber threshold.

that poorer households whose asset levels place them below A_S^M still benefit from insurance markets (in the sense that it improves their expected stream of utility), but the existence of the market by itself is inadequate to change their long-run economic prospects.[19]

The opposite behavioral change is observed for wealthier households with more than about 15 assets. For these households, access to an insurance market actually reduces investment. In the context of a livestock economy, this corresponds to the observation that households overinvest in livestock as a form of self-insurance. As McPeak (2004) notes, in the context of an open access range, such overinvestment can create externalities and result in a tragedy of the commons.[20] From a policy perspective, this negative impact on investment by the wealthiest households is important and matches the theoretical result reported in de Nicola (2015) who models the introduction of insurance without a poverty trap.

4 The Aggregate Impact of an Asset Insurance Market on Poverty Dynamics

The previous section revealed two primary effects of an asset insurance market: the *vulnerability reduction* effect and the *investment incentive* effect. While these insights speak to how an insurance market affects individuals occupying different

[19]The increase in the discounted stream of expected utility induced by the presence of an insurance market is about four-times higher for households impacted by the *vulnerability reduction* and *investment incentive* effects relative to households that are not.

[20]Empirically, McPeak does not find evidence of this, interpreting this to mean that overstocking has not reached these critical levels.

asset positions, they do not by themselves say anything about how insurance markets impact overall poverty dynamics. This section considers the aggregate impact of the two combined effects on poverty dynamics.

For this analysis, we will consider a stylized rural economy to better understand the impact on long-term poverty dynamics. We recognize the results presented in this section will stem from our assumptions regarding the initial asset distribution of the population. In interpreting the simulation results, it is useful to keep in mind that the impacts on poverty dynamics primarily stem from the alteration of the fate of households in the neighborhood of A_N^M who benefit from a reduction in vulnerability and/or from the *investment incentive* effect. The aggregate impact on poverty dynamics thus increases with the size of the population situated near A_N^M. For example, in an economy in which few households occupy the middle of the asset distribution where the *vulnerability reduction* and *investment incentive* effects come into play, the impacts of an insurance market are less striking than what follows below.

4.1 Simulating Long-term Poverty Dynamics

To explore the long-term consequences of an asset insurance market, consider an economy in which individuals are initially distributed uniformly along the asset continuum.[21] Given this initial asset distribution, we simulate what happens over

[21]Numerically, we assume that agents are uniformly distributed along the range of zero to fifty units of wealth. In results available from the authors, we also simulate poverty dynamics under an initially bi-modal distribution in which the middle ranges of the asset distribution are sparsely populated.

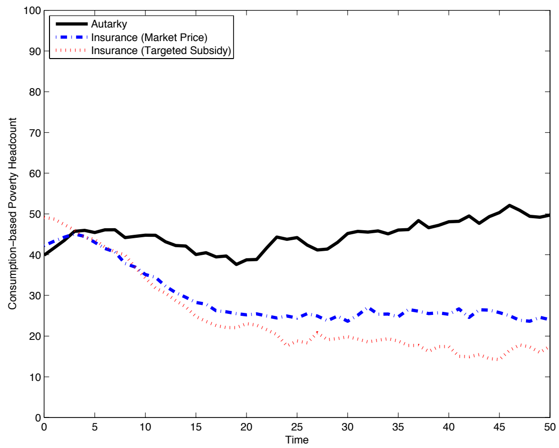
50-years for a stylized village economy comprised of 200 households. Random shocks are drawn each time period in accordance with the probability distributions listed in Table 1, and households behave optimally in accordance with the dynamic choice models laid out in Sections 2.1 and 3.1 above. To ensure the results do not reflect any peculiar stochastic sequence, we replicate the 50-year histories 1000 times. We focus our discussion on the average results taken across these histories.

To characterize poverty dynamics, we trace out the evolution of headcount and poverty gap measures in Figure 5. We examine both a consumption-based poverty measure and an asset-based measure, noting that the difference between the consumption and income-based measures sheds light on households' optimal decisions to consume, invest and/or purchase insurance. To calculate each index we define a poverty line of 10 assets, a level above the low welfare steady state, but below A_N^M - such that households below the poverty line are destined to become chronically poor in the baseline autarky model. Under this poverty line, an individual is classified as consumption poor if their chosen consumption is just below the level of consumption that is obtainable (and optimal) for a household with 10 assets, and an individual is asset-poor only if they have fewer than 10 assets.

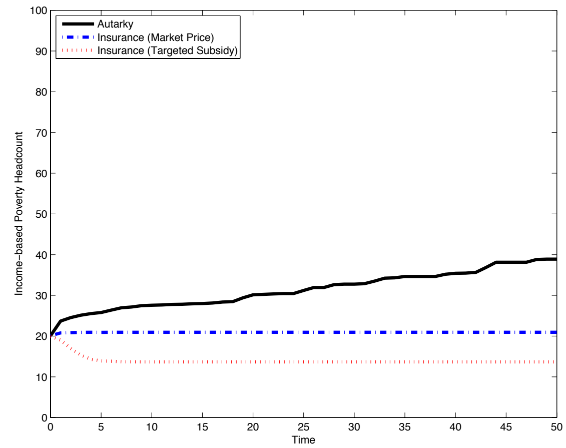
Before comparing the alternative scenarios, the contrast between the consumption- and asset-based poverty measures is instructive. In each plot, the solid (black) line is the average outcome across simulated histories in the baseline autarky scenario. Initially under autarky, approximately 20% of the population is asset-poor, while the consumption-based poverty measures are double that level. This difference reflects the accumulation decisions of vulnerable households. Those households located in

Figure 5: Poverty Dynamics

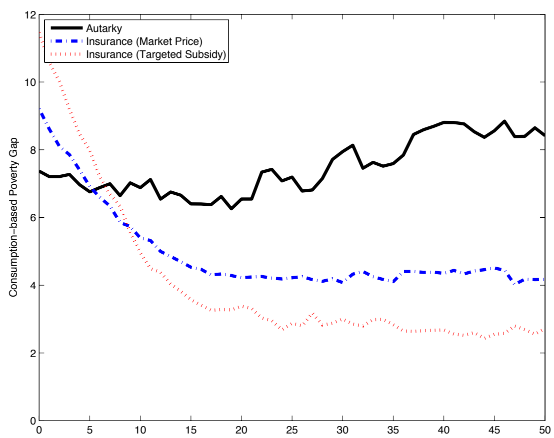
(a) Consumption Poverty Headcount



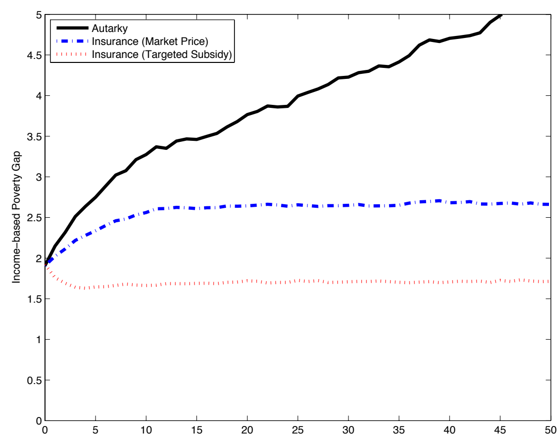
(b) Income Poverty Headcount



(c) Consumption Poverty Gap



(d) Income Poverty Gap



the neighborhood just above A_N^M suppress consumption in an effort to move away from the threshold and approach the higher level steady state equilibrium. Over time, the asset- and consumption-based poverty measures converge to similar values as these vulnerable households either succeed in reaching the higher steady state or they collapse into indigence around the low level steady state. After 50 years of simulated history, the poverty headcount under autarky settles down to approximately 40% to 50% of the population.

4.2 Poverty Dynamics with Unsubsidized Insurance

The dash-dot (blue) line in the four plots of Figure 5 illustrates how the introduction of an unsubsidized insurance market influences poverty dynamics in a stylized economy. Consider first the income-based measures of poverty. These measures show a long-term 50% reduction in income-based poverty (from roughly 40% to 20% of the population). This long-term drop in income-based poverty primarily reflects the *vulnerability reduction* effect of insurance, as a significant fraction of the vulnerable are protected from ultimate collapse to the low welfare steady state.

A similar long-term poverty reduction is observed using the consumption-based measures. Over the longer-term, consumption poverty falls by half to about 25% of the population. However, these measures show an initial small uptick in consumption poverty from 40% to 42% in the presence of an asset insurance market. The initial uptick in consumption-based poverty is a direct result of the *investment incentive* effect of insurance. As households with assets between A_N^M and A_I^M increase investment in an attempt to accumulate assets, they must subsequently lower their consumption relative to what it would have been had they been on a path of deaccumulation approaching the lower steady state. While these households are not asset poor (as can be seen by Figure 5b), their altered accumulation decisions render them temporarily consumption poor.

In addition to these effects on average outcomes, access to an insurance market also dampens the variability in poverty dynamics across histories. For example, absent insurance, in 10% of the simulated histories, asset poverty by year 15 is 50% higher than its mean level. However, with insurance, there is only small variation across histories. In other words, poverty dynamics are more stable across replications, revealing that the availability of insurance protects households against atypical sequences in which multiple bad years occur in succession.

4.3 Targeted Insurance Subsidies as Social Protection

In the spirit of government-provisioned social protection, in this section we consider a *targeted* subsidy in which all households with less than 15 units of assets receive a 50% subsidy off the market price, while anyone with 15+ assets can purchase insurance at the market price. This choice of a targeted subsidy is motivated by the Government of Kenya's livestock safety net and insurance program with differential targeting.[22] The dotted (red) line of Figure 5 plots each poverty measure when targeted subsidies for asset insurance are available.

The impacts are qualitatively similar to the impacts of unsubsidized insurance,

[22]The Government of Kenya's proposed program provides a 100% subsidy to the extreme poor (< .5 US$/day) and a 50% subsidy to low income households (<1 US$/day). See Janzen, Jensen, and Mude (2016) for details.

but larger in magnitude; the impacts increase by roughly one third when insurance is subsidized for the vulnerable and chronically poor. In our stylized economy, access to targeted subsidized insurance more than halves the long-term extent and depth of poverty. This difference is primarily driven by the *investment incentive* effect and the subsequent shift in the Micawber threshold.

While insurance subsidies are not cheap, neither is it cheap to let the ranks of the chronic poor grow. One way to explore the cost-effectiveness of insurance as a mechanism of social protection is to ask how the presence of an asset insurance market (with or without subsidies) would alter the cost of eradicating extreme poverty via a social transfer scheme. To do this, we calculate the amount of funds it would take to close the poverty gap for all poor households in our stylized economy.[23] The black (solid) lines in Figures 6a and 6b display those annual costs for each year of the simulation in the absence of an insurance market. Figure 6a uses our consumption-based poverty gap while Figure 6b uses the alternative income-based poverty gap measure

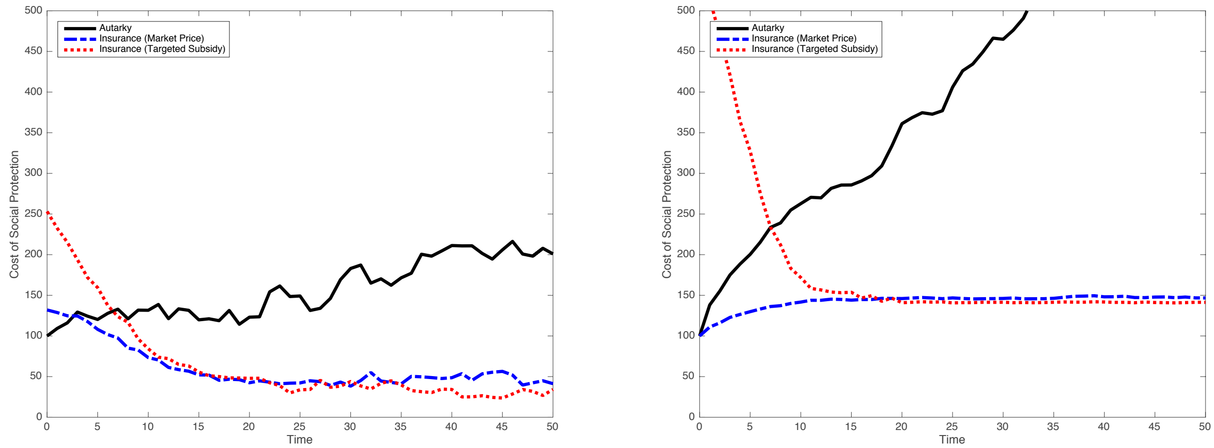
As Figure 6a shows, the cost of providing these (unanticipated) cash transfers climb as poverty rates increase. In the stylized economy without access to insurance, the costs of consumption-targeted social protection increase over the simulation period double. Starting from a much lower absolute level, the cost of income-targeted cash transfers increase more than 400% over the 50 years of the simulation.

The cost of providing social protection is dramatically reduced when an unsubsidized asset insurance market exists, as shown by the blue dash-dot line in Figures

[23] There are of course additional costs associated with high levels of poverty, but we ignore those here.

Figure 6: The Cost of Social Protection

(a) Consumption-based Poverty Line (b) Asset-based Poverty Line



6a and 6b. In this case, the only costs incurred by the public sector are those associated with the cost of the cash transfers - and these costs fall with insurance-induced declining poverty rates. Using a 5% discount rate the net present value of the public expenditure streams over the 50 year time horizon of the simulation are 55% lower when an insurance market exists.

To gauge the cost-effectiveness of insurance subsidies, we sum the cost of all required cash transfer payments and add to that amount the cost of targeted insurance subsidies. Note of course that the public expenditures are only a portion of the full cost of social protection under the insurance scheme as individuals are in some sense privately provisioning a portion of the cost of their own "social" protection. The red dotted lines in the same figures show these costs to the government. The provision of insurance subsidies adds to the government cost of social protection in the first few years of the program, but by year 15 the costs are comparable to the costs of social protection when unsubsidized insurance is available (under our model very few individuals are eligible for the subsidy by year 15).

Again using a 5% discount rate, the net present value of the public expenditure stream including insurance subsidies over the 50 year time horizon suggests this scenario costs 18% less than the autarky scenario, but 44% more than the scenario where individuals have access to unsubsidized insurance. Interpreting these results is challenging. Although more expensive than the scenario with unsubsidized insurance, these subsidies are able to achieve the lowest levels of poverty.

5 Conclusion

Risk and vulnerability play a key role in determining poverty dynamics. In addition to the *ex post* impacts of shocks, the *ex ante* anticipation of shocks discourages investment that might otherwise permit an escape from poverty. These effects are exacerbated in an environment where poverty trap mechanisms are at play. Despite these observations, there has been relatively little work to date on the implications of risk and vulnerability for the design of social protection schemes in the context of a poverty trap. An exception is the work of Ikegami et al. (2016) who consider the impacts of precisely targeting conditional social transfers to those in the neighborhood of a critical asset threshold. While these authors uncover important results about the potential for threshold-targeted protection to reduce long-term poverty rates, their analysis rests on an informationally-demanding (if not unrealistic) scheme. In this paper, we ask whether insurance contracts can be effectively used to deliver those contingent payments and whether self-selection into the purchase of those contracts can be used to solve the targeting problem.

With these questions in mind, we incorporate insurance into a theoretical poverty trap model. By employing numerical dynamic programming methods we reveal two primary effects that arise when an asset insurance market is made available. The *ex post vulnerability reduction* effect affects vulnerable households holding assets above the critical asset threshold, while the *ex ante investment incentive* effect positively affects households with assets below the original critical asset threshold who were otherwise destined for chronic poverty. These latter households strategically alter their investment behavior such that they are able to escape the poverty trap with some positive probability. In aggregate, these two effects imply lower poverty rates when households have access to an insurance market. As a result, the presence of an insurance market radically reduces the discounted present value of public expenditures on cash transfers to the chronically poor.

These findings not withstanding, the poverty reduction impacts of an insurance market are somewhat blunted because some of the most vulnerable will not (immediately) self-select into the purchase of insurance when sold at market prices. While these households have the most to gain from the conditional transfers afforded by insurance, they also have the highest shadow price of liquidity. Interestingly, this configuration of factors results in these households having highly price elastic demand for insurance, meaning that they respond to insurance subsidies. Although more expensive than the scenario with unsubsidized insurance, dynamic simulation shows that the provision of targeted insurance subsidies magnifies the positive effects of insurance, thereby reducing poverty rates even further.

These results have implications for microinsurance pilot projects being implemented in developing countries worldwide. The findings suggest that static empirical demand analyses may not capture the dynamic nature of demand. In a similar way, impact analyses will underestimate the impact if they take a short-run approach. Unfortunately, in the absence of adequate demand, pilots are often short-term. This study suggests that insurance is able to target vulnerable households only if they believe insurance will exist in the future, highlighting the importance of long-term commitments to established insurance markets.

This theoretical excercise obviously relies on a number of assumptions, including economic rationality, a poverty trap mechanism, and full understanding and trust in the insurance provider. Complementary empirical work will be essential for testing the implications of this theoretical exercise. That said, this paper presents a case for increasing access to insurance for poor and vulnerable households as part of a government's comprehensive social protection policy. Doing so could result in dramatically improved poverty dynamics for both chronically poor and vulnerable households.

Table 1: Functional Forms and Parameters used in Numerical Simulations

Production Technology and Parameters
$F^L(A_t) = \alpha A_t^{\gamma_L} + \underline{f}^L$ $F^H(A_t) = \alpha A_t^{\gamma_H} + \underline{f}^H$ $\gamma_L = 0.28$ $\gamma_H = 0.56$ $\underline{f}^L = 2.95$ $\underline{f}^H = 0.50$ $\alpha = 1.33$
Utility Function and Parameters
$u(c_t) = \frac{c_t^{1-\rho}-1}{1-\rho}$ $\beta = 0.95$ $\rho = 1.5$
Insurance Contract Parameters
Actuarially fair premium $= .0148$ $s = .15$
Random Shocks
$\theta = \{0.0, .05, .10, .15, .20, .25, .30, .35, .40, .45, .50, .55, .60\}$ $\varepsilon = \{0.0, .01, .02, .03, .04\}$ $\Pr(\theta) = \{.3415, .3415, .1494, .0640, .0427, .0213, .0107, .0075, .0043, .0043, .0043, .0043, .0043\}$ $\Pr(\varepsilon) = \{.2000, .2000, .2000, .2000, .2000\}$

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