Asset Insurance Markets and Chronic Poverty

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Abstract

This paper uses numerical dynamic stochastic programming methods to show that an insurance market can reduce the long-term extent and depth of poverty in a stylized, risk-prone rural region. This impact operates through both an *ex post* vulnerability reduction effect and an *ex ante* investment incentive effect. The result is not only lower poverty, but also substantial savings in public cash transfer expenditures that would be needed to close the poverty gap of all indigent households. Despite these results, the potential impacts of the insurance market are blunted, because initially vulnerable households do not (immediately) purchase insurance at market prices. These same households do, however, exhibit highly elastic demand for insurance. As a result, insurance subsidies further enhance the extent of poverty reduction that can be achieved with unsubsidized insurance. While targeted subsidies add to the cost of a traditional contingent cash transfer program in the short term, they actually provide significant cost savings over time compared to a conventional social protection scheme that operates in the absence of an asset insurance market. (JEL: D91, G22, H24, O16).

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The Impact of Asset Insurance Markets on 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 asset insurance markets might alter the forces that both drive and sustain chronic poverty. Our work is motivated by the risk-prone pastoral regions of the horn of Africa[2], yet it speaks in principal to the many rural areas of the developing world where risk looms large.[3] We 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 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

[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.

[2]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).

[3]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.

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. As in other similar models (for example, 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.[4] Individuals who find themselves at or below that threshold 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 that they will fall below the Micawber threshold and end up 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.

Using a similar model, Barrett, Carter, and Ikegami (2013) 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 indigent. 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.

While intriguing, the Barrett, Carter, and Ikegami (2013) results depend on strong informational assumptions, both about the location of the Micawber threshold

[4]The label 'Micawber' stems from Charles Dickens' 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 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.

and the precise asset levels of poor and vulnerable households. We here ask whether the state-contingent transfers explored by these authors can be implemented as an insurance mechanism that relies on self-selection and obviates the need for precise information on individual asset holdings, shocks, and the location of the Micawber threshold. We also explore the possibility that at least some of the cost of this kind of social protection can be privately provisioned, opening up the possibility that a given public budget can be stretched further.

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 provides the initial intuition for understanding optimal behavior by vulnerable households: that the optimal insurance decision depends jointly on the opportunity cost of future assets and the benefit-cost ratio of insurance. This leads to a seemingly counterintuitive result: the benefit of insurance is highest for the most vulnerable households, but a high opportunity cost of liquidity renders insurance purchase (in the current period) suboptimal. Despite low demand by vulnerable households, in Section 4 we decompose the impacts of insurance secured through reduced vulnerability and altered incentives for investment. The latter effect implies that vulnerable households, even semi-vulnerable households, are dynamically better off in an environment with insurance even if they don't insure in the current period. Because vulnerable households exhibit highly elastic demand for insurance, in Section 4.2 we explore the cost effectiveness of providing insurance subsidies as a supplement to traditional cash transfer programs. 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).

In this paper, we explore the challenge that a micro poverty trap mechanism 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 autarchically manage risk and fund asset accumulation by forgoing current consumption. Multiple dynamic equilibria can emerge in this model; individuals with assets below a critical threshold value inevitably gravitate toward a low level, poverty trap equilibrium, while others escape to a higher level equilibrium with some strictly positive probability. While a number of papers have confirmed empirical implications of this model in the East African pastoral regions that motivate our work,[5] 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.

The starting point for this exploration is the social protection paradox that emerges in the analysis of Barrett, Carter, and Ikegami (2013). These authors use a numerical dynamic programming simulation of a poverty trap model to compare conventional needs-based social protection (transfers go to the neediest first) with a "triage" policy that first uses resources to prevent the vulnerable non-poor from dropping below a critical asset threshold, thereby stemming their descent into poverty. Under this triage policy, only after transfers are made to the vulnerable non-poor, are resources used to address the needs of the current poor. Paradoxically, the exercise shows that while the extent and depth of poverty are lower in the short term under a conventional needs-based approach, those results are reversed in the medium term as both first and second degree Foster-Greer-Thorbecke poverty measures become lower under the triage policy. In other words, the poor are better off in the medium term when social assistance is first targeted to others.

The reason behind this paradoxical reversal is that if aid is concentrated solely on the neediest, then the number of aid-eligible people slowly swells, diluting the resources available for each poor individual. In contrast, payments to the vulnerable both prevent them from falling below the threshold (and becoming poor) and allow them to successfully build up assets and eventually move away from the threshold

[5] 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. Note, these findings do not generalize globally. Broad-based empirical evidence of poverty traps has been mixed (Subramanian and Deaton, 1996; Kraay and McKenzie, 2014), although 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.

and the vulnerability that it implies. Over time, an increasingly large share of the social protection resources are allocable to the poor whose ranks have not grown.

The triage policy considered by Barrett, Carter, and Ikegami (2013) 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.[6] The question we ask here is whether formation of an index insurance[7] 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 vulnerability, the inter-temporal tradeoff in the well-being of the poor, identified by Barrett, Carter, and Ikegami (2013), might be avoided.

Relatedly, two prior papers, Chantarat et al. (2010) and Kovacevic and Pflug (2011), have 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 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 Barrett, Carter, and Ikegami (2013).

[6]Unlike the model in this paper, Barrett, Carter, and Ikegami (2013) 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.

[7]Index insurance differs from traditional insurance in that the indemnity payments are based on an indicator which is outside the influence of the insured. It also does not require observation of individual shocks and losses. 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, f2015; Skees and Collier, 2008; Smith and Watts, 2009).

2 Poverty Dynamics 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. 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. Looking along a continuum of initial asset endowments, we explore the probability that an agent at any given asset level will be chronically poor. At low levels of initial assets, that probability is one. Beyond a critical asset level–which we label the Micawber Threshold–that probability begins to diminish. However, even beyond that threshold level, vulnerability to chronic poverty is not inconsequential. Both the analytical and numerical findings lay the ground work for Section 3's analysis of the impact of introducing asset insurance. We will later use the model to characterize aggregate poverty dynamics for a stylized economy comprised of agents distributed along an initial asset continuum.

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:

$$
\begin{aligned}
&\max_{c_t} \qquad \mathbb{E}_{\theta,\varepsilon} \sum_{t=0}^{\infty} u(c_t) \\
&\text{subject to:} \\
&\qquad c_t \leq A_t + f(A_t) \\
&\qquad f(A_t) = \max[F^h(A_t), F^l(A_t)] \\
&\qquad A_{t+1} = (A_t + f(A_t) - c_t)\,(1 - \theta_{t+1} - \varepsilon_{t+1}) \\
&\qquad A_t \geq 0
\end{aligned} \tag{1}
$$

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 that the 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 the preferred technology only for 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. It can also be thought of as an intertemporal budget constraint, with liquidity expressed in asset units. 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 stochastic elements will become important later when we consider feasible insurance mechanisms. 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.

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.

It is informative to express the household optimization problem in terms of the corresponding Bellman Equation. We consider the simple case where the 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. In this case, there is only one state variable, A_t.[8] 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 consumer is captured clearly 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.

[8]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 maybe 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).

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 if steady states exist both below and above $\tilde{A}$. If they do, there will exist a critical asset threshold where dynamically optimal behavior bifurcates, with those below the threshold deaccumulating assets and moving towards the low steady state, and those above it 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 subscript N indicates that no insurance market is present.

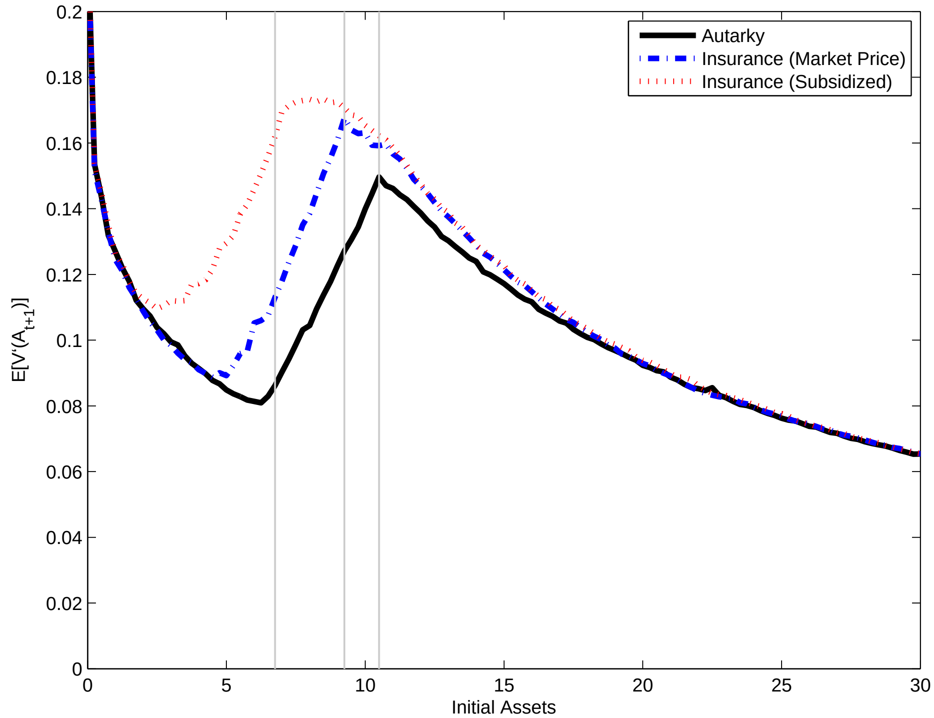
It is important to stress that if A_N^M exists, its location depends on parameters of the model, including the severity of risk (for example, Carter and Ikegami (2009) show how A_N^M shifts with risk). Also note that small changes in assets around the threshold will have strategy- and path-altering implications. For example, giving an additional asset unit to a household just below the threshold will incentivize them to invest in an effort to escape the poverty trap. Taking a single asset unit away from a household just above A_N^M will push them below the threshold and put them on a path toward the low equilibrium.

This latter observation suggests 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 equilibrium in the long-run. We illustrate this point by numerically analyzing this model using the parameterization described in the next section. 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 and increases sharply at the Micawber Threshold (numerically located at about 11 asset units). As discussed by Carter and Lybbert (2012), it is the high value of assets just above the Micawber Threshold that leads households in this asset neighborhood to smooth assets and destabilize consumption when hit with a shock.

2.2 Numerical Analysis of Chronic Poverty

To further explore the implications of this baseline or autarky model, we employ numerical analysis. The parameters selected roughly represent the stochastic structure and productivity parameters of the livestock economy of the semi-arid regions of northern Kenya and southern Ethiopia. This choice is motivated in part by the fact that these regions have been targeted with the sort of asset insurance contracts that

Figure 1: Opportunity Cost of Assets



motivate this paper.[9] Details regarding the numerical implementation and calibration procedures are outlined in the appendix. 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, we will refer to the low equilibrium as a poor standard of living. Any agent who ends up at the low equilibrium 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 herd size (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.[10]

Once we have identified the policy function, we 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 equilibrium 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 11, agents approach the low equilibrium with probability 1. This asset level defines the Micawber threshold, A_N^M, and all agents with assets below that level do not find it worthwhile to even attempt to approach the high equilibrium (if they did, at least some small fraction of them would escape).

Beyond A_N^M, agents find it dynamically optimal to try to reach the high equilibrium. But, as can be seen in Figure 2, they are far from assured of reaching

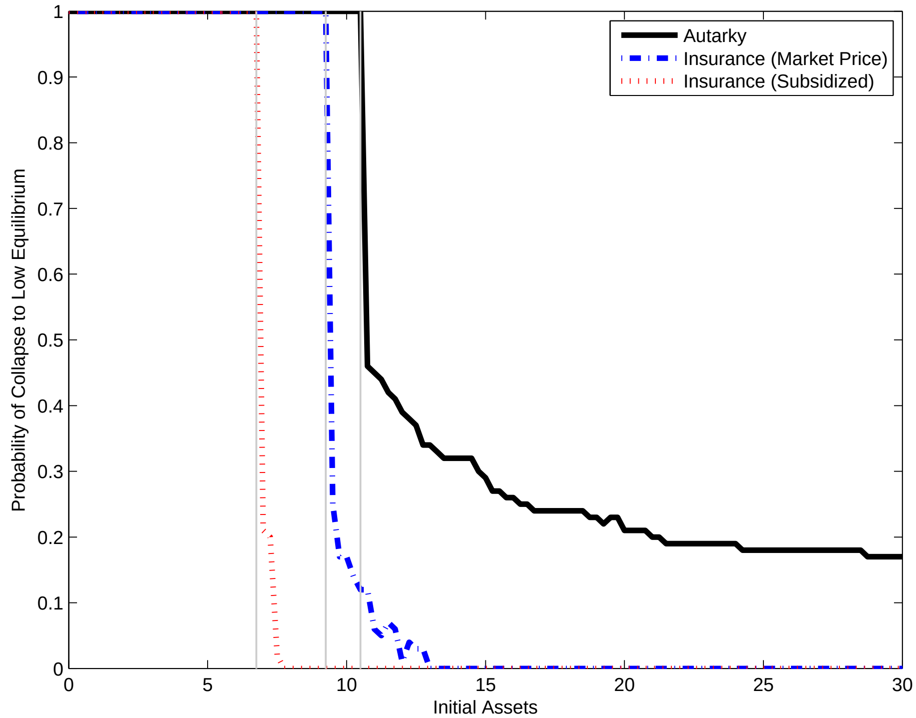
[9]The pastoralist livestock economy in this arid and semi-arid region of Kenya has also been characterized as an ideal example of a poverty trap (see Lybbert et al. (2004)).

[10]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}.

Figure 2: Probability of Collapse to a Low Level Equilibrium



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 reflect the fact that severe shocks, or even minor shocks, can have permanent consequences in this model. While the high value of future assets shown in Figure 1 will lead vulnerable agents to depress consumption and asset smooth to stay above A_N^M (see Carter and Lybbert (2012)), this is of course not possible if the shock itself pushes assets too far below this critical tipping point.

3 Insurance, Insurance Demand and Investment

The numerical simulation of the baseline model reveals the fundamental role that risk plays in driving chronic poverty. In this context, it would seem that asset insurance could play an important role in altering long-term poverty dynamics. As described above, insurance potentially reduces chronic poverty through a vulnerability reduction effect as well as through an investment incentive effect. The latter can be especially important if the presence of an insurance market alters the accumulation strategy of poor households, shifting the Micawber Threshold to a lower asset level. In this section, we explore the impact of insurance markets on chronic poverty.

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. Specifically, the insurance will cover only asset losses driven by covariant shocks. Initially, we consider a scenario in which the insured household pays the full cost of the insurance. In this way, we consider insurance as a privately provisioned "social protection" scheme. We later relax this assumption and assess the logic of public-private co-funding of asset insurance.

3.1 Extending the Baseline Model to Include Asset Insurance

This section modifies the model of Section 2.1 by giving the households the option to purchase asset insurance. If the household wants insurance, it must pay a premium equal to the price of insurance, p, times the number of asset units insured at time t,

I_t. We assume that the units of assets insured cannot exceed current asset holdings.[11]

In modeling the impact of asset insurance, we focus exclusively on index contracts designed to issue payouts based on the realization of the covariant, but not the idiosyncratic shock to assets.[12] To simplify notation, we assume that the covariant shock is observed directly without error and can function as the index that triggers payments. We denote $s \geq 0$ as the strike point or index level at which insurance payments begin. Assuming a linear payout function, indemnities, δ, are given by:

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

Note that $s$is the deductible since it denotes the level of stochastic asset losses not covered by the insurance (numerically, we assume $s = 15\%$). Under this specification, the insurance fully indemnifies all losses (driven by covariant events) beyond the deductible level.

The obvious weakness of this type of insurance is that it offers the insured only partial coverage of stochastic asset losses.[13] While individual loss insurance, in which payouts were calibrated to individual losses $(\theta_t + \varepsilon_{it})$, would offer complete insurance coverage, the history of individual indemnity contracts applied to low wealth and isolated rural populations, such as those of interest here, is that they are economically infeasible (Hazell (2006); Barnett, Barrett, and Skees (2008)). Conventional insurance relies on loss verification to control moral hazard. Unfortunately, for a low wealth, remote household (with modest assets to insure), a single loss verification can consume multiple years of actuarially fair premiums, rendering this kind of insurance economically infeasible. Similarly, individual-specific loss rating is non-economic for small contracts, exposing conventional insurance schemes to adverse selection. 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 is independent of the characteristics of those who choose to purchase insurance.

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

[12]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).

[13]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.

The household dynamic optimization problem with a market for insurance is now to choose consumption and a level of insurance which maximizes intertemporal utility:

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

subject to:

$$\begin{aligned} & c_t + pI_t \le A_t + f(A_t) \\ & f(A_t) = \max[F^h(A_t), F^l(A_t)] \\ & A_{t+1} = (A_t + f(A_t) - c_t)\,(1 - \theta_{t+1} - \varepsilon_{t+1}) + (\delta(\theta_{t+1}) - p)I_t \\ & \delta(\theta_{t+1}) = max\;((\theta_{t+1} - s),\ 0) \\ & A_t \ge 0 \end{aligned} \tag{5}$$

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

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

with 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 will only differ from the analogue to condition 3 for the autarky model, if 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. Returning to Figure 1, we see that the availability of unsubsidized insurance (assuming a 20% markup) marginally enhances the future value of assets. The second dashed line in the figure 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 substantially enhances the future value of assets, particularly for households holding assets near A_N^M.

Noting that the insurance price, p, is non-stochastic, the second first order condition can be rewritten as:

$$\mathbb{E}_{\theta,\varepsilon}[V_I'(A_{t+1})\delta(\theta)] = p\lambda(A_{t+1}), \tag{9}$$

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[14] under the credit constraints that define this model. The right hand side is thus the effective costs of insurance, the premium marked up by the shadow price of liquidity. Noting that $\delta(\theta) = 0, \forall\theta < s$, the left hand side can be rewritten as:

$$\Pr(\theta \;\; > \;\; s)\, \mathbb{E}_{\theta,\varepsilon}\left[V_I'(A_{t+1})(\delta(\theta))|\, \theta > s\right] \tag{10}$$

and is just the expected benefit of the insurance, which in bad covariant states of the world adds to the household's asset stock. First order condition 9 thus simply says that the expected marginal dynamic benefits of insurance are set equal to its effective marginal cost. Insurance payouts ($\delta(\theta)$) are valued by the derivative of the value function V_I. Note that 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. However, if idiosyncratic shocks, which are not covered by the insurance, are important, then the right hand side of 9 can also be large as large asset losses can occur without triggering a compensatory insurance payment.

Combining first order conditions, dynamically optimal choice by the household will fulfill the following conditions:

$$u'(c_t) = \beta \frac{\mathbb{E}_{\theta,\varepsilon}\left[V_I'(A_{t+1})\delta(\theta)\right]}{p} = \lambda(A_{t+1}). \tag{11}$$

In other words, the per-dollar marginal values of both consumption and insurance are set equal to the opportunity cost of foregone asset accumulation. Note that an asset shock that reduces A_{t+1} will increase the shadow price of liquidity, especially around the Micawber threshold, implying changes in both consumption and insurance demand.

It is of course this shock-induced increase in the shadow price of liquidity that can lead households to sharply reduce consumption and asset smooth in the wake of a shock. The impact on insurance demand is, however less transparent. While an asset shock raises the shadow price of liquidity, it may also increase 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 Demand for Asset Insurance

It is not immediately clear from the theoretical model whether vulnerable households will purchase asset insurance. Optimal choice depends largely on the insurance con-

[14] 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.

tract they are presented with, and the shadow price of liquidity. To answer the question of whether market-based social protection can reach vulnerable households, we return to numerical methods to solve a dynamic stochastic model. In addition to the parameters used to analyze the autarky case, we need to make some assumptions about the pricing of the insurance. In the analysis to follow, we assume that the market price of the insurance is 120% of the actuarially fair value. We then present policy functions assuming two different prices: the market price and a subsidized price (50% of 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 $[(i(\theta_t) - \theta_t) + \varepsilon_t])$ is quite small.[15]

Under these assumptions, Figure 3 plots the 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 equilibrium insure 80% 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 the Micawber Threshold. While insurance uptake increases as assets move beyond that critical threshold, even highly vulnerable households (with between 11 and 15 asset units) choose to insure less than half of their asset holdings.

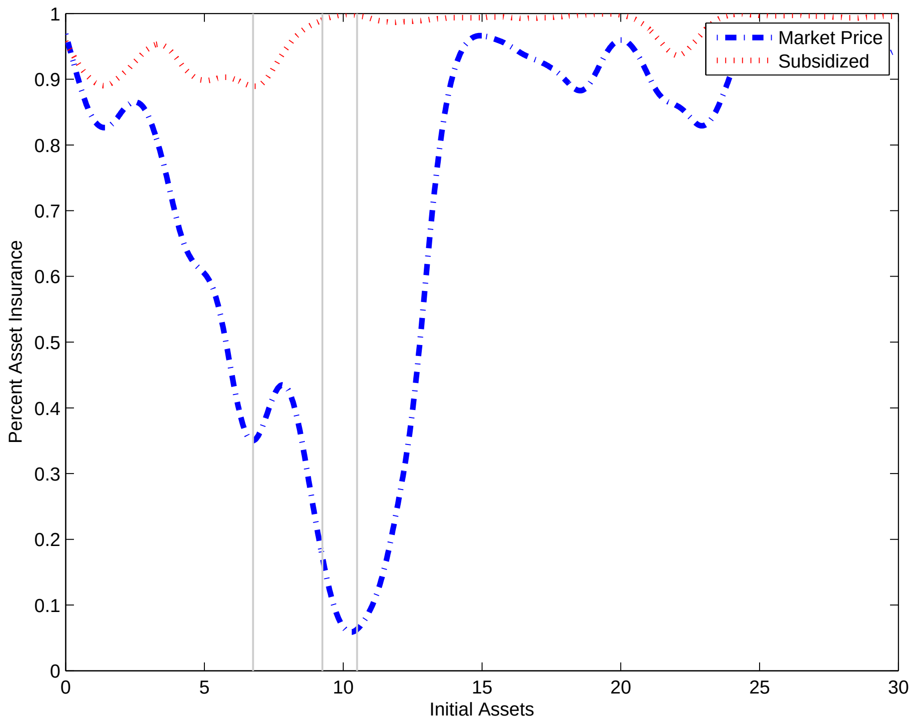
At first glance, this finding seems counterintuitive given that households in the neighborhood of the threshold are most at risk of collapse to the low equilibrium and would seem to have the most to gain from insurance. While this intuition is correct, it overlooks the fact that the effective cost of insurance $(p\lambda(A_{t+1}))$ is also highest in this same neighborhood. Indeed, insurance can actually increase λ by increasing the security and hence future value of asset stocks. Returning to Figure 1, we see that under our numerical parametrization, the availability of insurance indeed increases the shadow price of liquidity, especially in the neighborhood of A_N^M.

We thus see an irony of asset insurance, understood as a potential option for privately provided social protection. The benefit of insurance is highest for the most vulnerable households in the neighborhood of A_N^M; these households have the most to gain from protection of this kind, because protection offers dynamic path-altering benefits. But the opportunity cost of insurance is also highest for these same vulnerable households who are faced with a binding liquidity constraint.[16]

[15] As basis risk increases, demand for insurance across the asset spectrum will decrease.

[16] The cost of basis risk is 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,

Figure 3: Insurance Policy Function



This observation does not, however, mean that vulnerable households fail to benefit from the presence of the insurance market. Indeed, the demand pattern displayed in Figure 3 implies that a highly vulnerable household will shift its behavior and fully insure its assets if it succeeds in acquiring additional assets. Furthermore, insurance demand by this vulnerable population, it 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, further indicating that lack of demand by these households does not reflect lack of insurance value, but instead the high shadow price of insurance.

Finally, note that the first order conditions (Equation 11) imply that an increase in the shadow price of liquidity will reduce immediate household consumption. If these household consume less, but do 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 Impact of an Insurance Market on Investment

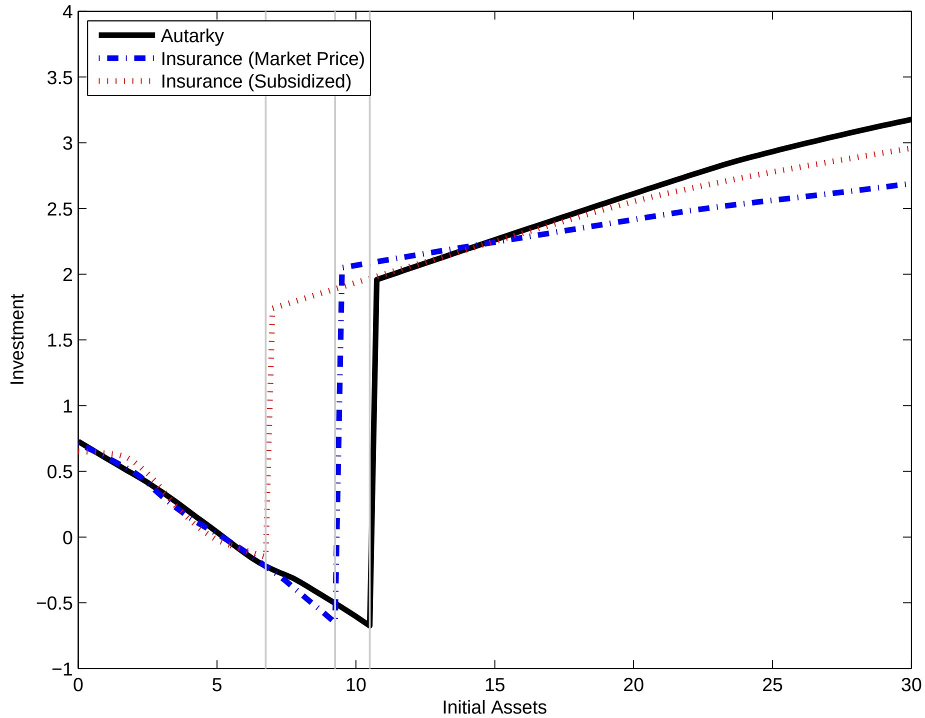
As noted above, Figure 1 reveals that the opportunity cost of future assets in the presence of an insurance market, $V_I'(A_{t+1})$, increases relative to the autarkic opportunity cost, $V_A'(A_{t+1})$, especially around the Micawber threshold. This shift implies that an asset carried into the future 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.

To explore these investment effects, Figure 4 shows the optimal investment policy function under autarky and when insurance can be purchased. First note that under either regime, the Micawber threshold is clearly visible in the sharp discontinuity in behavior. Under autarky this discontinuity is around 11 asset units. Absent an insurance market, households below A_N^M divest assets, instead enjoying greater consumption today, and move toward the low welfare equilibrium. Alternatively, households above A_N^M invest substantially, giving up contemporaneous consumption in the hopes of reaching the high welfare equilibrium.

Comparing now the investment policy function with and without an insurance market, we see three important changes that become increasingly pronounced as the price of insurance falls. First, for wealthier households with more than about 15 asset units, the insurance market actually reduces investment. In the context of a livestock economy, this corresponds to the observation that households overinvest

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.

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



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.[17] From a policy perspective, this negative impact on investment by the wealthiest households is important and matches the theoretical result reported in de Nicola (f2015) who models the introduction of insurance in a model without a poverty trap.

Second, for households at the original point of bifurcation, A_N^M, we see that optimal investment increases. At the market price this behavior implies a reduction of consumption without any purchase of insurance. This increase is more pronounced (and matters to more households) when insurance is subsidized as households further decrease consumption while using cash on hand to also purchase insurance. This suggests that the presence of an insurance market induces threshold households to take on more risk than they would in the absence of market intervention, by increasing investment.[18]

Third, the introduction of the insurance market (especially a subsidized insurance market) actually shifts the bifurcation point, or Micawber threshold, to the left. We denote the new point of bifurcation as A_I^M (where A_I^M also depends on the price of insurance). This shift is minor when insurance is unsubsidized, but becomes quite large (shifting by approximately six asset units) with the subsidy, a point discussed further in Section 4.2 below. 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 and, with probability one, head to the low equilibrium. With an insurance market, they begin to invest sharply, with investment increasing by almost two units from initial disinvestment. Note that this fundamental shift in behavior does not guarantee that these newly investing households will ultimately achieve the high equilibrium, but as will be discussed in the next section, their outlook for the future changes fundamentally.

In summary, the introduction of an insurance market induces some of the most vulnerable households to invest more.[19] Interestingly, as shown in the previous section, 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. These households exhibit a time-varying insurance strategy.

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

[18]As households become more risk averse, this behavioral response to insurance is weakened.

[19]This finding is sensitive to the discount rate. As the discount rate falls, households discount their future more heavily, and the impact on current behavior is reduced. More generally, households across the asset spectrum will insure less as the discount rate falls because the marginal benefit of preserving assets for the future declines.

4 The Impact of an Insurance Market on Poverty Dynamics

The analysis in the prior sections offers important clues into the likely longer term impacts of an insurance market on the dynamics of chronic poverty and vulnerability. As shown in Figure 2, the presence of an insurance market, even without subsidy, substantially reduces the probability of collapse to the low equilibrium for households with assets in excess of A_N^M. This reduction underlies the vulnerability reduction effect of asset insurance markets.

In addition, the presence of an insurance market shifts the Micawber threshold to the left. When insurance is subsidized, that shift is somewhat substantial, decreasing to A_S^M, where the S subscript denotes insurance (or from about 11 to 7 asset units under our numerical specification). As shown by the investment policy function in Figure 4, the investment response of households between the two thresholds is quite substantial, reflecting what the investment incentive effect. When insurance is not subsidized, the shift of the Micawber threshold is much less substantial (to about 9 asset units).

Without an insurance market, households with assets below A_N^M become chronically poor with probability 1. It is not dynamically rational for these households to reduce consumption, invest, and attempt to move to the high equilibrium. When insurance is available but not subsidized, some households just below A_N^M begin to invest heavily and face roughly a 80% chance of escaping chronic poverty and reaching the high equilibrium (see Figure 2). These are dramatically improved, if still not great, expectations. 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 equilibrium with near certainty. Note 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.[20]

While these insights speak to how an insurance market affects individuals occupying different asset positions, they do not by themselves say anything about how insurance markets impact overall poverty dynamics. These aggregate impacts will of course depend on the initial distribution of the population across these different

[20] The existance of an insurance market does boost 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.

asset positions. We turn now to consider these aggregate impacts for a stylized rural economy.

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 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 the appendix, and households behave optimally in accordance with the dynamic choice models laid out in Sections 2.1 and 3 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. We examine both a consumption-based poverty measure and an asset-based measure. An individual is consumption poor if their chosen consumption is at or below the level of consumption that is obtainable for a household with 10 units of asset.[22] We characterize an individual as asset-poor only if they have fewer than 10 asset units. The difference between the consumption and income-based measures sheds light on households' decisions to consume, invest and, or purchase insurance.

The four plots in Figure 5 display the consumption and income-based poverty dynamics for a village economy that begins with a uniform asset distribution. In each plot, the solid (black) line is the average outcome across simulated histories in the baseline (no insurance) scenario, the dash-dot (blue) line shows the measures when an insurance market exists, and dotted (red) line is the measure when subsidized asset insurance contracts are available. For shorthand, we refer to the case in which insurance markets do not exist as "autarky," as households must autarchically manage the risks they face by accumulating assets.

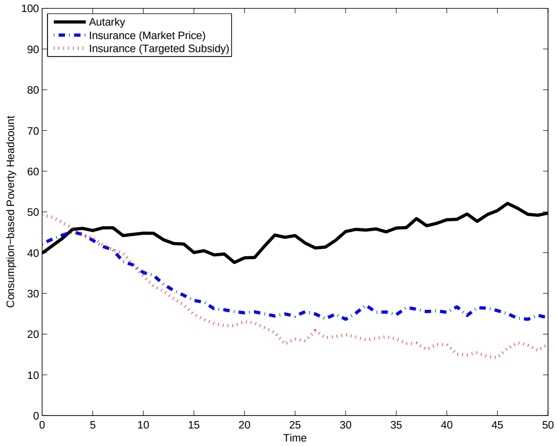
The contrast between the consumption- and asset-based poverty measures is instructive. Initially under autarky, approximately 20% of the population is asset-poor, while the consumption-based poverty measures are double that level. This difference reflects the accumulation decisions of vulnerable households. Those households lo-

[21]Numerically, we assume that agents are uniformly distributed along the range of zero to forty units of wealth.

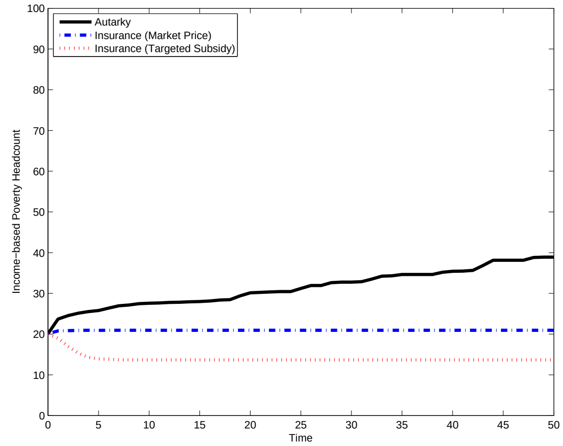
[22]In making these consumption choices, we will later assume that poor households receive cash transfer payments, but we assume these payments will be unanticipated.

Figure 5: Poverty Dynamics

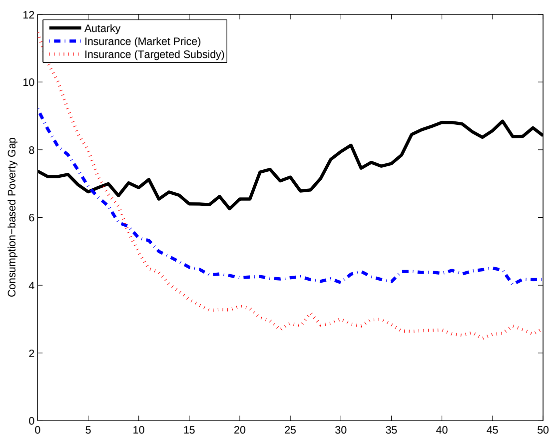
(a) Consumption Poverty Headcount



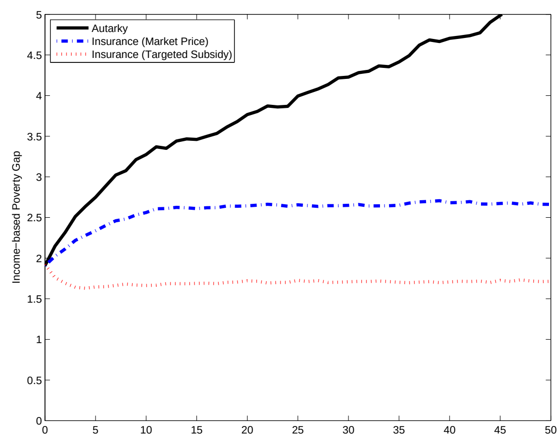
(b) Asseet Poverty Headcount



(c) Consumption Poverty Gap



(d) Asset Poverty Gap



cated in the neighborhood just above the Micawber threshold 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 equilibrium or they collapse into indigence around the low level equilibrium. After 50 years of simulated history, the poverty headcount under autarky settles down to approximately 40% to 50% of the population.

The contrast between these autarky poverty dynamics and the dynamics that emerge when subsidized asset insurance is available stands out clearly in Figure 5. In the spirit of government-provisioned social protection, we specifically 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.

Under this targeted insurance subsidy scheme, there is an initial uptick in consumption poverty from 40% to 50% in the presence of an asset insurance market. However, over the longer-term, consumption poverty falls to about 15% of the population, as opposed to the 50% level that occurs when there is no insurance market. This long-term drop in consumption poverty when insurance is available and subsidized reflects the fact that a significant fraction of the vulnerable ultimately escape the poverty trap. In contrast, without insurance, more of these vulnerable households fail and swell the ranks of the income poor. When an asset insurance market simply exists, but contracts are not subsidized, the impacts on poverty dynamics are qualitatively similar to the impacts of subsidized insurance, but quantitatively, the impacts are roughly two-thirds the magnitude of the impacts of subsidized insurance. The difference is driven primarily by the larger shift in the Micawber Threshold when insurance is subsidized.

A closer look at the time path of the consumption-based poverty measures reveals additional insights into the impact of insurance markets in this economy. As can be seen, when insurance is subsidized both the headcount and poverty gap measures are higher for the first 5 to 10 years of simulated history than they are under autarky. These higher poverty levels reflect the interplay between two forces. First, as shown in Figure 2, the presence of an insurance markets lowers the Micawber threshold, meaning that households between A_N^M and A_S^M (*i.e.*, those initially holding between 7 and 11 assets) now try to accumulate and move toward the upper equilibrium. Doing so, lowers their consumption relative to what it would have been had they been on a path of deaccumulation approaching the lower equilibrium. While these households are not asset poor, their accumulation (and insurance purchase decisions) render them consumption poor.

Second, when insurance markets exist, a number of vulnerable households whose initial assets place them above the initial Micawber threshold, A_N^M, purchase insurance, reducing the funds they have for both consumption and investment, as noted by Chantarat et al. (2010) and Kovacevic and Pflug (2011). However, in strong contrast to the findings of these authors, the availability of insurance–when optimally managed–halves long-term poverty rates compared to the autarky world, as shown by Figure 5.

Some of these same forces apply to the case when insurance is not subsidized. However, the effects are moderated as non-subsidized insurance has a much smaller impact on the Micawber threshold relative to subsidized insurance (see Figure 2 above).

Summarizing these observations, when insurance is subsidized, it more than halves the long-term extent and depth of poverty. These impacts come from both the vulnerability reduction and investment incentive effects. When insurance is not subsidized, but contracts are simply made available at a market price (assumed to be 20% above the actuarially fair price), the impacts on long-term poverty remain strong, but are more driven by the vulnerability reduction effect.[23]

The results presented in this section stem from our assumptions regarding the initial asset distribution of the population. The impacts on poverty dynamics revealed by Figure 5 occur because access to insurance markets alters the fate of vulnerable households around the Micawber threshold. The impact would be even larger if more households were vulnerable to becoming chronically poor. Alternatively, 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, as would be expected.[24]

4.2 Subsidies and Social Protection

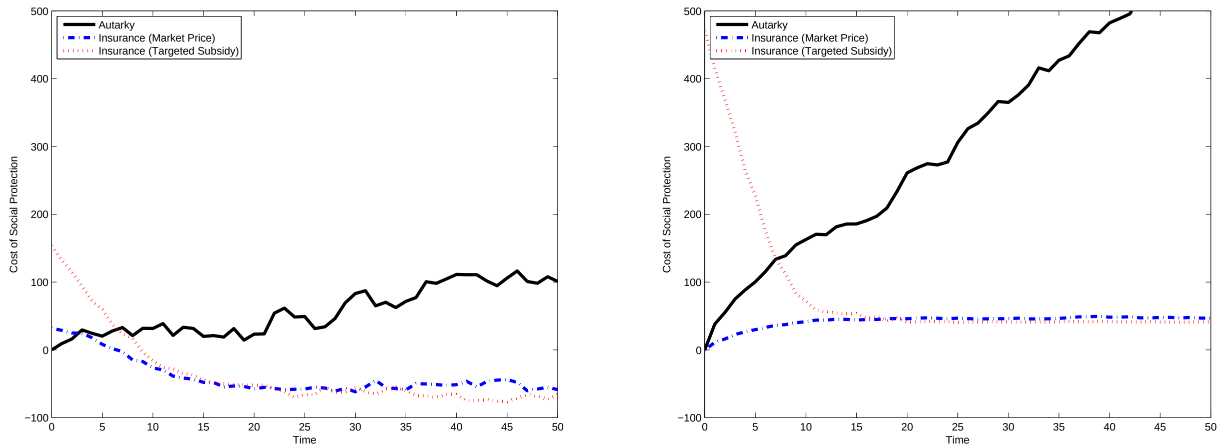
As shown in the prior section, an asset insurance market with targeted premium subsidies can, for some asset distributions, radically alter poverty dynamics. While insurance subsidies are not cheap, neither is it cheap to let the ranks of the indigent

[23]In addition to these effects on average outcomes, insurance markets 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% or higher than its mean level. However, with subsidized insurance, there are only small variation across histories. In other words, poverty dynamics are much more stable across replications, revealing that the availability of insurance protects households against atypical sequences in which multiple bad years occur in succession.

[24]In results available from the authors, we simulate poverty dynamics under an initially bi-modal distribution in which the middle ranges of the asset distribution are sparsely populated.

Figure 6: The Cost of Social Protection

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



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 using the stylized economy examined in section 4.1. 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 line while Figure 6b uses the alternative asset-based poverty line.

As Figure 6a shows, the cost of providing these (unanticipated) cash transfers under autarky increase over the simulation period by about 40% when they are consumption-targeted. Starting from a much lower absolute level, the cost of income-targeted cash transfers increase 400% over the 50 years of the simulation. At year 50, the absolute social protection costs are nearly the same under both income- and consumption-targeting.

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 (all households with less than ***15*** asset units receive a 50% discount on the cost of the insurance). The red dotted lines in Figures 6a and 6b show these costs, and reveal an intertemporal tradeoff. The cost of transfers cum insurance subsidies is initially quite high, but after 8 years total social protection costs become lower than they are under the scheme that only provides cash transfers. Achieving the lower long-term poverty measures afforded by insurance subsidies costs more money in the short-term, but leads to substantial long term savings. Using a 5% discount rate the net present value of the two public expenditure streams over the 50 year time horizon of the simulation are 16% lower under the targeted subsidy scheme.[25] 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.

Finally, Figure 6 also includes the budget implied if an asset insurance market exists, but contracts are not subsidized for poorer households (the blue dash-dot line). In this case, the only costs incurred by the public sector are those associated with the cost of the cash transfers. While this policy only achieves roughly two thirds the long-term poverty reduction of subsidized insurance, it avoids the large up-front costs associated with the insurance subsidies. This policy has the lowest discounted present value of all the social protection schemes considered here (roughly half the present discounted value of the cash transfers required absent an insurance market).

5 Conclusion

A growing literature on poverty traps suggests that we need to think carefully about the ways in which market failures, risk and asset thresholds (or tipping points) interact. When such a threshold exists, risk and vulnerability play a key role because realized shocks can have permanent consequences. In addition, the anticipation of those shocks further discourages investment that might permit an escape from poverty, further increasing long-term poverty rates.

Despite these observations, there has been relatively little work to date on the implications of poverty trap mechanisms for the design of social protection schemes. An exception is the work of Barrett, Carter, and Ikegami (2013) who consider the impacts of precisely targeting conditional social transfers to those in the neighborhood of the 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

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

contingent payments and whether self-selection into the purchase of those contracts can be used to solve the targeting problem.

Using numerical dynamic programming methods, we find that the simple existence of insurance markets (and individual self-selection into the purchase of insurance) can achieve many of the putative benefits of conditional, threshold-targeted social transfers. Indeed, over the course of our dynamic simulation, the presence of an insurance market radically reduces the discounted present value of public expenditures on cash transfers to the indigent.

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. Dynamic simulation shows that an insurance subsidy makes insurance a much more effective poverty reduction mechanism. By lowering the price of insurance, subsidies nudge vulnerable households into purchasing, and cuts the extent and depth of long-term poverty to less than half the level that emerges in the no insurance case. The public cost of this program (insurance subsidies to vulnerable and indigent households, plus cash transfer payments to all indigent households) is higher in early years of the dynamic simulation, but then drops off in later years. The discounted present value of all the public funds expended (on transfers to the indigent and on insurance subsidies) is lower under the insurance subsidy scheme and the traditional cash transfer scheme and achieves much lower rates and depths of chronic poverty.

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. However, our 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.

While perhaps striking, our results ultimately emanate from a model which assumes standard economic rationality and full understanding and trust in insurance. The strength of the reported results also depends on the initial asset distribution. If few households are found in the areas of extreme vulnerability, then the impacts of insurance on long-term poverty are less. That said, as climate becomes more highly variable, the range of vulnerability expands. As more countries struggle with the poverty implications of climate change, the theory here suggests there may be much to gain from using a mixed provisioning model of social protection, with the state transfer resources to the neediest but using a mixed public-private funding model to provide risk management tools to vulnerable households.

Appendix: Calibration

The model used in this analysis was designed to reflect the observed asset dynamics of the northern Kenyan arid and semi arid lands (ASALs), where a drought index-based livestock insurance (IBLI) contract was recently introduced. With this setting in mind, 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 from this region. We use the results of Lybbert et al. (2004) and Santos and Barrett (2011) as our benchmark. 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.

Specifically, we consider a population with identical preferences and access to a single asset-based production technology. 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 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).

In the model, we assume that risk primarily takes the form of covariate shocks. This reflects the risky environment that pastoralists find themselves in, where the vast majority of households report drought to be their primary risk. In order to establish a vector of covariate shocks (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. 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.

The actuarially fair premium 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. Parameters for the utility function (ρ and β) are homogeneous across the population, and specified using plausible values known from economic theory.

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

The specific functional forms and parameters used to solve the dynamic programming problem are reported in Table 1. The policy functions derived obviously depend on the parameters used in the simulations. Although these parameters are loosely calibrated to fit observed values from northern Kenya, we do not seek to make a direct prescription of household behavior in northern Kenya. Rather, we know that a household's decision to purchase insurance will depend on members' time discount rates, personal attitudes toward risk, perceptions regarding drought risk, and their perceived level and understanding of basis risk[26]. In addition, heterogeneous households likely have access to varied production technologies, further complicating the problem.

To evaluate the impact on poverty dynamics requires further assumptions. Rather than draw on an empirically observed asset distribution (that might lead one to think we are trying to predict poverty dynamics in this specific context), we chose to compare two contrasting scenarios that highlight the importance of the specific setting in which insurance is being introduced. In the analysis presented in the paper we consider a uniform asset distribution. An initially bimodal asset distribution was also considered. Those results are available from the authors upon request.

The work presented here is intended as a theoretical contribution which more broadly contributes to our understanding of insurance in the presence of poverty traps. This type of model, with a kinked production technology, is admittedly sensitive to the specified parameters. However, this assumption of a kinked production technology is grounded in both the theoretical and empirical literature of poverty traps, such that the analysis seems to be of great value, despite its sensitivity to the specified parameters.

[26]Jensen, Mude, and Barrett (2014) provide an empirical demand analysis that considers these factors in this setting

Table 1: Functional Forms and Parameters used in Numerical Simulations

Production Technology and Parameters
$F^h(H) = \alpha H_t^{\gamma_L} + \underline{f}$ $F^l(H) = \alpha H_t^{\gamma_H}$ $\gamma_L = 0.28$ $\gamma_H = 0.56$ $\underline{f} = 2.95$ $\alpha = 1.33$
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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