Can Insurance Markets Alter Poverty Dynamics and Reduce the Cost of Social Protection in Risk-prone Regions of Developing Countries?

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Abstract

This paper develops a dynamic theoretical model to assess the impact of asset insurance markets on intertemporal choice, poverty and the cost of social protection in risk-prone regions of the developing world. We analyze the model under two different assumptions about technology: a standard, globally concave production technology, and a fixed cost technology that creates a non-convex production set and a multiple equilibrium poverty trap. Under both technology assumptions, the introduction of an asset insurance market substantially reduces poverty, and the costs of the cash transfer required to close the poverty gap for all poor households. In the poverty trap world, there is a further public finance case for insurance subsidies targeted at vulnerable households. While the real world challenges of microinsurance are multiple, the analysis here suggests that the gains to solving those challenges are substantial.

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Can Insurance Markets Alter Poverty Dynamics and Reduce the Cost of Social Protection in Risk-prone Regions of Developing Countries?

Climate risk and poverty are deeply intertwined in many rural areas of the developing world. Realized shocks can make people poor, and the risk of future shocks can keep people poor by discouraging investment in assets and activities that would, on average, improve incomes. Policy response to climate shocks often takes the form of humanitarian assistance, typically funded by emergency appeals to the international community. More recently, countries like Ethiopia and Kenya have augmented “regular” emergency aid appeals in their risk-prone regions with systematic cash transfers targeted at populations already driven into poverty. However, similar to emergency aid appeals, cash transfers targeted at the already poor are an *ex post* response to shocks and may do little to address the root causes of systemic poverty and promote resilience.

In this context, this paper asks what role insurance markets might play in altering poverty dynamics and reducing the cost of social protection in risk-prone rural regions. Recent contributions by Clarke and Dercon (2016) and de Janvry, del Valle, and Sadoulet (2017) argue that insurance contracts can be used to pre-finance response to sudden onset disasters, assuring more rapid and effective social protection. The goal of this paper is to complement the more macro perspective of this other work with a micro-theoretic perspective on the impact of asset insurance markets on poverty dynamics. Our analysis highlights three relevant characteristics of insurance:

- It offers protection to the vulnerable, not just the already poor; and, by breaking the descent of the vulnerable into poverty, insurance can create a *vulnerability reduction* effect.

- It enhances investment incentives for both poor and vulnerable households, potentially creating an upward mobility or *investment incentive* effect.

- It can be offered on a partial subsidy, encouraging households to pre-finance a portion of the costs of social protection.

Together, these observations raise the possibility that insurance may not only make social protection more timely as Clarke and Dercon (2016) and de Janvry, del Valle, and Sadoulet (2017) argue, but it may also reduce its total cost if insurance can alter poverty dynamics.

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1Ethiopia instituted the Productive Safety Net Program (PSNP) program in xxxx, while Kenya introduced the Hunger Safety Net Program (HNSP) in 2009.
To explore these ideas, we extend an inter-temporal optimization model of consumption and investment in the face of credit constraints and risk to include the option of purchasing an asset insurance that pays off in bad states of the world. We approach the model analytically and using dynamic stochastic programming methods to study the impacts of a competitive asset insurance market on long-term poverty dynamics and the costs of social protection. Using parameters calibrated on the risk-prone pastoralist regions of the horn of Africa, we analyze the model under two alternative specifications about the nature of the asset-using production technology: one which admits multiple stochastic steady states, and one which does not.

Under the first specification, we assume that there is a fixed cost attached to employing a higher return production technique that offers an escape from poverty. Those who choose not to pay the fixed cost employ a lower return technology. Under this specification, optimal behavior can bifurcate with respect to wealth, and an asset-based poverty trap can emerge when insurance markets do not exist. Adding an insurance market to the inter-temporal household optimization problem for this model reveals a highly non-linear demand for insurance, with demand dropping sharply as assets increase to the level where the poverty trap tipping point occurs, and then recovering at higher asset levels ‘safely’ beyond the tipping point. Insurance demand is highly price elastic in the neighborhood of this tipping point. To analyze the impact of asset insurance market on poverty dynamics and the cost of social protection, we then use the model to conduct a 50-year simulation analysis for a stylized community of heterogeneously endowed households. Relative to the autarchy case with no insurance, we find that 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 effects that change behavior of households in the vicinity of the tipping point. The presence of an unsubsidized asset insurance market halves the cost of social protection (defined as the present value of the transfers needed to close the poverty gap for all poor households). Insurance subsidies, which further reduce the depth and extent of poverty over the long run also reduce the total cost of social protection, though less dramatically so once the costs of the insurance subsidies are added into the cost of social protection.

We then reanalyze the model, eliminating the fixed cost associated with using the higher return technology. Under this specification, no poverty trap exists and in the long run only transitory poverty exists as all households strive to reach the non-poor equilibrium. In this environment, the presence of an asset insurance market again substantially reduces the cost of social protection, primarily operating through
a vulnerability reduction effect. Insurance subsidies play a more modest role under this specification as the optimal demand for unsubsidized insurance is uniformly high for all households, irrespective of their asset holdings.

This paper is organized as follows. Section 1 situates are work in debates about the design of social protection policies. Section 2 first presents our alternative assumptions about the nature of production technologies and the core dynamic stochastic model. Adopting the fixed cost technology specification, this section goes on to use analytical and numerical dynamic programming methods to study the evolution of poverty without insurance markets. Section 3 incorporates insurance markets into the dynamic model and presents our decomposition of the vulnerability reduction and investment incentive effects of insurance. The aggregate impact of these effects on poverty dynamics and the costs of social protection are evaluated for a stylized economy in Section 4. In Section 5, we return to the assumption of a globally concave technology and reconsider the effects of insurance in this world where all poverty is ultimately transitory. Section 6 concludes with reflections on the implications of these theoretical findings for the real world in which the design and implementation of microinsurance is a non-trivial exercise.

1 The Social Protection Paradox

Governments in many developing countries address poverty using cash transfer programs. While initially the domain of middle-income developing countries, both Kenya and Ethiopia launched cash transfer programs in their most risk-prone regions in an effort to replace annual “emergency” food aid requests with a more regularized and reliable form of social protection. Launched in 2009, Kenya’s cash transfer program (the Hunger Safety Net Program, or HSNP) had hoped to put households on a pathway out of poverty by enabling asset accumulation and sustained investment in child health and education so as to avert future poverty (Hurrell and Sabates-Wheeler (2013)). While there is evidence that cash programs may diminish poverty inter-generationally through the human capital development of children (see reviews by Rawlings and Rubio, 2005, Baird et al., 2014 and Fiszbein et al., 2009), there is much less evidence that cash transfers offer a pathway out of poverty in the medium term. Indeed, the eligibility requirements of these programs may, if anything, dis-
courage efforts by beneficiaries to build assets and boost income. In addition, as an *ex post* palliative for those who have already fallen into poverty, cash transfer programs do not address the underlying dynamics that generate poverty 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.

The starting point for this exploration is the social protection paradox that emerges in the analysis of Ikegami et al. (2018) who compare 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 who have been hit by shocks. The authors find that under a fixed social protection budget, the welfare of the poorest will be higher in the medium term under the 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 and exhaust the fixed social protection budget. In their model, vulnerability-targeted aid also has a behavioral effect by crowding in asset accumulation and upward mobility by those who would otherwise stay in the poverty trap that emerges in their model. However, in the short-term, the prioritization of the vulnerable over the poor causes an increase in poverty.

The vulnerability-targeted policy considered by Ikegami et al. (2018) 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 very strong informational assumption that the government can observe shocks and precisely target contingent transfers to the vulnerable. 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 Ikegami et al. (2018) 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. (2018), might be avoided.

Two related papers, Chantarat et al. (2017) and Kovacevic and Pflug (2011), have also analyzed the workings of insurance in the presence of poverty traps. Unlike this paper, Chantarat et al. (2017) and Kovacevic and Pflug (2011) ask what happens impacts of cash transfers on earned income are when cash transfers are paired with ancillary business development programs targeted at cash transfer recipients.
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 a 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 favorably alters poverty dynamics and ultimately reduces the inter-temporal cost of social protection.

2 Asset Accumulation and Poverty under Financial Autarky

This section establishes a baseline, single asset model of poverty dynamics in the presence of risk, but in the absence of insurance or access to other financial markets. After discussing the relevance of considering alternative specifications of the production technology (one with non-convexities in the production set and the other without), we lay out the basic intertemporal model of consumption and accumulation in the face of risk. The remainder of this section then focuses on the more complex case of a non-convex technology. 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 this baseline 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. We revisit the implications of the model with a purely concave production set in Section 5 below.

2.1 Production Technologies

In our analysis of poverty dynamics and insurance, we focus on an economy in which households can accumulate a single asset that produces a flow of income and also can be liquidated and used to support consumption in time of need. This single asset economy mirrors the reality of the pastoralists regions that motivate this study where livestock is both the major productive asset and store of wealth for households (see McPeak; McPeak and Barrett). In the dynamic analysis to follow, we write the production set as:

\[ F(A_t) = \max[f^H(A_t), f^L(A_t)] \]
where $A_t$ are assets held at time $t$ and $f^H(A_t)$ and $f^L(A_t)$ are respectively a high returning and low returning concave technologies. If there are no fixed costs associated with the adoption of $f^H(A_t)$, then $f^H(A_t) > f^L(A_t) \forall A$ and the production set becomes $F(A_t) = f^H(A_t)$ and is concave. If there are fixed costs, then $f^H(A_t)$ exceeds $f^L(A_t)$ only if assets exceed some minimum level (which we denote here as $\hat{A}$) and the production set $F(A_t)$ is non-convex.

Going back to Skiba (1978), a number of studies have shown that a non-convex production set can generate multiple equilibria and what Barrett and Carter, 2013 call a multiple equilibrium poverty trap (see Buera (2009); Capra et al., 2009; Dercon, 1998; Dercon and Christiaensen, 2011; Ghatak, 2015). Although broad-based empirical evidence of poverty traps has been mixed (Kraay and McKenzie, 2014; Subramanian and Deaton, 1996), Kraay and McKenzie (2014) conclude that the evidence for the existence of poverty traps is strongest in rural remote regions like the arid and semi-arid lands of East Africa that motivate our work.3

In the analysis to follow, we will analyze the impact of insurance on poverty dynamics and the cost of social protection with and without non-convexities in the production set. We will begin our analysis with the non-convex case as it exhibits greater complexity and a richer set of implications. Once those implications are established, results under the case of a purely concave technology is straightforward.

2.2 Intertemporal Choice Model Absent Insurance Markets

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:

3In these risk-prone regions, there is evidence that adoption of more productive herd management strategies are subject to the kind of substantial fixed costs that generate a non-convex production set. As discussed by Toth (2015), seasonal migration allows pastoralists to obtain higher returns from their herds than a sedentary strategy. However, in any given year, the fixed costs of moving and protecting a herd make the high returning technology preferred only by households with assets above some minimum level. While the presence of this fixed cost, does not by itself preclude households from building up assets and eventually crossing the technology switch point line, Toth (2015) suggests that their presence underlies the empirical evidence of poverty traps in the livestock-based economies of East Africa’s arid and semi-arid pastoralist regions. Lybbert et al. (2004) and Barrett et al. (2006) estimate 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, poverty trap equilibrium.
\[
\max_{c_t} \quad \mathbb{E}_{\theta, \varepsilon} \sum_{t=0}^{\infty} u(c_t)
\]
subject to:
\[
c_t \leq A_t + f(A_t) \\
F(A_t) = \max[f^H(A_t), f^L(A_t)] \\
A_{t+1} = (A_t + F(A_t) - c_t)(1 - \theta_{t+1} - \varepsilon_{t+1}) \\
A_t \geq 0
\] (1)

The first constraint restricts current consumption to cash on hand (current assets plus income). The second is the production set discussed above. 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 \( \theta_{t+1} \) is the same for all households in a given period, but idiosyncratic shock \( \varepsilon_{t+1} \) 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.\(^4\) 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 for 1 is:
\[
V_N(A_t) = \max_{c_t} \quad u(c_t) + \beta \mathbb{E}_{\theta, \varepsilon}[V_N(A_{t+1}|c_t, A_t)]
\] (2)

\(^4\)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 \( \theta \) and \( \varepsilon \) in addition to \( A_t \). This extension is considered in the absence of a poverty trap in Ikegami, Barrett, and Chantarat (2012).
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 by the first order condition:

\[ u'(c_t) = \beta E_{\theta,\varepsilon}[V'_N(A_{t+1})] \]  

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. We will refer to the right hand side of 7 as the shadow price of liquidity, or $\lambda_N(A_{t+1})$, where the subscript $N$ denotes this shadow price for the case with no insurance markets.

The nature of the right hand side of equation 2 can be shaped fundamentally by the nature of the production set. For the remainder of this section, and for the next two, we will focus on this model under the assumptions of fixed costs and non-convexities in production.

As has been analyzed for models similar to 1 (e.g., Skiba (1978), Buera, 2009), non-convexity in the production set can, but need not, generate a bifurcation in optimal consumption and investment strategies. This bifurcation happens only if steady states exist both below and above $\tilde{A}$, the technology switch point. 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,\(^5\) and denote it as $A^M_N$, where the $M$ superscript denotes “Micawber” and the subscript $N$ again indicates that no insurance market is present. Intuitively, small changes in assets around $A^M_N$ 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 $A^M_N$ will push them below the threshold and put them on a path toward the

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\(^5\)While this switch point could be labeled the “Skiba Point,” the more poetic 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 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.

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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.

2.3 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. Even with a non-convex production, problem 1 will not necessarily have multiple steady states, and if $A_N^M$ exists dividing the multiple steady state, 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).

For the analysis here, we 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, as discussed above. 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., 2013) 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 (such as drought), we roughly discretize the estimated empirical distribution of livestock mortality in northern Kenya reported in Chantarat et al. (2013). 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

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\(^6\) 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 in this setting. In Carter and Janzen (2018) 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.
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 that generate a stable result. 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 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. 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 (the shadow price of liquidity, \( \lambda_N(A_{t+1}) \)) as a function of current asset holdings. As can be seen, this term—which represents the future value

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

9To 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 \( \theta_{t+1} \) and \( \varepsilon_{t+1} \) 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 1: Opportunity Cost of Assets

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 strategies and thereby identifies the Micawber threshold. In other words, $A_{MN}^N = 11$. 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.

To characterize poverty dynamics and assess vulnerability, we next run 1000 simulations of 50-year length for a sequence of initial asset endowment levels. For each year, optimal consumption and investment are determined according to problem 1, random variables are realized, asset stocks are updated, and so on. 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. The solid line in Figure 2 graphs these probabilities for the baseline autarky model. As can be seen, for all initial asset positions below $A_{MN}^N = 11$, 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 \( A^M_N \), 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 \( A^M_N \) is around 45%, and only slowly declines as initial endowment increases. We label households with assets greater than \( A^M_N \), but who still face a significant probability of becoming chronically poor as the \textit{vulnerable non-poor}.

These chronic poverty vulnerability rates in Figure 2 make clear why the shadow value of assets in Figure 2 is highest for those in the neighborhood of \( A^M_N \). Every additional unit of assets beyond \( A^M_N \) reduces the probability that a shock pushes the household into the low equilibrium of chronic poverty. As we will see later, the high shadow value of liquidity in the neighborhood of \( A^M_N \) will have consequences for
the optimal demand for insurance.

3 Introducing Asset Insurance

The numerical simulation of the baseline model reveals the fundamental role 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; 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 first consider the impact of insurance when it is a purely private good, the full cost of which must be paid by those who choose to purchase it. To set up the later analysis of the costs of social protection, we will also consider the impact of partial subsidies on insurance demand.

In an effort to make our exploration of insurance meaningful, we will consider a type of partial insurance (index insurance) that only covers the covariant shock, $\theta$, but not the idiosyncratic shock, $\epsilon$. The uninsured idiosyncratic risk can be termed basis risk. Because index insurance only requires measurement of the common shock which can be remotely sensed at low cost,\(^\text{10}\) it can in principal can be implemented amongst a dispersed, low-wealth population without costly loss assessment and the problems of moral hazard and adverse selection that historically have crippled efforts to introduce insurance to such populations (see Carter et al. (2017) and Jensen and Barrett (2017) for discussion on the logic and current state of index insurance in developing countries).

\(^{10}\) See Chantarat et al. (2013) for the case of index insurance based on remote sensing for the pastoralist regions of Northern Kenya.
3.1 Extending the Baseline Model to Include Asset Insurance

This section modifies the model of Section 2.2 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.\(^{11}\)

We assume an index contract 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 so that the shock itself functions as the index that triggers payments.\(^{13}\) We denote \( s \geq 0 \) 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, \( \delta \), are given by:

\[
\delta(\theta_t) = \max((\theta_t) - s), 0).
\]

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

\(^{11}\)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.
optimization problem becomes:

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

subject to:

$$c_t + pI_t \leq A_t + f(A_t)$$

$$F(A_t) = \max[f^H(A_t), f^L(A_t)]$$

$$A_{t+1} = (A_t + f(A_t) - c_t) (1 - \theta_{t+1} - \varepsilon_{t+1}) + (\delta(\theta_{t+1}) - p)I_t$$

$$\delta(\theta_{t+1}) = \max((\theta_{t+1} - s), 0)$$

$$I_t, A_t \geq 0$$

(5)

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

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

(6)

with two corresponding first order conditions:

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

(7)

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

(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:

$$\Pr(\theta > s) \mathbb{E}_{\theta, \varepsilon}[V'_I(A_{t+1})(\delta(\theta))| \theta > s] = p\lambda_I(A_{t+1})$$

(9)

where $\lambda_I(A_{t+1}) \equiv \beta \mathbb{E}_{\theta, \varepsilon}[V'_I(A_{t+1})]$ is the opportunity cost or shadow price of liquidity\textsuperscript{14} in the presence of insurance under the credit constraints that define this model. The right hand side of equation 9 is thus the effective cost of insurance, the premium

\textsuperscript{14}Each unit of insurance purchased directly implies a reduction in future assets, whose value is given by the derivative of the value function $V_I$. 

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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
side of 9 can also be large, since large asset losses can occur without triggering a
compensatory insurance payment. This highlights the importance of uninsured or
basis risk in the household’s decision problem: basis risk increases the opportunity
cost of liquidity.\(^{15}\)

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

$$u'(c_t) = \beta E_{\theta, \varepsilon}[V'_I(A_{t+1})\delta(\theta)] = \lambda I(A_{t+1}).$$

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 insur-
ance. 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 vulnera-
able households, we return to numerical methods. In order to parameterize the model,
the actuarially fair premium ($p = .0148$) is calculated using the assumed distribution
of covariate shocks and the strike point found in the actual insurance contract re-
cently made available to pastoralists in the region ($s = 15\%$) (see note 10 above).
We assume the market price of insurance is 120% of the actuarially fair value. We

\(^{15}\)This explains the proposition presented in Clarke (2016) that optimal insurance coverage will
be decreasing in basis risk.
consider insurance demand both when the household must pay the full market price of insurance and when government gives them a 50% subsidy off the market price.

Before beginning our analysis, note that our assumptions about the structure of risk are relatively favorable for index insurance as we assume that uninsured idiosyncratic shocks are small and that covariate losses are perfectly observed. To illustrate how insurance changes the consumer’s problem, we return to Figure 1. In that figure, 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 (with roughly 11-18 asset units) 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 purchased in optimal amounts 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% 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 \( A_N^M \). The fact that insurance purchase is not optimal for the vulnerable non-poor explains why Chantarat et al. (2017) and Kovacevic and Pflug (2011) find that forcing the vulnerable non-poor to buy insurance makes them worse off, increasing the probability that they collapse into chronic poverty.

The fact that the vulnerable non-poor do not optimally purchase insurance does not mean that insurance markets have no value to these households. To the contrary, Figure 2 shows that the presence of an insurance market radically decreases the probability that the vulnerable, non-poor collapse to the low equilibrium steady state. For example, in the absence of an insurance market, a household with 15 asset units has an approximately 30% chance of becoming chronically poor in the future, whereas that probability falls to 0% when the household has access to insurance. We call this the \textit{ex post vulnerability reduction} effect of insurance. This effect occurs because, as Figure 3 shows, the vulnerable non-poor quickly insure once they modestly build up their stock of productive assets.

These results reveal 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 households who face a binding liquidity constraint. In other words, those with the most to gain from insurance face the highest shadow price \((p\lambda_t(A_{t+1})\) to purchase it.\(^{16}\)

Further insight into the workings of insurance can be garnered by examining the impact of a price subsidy on insurance demand in Figure 3. The 50% insurance subsidy induces the vulnerable non-poor to elastically respond to the subsidy by moving 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. (Chantarat, Mude, and Barrett, 2009) implemented a willingness to pay for insurance experiment in the

\(^{16}\)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.
pastoralists regions of Northern Kenya and found that households most vulnerable to falling into poverty trap had highest price elasticity of demand for insurance.

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 is not insured today. The impact is subtle, but important. First, the demand pattern displayed in Figure 3 implies a time-varying insurance strategy; over time, a highly vulnerable household will shift its behavior and fully insure its assets if it is able to increase its asset base.\textsuperscript{17} 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 functions 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 $A^M_N$ divest assets, instead enjoying greater consumption today, and move toward the low welfare steady state. Alternatively, households above $A^M_N$ 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, $A^M_I < A^M_N$ where subscript $I$ denotes a market for insurance.\textsuperscript{18} The behavior of households with asset stocks

\textsuperscript{17}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.

\textsuperscript{18}More completely, $A^M_S < A^M_I < A^M_N$ where subscript $S$ denotes the availability of subsidized
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,\textsuperscript{19} inducing these households to take on additional risk by investing sharply. We call this the \textit{ex ante investment incentive} effect of insurance.

The importance of this \textit{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. This fundamental shift in investment behavior does not

\textsuperscript{19}In fact, the opportunity cost of assets peaks at the Micawber threshold.
guarantee these newly investing households will ultimately achieve the high steady state, but they strive for it. 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, the Micawber threshold shifts further left to $A_N^M$, 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. 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.\(^{20}\)

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 (2004b) notes, in the context of an open access range, such overinvestment can create externalities and result in a tragedy of the commons.\(^{21}\) 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.

\section*{4 Impacts of Insurance on Poverty Dynamics and the Cost of Social Protection}

The previous section revealed two primary effects of an asset insurance market: a vulnerability reduction effect and an investment incentive effect. 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. 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. Results in this section are sensitive to

\(^{20}\)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.

\(^{21}\)Empirically, McPeak does not find evidence of this, interpreting this to mean that overstocking has not reached these critical levels.
assumptions regarding the initial asset distribution in the stylized economy. 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 $A^M_N$ 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 $A^M_N$. 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. Alternatively, in an economy with households normally distributed with a mean of $A^M_N$, the impacts of an insurance market are much stronger 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.\(^\text{22}\) 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 Table 1, and households behave optimally in accordance with the dynamic choice models laid out in Sections 2.2 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 $A^M_N$ - 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.

\(^{22}\)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.

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Figure 5: Poverty Dynamics

(a) Consumption Poverty Headcount

(b) Income Poverty Headcount

(c) Consumption Poverty Gap

(d) Income Poverty Gap
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 the neighborhood just above $A^M_N$ 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 Cost of Social Protection 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 $A^{M'}_N$ and $A^{I'}_I$ 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 Cost of Social Protection with Targeted Insurance Subsidies

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 of insurance, while anyone with more than 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. 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, 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 conventional cash transfer scheme. To do this, we calculate the amount of funds it would take to close the consumption-based poverty gap for all poor households in our stylized economy. The black (solid) line in Figure 6 displays those annual costs for each year of the simulation in the absence of an insurance market.

As Figure 6 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 double over the simulation period. Although we do not present the results here, starting from a much lower absolute level, the cost of income-targeted cash transfers increase 400% over the 50 years of

\[\text{23}\] 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.

\[\text{24}\] There are of course additional costs associated with high levels of poverty, but we ignore those here.
The cost of social protection is dramatically reduced when an unsubsidized asset insurance market exists, as shown by the blue dash-dot line in Figures 6. In this case, the only costs incurred by the public sector are those associated with the cost of the cash transfers. These costs fall over time with insurance-facilitated 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 relative to the autarky case.

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. From a public finance perspective, insurance subsidies more than pay for themselves as each dollar spent on subsidies reduces expenditures on cash transfers by more than a dollar. Subsidizing insurance also results in the lowest total number of poor people compared to both the no insurance and unsubsidized insurance social protection scenarios.

5 Insurance and the Cost of Social Protection in a Model without Poverty Traps

Under the assumption of a non-convex production set that can generate poverty traps, the analysis has so far shown that asset insurance, and asset insurance subsidies can reduce poverty in the long-run and result in substantial public savings on the cost of social protection, even when insurance is publicly subsidized. But how robust are these results to the removal of the assumption of a non-convex production technology? That is, what impact do insurance and insurance subsidies have on the cost of social protection in an risk-prone economy with a simple concave production technology?

To explore this question, we eliminate the fixed costs associated with the high technology, $f^H(A_t)$, such that this technology dominates the low technology for almost all asset levels. We then reanalyze models (1) and (5) using the same parameter values as before. The revised model admits only a single equilibrium, specifically, the equilibrium associated with the high technology. While all agents in the model will strive for this high equilibrium, poverty can still exist (and persist) at any point in time, both because it takes time for self-financed accumulation to eliminate poverty, and also because vulnerability remains and stochastic shocks will probabilistically knock some households to a lower standard of living. All poverty is thus transitory in this model. Structural persistent poverty, and the analytical complexities associated with the poverty trap model, do, however evaporate.\footnote{25}{For example, the opportunity cost of assets—illustrated in Figure 1 for the poverty trap case—is strictly downward sloping and overlaps at asset levels above 11 units.}
Figure 7 illustrates the results of the numerical dynamic programming analysis. Although we do not show it here, income-based poverty goes to zero in the long-term, as would be expected in the absence of structural poverty. What remains instead is oscillation around the remaining steady state following exposure to negative shocks. Comparing Figures 7a and 7b with their analogues in Figures 5a and 5c, we first notice that consumption-based poverty in the early periods of the simulation is actually a bit higher. This reflects the investment incentives facing some households. In the poverty trap world, these households would have chosen consumption over investment, recognizing that the optimal choice was to consume a bit more of their “excess assets” and move toward the low equilibrium. In the absence of a dominant low technology, these households now temporarily reduce consumption in order to invest. In the longer term, this asset accumulation under autarky sharply cuts, but does not completely poverty as shocks followed by subsequent asset reaccumulation move households into and out of poverty. In the long-term, absent insurance markets, the consumption-based poverty headcount settles down at 15%, whereas that figure was 50% in the presence of a poverty trap mechanism. While poverty is transitory, under our parameterization the average poverty spell lasts for 5.5 time periods.

While we thus see that individual accumulation and income growth can by itself put a serious dent in poverty under these more favorable technological assumptions, poverty, and vulnerability to poverty, remain. What impact, then, will the introduction of an asset insurance market have in this world? As discussed above, in the poverty trap world, insurance can have both a vulnerability reduction effect and an investment incentive effect. The latter is no longer relevant in a non-poverty trap world as there is no Micawber Threshold to shift. The former may continue to play some importance.

Figure 7c graphs optimal demand for insurance when fixed costs are eliminated and the production set is strictly concave. In contrast to the u-shaped relationship in Figure 3, we see that optimal demand for insurance is uniformly high across the asset continuum. The demand for insurance responds to a targeted 50% insurance subsidy, but the elasticity of that response is uniformly modest across the asset continuum, again in contrast to the high price responsiveness of vulnerable households facing a poverty trap.

Returning to Figures 7a and 7b, the availability of insurance nearly eliminates consumption poverty after about 25 years of simulated history. It does, however, increase the duration of poverty from 5.5 time periods without insurance, to 7.9 time periods with unsubsidized insurance. The duration of poverty is longer with insurance because people have to give up consumption to pay for insurance, and it therefore takes longer to recover to a non-poor standard of living. For similar
Figure 7: Asset Insurance without a Poverty Trap

(a) Consumption Poverty Headcount

(b) Consumption Poverty Gap

(c) Insurance Policy Function

(d) Cost of Social Protection

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reasons, the time spent in poverty decreases to 6.6 periods when a targeted subsidy is provided (relative to the no subsidy case), but it still takes longer than in the autarky case.

To examine the public cost of social protection, we again calculate how much a government would have to spend in cash transfers to close the poverty gap for all poor households. Compared to the poverty trap world (Figure 6), the cost of social protection are much lower as successful asset accumulation eliminates a large portion of the poverty case load (Figure 7d). Even so, the development of the insurance market further reduces the costs of providing social protection in the long run. As before, insurance subsidies continue to pay for themselves as the discounted value of total expenditures on subsidy plus the cash transfers required to close the poverty gap for all poor households is reduced.

6 Conclusion

Risk and vulnerability play key roles in shaping the dynamics of poverty. In addition to the \textit{ex post} impacts of shocks, the \textit{ex ante} anticipation of shocks discourages investment that might otherwise permit an escape from poverty. These effects would likely be exacerbated in an environment where poverty trap mechanisms are at play. These observations raise the intriguing possibility that spending money on insurance, or insurance-like transfer mechanisms, may lower the total cost of social protection. That is, can insurance programs effectively pay for themselves by reducing the amount of funds needed for cash transfers required to close the poverty gaps for all households who have become poor? Does the answer to this question depend on the presence or absence of a poverty trap mechanism?

With these questions in mind, we incorporate the option to buy insurance into a dynamic stochastic model in which risk-exposed households optimally choose how much to consume, how much insurance to buy, and how much to invest in a productive asset each time period. We analyze the model under the assumption of a standard, globally concave production technology, as well as under the assumption that fixed costs create a non-convex production set that creates a multiple equilibrium poverty trap. Under both technology assumptions, the introduction of an asset insurance market substantially reduces poverty, and the costs of the cash transfer required to close the poverty gap for all poor households. In the poverty trap world, the extremely high shadow price of liquidity for households near the tipping point in the multiple equilibrium dynamic system makes them reluctant to purchase insurance. Optimal demand for insurance by these households is highly price elastic, and we show that insurance subsidies crudely targeted at these households more than
pay for themselves by reducing the budget needed for cash transfers.

Stepping back, the implications of the theoretical analysis here is that there is a public finance case for a more comprehensive approach to social protection. Social protection is conventionally reactive, transferring food or cash to those who have already become poor. A comprehensive approach would also devote resources to the creation and perhaps subsidization of risk transfer markets that can alter the underlying poverty dynamics by braking shock-driven descent into poverty, and relaxing risk constraints on the investment needed to ascend from poverty. These dynamic behavioral changes (the vulnerability reduction and investment incentive effects, as we term them here) ultimately complement the timeliness argument made by Clarke and Dercon (2016) for integrating insurance into systems of social protection.

Finally, the results presented here stem from a theoretical exercise that relies on a number of assumptions, including economic rationality, an imperfect, but still high quality index insurance contract, and full understanding and trust in the insurance provider. In the real world of microinsurance, each of these assumptions has proven problematic (e.g., see the discussion in Carter et al. (2017) and Jensen and Barrett (2017)). Nonetheless, the analysis here suggests that the potential gains to solving these problems and integrating index insurance into a comprehensive system of social protection can be substantial.
Table 1: Functional Forms and Parameters used in Numerical Simulations

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<td>$F^H(A_t) = \alpha A_t^\gamma H + I^H$</td>
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<td>$\gamma_H = 0.56$</td>
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<td>$f^L = 2.95$</td>
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<td>$f^H = 0.50$</td>
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<td>$\beta = 0.95$</td>
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<td>$\rho = 1.5$</td>
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<td>$s = .15$</td>
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<tr>
<td>$\varepsilon = {0.0, .01, .02, .03, .04}$</td>
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<td>$Pr(\theta) = {.3415, .3415, .1494, .0640, .0427, .0213, .0107, .0075, .0043, .0043, .0043, .0043, .0043}$</td>
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References


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