EMPIRICAL DETECTION OF POVERTY TRAPS AND UNNECESSARY DEPRIVATION*

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Abstract

A poverty trap exists when individuals are in equilibrium at a poor standard of living, and will not of their own volition escape poverty. Dynamic models of asset accumulation and occupational choice can create two types of poverty traps: conditional convergence poverty traps and unnecessary deprivation poverty traps. While distinguishing between these two types of chronic poverty is vital from a policy perspective, we show that existing empirical methods of detecting poverty traps are at best able to identify if multiple equilibria exist, but they are unable to distinguish between the two types of traps. In this paper, we fill this lacunae by developing a threshold-based method to detect poverty traps that provides a well-structured test that distinguishes between conditional convergence and unnecessary deprivation traps. We emphasize the importance of shocks in distinguishing between the two. To illustrate the properties of ours and other approaches to test for poverty traps, we use a dynamic stochastic programming model to create simulated longitudinal data on households and their living standards. By manipulating the underlying parameters of the model, we create distinctive data generation processes characterized by no poverty traps, only one type of trap, or both types of traps coexisting in equilibrium. These different processes in turn allow us to reveal the strengths and weaknesses of these different approaches, and to stress test them and reveal their robustness to common survey complexities.

Keywords: Poverty Traps, Well-being Dynamics

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1 Introduction

A poverty trap can be broadly defined as a self-reinforcing mechanism that causes poverty to persist (Azariadis and Stachurski, 2005). More specifically, a poverty trap exists when individuals are in equilibrium at a poor standard of living, and will not of their own volition accumulate their way out of poverty. Dynamic models of occupational choice, in which individuals choose between a low-paying, casual wage labor occupation and a potentially more remunerative entrepreneurial occupation that requires capital and business skill, show that two different types of persistent poverty can emerge and, importantly, coexist.[1] The first type is the convergence of low skill individuals to the poor, wage labor occupation. Even if positively shocked with a capital grant, these individuals will optimally return to the poor standard of living. We refer to this kind of persistent poverty as resulting from a *conditional convergence poverty trap*. Individuals in this position always converge to the poor equilibrium conditional only on their low skill level.

The second type of persistent poverty that can emerge is when, in the absence of well-functioning credit markets, perhaps more highly skilled individuals, who have the capacity to achieve the higher income entrepreneurial equilibrium end up at the impoverished casual wage labor equilibrium because of either low initial capital endowments or a history of negative shocks. Had they been born wealthier (or received a positive asset grant) and, or had a more favorable shock history, these individuals would end up in dynamic equilibrium at the non-poor, entrepreneurial occupation. Following Ikegami et al. (2019), we refer to this second type of persistently poor individual as unnecessarily deprived and caught in an *unnecessary deprivation poverty trap*.[2]

In this paper, we show that existing approaches to test for poverty traps cannot differentiate between conditional convergence and unnecessary deprivation traps. Using data drawn from a simulation of a flexible dynamic optimization process, we show that existing methods can detect multiple equilibria—when using relatively well-measured capital and with minimal heterogeneity. However, even under these conditions, the tests do not differentiate between the two types of persistent poverty. We highlight the importance of measured shocks (both positive and negative) in differentiating between the two types of poverty traps and propose a shocks-based threshold estimation approach that can both detect a multiple-equilibrium trap and identify its type.

Distinguishing between these two types of poverty traps is vital for the design of

[1] See Buera (2009) and discussion in Barrett and Carter (2013). We provide a stylized model illustrating this co-existence in this paper.

[2] This is not to say that any poverty is necessary. We use this nomenclature to differentiate between poverty due to individual/household characteristics (here skills which we assume does not change) and poverty due to state dependence of a specific kind which we might also refer to these as *hysteresis* poverty traps.

poverty reduction programs. Individuals caught in an unnecessary deprivation poverty trap can be assisted by capital grants or even the development of financial institutions that can meet their credit and risk management needs. In contrast, such programs would have no durable impact on those caught in conditional convergence poverty traps. Addressing the poverty of this latter group requires regular income transfers, and/or waiting for general economic growth to raise wages and do what Ravallion (2016) calls the heavy lifting of poverty reduction.

In their impact evaluation of a capital grant program for ultra-poor women involved in casual wage labor occupations, Bandiera et al. (2016) indicate that the grant would have no durable impacts if the women lacked the skills to succeed as entrepreneurs, or, in our language, if they were caught in conditional convergence poverty trap. Interestingly, their empirical results based on quantile treatment effects show that the program had no impact on about 40% of the population, whereas it had quite substantial and long-lasting effects for the other 60%. Their results thus appear to corroborate the theoretical insights we present in this paper and proposed previously by Buera (2009) regarding the coexistence of both conditional convergence and unnecessary deprivation poverty traps.

While well-designed impact evaluation of positive shocks can shed light on the coexistence of these two types of poverty traps and their relative preponderance, there has long been interest in using longitudinal and other observational data to gain a more general idea about the existence of poverty traps.[3] In this paper, we show that the approaches to detect poverty traps that have been developed and used to date in the literature are ill-equipped to say if any detected multiple-equilibria reflect simply a conditional convergence trap or if there is evidence an unnecessary deprivation poverty trap. Given that the meaning and policy implications of these two types of poverty traps are quite distinctive, we discuss clearly the importance of measured shocks and put forward a method that can identify the presence of unnecessary deprivation and is robust to the coexistence of conditional convergence poverty traps. We also explore the sensitivity of ours and other methods to the features of the data generation process that make poverty trap detection difficult.

To do so, we use a dynamic stochastic model of occupational choice and asset accumulation to generate simulated data.[4] This approach allows us to control the underlying data generation process (DGP). Specifically, we modify the model such that the DGP allows only one of the type of poverty trap, both types of poverty traps, or no poverty trap at all. These distinct DGPs then allow us to explore the performance of different candidate poverty trap detection approaches. Insights from the underlying theoretical model also allows us to propose an identification strategy that allows us to distinguish unneces-

[3] Prominent examples include Ravallion and Lokshin (2002) and Antman and McKenzie (2007); Barrett and Carter (2013) provide a summary.

[4] The model we employ is built on Ikegami et al. (2019) and Janzen, Carter and Ikegami (2021).

sary deprivation traps from conditional convergence traps as long as realized shocks can be observed. Specifically, our proposed threshold estimator of excess shock sensitivity exploits the fact that shocks (positive or negative) have persistent effects on the well-being of individuals who are subject to unnecessary deprivation traps. In contrast, poor individuals caught in a conditional convergence trap will not exhibit this pattern as the impact of shocks will dissipate over time.

In addition, we test the robustness of our and other approaches to common survey complexities. We vary the extent of measurement error, initial correlation between assets and latent skill, and the amount of heterogeneity in the population. We systematically show that the reliability of these tests (even in finding multiple-equilibria) is highly dependent on these complexities that are surely evident in any panel dataset. Finally, we use our known DGP to illustrate the difficulty of using consumption-based measures of economic well-being to detect traps.

The remainder of this paper is organized as follows. Section 2 presents a basic dynamic stochastic model of occupational choice and capital accumulation in the presence of heterogeneous endowments of entrepreneurial skill and initial (inherited) wealth. We illustrate the workings of the model and show we use it to generate the simulated data under different data generation processes. The model also provides insights into the identification strategy that we propose to use to distinguish conditional convergence from unnecessary deprivation poverty traps. Section 3 reviews the literature on the detection of poverty traps and illustrates the performance of the different approaches in the face of different data generation processes. Section 4 then presents our novel threshold estimator of excess shock sensitivity and illustrates its operation in the face of the same data generation processes used to show the strength and weaknesses of existing poverty trap estimation techniques. Section 5 then stress tests all methods. Section 6 concludes.

2 A Dynamic Stochastic Model of Occupational Choice

While a number of models can generate poverty traps (see Barrett and Carter (2013), Kraay and Mckenzie (2014), and Ghatak (2015) for recent reviews), we focus here on a parsimonious occupational choice model that is sufficiently general to allow the coexistence of conditional convergence and unnecessary deprivation poverty traps.[5] Because the goal of our paper is primarily the empirical methods used to detect poverty traps, we less interested in theory per se and more interested in having a known and manipulable data generation process that will allow us to test different approaches for detecting poverty traps.

[5] See Appendix C for a summary of the literature on micro-based poverty traps.

2.1 Coexistence of Two Types of Poverty Traps

We assume that individuals (hereafter agent) are born with a stock of wealth and an endowment of entrepreneurial skill. These resources can be used to generate income via a casual wage labor technology, which yields:

$$F_w = w_0 + f_w(k_{it})$$

where w_0 is the return from participation in the casual labor market, and f_w gives the returns to wealth when invested, where we assume that f_w has positive and decreasing returns to scale. For discursive purposes, we assume that F_w is below the poverty line.

Alternatively, the agent can choose an entrepreneurial occupation which yields income:

$$F_e = [w_0 - F] + \alpha f_e(k_{it})$$

where $F \leq w_0$ are the casual labor market earnings that are foregone when the agent pursues the entrepreneurial activity, α is the agent's innate skill as an entrepreneur and f_e, which like f_w exhibits diminishing returns, but is more productive than f_w in the sense that $f_e(k) > f_w(k) \forall k$.

This model is similar to that of Buera (2009) although in his theoretical model an individual is required to give up their entire wage when committing any time to the entrepreneurial activity.

Note that under these occupation-specific earnings specification, agents with low wealth endowments will, in any given period, make more money under the casual labor occupation than as an entrepreneur. We define $\hat{k}(\alpha)$ as the point where entrepreneurial activity becomes more remunerative in any given period to an agent with skill level α. We assume that at any point in time, the agent will choose the most remunerative occupation, but can shift occupations costlessly. These assumptions imply that the agent's production set as the outer envelope of the two occupation specific income processes:

$$F(\alpha, k) = max\, [F_w, F_e].$$

As with other models that lead to poverty traps, we assume imperfect markets with credit constraints where we rule out borrowing against future earnings, and so capital can only be accumulated via foregone consumption. Thus, capital evolves following this equation of motion:

$$k_{it} = (k_{it-1} + F(\alpha_i, kit-1) - c_{t-1})(\theta_t - \delta)$$

where δ is natural rate of depreciation and $0 \leq \theta_t \leq 1$ is a random negative capital or depreciation shock. We assume that agents know the distribution of θ_t.

To study the dynamics of occupational choice and poverty dynamics, we assume that agents solve the following inter-temporal maximization problem:

$$\max_{c_{jt}} \quad E_\theta \sum_{t=0}^{\infty} \beta^t u(c_{jt})$$

subject to:

$$\begin{aligned}
& c_{jt} \leq k_{jt} + F(\alpha_j, k_{jt}) \\
& F\left(\alpha_j, k_{jt}\right) = max\left[F_w, F_e\right] \\
& k_{jt+1} = \left(k_{jt} + f(k_{jt}) - c_{jt}\right)\left(\theta_{jt+1} - \delta\right) \\
& k_{jt} \geq 0
\end{aligned}$$

where c_{jt} is an agent's consumption in time t . E_θ is the expectation taken over the distribution of the negative shocks and β if the time discount factor. $u(c_{it})$ is the utility function defined over consumption and satisfies Inada conditions.

This model is flexible: it allows for conditional convergence to a low equilibrium based on skill level. For those with an α small enough, their long-run optimal strategy is to sort into the wage occupation even if in the short-run their capital level allows them to participate in entrepreneurial activities. For a middle skill group, there exists a level of capital $\tilde{k}(\alpha)$ where an agent's optimal dynamic choice is to accumulate capital in order to access entrepreneurial activity. Finally, for the very skilled, it is always optimal to accumulate capital through saving to access entrepreneurship even if they start with or are shocked to a low level of capital and are participating in wage labor for the time being.

2.2 Theoretical Implications and Insights for an Identification Strategy

We illustrate this flexible model and its theoretical implications through simulations. We numerically simulate this economy with random shocks with 50 different starting capital (wealth) levels and 30 different ability levels. From the simulated process above where there is heterogeneous ability and random starting positions, we simulate 25 cycles for every possible starting capital position and ability level for 1,000 different random negative shock profiles spanning the 25 cycles. We assume no positive shocks in our simulation. This creates 1,581,000 life cycles with 1,000 different different idiosyncratic and covariate shock sets for 1,530 ability and starting capital combinations.

In Figure 1, we show the probability that an agent in our simulation is poor after 25 cycles. This essentially shows the probability of an agent being in the low-level equilibrium

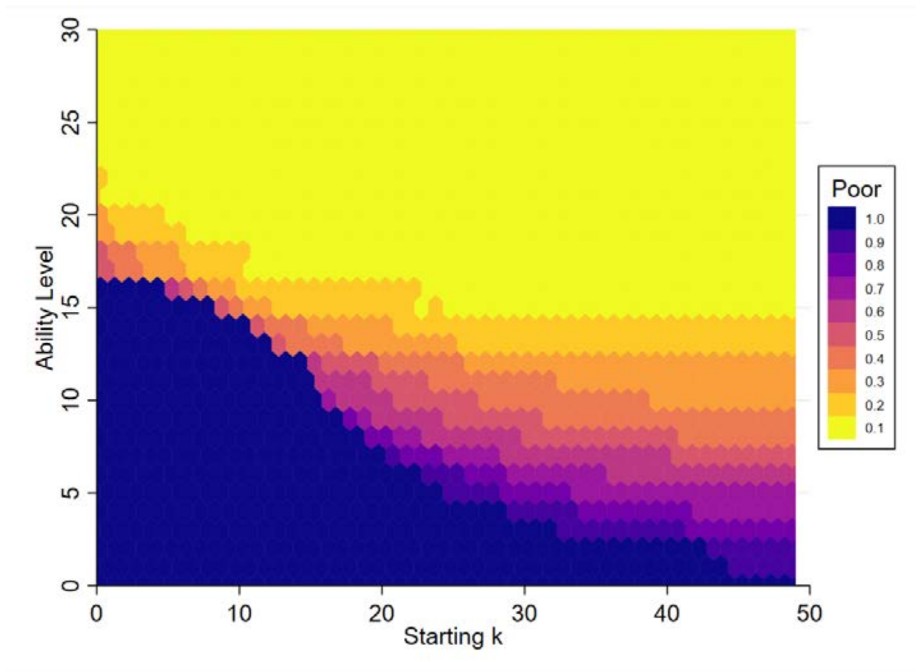


FIGURE 1: Probability Poor After 25 Cycles: We show the probability from our simulations that agents adopt the wage labor in the long-run.

earning a wage and not participating in entrepreneurial activities in the long-run. Initially, in time 0, our simulation has no correlation between ability and starting capital. After 25 cycles, those with higher ability are less likely to be at the low-equilibrium. In Figure A.1 in the Appendix, we show intermediate cycles illustrating the process over time. Moreover Figure A.2 shows a similar situation if borrowing constraints were eased.

As can be seen in Figure 1, it is possible to divide the domain of initial skill into 3 types:

1. ***Type A***: Agents with high skill positions who will always move toward non-poor standard of living by saving to access the entrepreneurial occupation irrespective of initial endowment and shock history.

2. ***Type B***: Agents with intermediate skills levels whose long-term fate depends on their initial capital endowments and history of shocks.

3. ***Type C***: Agents with low skill endowments who will always move toward the casual wage-labor occupation and a poor standard of living irrespective of initial endowment and shock history.

Type A agents who start with a lot of capital are automatically involved in the entrepreneurial activity and remain at the high equilibrium. Even if they face a series of shocks, their high skills mean they will recover to the high-equilibrium in the long-run.

Among Type A agents who start with low amounts of capital, they are initially involved in wage labor but given their skill level, their dynamically optimal behavior is to save their way into entrepreneurial activity. Positive shocks would get the less capital endowed Type A agents to the high-equilibrium faster but they do not play a significant role in determining their equilibrium the long-run.

Type C agents are low skilled and no matter what their initial endowment of capital is, their optimal behavior is to sort into wage labor. Even if they start with high levels of capital, they consume their capital away to settle into wage labor and a low-level equilibrium. Thus, in our model, their skill level holds them in poverty. Negative or positive shocks will not have a long-term effect on Type C agents—they will end up at the same low-equilibrium only they might get there a little bit more quickly or slowly if faced with different shocks.

Types A and C agents are, conditional on their skill, converging to a high- and low-level equilibria, respectively. Type B agents, on the other hand, can be unnecessarily deprived of the high-level equilibrium. Among type B agents, the model identifies a critical asset level $\tilde{k}(\alpha_i)$ around which behavior bifurcates. If an agent with skill α_i is above this critical level of capital, they will decide to accumulate the capital they need to enter into entrepreneurial activities and reach a high-level equilibrium in the long-run. If at any point a negative shock places them below this threshold, their new dynamically optimal behavior will be to de-accumulate and settle into wage labor at the low equilibrium. If they begin below this threshold, they will remain in wage labor (without a positive shock that puts them above the threshold). For example, a type B agent of ability level 11 faces a bifurcation threshold of 16. If their initial level is below, they remain in wage labor. If their initial capital is above 16, they will attempt to save their way into entrepreneurial activities, however, with unfavorable shocks, they may end up below 16 at which point their dynamically optimal behavior is to de-accumulate their capital and settle in the low-equilibrium. For a group of Type B agents with middle levels of capital endowments, shocks can have lasting impacts in the long-run.

To further illustrate the unnecessary deprivation trap for Type B agents, in Figure A.3 in the Appendix, we again focus on agents whose ability level is 11. We plot average growth rates by baseline capital levels and clearly see a discontinuity at capital level 16. This figure shows the bifurcation threshold where individuals above capital level 16 will grow over time (on average) and those below will de-accumulate and reach the low level equilibrium.[6] Plotting average growth, however, gives us more information; we are able to see where the low- and high-level equilibria are—where our two discontinuous curves in-

[6] This plot reinforces the intuition in the method proposed by Arunachalam and Shenoy (2017) on poverty trap detection using probability of negative growth by baseline well-being levels which we will discuss in the next section.

tersect the 0-growth horizontal line. For agents of ability level 11 who are facing a poverty trap, we can see that their low-level equilibrium is at 4 units of capital and their high level is 38. However, as we will show below, the method proposed by Arunachalam and Shenoy (2017) (among others) cannot differentiate between data generating processes with unnecessary deprivation (Type B) only or conditional convergence (Type A and C) only.

Finally note that the studies in the literature often distinguish between single equilibrium poverty trap models, multiple equilibrium poverty trap models, and models without poverty traps. For example, Balboni et al. (2022) present clear differences between conditional convergence models with a low and high equilibrium and a state-dependence poverty trap models (which we refer to a unnecessary deprivation poverty traps) to illustrate the difference between the two. Our model here illustrates that they can coexist in a single economy with heterogeneously skill endowed agents are subject to the same technology choices.

2.3 Simulating Alternative DGPs

By restricting the domain of skills that we allow to enter the model above, we can manipulate the data generating process to allow us to explore the robustness of different poverty trap detection methods. In particular, we will consider four distinct data generation processes depending on what types of equilibria they admit:

1. *DGP1–No Poverty Traps:*
   By setting the fixed cost associated with the entrepreneurial technology to zero, we create a DGP in which all agents, irrespective of skill, will converge toward the non-poor entrepreneurial equilibrium.

2. *DGP2–Unnecessary Deprivation Traps Only*
   By restricting the skill domain to include only Type B agents, we create a DGP where all agents are potentially subject to unnecessary deprivation poverty traps. To remove complexity, for this DGP, we restrict the skill level to 11 (See Figure 1).

3. *DGP3–Conditional Convergence Traps Only*
   By excluding Type B agents, we are left with Type A and C agents and a resulting DGP with two groups converging to a low and a high-equilibrium but no unnecessary deprivation through hysteresis.

4. *DGP4–Coexisting Conditional Convergence and Unnecessary Deprivation Traps*
   This DGP admits all three types of agents, meaning that a twin peak income distribution will be expected to emerge, and that the lower peak will be comprised of both low ability "conditional convergers" as well as unnecessarily deprived Type B.

To illustrate our approach and the limitations of other approaches, we will draw samples from these different data generating processes. In our main analysis, we will add a small amount of classical measurement error. In section 5, we explore sensitivity to measurement error and other survey complexities.

An additional consideration that will influence the efficacy of different estimation methods is the degree to which initial assets and entrepreneurial skill are correlated. When these two endowments are weakly correlated, it will imply that there will be a lot of noise in the data in the sense that two individuals with the same initial capital endowments, but radically different skill levels may tend to accumulate in opposite directions, making it hard to detect patterns and even multiple equilibrium. At the other extreme, if initial capital and skill are perfectly correlated, then multiple equilibria become easy to detect and the fact that skill is latent is of no consequence.

Over time, the skill-capital correlation will tend to increase when individuals follow the optimization model shown above. However, in contrast to this theoretical model of infinitely lived agents, in the real world, generational change will tend to weaken that correlation as assets are divided amongst children and as skill shifts between generations. In an effort to capture the flavor of the real world that makes poverty trap detection difficult, we will assume an intermediate level of correlation (0.5) between initial assets and entrepreneurial skill. Section 5 returns to explore the robustness of the different estimators to higher and lower levels of skill-asset correlation.

3 Existing Empirical Methods to Detect Poverty Traps

A variety of empirical methods have been used in the literature to test for the presence of poverty traps. In line with the microeconomic focus of this paper, we will discuss here only methods used to test for traps at the individual or household levels. Likely due to the empirical difficulty in modeling the dynamics of individual and household well-being and the high levels of panel data requirements, there is a dearth of studies *directly* testing for poverty traps (Barrett, Garg and McBride, 2016).

Early work on poverty traps would test for bi-modal distributions of income or assets. While bi-modal distributions are not sufficient conditions for poverty traps, they are expected in settings with low heterogeneity. We expect, over time for individuals to either fall into a low equilibrium or climb to a high one based–at least partially–on their initial levels of well-being. In fact, implicit in the poverty trap models is instability in the middle near the bifurcation threshold and thus we do not expect to find a concentration of observations in the middle. Quah (1996) looks at the bivariate density of national output and its fifteen-year lag, taking density with two peaks as evidence of a poverty trap. In Balboni et al. (2022), the authors show bi-modal asset distributions as supportive evidence for the existence of poverty traps among very poor women in Bangladesh.

Other empirical methods have been used to directly estimate the dynamics of economic well-being essentially testing if the data shows S-shaped dynamics and to see if the non-linear relationship between current and past measures of well-being cross the 45 degree line more than once and specifically from below (see Antman and McKenzie (2007), Lybbert et al. (2004), and Balboni et al. (2022), for examples). Parametric, semi-parametric, and non-parametric methods have been used in the literature to estimate dynamics of well-being using measures such as income, consumption, or assets. We discuss these briefly below.

Parametric Methods—Studies mainly using parametric methods have estimated higher order polynomials of state-dependence (for example, current income on polynomial of lagged income) using a variety of methods to control for heterogeneity and other forms of endogeneity. Some have used flow measures of well-being such income and/or expenditure (Lokshin and Ravallion, 2004; Jalan and Ravallion, 2002; Antman and McKenzie, 2007) while others used asset stocks (Barrett et al., 2006; Balboni et al., 2022). To control for individual fixed effects and avoid Nickel bias present in dynamic fixed effects models (Nickell, 1981), many authors use dynamic panel data methods (Arellano and Bond, 1991). This increases the data requirements of these panels as these methods use lagged values as instruments. Most of these studies using parametric methods on representative data find dynamics that are non-linear while the evidence on bifurcation thresholds and multi-equilibirum poverty traps is mixed.

Semi- and Non-parametric Methods—Several studies have used non-parametric estimation to model well-being dynamics. Lybbert et al. (2004) apply this to show clear S-shaped dynamics in herd size among Ethiopian pastoralists. In South Africa, Adato, Carter and May (2006) analyze asset dynamics with local linear regressions, while Barrett et al. (2006) and Kwak and Smith (2013) also apply non-parametric methods to their data. Balboni et al. (2022) use local polynomial regressions to estimate the dynamics of assets using experimental data.[7] However, non-parametric methods are limited in the ability to control for other covariates. Naschold (2012) uses semi-parametric techniques to estimate asset dynamics to test for poverty traps in India and again in Pakistan and Ethiopia (Naschold, 2013). Similar to parametric methods, the evidence is mixed in its conclusions regarding the existence of poverty traps.

Indirect Tests—Other indirect tests of poverty traps are guided by the theoretical predictions of the models that suggest certain behaviors around the bifurcation thresholds.

[7]They authors use a variety of methods; they show bi-modal distributions, show parametric cubed specifications in their Appendix, and use non-parametric methods to show S-shaped dynamics and testing the relationship's convexity.

For example, one common prediction of a poverty trap model is that individuals around the threshold would take a hit to their consumption in the face of a shock in order to smooth (protect) their assets over time Barrett and Carter (2013). Studies such as those by Carter and Lybbert (2012) and Hoddinott (2006) clearly show such asset smoothing behavior. Lybbert and McPeak (2012) show that preferences regarding risk and discounting are consistent with multi-equilibrium poverty trap models. Another indirect test by Santos and Barrett (2011) shows that informal lending is highest among those near the bifurcation threshold where the returns are highest.[8]

Still more, Carter et al. (2007) use a large negative shocks of a hurricane and show differential growth rates based on asset levels as evidence of poverty traps. Similarly, Arunachalam and Shenoy (2017), henceforth A&S, use a similar intuition regarding growth to set up a test for poverty traps. The intuition behind their method is that when a poverty trap exists, the probability of negative growth should increase near the threshold (from below) and decrease after it. Dynamics with convergence would show an ever increasing probability of negative growth while dynamics with poverty traps would show a drop in the middle of the distribution. A&S propose testing for poverty traps by calculating the probability of negative growth by baseline well-being decile.

Feedback Loops—One last approach that specifically focuses on behavioral traps attempts to estimate the feedback loop between well-being and psychological well-being. If the average effects in either direction combined are large enough, this can lead to a downward (or upward if we assume symmetric effects) spiral. The results on psychological poverty traps are also mixed (Alloush, 2022; Haushofer, 2019).

A number of papers have found evidence suggesting the existence of traps. On the other hand, a large literature has failed to find strong evidence poverty traps or conditions that might lead to traps. We posit (among others) that this does not necessarily mean that multi-equilibrium poverty traps do not exist. In Appendix D, we describe important real-world and data collection complexities that make multi-equilibrium poverty traps difficult to empirically detect. Moreover, in the next section, we show that finding evidence for traps does not necessarily mean that the traps are of the unnecessary deprivation type—although this is the type of trap that is usually implied.

3.1 Existing Direct Methods Can Detect Poverty Traps, But what Kind?

We will focus on general direct tests for poverty traps. We argue that these tests can detect multi-equilibria under some conditions, but cannot differentiate between unnecessary deprivation (the implied type of trap) and conditional convergence. We illustrate this by

[8] Similarly, Keswell and Carter (2014) show, using positive shocks, that large future outcomes can be explained by transfers unlocking higher equilibria.

applying four approaches to samples from the different data generating processes in our simulation. In this section, we add a small amount of classical measurement error (correlation between observed and actual capital is 0.95).[9]

We use the universe of observations in our simulated dataset to represent a population with a data generating process with heterogeneity; conditional convergence and unnecessary deprivation traps co-exist. We have heterogeneity based on ability that leads to different types and differences in the long-run equilibrium. The other source of heterogeneity is random negative shock profiles over their life cycle.[10] This is significantly lower levels of heterogeneity than what we expect to find in real-world settings.

To emulate data collection through surveys, we randomly sample 5,000 agents into our panel. We will assume no attrition and start with relatively well-measured data. To take into account the possibility that we may observe agents in different parts of their life-cycle, we randomly generate a number between 1 and 13 for each agent which we designate as the first observation in their own life cycle.[11] We then keep data for 5 "waves" that are 2 cycles apart for each individual. A panel dataset with 5,000 households and at least five waves is becoming more common (for example the Indonesia Family Life Survey or India's ICRISAT). This specific format was inspired by the National Income Dynamics Study of South Africa.

To start, we observe agents' capital level k_{it} and consumption c_{it} with small amounts of measurement error. Earlier in this section, we describe common methods used in the literature to test for poverty traps. Below, we apply the some of these approaches on our simulated data which known data generating processes. We will start with the simplest case where we do not have any poverty trap (DGP1) and show the results for the other three cases where we have unnecessary deprivation only, conditional convergence only, and the mix of the two. We show that these common approaches cannot differentiate between poverty traps and conditional convergence.

3.2 No Trap

In this section, we sample data from a population where there are no costs to entering entrepreneurial activities (DGP1) where all agents converge to a high-equilibrium and thus this data generating process has no poverty trap (See Figure A.2).

[9] The results do not change without measurement error, however, as we show in Section 5, detection of multiple-equilibria is sensitive to measurement error.

[10] There are two types of random shocks; idiosyncratic shocks of size 0.01, 0.02, 0.03, 0.04, and 0.05 and covariate shocks that can be larger up to 0.6. Approximately 80% of the time, covariate shocks are zero; the distribution of the non-zero covariate shocks can be found in the Appendix (Figure A.4).

[11] Since we start with a random allocation of capital for each ability level, the earlier we observe the agent, the less correlated their capital stock is with their ability.

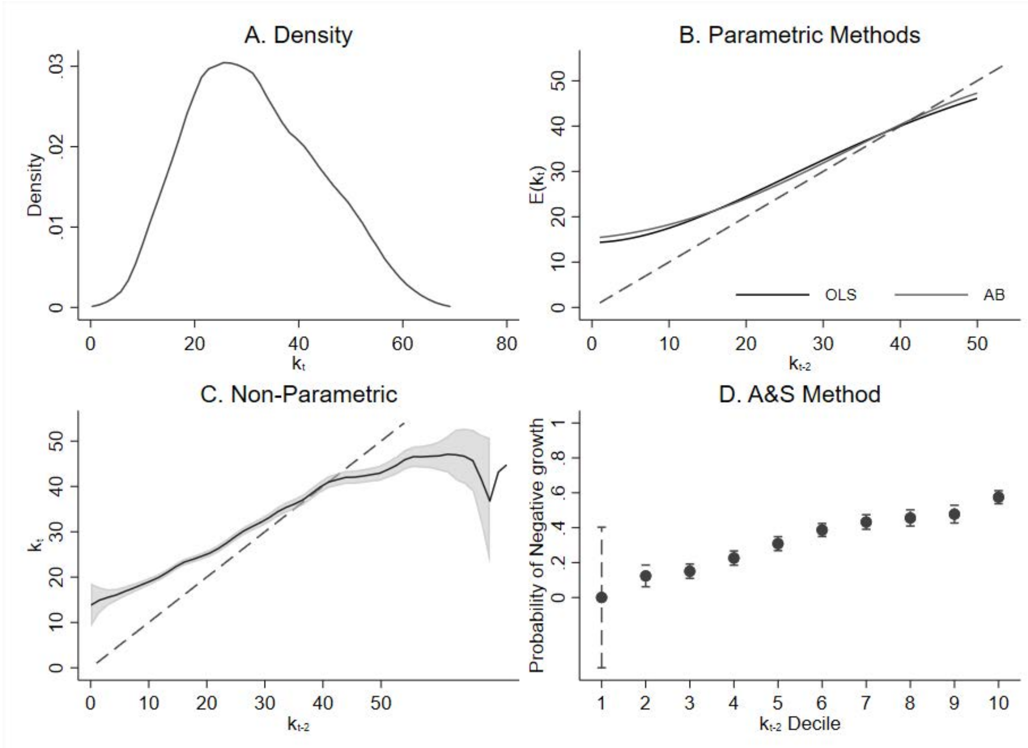


FIGURE 2: DGP1–No Poverty Traps

For our main results, we will use capital as our main variable of interest. We show four sets of results: first, we present density plots that aim to show bi-modal distributions. Second, we show results that estimate well-being dynamics using OLS and dynamic panel data methods that take into account agent fixed effects (Arellano and Bond, 1991). We then show non-parametric estimation of the dynamics (using local linear regressions),[12] and finally we show results using the method proposed by Arunachalam and Shenoy (2017). Details on each of these approaches can be found in Appendix E. For all of these methods, our baseline specifications use a lag of two which is essentially four cycles. In these studies, for comparison purposes, we restrict the analysis to the last observed wave; the econometric setup of Arellano and Bond (1991) requires the use of lags as instruments thus restricting the sample used in the method.[13]

Figure 2 clearly shows a data patterns that do not suggest the existence of traps or multiple equilibria. Here, the patterns show convergence to a high-level equilibrium. In Panel A, we do not see a bi-modal density; in Panels B and C, parametric and non-parametric approaches to estimate the dynamics of capital do not show patterns that suggest the exis-

[12]In this simulated economy, covariates are limited and thus we do not see it necessary to use semi-parametric methods.

[13]The results of the other methods do not differ in a meaningful way if we use data from other available waves in the estimation.

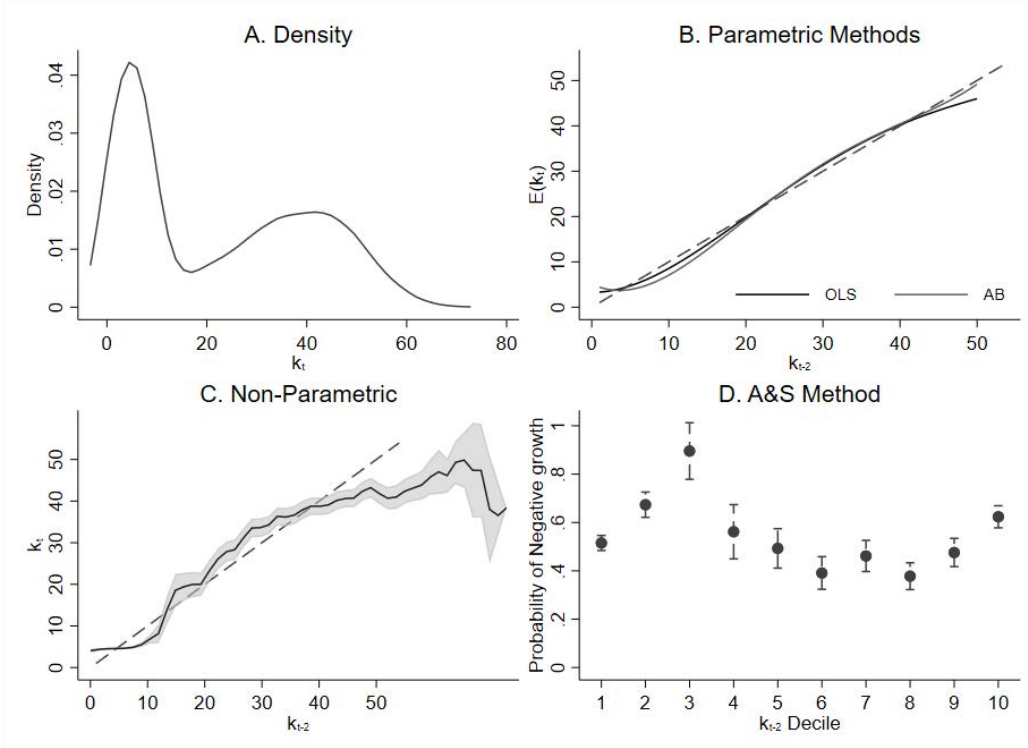


FIGURE 3: DGP2—Unnecessary Deprivation Traps Only: For a group with a in a narrow ability range (10-12), all facing a bifurcation threshold of approximately the same value, all methods support the existence of poverty traps.

tence of more than one equilibrium. The results are suggesting an average equilibrium at $k = 40$. Finally, using the A&S method looking at the probability of negative growth at different baseline deciles of well-being, we see an increasing likelihood of negative growth, a pattern you expect when there are no multiple equilibria.

3.3 Unnecessary Deprivation

Next we will look at a simple case where all agents in our sample are of ability level 11 where they all face a trap with a bifurcation threshold capital level that is the same. This is state-dependence case that typifies poverty traps in the literature. Agents can end up at the high-equilibrium if they start with a high level of capital and do not face a shock history that places them below the threshold. None of the agents here necessarily will end up at the low equilibrium. Their skill level is such that their long-run status in terms of entrepreneurship is based on their starting level of capital and their shock history—not their ability. As opposed to Type C (low ability) agents, those who are poor here are unnecessarily deprived.

The results for this simple case with unnecessary deprivation traps are shown in Figure

3. We can see from the four panels of the figure that each of the methods suggests the existence of poverty traps. The density-based approach in Panel A suggest two groupings of capital at the low- and high-level equilibria and a low density around the threshold where we would expect instability given the theoretical model the simulation is built on. Parametric methods estimating a higher order polynomial regression in Panel B show S-shaped dynamics that cross the 45 degree line from below and above suggesting a multi-equilibrium poverty trap with low and high equilibria at around 5 and 39, respectively. In Panel C, we present the results of non-parametric local linear regressions which show non-convex dynamics of capital that intersect the 45 degree line from below. This approach correctly suggest levels for the low and high equilibria but also exhibits a very steep curve at baseline capital levels 15-17 suggesting a bifurcation threshold around that level.

Finally in Panel D, using the A&S method estimating the probability of negative asset growth based on initial capital deciles, we see an increase in the probability of negative growth and a then a clear drop at the 4th decile—strongly suggesting the existence of a threshold where agents below this threshold are de-accumulating assets and those above are accumulating to enter the entrepreneurial activity. It is not straightforward to map the low- and high-level equilibria or the bifurcation threshold when using this approach. However, the method is intuitive, simple to implement, and can potentially be applied in very general settings.

3.4 Conditional Convergence

In this section, we take away agents facing unnecessary deprivation traps (Type B) and leave in two very different groups; low ability (Type C) bound for the low return wage occupation and a low level equilibrium, and high ability (Type A) bound for the high equilibrium.[14] In this data generating process, there is no unnecessary deprivation poverty traps. For our agents, conditional on their ability level, they are either converging to the low equilibrium or the high one. Their shock history and initial capital endowments do not matter in determining whether they participate in entrepreneurial activities and reach the high-level equilibrium in the long-run.

Figure 4 shows the same tests commonly used to test for poverty traps for a sample from this economy with a conditional convergence poverty trap—just two groups with unobserved characteristics correlated with the baseline level of capital that determine which technology they sort into in the long run. The pattern observed in this data generating pro-

[14] In the baseline period, the correlation between ability and capital is approximately 0.5. In this conditional convergence setup, this occurs at cycle 8. In the start of our simulation, there is no correlation between starting ability and starting capital. By cycle 8, the correlation is reaches 0.5. We show how these results differ by this initial baseline correlation levels in Section 5.

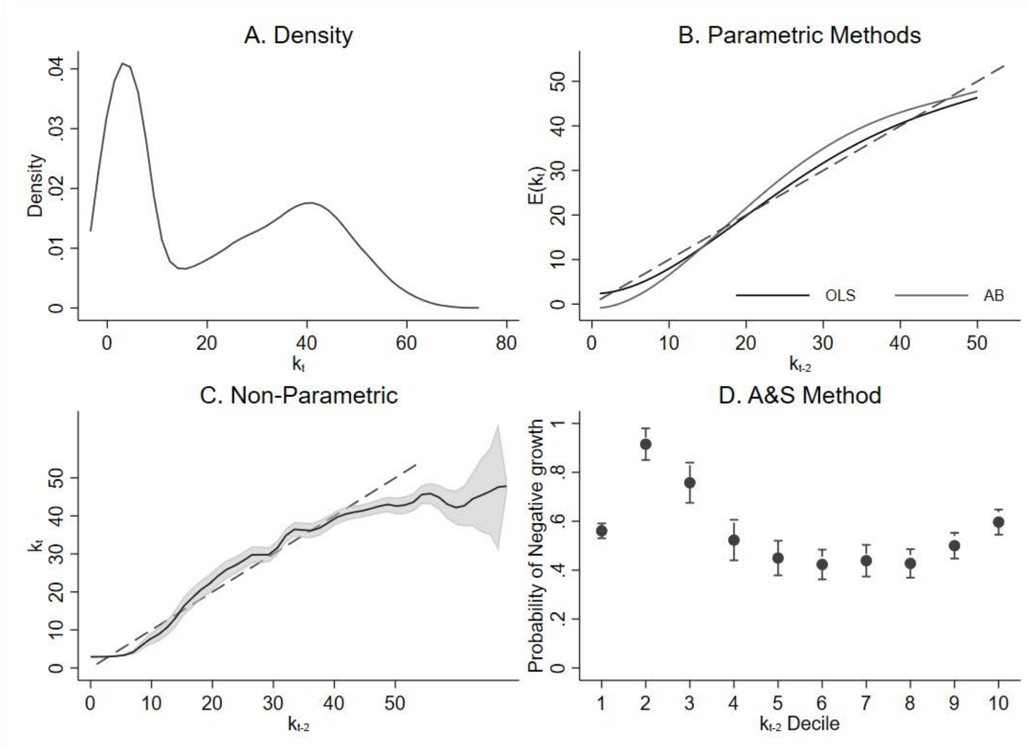


FIGURE 4: DGP3–Conditional Convergence Traps Only: Applying these methods to a data generating process with no unnecessary deprivation (poverty traps) but two groups conditionally converging to different equilibria shows similar patterns.

cess is similar to what we observe in Figure 3. When we draw a sample from a population with two groups sorting into different technologies based on unobserved characteristics, we cannot differentiate, using these methods, between this process of sorting and proper poverty traps where an individual can end up either at the high or low equilibrium based on their initial endowment of capital (and the shocks they face). The similarity in the observed patterns is noteworthy as these approaches are usually testing to state-dependence and thus unnecessary deprivation traps.

3.5 Heterogeneity

Realistically, when are studying representative samples, we will likely have significant heterogeneity. It may well be that conditional convergence and unnecessary deprivation co-exist in the population. In Figure 5, we show the results of these tests when we draw our sample from the population of full ability levels of our simulation. Perhaps unsurprisingly given the patterns we observe in Figures 3 and 4, when both types of processes co-exist,

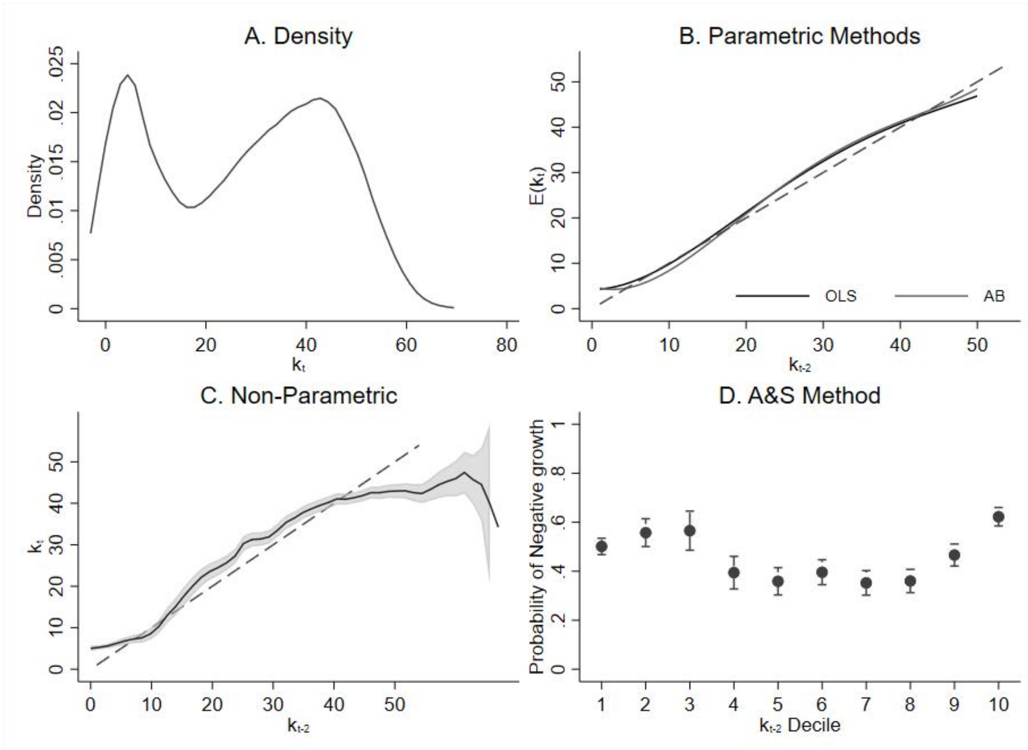


FIGURE 5: DGP4–Coexistence of conditional convergence and unnecessary deprivation poverty traps: Full ability spectrum with mix of unnecessary deprivation and conditional convergence traps.

the patterns look quite similar suggesting a multi-equilibrium process.

Not all forms of heterogeneity lead to the same patterns. If the heterogeneity is one-sided—that is, if we only have Type B and Type A or Type B and Type C—these tests may no longer suggest multiple-equilibria in the first place. At any given point, the number of agents around the threshold is small making it statistically difficult to see these patterns especially when we have measurement error.

To sum, in this section we show, using simulated data, that existing methods to test for poverty traps cannot differentiate between sorting into different occupations (wage vs entrepreneurial activity) based on unobserved agent characteristics (conditional convergence traps) and a process where there is unnecessary deprivation whereby agents end up in different occupations based on their initial endowment of capital and their shock histories.

4 A Novel Threshold-based Approach

We propose a threshold-based poverty trap estimator that both detects traps (when they exist), but also allows us to identify whether or not unnecessary deprivation traps exist. We first argue that without well-measured shocks, we cannot differentiate between the conditional convergence and unnecessary deprivation.

Intuitively, it should not be surprising that the two processes lead to similar patterns in the data. In the extreme case where there is no shuffling (every one is born at a high or low equilibrium—the appropriate one under conditional convergence) and there are no shocks, in the long run we will observe two concentrations of capital (and income) at the low and high equilibria for both DGPs. However, this does not tell us how the agents arrived at each equilibrium. If we were able to observe skill, in the conditional convergence case, we will have very high rates of correlation between skill and capital while in the unnecessary deprivation case we will have none (if all agents have the same skill level) or low correlation (if we have a wider range all potentially facing unnecessary deprivation, for example skill levels 10-15 in Figure 1.).

In the other extreme where initial capital is completely random (as in the start of our simulation), this will allow us to differentiate between DGP2 (unnecessary deprivation only) and DGP3 (conditional convergence only). However, real-world panel survey data does not start with completely random allocations of capital.

In order to differentiate between the two, we require something that is not a natural part of the data generating process. Shocks, especially well-measured shocks, give exogenous variation that allows us to differentiate between unnecessary deprivation and conditional convergence. Intuitively, shocks add some degree of *shuffling* into the economy that create conditions closer to random allocation than an economy without shocks.

To solidify ideas, consider the simplest case where all agents face potential unnecessary deprivation (Type B). At any given point, we have three groups within Type B:

1. **Group 1:** Agents who are below their threshold $\tilde{k}(\alpha)$ and are at or converging to the low-level equilibrium.

2. **Group 2:** This group of agents are right above their threshold capital level; for the time being their optimal behavior is to save and accumulate capital and participate in entrepreneurial activities. However, they are vulnerable and shocks may be large enough to push them below their threshold after which their optimal path is to de-accumulate capital and stay in wage labor.

3. **Group 3:** This group of moderately skilled agents are far above their threshold (either because of their initial endowment or accumulation with favorable shock profiles)

and are relatively safe at the high-equilibrium unless a series of large shocks brings them below—which is possible but unlikely.

Under the assumption of no massive positive or negative shocks, Groups 1 and 3, despite being Type B, are conditionally converging towards the low and high equilibria, respectively. In our simulation, the impact of shocks among these groups in the long run should not be large and will decay over time.

In Group 2, shocks can have large ***lasting*** impacts. Assume we divide these groups by capital levels in time t. A shock in time $t+1$ or $t+2$ may have important impacts because it might push the agent below their bifurcation threshold. In time $t+5$, without significant shocks in between t and $t+5$, the agent may have accumulated their way to be in Group 3, or if they did experience shocks, they may be de-accumulating to become part of Group 1. Thus, shocks in later periods will likely have smaller effects on capital, income, or poverty status in the future relative to shocks closer to the period in which defined the groups.

Now consider a case where all agents face conditional convergence (DGP3 with Type A and C only). Here, we do not have bifurcation thresholds (though there are levels of capital where agents switch from wage labor to entrepreneurship) and we just have two types: Type A agents who are either at the high-equilibrium and set or they are below and are saving to accumulate enough assets to become entrepreneurs and eventually settle at the high equilibrium. We also have Type C agents who are either at the low equilibrium, or if they happen to start with capital (an endowment from their family for example) are slowly de-accumulating their capital until they settle at the low equilibrium.

Shocks among agents following this data generating process do not have irreversible effects as they do among the Type B-Group 2 agents. These agents are conditionally converging and the effect of shocks will decay over time. Without shocks, it is difficult to distinguish between these two different processes by estimating their dynamics. Below, we outline a threshold-based approach that uses shocks to distinguish between conditional convergence and unnecessary deprivation.

4.1 The Threshold-based Poverty Trap Test

We assume we have a panel with two periods with data on exogenous shocks in between the two observations. In the scenario where we observe an individual in time t and after k cycles where we have information on the shocks in each cycle, we can estimate the following equation on the dynamics of capital and the lasting effect of shocks on it:

$$ln(y_{i,t}) = \alpha + \beta ln(y_{i,t-k}) + \sum_{j=1}^{k} \delta_j \theta_{i,t-j} + e_{i,t}$$

where $y_{i,t}$ is a measure of capital in time t and $\theta_{i,t-k}$ is a measure of shocks (in percent) in k cycles ago. Estimating this equation for all in our sample would average out the dynamics and the effect of shocks. Under conditional convergence, the effect of shocks would dissipate over time and thus the estimated coefficients would should decay—δ_5, the coefficient on $\theta_{i,t-5}$ (measure of the shock 5 cycles ago) would be less than δ_4 and less than δ_3 and so on.

However, if unnecessary deprivation exists, then there is a group (Type B-Group 2) of agents who are especially sensitive to shocks—for them shocks can have irreversible consequences. In the case where all agents face potential unnecessary deprivation (all Type B), then the only variable identifying groups 1, 2, and 3 is the baseline level of capital. For baseline capital levels just above the threshold, there is high sensitivity to the size of the shock they face in the cycles right after the baseline when these groups are defined.

Given that we generally do not know what the threshold is, we can use a threshold estimation approach (Hansen, 2000) to split the sample by baseline capital and estimate the above equation for each group separately. For simplicity of illustration, we do this for two thresholds and thus three groupings.[15] The equation can be represented as such:

$$
\begin{aligned}
ln(y_{it}) = (\alpha_1 + \beta_1 ln(y_{i,t-k}) + \sum_{j=1}^{k} \delta_{1,j}\theta_{i,t-k})\mathbb{1}_{(-\infty<y_{t-k}<\gamma_1)} \\
+ (\alpha_2 + \beta_2 ln(y_{i,t-k}) + \sum_{j=1}^{k} \delta_{2,j}\theta_{i,t-k})\mathbb{1}_{(\gamma_1<y_{t-k}<\gamma_2)} \\
+ (\alpha_3 + \beta_3 ln(y_{i,t-k}) + \sum_{j=1}^{k} \delta_{3,j}\theta_{i,t-k})\mathbb{1}_{(\gamma_2<y_{t-k}<\infty)} + e_{it}
\end{aligned}
$$

where γ_1 and γ_2 represent the possible threshold levels of capital. This approach minimizes least squares allowing for the possibility of three different regimes. In our simple case where all are facing potential unnecessary deprivation, the early δs will be large among those right above the bifurcation threshold and statistically different from the coefficients in the other two regimes that are conditionally converging to the low and high equilibria. If we observe several shocks, we should expect a the effect of shocks to decrease among those in the middle group as they accumulate or de-accumulate their way either to group 1 or 2.

Intuitively, it is clear that the reliability of this approach depends on having measured shocks as close to the baseline time period as possible. For example, with positive shocks, having a baseline right before transfers is ideal. If we measure the shocks too late, those in

[15]In practice, we allow for a maximum of 4 thresholds to be determined by the data and thus 5 regions. We allow the data to determine if the coefficients in the regions are statistically different enough to warrant different grouping.

group (defined by the baseline levels of capital) will likely fall into the two other groups (1 and 3) and shocks in later cycles are unlikely to show large effects.

4.2 Using shocks to Identify Unnecessary Deprivation

We use this approach with a series of different data structures. First, we will we illustrate the method with a data intensive example. We will then discuss how this approach can be used when we only observe 1 shocks and its efficacy based on how far the shock is from the baseline data collection.

4.2.1 Many shocks: Decay vs Lasting Effects

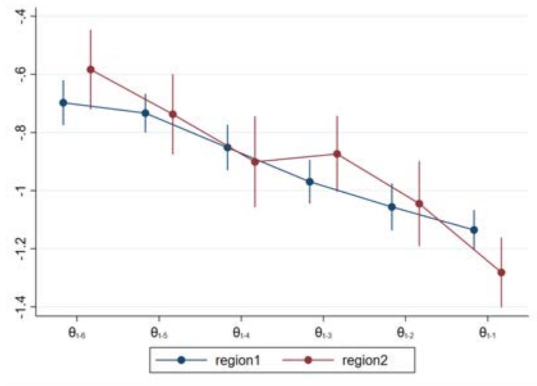
In this section, we apply the method to our four data generating processes assuming a wealth of well-measured data on shocks in between the two periods. For illustrative purposes, we show use two measures of capital 6 cycles apart with shocks sizes recorded between waves.

Figure 6 shows this method applied to the four different data-generating processes. Allowing for a data-driven selection of the optimal number of thresholds leads to an indirect first-stage test. When there are identifiable unnecessary deprivation traps, there should be three different regimes based on the baseline capital levels. Assuming enough of a density in the middle and large enough shocks, the effect of these right after the baseline shocks should necessarily be large.

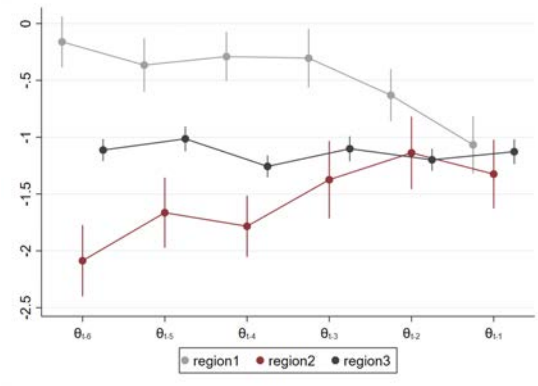
Under DGP1 where no traps exist, the approach suggests two regions, however the effect of shocks is very similar across the two regimes. The shocks show a decaying trend as would be expected under convergence.

Under DGP2 where we have unnecessary deprivation, the method splits the baseline capital into three regions. It identifies a vulnerable group starting around the correct bifurcation threshold. In Figure 6(B), this group is represented by region 2 where early shocks (those just after the baseline measurement of capital) have an outsized effect on capital several cycles into the future. Among this group, the estimated effect of shocks (in time $t-k$) on capital in time t becomes smaller as k becomes smaller because most of members of this group identified through capital levels at $t-6$ has either gone down or up (group 1 or 3) and has begun to conditionally converge to a low or high equilibrium. The key is to observe the shock close to the time of the baseline.[16]

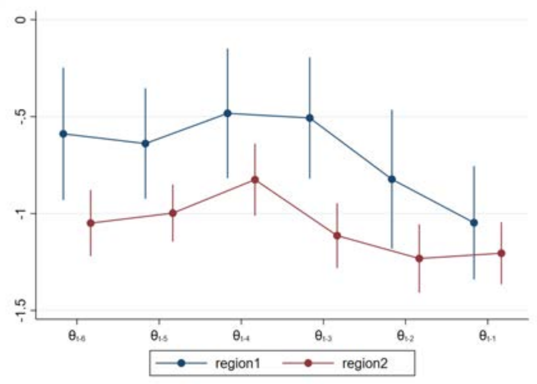
[16]Regressing growth on lagged capital and shocks for each region allows us to determine the equilibrium capital levels by using the coefficients and solving for zero growth—or plotting growth on capital for the three regions as we show in Appendix Figure A.5. For region two, when accounting for shocks, this approach correctly shows that this group is never in equilibrium and is growing.



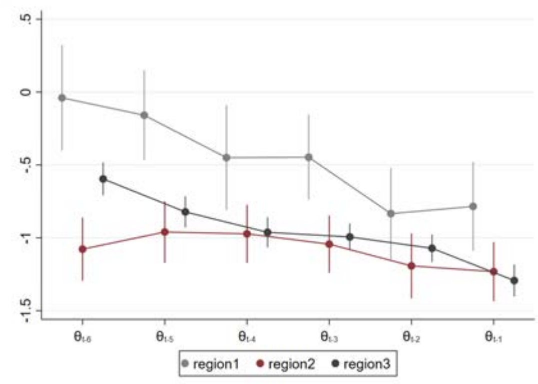
(A) DGP1–No Traps



(B) DGP2–Unnecessary Deprivation only



(C) DGP3–Conditional Convergence Only



(D) DGP4–Mix

FIGURE 6: We apply this shocks-based approach to the four different DGPs. For DGP2, the shocks-based threshold estimation approach identifies 3 groups when there is unnecessary deprivation. The middle group shows high sensitivity to shocks early on. This follows the intuition of unnecessary deprivation traps.

Under DGP3 where agents face conditional convergence, the method identifies only two regions where there is decay, although it is not as severe as under DGP1. In our data the correlation between baseline capital and skill is 0.5 and thus there is still a certain amount of shuffling at baseline. There are still high skill accumulating capital and low skill de-accumulating slowly. Shocks could play a role slowing down accumulation or speeding up de-accumulation. With higher levels of correlation, the decay would be steeper.

Finally, under DGP4 where there is co-existence of conditional convergence and unnecessary traps, the method finds three regions. It important to note that those in region 2 (middle group) now are a mix of Type B group 2 agents, Type A agents accumulating capital, and Type C agents de-accumulating capital. Type A and C agents are not as sensitive to shocks and thus add noise to this approach. Yet the data suggests three regions based on sensitivity to shocks and identifies the existence of unnecessary deprivation.

4.2.2 One Shock

It is necessary for this approach to differentiate between conditional convergence and unnecessary deprivation that we observe shocks close to the baseline—or the time period where we observe capital and split the sample. We are using baseline line data to split the sample and the information we get from estimating the impact of the shock becomes less relevant to the question at hand when the measured shock is not close enough in time to the baseline.

In the illustration above, we use simulations where the incidence of large shocks is not very high (see Appendix Figure A.4 for the distribution of negative shocks). From Figure 6, we can see that if we have information on only one shock, the closer it is to the baseline, the more likely it is we reject the equality of the coefficients. The same is true for finding three regions. This could be used, for example, for a randomized controlled trial with a large shock soon after the baseline. Examples of this are positive shocks in randomized controlled trials (for example Balboni et al. (2022)) or negative shocks through natural disasters (for example Carter et al. (2007)).

5 Robustness & Caveats

In the previous sections we showed the existing methods do not differentiate between conditional convergence and unnecessary deprivation traps. We propose a shocks-based threshold estimation approach that uses sensitivity to shocks to identify unnecessary deprivation. To this point, we have assumed low amounts of measurement error (correlation of 0.95 between observed and actual capital/shocks). We have also assumed a correlation (where possible) between ability and capital at baseline of 0.5.[17]

In this section, we discuss the sensitivity of existing approaches to test for traps as well as our to variations in this parameters.

5.1 Measurement Error

In this section, we show the effect of measurement error in our data—something that we expect in micro-level surveys, especially among the poor. In rare cases, asset measurement

[17]This is only possible when we have conditional convergence and co-existence of conditional convergence and unnecessary deprivation.

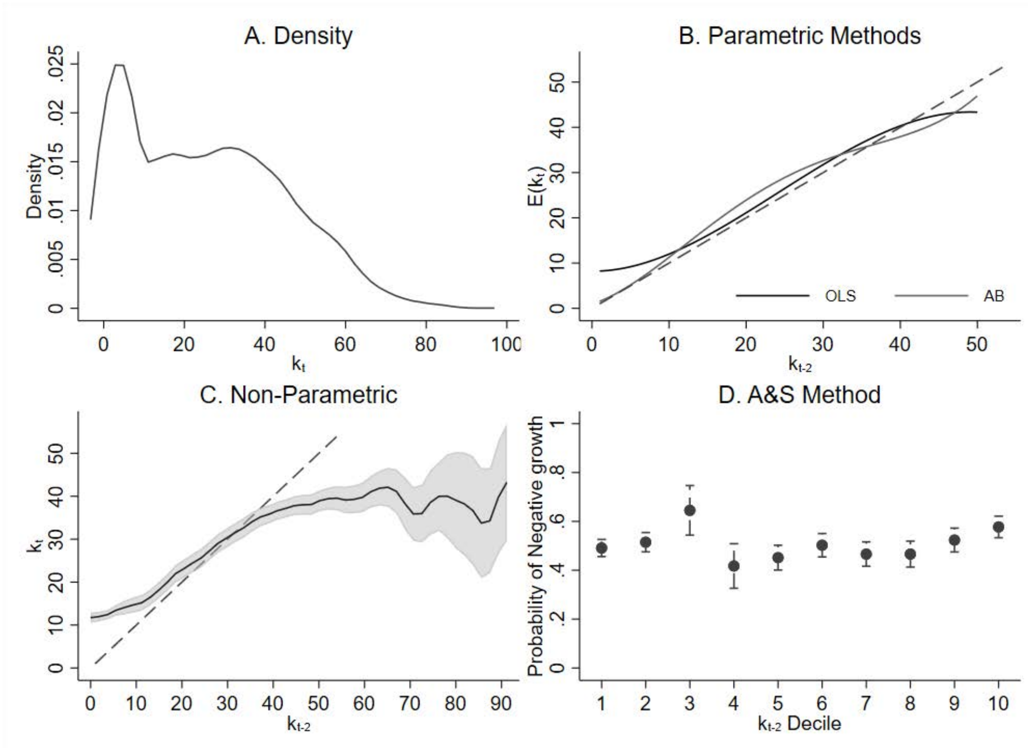


FIGURE 7: DGP2–Unnecessary Deprivation Traps: Adding measurement error to measurement of capital leads to failure of some of the methods in detecting poverty traps. With heterogeneity, i.e. DGP4, multi-equilibria are more difficult to detect in the presence of some measurement error. See Appendix Figure A.6.

may be a straightforward. In most cases, assets and other measures of well-being are difficult to measure and may be misreported.

We only show results with measurement error that increases with capital levels. Classical measurement error that is the same for low and high wealth leads to worse overall detection for a fixed level of overall correlation between observed and actual capital levels.

In Figure 7, we show the results of the four approaches for testing for poverty traps when we have more measurement error–the correlation is now 0.8 between observed and true capital.[18] As expected, the bi-modality is tempered and we no longer clearly see two peaks. The results from both the parametric and non-parametric methods in Panels B and C no longer intersect the 45 degree line from below, however, we still see some non-convex dynamics. Finally, the decreasing pattern in the probability of negative growth is still discernible, although even without much heterogeneity in our agents, the drop in

[18] Note that we censor capital at 0 and thus the error for the lowest levels of capital is not strictly classical.

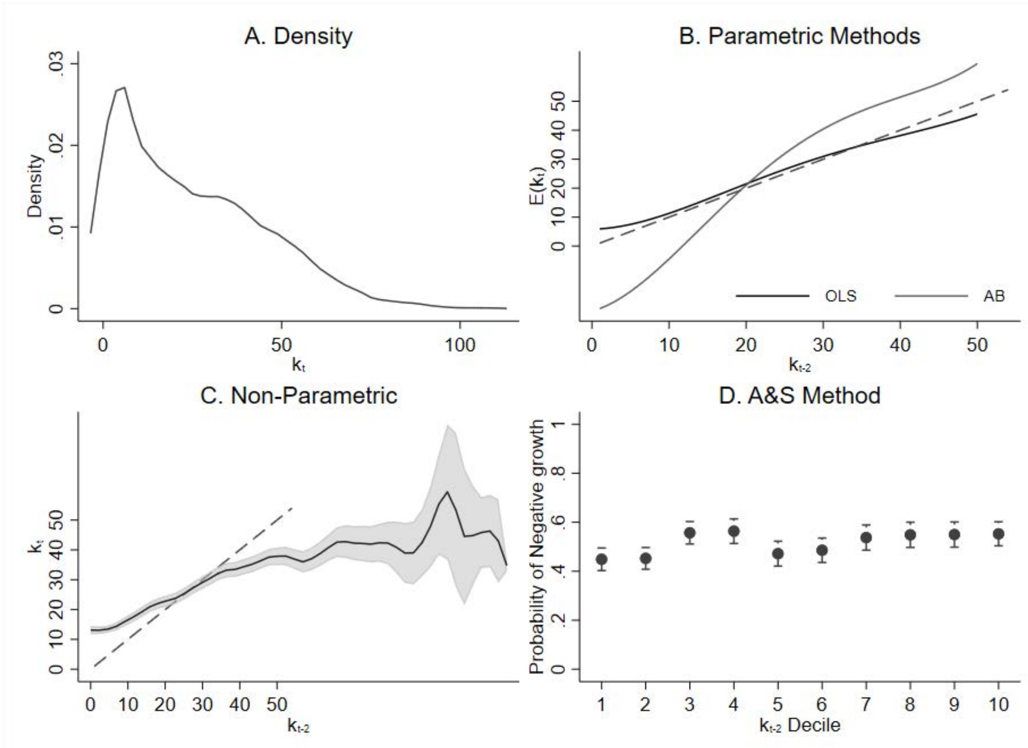


FIGURE 8: DGP3–With less correlation between skill and baseline capital levels (0.2 instead of 0.5), we do not get results similar to that of unnecessary deprivation with common approaches.

probability of negative growth is not as stark as the previous Figure 3.[19]

Our threshold-based estimator also fails when we have more measurement error in capital. This is not surprising since our sample splitting is based on the measure of capital in the baseline. In section 4, our proposed estimator relies on well-measured shocks. However, our method is robust to measurement error in the shocks.

5.2 Correlation Between Baseline Well-being and Skill

When there is less correlation between baseline well-being and unobserved skill, the common tests for traps will not show a pattern that is usually attributed to unnecessary deprivation traps. To illustrate this, we show these results in the Figure 8 where we draw our sample from early in the life cycle where the correlation between skill and baseline level of capital is 0.2 instead of 0.5.

[19] With more heterogeneity it is unlikely that we would be able to statistically differentiate the coefficients. See Figure A.6 in the Appendix.

5.3 Other Measures Of Well-being

Finally, we give a word of caution on using fluid measures of well-being such as consumption. In some studies, authors use other measures of well-being found in surveys. Capital or assets are often complicated to measure; some indices have been used but as Michelson, Muiz and DeRosa (2013) show, arbitrary choices in constructing these indices can matter. Often it is easier to use a value of consumption or household income and to study the dynamics of these different measures that are already in an easy-to-interpret currency value.

We argue that consumption is a bad measure to use when thinking about modeling the dynamics of well-being for a variety of reasons. Most importantly, following most theoretical models of poverty traps, agents may experience high levels of consumption while de-accumulating assets to reach their long-term equilibrium at the low end. In fact we can see this in our data if we focus on two agents with the same ability and asset level who experience different sized shocks; one is just under the threshold post-shock and the other is just above. Comparing the consumption pattern of these two for a few periods after the shock shows that the agent bound for the low-equilibrium exhibits higher levels of consumption for a few cycles while the agent is taking a hit to consumption in order to invest and re-accumulate their capital. This follows the prediction of theoretical models regarding asset smoothing and have been shown to be evident in real-world data (Carter and Lybbert, 2012).

Figure A.7 in the Appendix shows the results of the four tests of poverty traps when we used perfectly measured consumption where all agents face a poverty trap (DGP2). The dynamics here are more complicated and even with perfect measurement does not unequivocally suggest multiple equilibria as do the results in Figure 3. Adding any measurement error would certainly make it harder to observe the poverty trap. It is easy to imagine consumption measurement to be riddled with measurement error in surveys. Adding heterogeneity would further complicate the identification of multiple equilibria. Our proposed method also suffers from this limitation because are sample splitting relies on the baseline measure of well-being.

6 Conclusions

We show that common tests for poverty traps cannot differentiate between conditional convergence traps and unnecessary deprivation—despite most claiming to test for the latter. We argue the importance of random shuffling (through shocks) and propose a threshold-based method that uses shocks to differentiate between the two forms of traps. Moreover, we show that these tests are sensitive to common survey complexities and that even showing multiple equilibria is difficult in the presence of measurement error, heterogeneity, and use of different measures of well-being such as consumption.

While previous studies have discussed the complexities of empirically detecting poverty traps, in our paper, we systematically show how these complexities can make it difficult to detect multiple equilibria even with simulated with low amounts of overall heterogeneity.

Our results should caution researchers working on detecting poverty traps. Even in simple cases such as in our simulation, there is significant complexity in empirical patterns related to poverty traps and unnecessary deprivation. Using shocks is necessary to accurately describe the type of poverty trap present.

References

Adato, M., Michael Carter, and Julian May. 2006. "Exploring poverty traps and social exclusion in South Africa using qualitative and quantitative data." *Journal of Development Studies*, 42(2): 226—247.

Aizer, Anna, Shari Eli, Joseph Ferrie, and Adriana Lleras Muney. 2016. "The Long Term Impact of Cash Transfers To Poor Families." *American Economic Review*, 106(4): 935–971.

Alloush, M. 2022. "Income, Psychological Well-being, and the Dynamics of Poverty." *Working Paper*.

Alloush, Mo, and Jeffrey R Bloem. 2022. "Neighborhood violence, poverty, and psychological well-being." *Journal of Development Economics*, 154: 102756.

Antman, Francisca, and David McKenzie. 2007. "Poverty traps and nonlinear income dynamics with measurement error and individual heterogeneity." *Journal of Development Studies*, 43(6): 1057–1083.

Arellano, Manuel, and Stephen Bond. 1991. "Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations." *The Review of Economic Studies*, 58(2): 277.

Arunachalam, Raj, and Ajay Shenoy. 2017. "Poverty traps, convergence, and the dynamics of household income." *Journal of Development Economics*, 126(December 2016): 215–230.

Azariadis, Costas, and John Stachurski. 2005. "Poverty traps." *Handbook of economic growth*, 1: 295–384.

Balboni, Clare, Oriana Bandiera, Robin Burgess, Maitreesh Ghatak, and Anton Heil. 2022. "Why do people stay poor?" *The Quarterly Journal of Economics*, 137(2): 785–844.

Bandiera, Oriana, Robin Burgess, Narayan Das, Selim Gulesci, Imran Rasul, and Munshi Sulaiman. 2016. "Labor markets and poverty in village economies." *Working paper*, , (July): Advance online publication.

Banerjee, Abhjit, and Sendhil Mullainathan. 2010. "The Shape of Temptation: Implications for the Economic Lives of the Poor." *NBER Working Paper*, 15973.

Barrett, Christopher B. 2005. "Rural poverty dynamics: development policy implications." *Agricultural Economics*, 32: 45–60.

Barrett, Christopher B, and Michael R Carter. 2013. "The economics of poverty traps and persistent poverty: Empirical and policy implications." *Journal of Development Studies*, 49(7): 976–990.

Barrett, Christopher B, Paswel Phiri Marenya, John McPeak, Bart Minten, Festus Murithi, Willis Oluoch-Kosura, Frank Place, Jean Claude Randrianarisoa, Jhon Rasambainarivo, and Justine Wangila. 2006. "Welfare dynamics in rural Kenya and Madagascar." *The Journal of Development Studies*, 42(2): 248–277.

Barrett, Christopher B, Teevrat Garg, and Linden McBride. 2016. "Well-being dynamics and poverty traps." *Annual Review of Resource Economics*, 8: 303–327.

Basu, Kaushik. 1999. "Child labor: cause, consequence, and cure, with remarks on international labor standards." *Journal of Economic literature*, 37(3): 1083–1119.

Bhalotra, Sonia, and Samantha Rawlings. 2013. "Gradients of the intergenerational transmission of health in developing countries." *Review of Economics and Statistics*, 95(2): 660–672.

Bharadwaj, Prashant, Matthew Gibson, Joshua Graff Zivin, and Christopher Neilson. 2017. "Gray matters: Fetal pollution exposure and human capital formation." *Journal of the Association of Environmental and Resource Economists*, 4(2): 505–542.

Bianchi, Marco. 1997. "Testing for convergence: evidence from non-parametric multimodality tests." *Journal of Applied Econometrics*, 12(4): 393–409.

Buera, Francisco J. 2009. "A dynamic model of entrepreneurship with borrowing constraints: theory and evidence." *Annals of finance*, 5(3): 443–464.

Carter, Michael R., and Travis J. Lybbert. 2012. "Consumption versus asset smoothing: testing the implications of poverty trap theory in Burkina Faso." *Journal of Development Economics*, 99(2): 255–264.

Carter, Michael R., Peter D. Little, Tewodaj Mogues, and Workneh Negatu. 2007. "Poverty Traps and Natural Disasters in Ethiopia and Honduras." *World Development*, 35(5): 835–856.

Dasgupta, P., and D. Ray. 1986. "Inequality as a Determinant of Malnutrition and Unemployment." *The Economic Journal*, 6(2): 1011–1034.

Dasgupta, Partha. 1997. "Nutritional status, the capacity for work, and poverty traps." *Journal of Econometrics*, 77(1): 5–37.

De Mel, Suresh, David McKenzie, and Christopher Woodruff. 2013. "The demand for, and consequences of, formalization among informal firms in Sri Lanka." *American Economic Journal: Applied Economics*, 5(2): 122–50.

Duflo, Esther, Michael Kremer, and Jonathan Robinson. 2011. "Nudging farmers to use fertilizer: Theory and experimental evidence from Kenya." *American economic review*, 101(6): 2350–90.

East, Chloe N, Sarah Miller, Marianne Page, and Laura R Wherry. 2017. "Multigenerational impacts of childhood access to the safety net: Early life exposure to Medicaid and the next generationâs health." National Bureau of Economic Research.

Fafchamps, Marcel, David McKenzie, Simon Quinn, and Christopher Woodruff. 2014. "Microenterprise growth and the flypaper effect: Evidence from a randomized experiment in Ghana." *Journal of development Economics*, 106: 211–226.

Flechtner, Svenja. 2014. "Aspiration Traps: When Poverty Stifles Hope." *The World Bank. Inequality in Focus*, 2(4): 1–4.

Galor, Oded, and Joseph Zeira. 1993. "Income distribution and macroeconomics." *The review of economic studies*, 60(1): 35–52.

Ghatak, Maitreesh. 2015. "Theories of poverty traps and anti-poverty policies." *The World Bank Economic Review*, 29(suppl_1): S77–S105.

Hansen, Bruce E. 2000. "Sample splitting and threshold estimation." *Econometrica*, 68(3): 575–603.

Haushofer, Johannes. 2019. "Is there a Psychological Poverty Trap?" Working Paper.

Hoddinott, John. 2006. "Shocks and their consequences across and within households in rural Zimbabwe." *The Journal of Development Studies*, 42(2): 301–321.

Ikegami, Munenobu, Michael R Carter, Christopher B Barrett, and Sarah Janzen. 2019. *Poverty Traps and the Social Protection Paradox.* University of Chicago Press.

Jalan, Jyotsna, and Martin Ravallion. 2002. "Geographic poverty traps? A micro model of consumption growth in rural China." *Journal of applied econometrics*, 17(4): 329–346.

Janzen, Sarah A, Michael R Carter, and Munenobu Ikegami. 2021. "Can insurance alter poverty dynamics and reduce the cost of social protection in developing countries?" *Journal of Risk and Insurance*, 88(2): 293–324.

Keswell, Malcolm, and Michael R. Carter. 2014. "Poverty and land redistribution." *Journal of Development Economics*, 110: 250–261.

Kraay, Aart, and David Mckenzie. 2014. "Do Poverty Traps Exist?" *Journal of Economic Perspectives*, 28(3): 127–148.

Kremer, Michael, Jean Lee, Jonathan Robinson, and Olga Rostapshova. 2013. "Behavioral biases and firm behavior: Evidence from Kenyan retail shops." *American Economic Review*, 103(3): 362–68.

Kwak, Sungil, and Stephen C Smith. 2013. "Regional agricultural endowments and shifts of poverty trap equilibria: Evidence from Ethiopian panel data." *The Journal of Development Studies*, 49(7): 955–975.

Lajaaj, Rachid. 2017. "Endogenous Time Horizon and Behavioral Poverty Trap: Thoery and Evidence from Mozambique." *Journal of Development Economics*, 127.

Lokshin, Michael, and Martin Ravallion. 2004. "Household income dynamics in two transition economies." *Studies in Nonlinear Dynamics and Econometrics*, 8(3).

Loury, Glenn C. 1981. "Intergenerational transfers and the distribution of earnings." *Econometrica: Journal of the Econometric Society*, 843–867.

Lybbert, Travis J, and John McPeak. 2012. "Risk and intertemporal substitution: Livestock portfolios and off-take among Kenyan pastoralists." *Journal of Development Economics*, 97(2): 415–426.

Lybbert, Travis J., Christopher B. Barrett, Solomon Desta, and D. Layne Coppock. 2004. "Stochastic wealth dynamics and risk management among a poor population." *The Economic Journal*, 114(498): 750–777.

Mani, Anandi, Sendhil Mullainathan, Eldar Shafir, and Jiaying Zhao. 2013. "Poverty impedes cognitive function." *Science*, 341(6149): 976–80.

McKenzie, David J., and Christopher Woodruff. 2006. "Do Entry Costs Provide an Empirical Basis for Poverty Traps? Evidence from Mexican Microenterprises." *Economic Development and Cultural Change*, 55(1): 3–42.

Michelson, H, M Muiz, and K DeRosa. 2013. "Measuring poverty in the Millenium Villages: The impact of asset index choice." *Journal of Development Studies*, 49: 917–35.

Moya, Andrés. 2018. "Violence, psychological trauma, and risk attitudes: Evidence from victims of violence in Colombia." *Journal of Development Economics*, 131(November 2017): 15–27.

Moya, Andrés, and Michael R. Carter. 2019. "Violence and the formation of hopelessness: Evidence from internally displaced persons in Colombia." *World Development*, 113: 100–115.

Munshi, Kaivan, and Mark Rosenzweig. 2015. "Insiders and outsiders: local ethnic politics and public goods provision." National Bureau of Economic Research.

Naschold, Felix. 2012. "âThe Poor Stay Poorâ: Household Asset Poverty Traps in Rural Semi-Arid India." *World Development*, 40(10): 2033–2043.

Naschold, Felix. 2013. "Welfare Dynamics in Pakistan and Ethiopia–Does the estimation method matter?" *The Journal of Development Studies*, 49(7): 936–954.

Nickell, Stephen. 1981. "Biases in dynamic models with fixed effects." *Econometrica: Journal of the econometric society*, 1417–1426.

Oreopoulos, Philip, Marianne E Page, and Ann Huff Stevens. 2006. "The intergenerational effects of compulsory schooling." *Journal of Labor Economics*, 24(4): 729–760.

Oreopoulos, Philip, Marianne Page, and Ann Huff Stevens. 2008. "The intergenerational effects of worker displacement." *Journal of Labor Economics*, 26(3): 455–483.

Quah, Danny T. 1996. "Twin peaks: growth and convergence in models of distribution dynamics." *The economic journal*, 106(437): 1045–1055.

Ravallion, Martin. 2016. *The economics of poverty: History, measurement, and policy.* Oxford University Press.

Ravallion, Martin, and Michael Lokshin. 2002. "Self-rated economic welfare in Russia." *European Economic Review*, 46(8): 1453–1473.

Ridley, Matthew, Gautam Rao, Frank Schilbach, and Vikram Patel. 2020. "Poverty, depression, and anxiety: Causal evidence and mechanisms." *Science*, 370(6522): eaay0214.

Santos, Paulo, and Christopher B. Barrett. 2011. "Persistent poverty and informal credit." *Journal of Development Economics*, 96(2): 337–347.

Schaner, Simone. 2018. "The persistent power of behavioral change: Long-run impacts of temporary savings subsidies for the poor." *American Economic Journal: Applied Economics*, 10(3): 67–100.

Shah, Anuj K, Sendhil Mullainathan, and Eldar Shafir. 2012. "Some consequences of having too little." *Science (New York, N.Y.)*, 338(6107): 682–5.

Stiglitz, Joseph E. 1976. "The efficiency wage hypothesis, surplus labour, and the distribution of income in LDCs." *Oxford economic papers*, 28(2): 185–207.

Strauss, John, and Duncan Thomas. 1998. "Health , Nutrition , and Economic Development." *Journal of Economic Literature*, 36(2): 766–817.

Subramanian, Shankar, and Angus Deaton. 1996. "The demand for food and calories." *Journal of political economy*, 104(1): 133–162.

Appendix

Figures

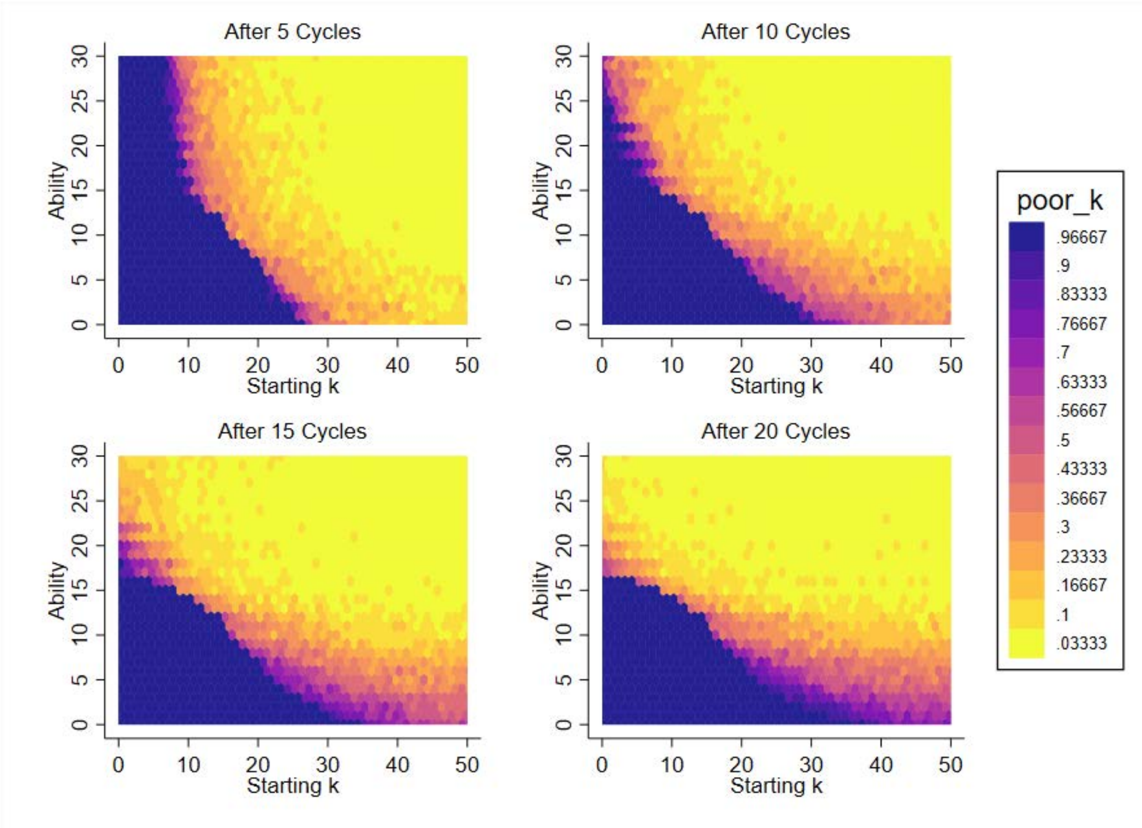


FIGURE A.1: Simulations of this process show that both ability and starting positions play a role in determining poverty (measured with capital k). Those both poor and with low abilities are trapped. Those with high abilities will eventually escape poverty no matter what their starting position is.

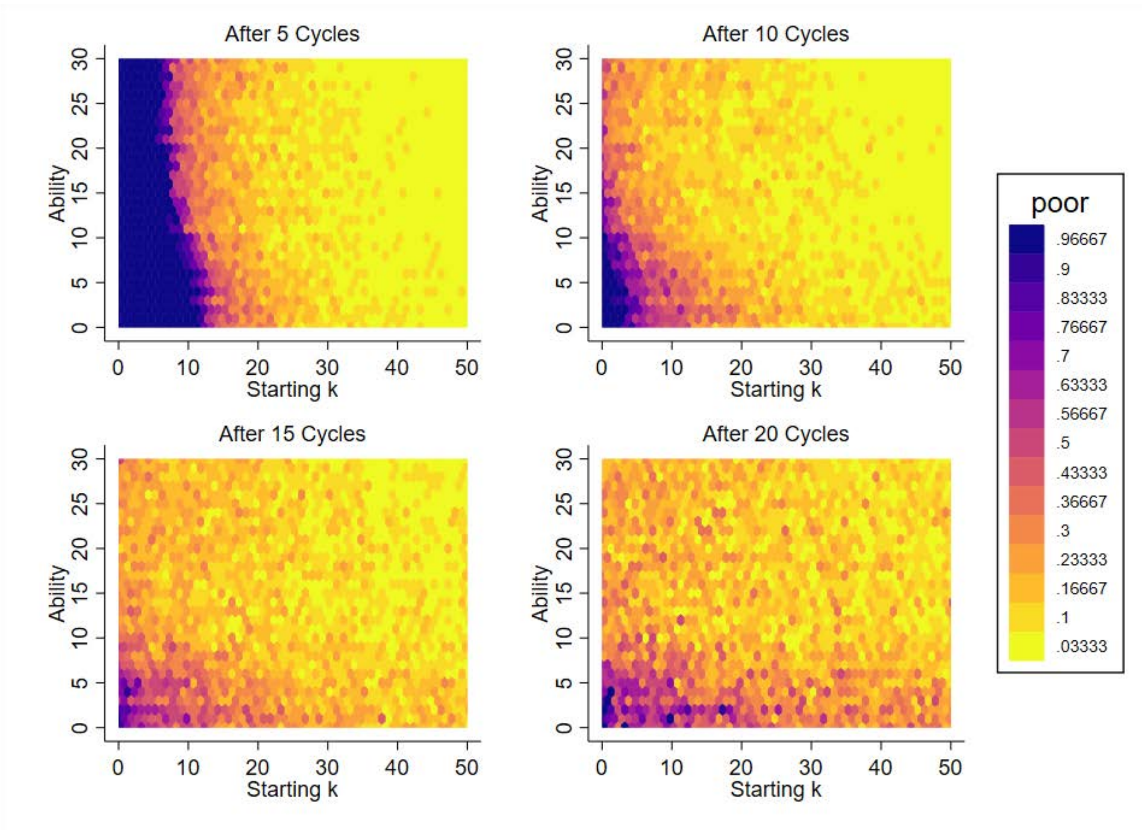


FIGURE A.2: Simulations of a version of this process without a poverty trap show that neither ability and starting positions play a role in determining poverty in the long-run.

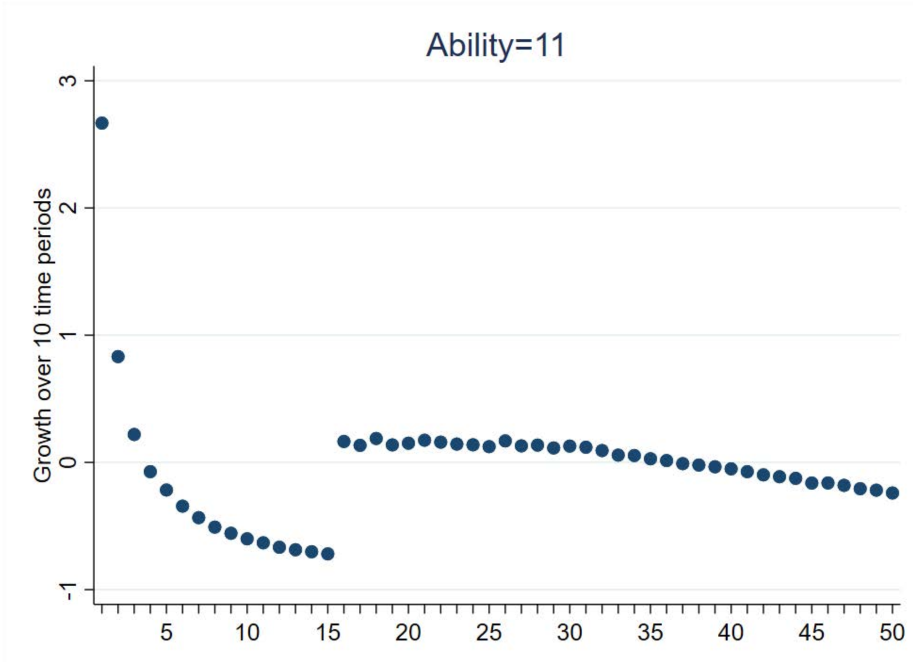


FIGURE A.3: Ability Level 11: Facing a clear trap clearly showing divergent behavior when focusing on growth.

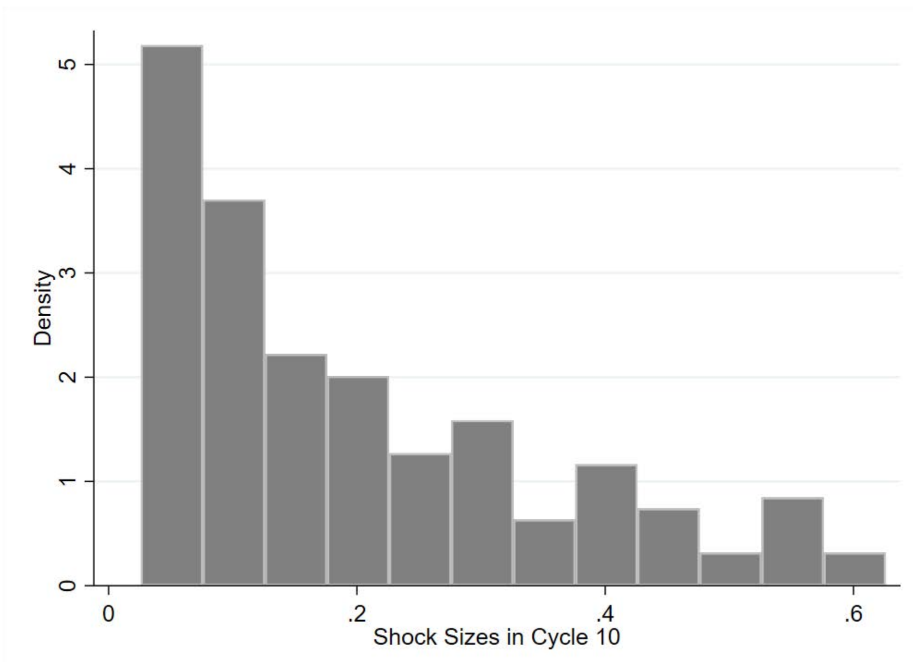


FIGURE A.4: Histogram showing shocks. 80% of cycles do not have any co-variate shocks. This figure shows the distribution of the other 20%.

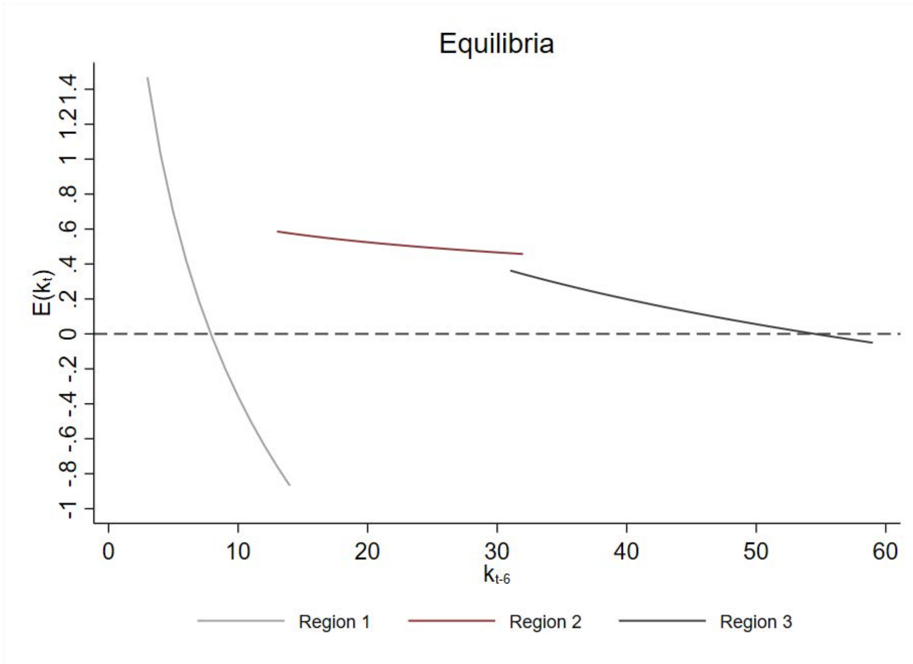


FIGURE A.5: Growth regressions allow us to estimate the equilibrium capital levels.

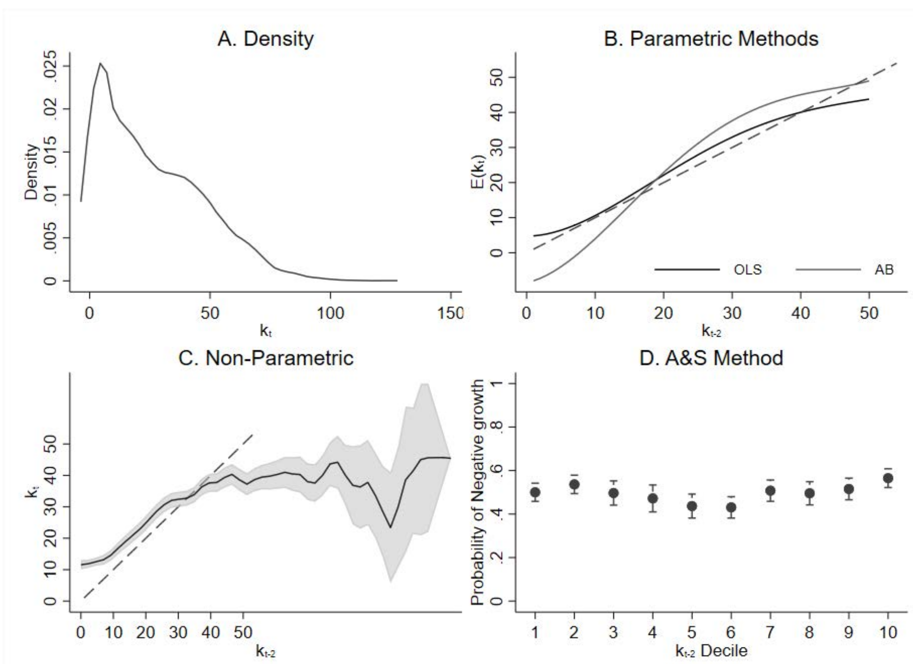


FIGURE A.6: Measurement error and heterogeneity (DGP4) make it more difficult to detect multi-equilibria.

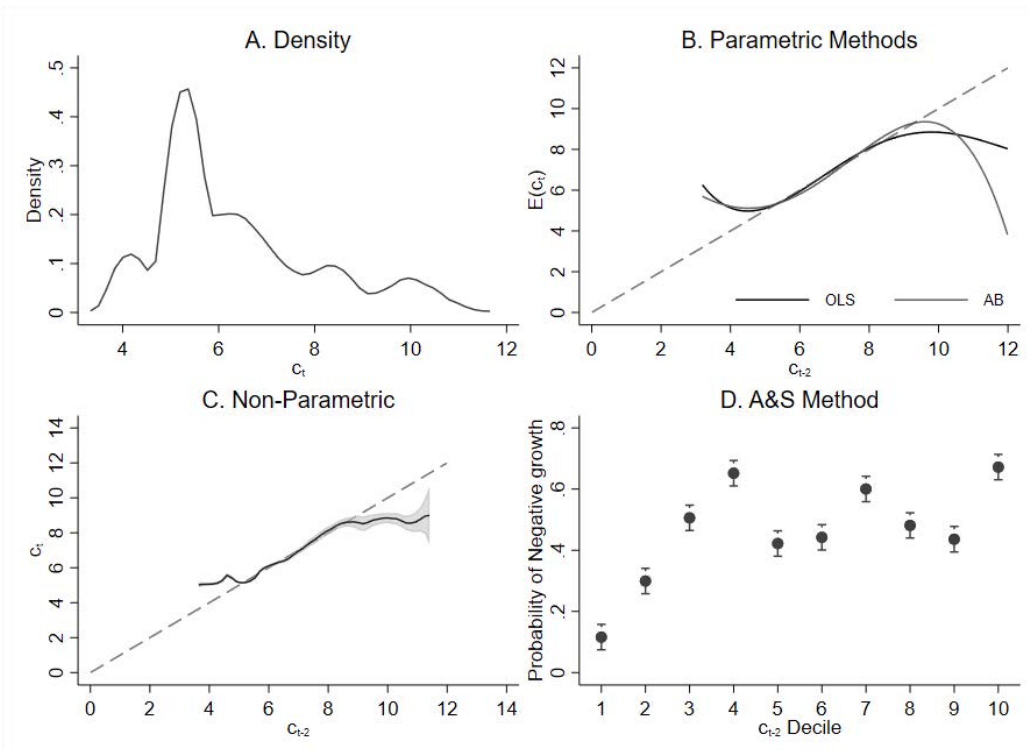


FIGURE A.7: Using perfectly measured consumption where all are facing a trap (ability 11) shows mixed results.

Appendix C

The Theory of Micro-based Poverty Traps

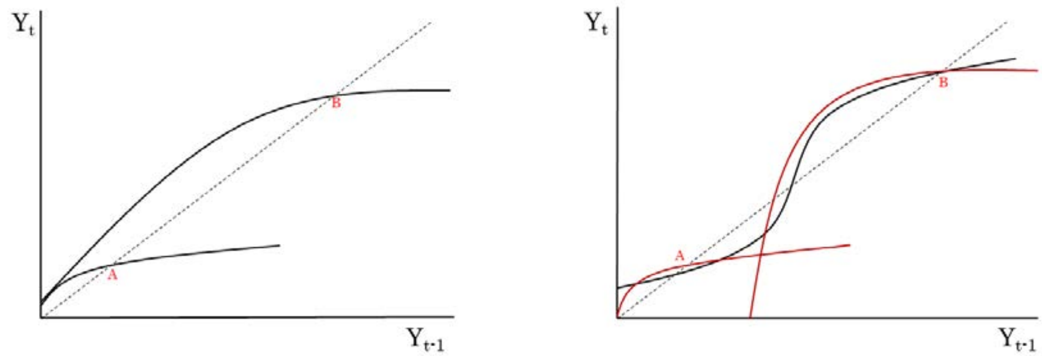
There are several thorough review papers summarizing the literature on poverty traps at the macro and micro-levels. Recent work include Barrett, Garg and McBride (2016), Kraay and Mckenzie (2014), and Barrett and Carter (2013). It is not our aim to provide yet another review of the literature, but here we briefly discuss the theoretical underpinnings of microeconomic poverty traps.

Poverty traps are self-reinforcing mechanisms that cause poverty to persist (Azariadis and Stachurski, 2005; Barrett and Carter, 2013). Poverty traps can be viewed as dynamic process with a specific type of state-dependence where a unit (be an individual, a household, a firm, a village, a region, or a country) is stuck in a low-level equilibrium and unable to escape to the existing higher-level equilibrium because they are poor to begin with. This can arise when there is a specific non-linear relationship between current well-being and future well-being. This is different from theories of convergence or conditional convergence illustrated in Panel A of Figure A.8. Under conditional convergence, initial well-being levels do not matter in determining which equilibrium level one ends up at in the long run. There could be many different equilibria, some low, and those who end up at the low equilibrium are there due to some characteristics or circumstance—not their baseline level of well-being or capital.

Poverty traps can theoretically arise in the presence of a mix of market failures and non-linearities. The main market failure that describes many poor settings are the non-existence of credit markets or the exclusion of the poor from credit markets (for example because of an inability to provide collateral). On the other hand, non-linearities have been suggested in many different domains. For example, theoretical models by Dasgupta and Ray (1986) suggest that if the link between labor productivity and food intake is non-linear (with an increasing return early on at very low levels of consumption), then this could trap individuals in low nutrient intake, low/no productivity equilibrium. This is closely related to the efficiency wage hypothesis (Dasgupta, 1997; Stiglitz, 1976).[20]

From a production point of view, non-convex production processes could theoretically lead to poverty traps. An S-shaped production process with an increasing early returns to scale with respect to capital could trap those who start with low levels of capital in poverty. This is illustrated in Panel B of Figure A.8 with the black S-shaped curve where there are two stable equilibria at point A (low) and point B (high) and where one ends up depends

[20] As Kraay and Mckenzie (2014) summarize, this seems unlikely to be resulting in poverty first because calories are fairly cheap around the world (Subramanian and Deaton, 1996). And second, even if healthy micronutrients should be differentiated from simple calorie intake, studies do not suggest that the relationship between either calorie or micronutrient intake and productivity is nonlinear (Strauss and Thomas, 1998).



(A) Conditional Convergence

(B) Trap Dynamics

FIGURE A.8: A Trap could be caused either by S-shaped dynamics or two different technologies with a fixed cost.

on their previous level of well-being, Y_{t-1}. More realistically, lumpy investments (in education or physical capital) create a large fixed cost that, the in absence of credit markets, could create a poverty trap (Loury, 1981; Galor and Zeira, 1993). This scenario is also illustrated in Panel B of Figure A.8 with the red curves showing two different technologies. This is the main theoretical model suggested when considering poverty traps. The higher-level technology requires a lumpy investment; in theory, one should be able to borrow but in many settings this type of credit is either unavailable or the poorest of the poor may be unable to access the credit needed to make lumpy investments. This can be generalized to getting a higher level of education to access higher paying jobs or being stuck in minimum wage paying jobs.[21]

In the last 10 years, more work has focused on self-reinforcing behavioral mechanisms that could potentially trap people in poverty. Banerjee and Mullainathan (2010) develop a theoretical model where individuals spend on temptation and nontemptation goods where the share of income spent on temptation good declines with income; this results in the poor staying poor. Other work suggests that self-control is lower among the poor due to limited mental bandwidth (Shah, Mullainathan and Shafir, 2012) lower cognitive function Mani et al. (2013). Both of these could hinder the poor from being productive enough to escape poverty and are caused and reinforced by poverty themselves. These could theoretically create traps if the feedback loop is strong enough or there are strong non-convexities in at least one of the relationships.

[21]A group of studies specifically test for non-convexities in returns to investment in micro-enterprises in Mexico and Sri Lanka (McKenzie and Woodruff, 2006; De Mel, McKenzie and Woodruff, 2013); their work and that of others do not seem to suggest non-covexity in returns to investment and suggests that people can accumulate slowly.

Other self-reinforcing processes have been suggested such as through social exclusion and endogeneity of social networks (Munshi and Rosenzweig, 2015), mental health (Flechtner, 2014; Moya and Carter, 2019; Alloush, 2022; Ridley et al., 2020; Haushofer, 2019), exposure to violence (Alloush and Bloem, 2022; Moya, 2018), or changes to economics parameters such as planning horizons (Lajaaj, 2017), or risk aversion (Moya, 2018). Other suggest the endogeneity of self-control (Fafchamps et al., 2014) and overall lower than expected investment in high marginal return investments (Duflo, Kremer and Robinson, 2011; Kremer et al., 2013; Schaner, 2018).

In addition, inter-generational models of poverty reinforcing future poverty in different generations have been posited for some time in economics. This can start early as the poor are more likely to experience shocks during pregnancy (Aizer et al., 2016), and living in poverty in early life leads to lower levels of human capital accumulation and health, for a variety of reasons such as malnutrition or child labor (Basu, 1999; Loury, 1981; Bhalotra and Rawlings, 2013; Oreopoulos, Page and Stevens, 2008, 2006; East et al., 2017). In addition, the poor are more likely to experience violent events and environmental shocks and these are shown to have long-term consequences for children (Bharadwaj et al., 2017).

Appendix D

Empirical Complexities

Disentangling poverty traps or a conditional state dependence of a certain form is difficult. As discussed in Barrett and Carter (2013) and in Arunachalam and Shenoy (2017),[22] detecting traps at the household or individual level using survey data is difficult for a variety of different reason that include:

1. In large broadly representative samples, we will have heterogeneity. While some might face a proper poverty trap, others in our representative dataset do not. For example, highly skilled individuals will likely succeed no matter what their initial endowment is, while highly unskilled individuals will likely be at a low equilibrium in the longer regardless of their initial asset level. We do not know if groupings exist and we do not know which group an individual belongs to.

2. Even among those who are facing poverty traps, the thresholds where their incomes bifurcate towards low and high equilibria could be endogenous to skills and other relevant often unobservable variables. This household/individual-level heterogeneity makes identifying the threshold difficult. Generally, Hansen (2000) threshold estimation method is usually used to identify poverty trap thresholds (Carter et al., 2007), however fixed effects threshold estimation methods are not well developed.

3. Some recent tests for household- or individual-level poverty traps rely on asset-based measures. Asset-based approaches are appealing, but they are slow moving and often hard to pin down a proper value for. Asset indices can solve the latter problem, however empirical tests for poverty traps can be sensitive to arbitrary choices made when constructing the asset index (Michelson, Muiz and DeRosa, 2013).

4. Some tests for multi-equilibrium poverty traps simply try to find multi-modal cross-sectional asset or income distributions (Quah, 1996; Bianchi, 1997). However, as shown in Barrett (2005) and Kwak and Smith (2013), certain stochastic errors in the data-generating process can produce uni-modal cross-sectional distributions.

5. First, disentangling poverty traps (conditional state dependence of a certain form) is difficult when individual characteristics that may lead to different conditional steady states are themselves endogenous to initial well-being. This is slightly different from

[22] For a thorough discussion of the issues that make poverty traps difficult to detect empirically see Barrett and Carter (2013).

point 1–even if we are able to perfectly measure a covariate such as ability or self-control; studies have shown these to be endogenous to well-being and can change. This further complicates pinning down a threshold-based poverty trap.

6. There are several different self-reinforcing mechanisms that could create poverty traps: different mechanisms imply different empirical patterns that may all be present.

7. The thresholds determining traps and the resulting equilibria may move over time in response to changing market and non-market conditions and this may vary across individuals.

8. We are usually unable to control for the many small and large shocks individuals and households face. When thinking about data and panels, we have to balance between two things: One, we need enough time for the trap process to make its mark in order for us to observe it. However, with longer panels, the likelihood of shocks increases and the likelihood of changing market and non-market conditions (that change the dynamic process) also increase.

9. *Econometrics-specific reasons*: If, for example, multiple equilibria exist, then one should find few observations in any sample around the threshold. Therefore the resulting asset dynamics might be mistaken for heteroskedastic and positively autocorrelated errors Barrett (2005). This problem is worsened when individuals who identify the out-of-equilibrium dynamics are a non-random sub-sample with unknown selection, and there is non-random attrition.

Given these complexities, it perhaps not surprising that studies seeking to find evidence multi-equilibrium poverty traps have failed. Recent evidence by Balboni et al. (2022) experimentally showing evidence for poverty traps in Bangladesh has renewed the debate on poverty traps.

Appendix E

Methods description

In this section we briefly describe four popular methods used in the literature to test for poverty traps.

Bi-modal distributions—The simplest of the methods uses the intuition that poverty traps show lead to high and low equilibria and thus bi-modal distributions. In this, draw densities with bandwiths chosen by *Stata*.

Parametric Methods—For this method, we estimate a flexible 4-th degree polynomial equation in two different ways. The first is simply using OLS. THe second, we use panel data methods proposed by Arellano and Bond (1991) and refined over time by many others to estimate the polynomial equation using information from lagged observations of capital. This GMM approach requires assumptions on the dynamics that are easily met in our simulation, however, can be tricky in real panel data.

Non-Parametric Methods—Here we use local linear regressions to estimate the shape of dynamics. Optimal bandwidths are chosen automatically through *Stata*.

Probability of Negative Growth—As suggested by Arunachalam and Shenoy (2017), we run a regression where our dependent variable is a dummy variable indacting a decrease in capital over the relevant time period (negative growth). Our regressors are dummy variables for the baseline decile one belongs to (with no constant). We plot the estimated coefficients.