Why Do People Stay Poor?

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Abstract

There are two broad views as to why people stay poor. One emphasizes differences in fundamentals, such as ability, talent or motivation. The other, poverty traps view, differences in opportunities which stem from differences in wealth. We exploit a large-scale, randomized asset transfer and panel data on 6000 households over an 11 year period to test between these two views. The data supports the poverty traps view - we identify a threshold level of initial assets above which households accumulate assets, take on better occupations and grow out of poverty. The reverse happens for those below the threshold. Structural estimation of an occupational choice model reveals that almost all beneficiaries are misallocated in the work they do at baseline and that the gains arising from eliminating misallocation would far exceed the program costs. Our findings imply that big push policies which transform job opportunities represent a powerful means of addressing the global mass poverty problem.

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1 Introduction

Why do people stay poor? This is one of the key questions in economics. Understanding what causes poverty and its potential persistence is key to solving the mass poverty problem that motivated early contributors to development economics (Lewis, 1954; Myrdal, 1968; Schultz, 1980) and continues to motivate current generations. It is also the central goal of development policy — the main Sustainable Development Goal, endorsed by 193 of 195 of the world's governments, is to "eradicate extreme poverty for all people everywhere by 2030". Given that in 2015, when these goals were set, 10% of the world's population (735 million people) was classified as living in extreme poverty, this is an ambitious objective and particularly so in light of the current pandemic.[1] Finding answers ultimately requires us to understand why people stay poor and to design policy accordingly.

Most of the world's poor are employed but have low earnings, so to understand why they stay poor we must understand why they work in low-earning jobs. One view is that the poor have the same opportunities as everyone else, so if they work in low-earning jobs they must have traits that make them unsuitable for other occupations. The alternative view is that the poor face different opportunities and hence do low-earning jobs because they are born poor. That is, the poor are stuck in a poverty trap. The concept of poverty traps is central to development economics and has been studied in a long and distinguished literature, as reviewed in Azariadis (1996), Carter and Barrett (2006), and Ghatak (2015).[2]

Distinguishing empirically between these two views is as important as it is difficult. It is important because they have dramatically different policy implications. In the presence of poverty traps big push polices that help move people into more productive forms of employment might constitute a powerful means of addressing the global mass poverty problem (Murphy, Shleifer, and Vishny, 1989; Hirschman, 1958). Consequently, the search for evidence on poverty traps has been referred to as "a very big question" for development economists (Banerjee, 2020). It is difficult because both explanations produce outcomes that are observationally equivalent in a cross-section and indeed it has been remarkably hard to empirically identify poverty traps. The main problem in identifying poverty traps is that, by definition, the potential threshold is an unstable equilibrium, so we normally do not observe anyone near it. Moreover, even if we track the capital accumulation behavior of a set of individuals over time, unless there are big and exogenous shocks to their assets, we cannot infer whether their responses in terms of asset accumulation or decumulation

[1] Atamanov et al. (2019).

[2] Theoretical mechanisms underlying this debate can be traced back to growth models with convergence (Solow (1956)) or with multiple steady states (Rosenstein-Rodan, 1943; Nurkse, 1961; Myrdal, 1957; Myrdal, 1968; Rostow, 1960). Typical poverty trap models generally focus on the combination of a fixed investment coupled with external frictions, such as borrowing constraints (Galor and Zeira, 1993; Banerjee and Newman, 1993), or on scarcity-driven behavior, leading to either nutritional (Dasgupta and Ray, 1986; Dasgupta, 1997; Ray and Streufert, 1993) or behavioral (Banerjee and Mullainathan, 2008; Bernheim, Ray, and Yeltekin, 2015; Ridley et al., 2020) poverty traps.

are suggestive of poverty traps or the result of other time-varying factors. This is what makes it difficult to identify poverty traps in observational data.

The main contribution of this paper is to provide an empirical test for the existence of poverty traps using individual-level panel data we gathered over the course of 11 years studying the impact of an large asset-transfer program in rural Bangladesh. This is part of a larger survey effort we conducted covering 23,000 households across the wealth distribution in over 1309 villages. These villages are situated in the poorest districts of Bangladesh. We track 6000 poor households across 2007, 2009, 2011, 2014 and 2018, half of which are randomly selected to receive a large asset transfer in 2007.[3] Being able to track the long-run dynamics of assets, occupations and poverty across 11 years is important as a central prediction of poverty trap models is that one time policies can have permanent effects if they get people out of the trap.

The occupational structure of these villages is very simple and highly correlated with asset ownership. Those who own land or livestock combine it with their labor and hire those who do not on a casual basis. Land cultivation and livestock rearing yield higher earnings than casual labor. This very simple occupational structure, where the more unproductive occupations (agricultural laborer and domestic servant) do not require assets whereas the more productive ones (livestock rearing and land cultivation) do, aids us in our search for the existence of asset threshold levels above which poor households take on asset reliant occupations and rise out of poverty and below which they remain trapped.

We begin by showing that the distribution of productive assets is bimodal. The question is whether the bimodality is symptomatic of a poverty trap, namely whether poor people do casual jobs and hold nearly no productive assets because they do not have the talent to do anything else or whether being poor prevents them from acquiring the assets needed to climb the occupational ladder into the jobs that the richer women in the villages do.

Given that the main problem in identifying poverty traps is the lack of observations around the threshold (as it is an unstable steady state), what makes our setting exceptional is that, fortuitously, BRAC's Targeting the Ultrapoor program (Bandiera et al., 2017) transfers large assets (cows) to the poorest women in these villages and the value of the transfer is such that it moves over 3,000 households from the low mode to the lowest density point of the asset distribution in treated areas.[4] Tracing how assets evolve after the transfer allows us to test for poverty traps. The intuition is that while the equal opportunity and the poverty trap views of poverty are observationally equivalent in steady state, they produce different transition equations off equilibrium. In the equal opportunity view the transition equation is continuous and concave, while in the poverty trap view it is S-shaped or discontinuous.

Since BRAC targeted the program at households without significant productive assets, there are small initial differences in asset ownership before the transfer. As the asset transfer moves

[3]Control households are offered the program after 2011.

[4]The (large) size of the transfer therefore is central to our ability to identify poverty traps.

beneficiaries out of their steady state, we can exploit these marginally different levels of productive assets to estimate the transition equation between capital after the transfer and capital four years later. We can then use later survey waves to test the predictions of the poverty trap model for up to 11 years after the original transfer, namely that beneficiaries above the threshold accumulate assets, move to more productive occupations and grow out of poverty whereas those below do not.

We are therefore testing for the existence of an occupational poverty trap whereby all beneficiaries receive the same value of transfers, but where those above the threshold have sufficient initial productive assets to successfully take on the new livestock occupation whereas those below do not. In this way, small differences in initial asset holdings can lead to divergent trajectories in terms of assets, occupations and welfare depending on whether a household begins above or below the threshold. The range of initial asset holdings across poor households is small relative to the size of the transfer.

Nonetheless, because it is the asset transfer that is randomized, not the level of initial assets, we carry out a range of checks on our identifying assumptions to ensure that these small differences are not proxying for unobserved household characteristics which, in turn, might be driving our results. To do this, we both control for shocks at differing initial asset levels using our control households and also exploit heterogeneous thresholds for individual households so that we can compare households with the same level of initial assets. Both these checks support our identifying assumption that variations in baseline assets are orthogonal to unobservable determinants of post-program changes in assets.

Our main results are as follows. First, in treatment areas we find that the transition equation is S-shaped with an unstable steady state at 2.333 log points, that is when productive assets are worth 9,309 Bangladeshi Taka (BDT, 504 USD PPP).[5] This matches closely the point of lowest density between the two modes of the distribution of productive assets at baseline, which is consistent with the nature of an unstable steady state that it pushes those near it in either direction. The fact that two different methods applied independently on different samples yield the same threshold increases our confidence in the results.[6]

Second, we show that the path of asset accumulation for beneficiaries that receive the transfer in the 4 years after the treatment is consistent with poverty trap dynamics. Treated households whose baseline assets were so low that the transfer was not enough to bring them past the unstable steady state are more likely to slide back into poverty, whilst those who manage to go past the

[5]Throughout, we use the 2007 PPP adjusted exchange rate of 18.46 BDT to one dollar. For comparison, the median value of a cow for the ultra-poor in treatment villages is around 9,000 BDT (488 USD PPP).

[6]This, of course, begs the question of why it has been so difficult to find evidence of poverty traps in observational data. To answer this question we trace out the transition equation for control households in our experiment. The local polynomial estimates of the transition equation for these households crosses the 45 degree line only once at 0.7 log points, which corresponds to the lower mode in the bimodal asset distribution. This makes it clear why we cannot detect poverty traps using observational data because, in equilibrium, there are few observations around the unstable steady state. What enables us to test for a poverty trap is that our experiment pushes households into the vicinity of this unstable steady state and allows us to examine how they transition away.

threshold escape poverty. This divergence is not due to a differential pattern of shocks correlated with baseline assets. When we run the same regression with control households using a placebo threshold, we only find evidence for mean reversion but not systematic divergence. We also show that in conditions favorable to asset accumulation, such as high village level earnings potential, households' poverty thresholds are lower. Households under such conditions are more likely to escape poverty, even holding constant the level of baseline assets.

Third, we follow treatment households above and below the poverty threshold over the 11 year period covered by our five survey waves. Consonant with a poverty trap model we find that the two groups diverge over time - beneficiaries who start above the threshold accumulate assets (including land), move into more productive occupations and increase consumption. The divergence is starker if we account for the underlying pattern of asset accumulation over the life cycle. Data from control villages show an inverse U pattern whereby households accumulate assets until the beneficiary is in her mid-40s and decumulate after that. In line with this we find that the difference above and below the threshold is mostly driven by beneficiaries younger than 35 at treatment, and hence younger than 46 at endline. Younger beneficiaries above the threshold sacrifice consumption for longer, to buy more assets later. By 2018, almost half of them have more assets than those transferred by the program, while one third of their counterparts below the threshold do.

These results provide evidence that the average household is trapped in poverty: they cannot move into productive occupations due to an initial lack of assets. However, some individuals might not be trapped at all, while others might remain in poverty no matter how many assets they obtain.[7] To look at this, we construct a structural model of occupational choice to assess the *quantitative* importance of the poverty trap. The model also allows us to measure the extent of occupational misallocation, benchmark general equilibrium effects and simulate policy counterfactuals. We find that in the absence of credit constraints only 2% of households would be best off doing wage labor, while 97% of households are exclusively reliant such work at baseline. Conversely, only 1% work in livestock when 90% would do so if they had access to the same asset wealth as the middle and upper classes. Overall, this implies that 96% of households are forced to misallocate their labor. This is an important set of findings, as it suggests that almost no-one is innately unable to take up a better occupation. Evaluated in monetary terms, the misallocation resulting from this lack of opportunity is 15 times larger than the one-off cost of taking households across the poverty threshold. General equilibrium effects that reduce the returns to livestock rearing through a reduction in produce prices can counteract the benefits of asset accumulation. Simulating the effect of price changes, we find that returns would have to fall by 89% to equalize the cost of eliminating the trap and the value of misallocation.

[7] Barrett and Carter (2013) highlight the fact that within a single population some individuals might be subject to multiple equilibria, while others are not and note that this poses a challenge to the empirical identification of poverty traps.

The implications of the existence of occupational poverty traps for development policy are profound. Most people are not poor because they lack innate ability, instead they are constrained by a lack of access to more productive activities. Interventions that do not suffice to move people above the threshold will not be successful at improving outcomes in the long run. On the other hand, big push policies that move a large share of households past the threshold can be effective at lifting them out of poverty permanently. The critical differentiating feature of these two sets of policies is that the latter enables occupational change, whereas the former might not, due to the inadequacy of the transfer to effect this. In the last part of the paper we compare different poverty alleviation policies through the lens of a poverty trap framework. How many lives will be permanently impacted by a given transfer policy depends on the size of the transfer and the initial asset distribution, relative to the poverty threshold. This is an important finding because it implies that a big-push, time-limited approach to poverty alleviation might dominate more continuous consumption support programs which have been the norm around the world.[8]

This study builds on the literature trying to find evidence for (or against) the existence of poverty traps, ranging from cross-country studies to micro-level studies. In their recent review, Kraay and McKenzie (2014) argue that there is no conclusive evidence supporting the assumptions of many poverty trap models. The review by Barrett and Carter (2013) highlights some of the problems of observational data, such as unobserved heterogeneity and the fact, as we argue above, that one would expect few observations in the sample around an unstable equilibrium. This is consistent with the fact that a number of studies that have followed income and assets over time have not found evidence for the characteristic S-shaped dynamics that could give rise to poverty traps when combined with market frictions (Jalan and Ravallion, 2004; Lokshin and Ravallion, 2004; Naschold, 2013; Arunachalam and Shenoy, 2017). In contrast, Barrett et al. (2006) finds evidence on multiple equilibria when analyzing detailed panel data from several remote sites in Kenya and Madagascar where the simple occupational environment enables them to study household asset dynamics. Consistent with the existence of poverty traps they find evidence of locally increasing returns to assets and of risk management behavior consistent with poor households trying to maintain a critical asset threshold through asset smoothing.

A number of studies on Ethiopian rural pastoralist communities generating income from a single asset, namely cattle, find similar dynamics (Lybbert et al., 2004; Santos and Barrett, 2011; Santos and Barrett, 2016): on average, cattle herd size tends to fall below and grow above a threshold level of initial size, consistent with two stable and one unstable steady state herd size. They find that without a minimum herd size, migratory herding in response to water variability and forage is not worthwhile, and those with a herd-size below this stay near their base, where due to land degradation only a small herd can be maintained. Individuals therefore expect increasing returns to assets around the threshold, and take extensive risk and informal loans when they are

[8]This is in line with the finding that microfinance generally fails unless the borrowers already had a business, as these are probably closer to their thresholds (see Banerjee et al., 2019, Banerjee et al., 2015a, Meager, 2019).

in danger of falling below the threshold.[9]

Our work builds on this important set of contributions. Our primary contribution is, the asset transfer in our study allows us to explore the dynamics of a large exogenous shock and this overcomes the difficulty in this literature in distinguishing between dynamics and the steady state that arises in the case of observational data. Moreover, our structural analysis allows us to explore a different mechanism than the one that these studies consider in the context of pastoralists, for example, the non-linear dynamics being driven by the fact that herders need a minimum amount of cows to be geographically mobile (Lybbert et al. (2004)). In our setting of landless individuals with very low assets but where livestock farming is the main self-employment activity provides complementary evidence through a different mechanism, namely, indivisibility of assets and borrowing constraints.

Our evidence also complements a recent wave of papers that evaluate the medium and long run effects of big push policies, as discussed in Bouguen et al. (2019). There has been a growing interest in whether big push, time-limited transfers of assets or cash can permanently lift people out of poverty, as this may be a more powerful and cost-effective route to improving welfare than continuous consumption support. The emerging evidence suggests that though the the evidence on cash transfers is mixed, large asset transfer programs like the one we study seem to have persistent effects (Blattman, Fiala, and Martinez, 2013; Banerjee et al., 2015b; Araujo, Bosch, and Schady, 2017; Bandiera et al., 2017; Blattman, Fiala, and Martinez, 2020; Haushofer and Shapiro, 2018; Millán et al., 2020; Banerjee, Duflo, and Sharma, 2020). Our paper makes precise the conditions under which transfers can have a permanent effect by lifting people out of an occupational poverty trap. Because of this, very similar programs can have strikingly different effects depending on how many people they push past the threshold.

The rest of the paper proceeds as follows. Section 2 details the context, data, and the intervention we study. Section 3 describes the framework, methods and identification strategy we use to test for poverty traps. Section 4 uses short-term responses to the program to distinguish between the two views of why people stay poor. In Section 5 we use data over 11 years to test whether households experience different asset, occupation and poverty trajectories depending on whether they are above or below the poverty threshold. In Section 6 we outline and estimate our structural model of occupational choice that allows us to quantify the extent of misallocation in the work that people do. In Section 7 we draw out the key policy implications from our findings. Finally, Section 8 concludes.

[9]When proxying for individual ability, Santos and Barrett (2016) find that low-ability herders have a unique low steady state, while high-ability herders have multiple steady states.

2 Background and Data

We test for the existence of a poverty trap using data collected to evaluate BRAC's Targeting the Ultra-poor Program in Bangladesh (Bandiera et al., 2017). The data covers 23,000 households living in 1,309 villages in the 13 poorest districts of the country. Of these households, over 6,000 are considered extremely poor. The program offers a one-off transfer of productive assets and training with the aim of simultaneously relaxing credit and skill constraints to create a source of regular earnings for poor women who are mostly engaged in irregular and insecure casual labor.[10] Beneficiaries are offered to choose from several asset bundles, all of which are valued at around 490 USD in PPP and can be used for income-generating activities. Out of all eligible women, 91% chose an asset bundle containing a cow. BRAC encourages respondents to retain the asset for at least two years, after which they can liquidate it. To identify beneficiaries, BRAC runs a participatory wealth assessment exercise in every village. This yields a classification of households into three wealth classes (poor, middle and upper class) which forms our sampling frame. We survey all of the poor and 10% of the other classes in each village. The group of poor households is further split into program eligibles (ultra-poor) and non-eligibles (other poor) according to BRAC's eligibility criteria. A baseline survey was conducted before the intervention in 2007, three follow-up surveys in 2009, 2011, 2014, and the initially ultra poor where again interviewed in 2018. This enables us to track occupation, asset and welfare dynamics over an 11-year period. Attrition between 2007 and 2018 is 14%.[11]

To evaluate the program, we randomize its roll-out so that 20 areas, defined by the region served by the same BRAC office, are treated in 2007 and the other 20 in 2013. For the first three waves, we thus have a control group of 20 villages. While our main results focus on the 3,276 ultra-poor households that receive the treatment in 2007, we use the control group to illustrate the difficulty in identifying poverty traps with observational data, as well as to support our identification. Data from the other wealth classes is used in the structural model to determine what occupations the ultra-poor would engage in if they had a higher endowment of productive assets.

Table 1 describes the economic lives of the women in these villages by wealth class before the program was implemented in 2007. Panel A shows that labor force participation is nearly universal with rates above 80% in all wealth classes. However, poor women work more hours in fewer, longer days and earn much less, both in total and per hour worked. Panel B illustrates how differences in labor outcomes are correlated with differences in human and physical capital. Human capital is very low in these villages, and, while there are differences across classes, even the richest women

[10] The program also includes consumption support in the first 40 weeks after the asset transfer, as well as health support and training on legal, social, and political rights in the two years following program onset.

[11] Migration is rare in our sample, as the median age of of ultra-poor women is 35 and they lack the means to move. Split-households are excluded from the analysis. If the main respondent dies, the household is still tracked and another household member interviewed. With regard to the long-run results of Section 5, attrition is balanced above and below the poverty threshold and the results are unchanged when using the balanced panel of households that are observed in every survey wave.

have only 3.7 years of education on average and 49% of them are illiterate. Ownership of physical capital is what sets apart rich women from poor women in these villages. We measure physical capital as the sum of all productive assets (poultry, livestock, tools, machines, vehicles, and land) and find that the average upper-class household owns 94 times more productive assets than the average poor household.[12]

We argue that ownership of productive assets is a crucial determinant of occupation and (hence of) welfare and so a lack of these may trap people in poverty. A first indication of this is seen in Figure 1a which shows a kernel density estimate of the distribution of productive assets pooling all wealth classes. The distribution is bimodal, with a mass of households around 0.25 and 6.5, and hardly anyone in between.[13] Households in these village economies either own a lot of productive assets or almost none. Differences in asset ownership relate directly to differences in consumption. For example, households at the low mode with assets of less than 0.5 have an average annual per capita expenditure of 637 USD. For those at the high mode with assets between 6 and 7 this number is 1110 USD. Figure 1b shows the distribution of productive assets after a random fraction of ultra-poor households receive the asset transfer. More than 3,000 households have been moved from the low mode to the low density part of the distribution. It is the fortuitous placement of over 3000 households in this area and our ability to track occupation, asset and welfare dynamics over an 11-year period that allows us to test for the existence of poverty traps.

Richer households do not just own more assets, they also own more expensive assets. Figure 2a shows that the program beneficiaries, 85% of whom own assets valued less than 2 log points (7,390 BDT), own mostly poultry and goats, whilst their richer counterparts own cows and land. This ordering corresponds to the unit value of these assets. The median unit price of chickens and goats is 100 BDT and 1,000 BDT, respectively, while a typical cow costs around 9,000 BDT. The fact that people with more assets own more expensive assets rather than more of the same assets suggests that indivisibilities might be important. With imperfect rental markets it may not be possible to obtain livestock or complementary inputs for a share of the time and the price. Furthermore, differences in asset composition give rise to differences in occupational choice. Figure 2b, shows how hours allocated to different occupations vary with the value of a household's productive assets. Casual employment in agriculture or domestic services prevail at low levels of

[12]In detail, the list of productive assets comprises of land, cows, goats, sheep, chickens, ducks, power pump, plough, tractor, mowing machine, unit for keeping livestock, shop premises, boat, fishnet, rickshaw/van, trees, cart. Our asset measure also includes asset values reported under 'other productive assets' in the questionnaire so that various small assets not included on this list are captured as well. Assets belong to the household rather than to the individual. The Bangladesh rural CPI is used to deflate the value of productive assets to 2007 BDT and we report the value of productive assets in 1,000 BDT converted to logs using the formula $ln(X + 1)$. This avoids dropping observations with zero assets, but as this transformation is arbitrary and may be biased we also check that our main results are robust to using the inverse hyperbolic-sine transformation method suggested by Bellemare and Wichman (2020).

[13]Sampling weights are used to account for the different sampling probabilities of households across wealth classes. To test for the statistical significance of the bimodality, we employ the simulation-based dip test by J. A. Hartigan and P. M. Hartigan (1985) The test rejects the null hypothesis of a unimodal distribution with $p < 0.01$.

productive assets while self-employment in livestock rearing and land cultivation gradually take over as the ownership of productive assets increases.

By transferring livestock the program thus gives the poorest women in these villages the opportunity to access the same jobs as their rich counterparts. It is key to note that this opportunity would not have arisen without the program. Appendix Figure B1 plots the share of households in control villages whose log assets change by more than any multiple of 0.1 BDT in the $(0, 4)$ interval. The figure shows that changes of the same magnitude as the BRAC transfer occur rarely: only 5.9% of control households experience such changes in the absence of the program. This probability is almost identical over the two-year and four-year horizon, indicating that shocks are mostly transitory.[14] Indeed, in control villages, only 3% of the households that are poor at baseline reach the assets stock of a median middle-class household within four years. The probability of catching up with the upper classes is therefore close to zero. This is thus a setting where the poor stay poor. The key question is whether this reflects differences in immutable characteristics such as talent for different occupations, or different access to capital. The next section illustrates how we can use responses to the program to test between the two views.

3 Framework, Method, and Identification

3.1 Framework

We present a simple framework to illustrate two ways in which the observed differences in asset holdings can be explained: (1) differences in individual characteristics and (2) asset dynamics that create a poverty trap. We then use this framework to test between the two views.

As mentioned earlier, the notion of an individual poverty trap that we focus on is closely related to the dynamics of capital accumulation. To formalize this notion in a general way, define the transition equation as the function that relates individual i's capital stock across two time periods:

$$K_{i,t+1} = \Phi_i(K_{i,t})$$

where $K_{i,t}$ denotes i's capital, or productive assets, at time t. To fix ideas, assume that individual i in village v generates earnings according to $Y_i = A_{iv} f(K_i)$, where $f(\cdot)$ is the production function[15] and A_{iv} captures all immutable traits—either of individuals or of the village—that determine productivity. Let s_i denote the individual's savings rate and δ a common rate of depreciation. In

[14] In the control group, log changes in assets between 2007-2009 are negatively correlated with changes between 2009-2011. An OLS regression of changes in the latter period on the first yields a coefficient of -0.44 ($se = 0.02$). This suggests that many positive shocks are reversed within two years. However, we cannot disentangle the real pattern of shocks from mean reversion induced by measurement error.

[15] The production function here should be interpreted as the results of households' optimization across the choice of all available occupations or production technologies. This can be fleshed out by endogenizing occupational choice, as we do in Section 6.

this special case, the transition equation can be expressed as:[16]

$$\Phi_i(K_{i,t}) = s_i A_{iv} f\left(K_{i,t}\right) + (1-\delta)\, K_{i,t} \tag{1}$$

To capture the idea of persistence, define a steady state as a fixed point of $\Phi_i(\cdot)$, that is a level of capital, K_i^*, such that $K_i^* = \Phi_i(K_i^*)$. In the above example, this is a point where the amount of savings exactly offsets the amount of depreciation.

This framework allows us to precisely define a poverty trap. For illustration consider the transition equations depicted in the top panels of Figures 3a and 3b. In each graph, the diagonal 45° line represents the set of points such that $K_{i,t+1} = K_{i,t}$. The transition equation in Figure 3a is globally concave and has a unique steady state, K_i^*. This transition equation can arise in the above example under the assumptions of constant s_i, A_{iv} and δ, and a production function, $f(\cdot)$, that satisfies the Inada conditions. In our context, a transition equation like this implies that each household eventually converges to a household specific steady state K_i^*, determined by the household's productivity A_{iv} and savings rate s_i. An explanation for poverty, in this view, is that poor households have low productivity, which yields a low steady-state level of productive assets, and hence, low income.

Another example of a transition equation is given in the top panel of Figure 3b. In this case, there are three steady states: two stable steady states, K_{iP}^* and K_{iR}^*, and an unstable steady state, $\widehat{K_i}$, between them. If this is an accurate description of households' capital accumulation dynamics, then poverty can arise because of a low initial endowment. Households with initial capital below $\widehat{K_i}$ lose capital over time and converge towards the low steady state, K_{iP}^*. The same household (or a household with identical productivity and savings rate) could be at a higher steady state capital level, and hence higher income, had it had access to an initial endowment above $\widehat{K_i}$. Note that the S-shape of the transition equation can be due to different mechanisms. If the true relationship between $K_{i,t+1}$ and $K_{i,t}$ is given by Equation (1) above, such a shape could for example arise due to increasing returns to scale in $f(\cdot)$ or if s_i is an increasing function of $K_{i,t}$.[17]

The S-shaped transition equation is not the only way in which there can be a poverty trap. Figure 3c shows a transition equation with a discontinuity. There are again two stable steady states, K_{iP}^* and K_{iR}^*, but now there is no steady state between them. Instead, households at and above the discontinuity point $\widehat{K_i}$ accumulate capital whereas those just below $\widehat{K_i}$ decumulate. Such a transition equation can describe a situation where households choose between two different production technologies and where switching to the 'high capital' technology requires an investment in a large indivisible asset. In our context, where physical asset ownership is a determinant of occupational choice, the two parts of this transition equation might represent different occupa-

[16]Note that we are here also assuming that there are no credit or rental markets. If there is a frictionless credit market, individuals will immediately borrow the amount needed to produce at the optimal level of capital input. For details see Ghatak (2015).

[17]For a review of different micro foundations see Ghatak (2015).

tions, with a threshold capital level,$\widehat{K_i}$, required to access the more profitable occupation. While this is a plausible story in this setting, it is empirically challenging to distinguish 3c from 3b, as we discuss below.

The bottom panels of Figures 3a, 3b, and 3c show the change in capital over one period, $\Delta K_{i,t+1} = K_{i,t+1} - K_{i,t}$, against the initial level of capital implied by each of the transition equations. We will use these to interpret the empirical results, where we measure $\Delta K_{i,t+1}$ as the change in productive assets in the four years following the asset transfer.

Returning to Figure 1a, this framework illustrates different interpretations of the baseline distribution of productive assets. Even in the presence of shocks and measurement error, households will, on average, be close to steady state at baseline. If asset dynamics are governed by a concave transition equation with a unique steady state as in Figure 3a, then the bimodal distribution of assets suggests that there are two groups of inherently different households: those whose steady state is close to zero and those who have a high steady state.[18] By contrast, if asset dynamics are better described by Figures 3b or 3c, then a bimodal distribution of assets might naturally arise as some households conglomerate at a low steady state K^*_{iP}, and others at the high steady state, K^*_{iR}. This could happen even if households are identical with respect to their immutable characteristics captured in A_{iv}. In which of the two steady states any individual household ends up here only depends on their initial asset endowment.

3.2 Method

We can glean two general insights from the discussion above. First, if the transition equation, $\Phi_i(k_{it})$ is globally concave, there cannot be multiple stable equilibria in the capital accumulation process, and hence no poverty trap as we have defined it above. The first step of the empirical analysis therefore formally tests the concavity of $\Phi_i(k_{it})$ using the non-parametric shape test developed by Hidalgo and Komarova (2019).[19]

The second insight from the previous section is that we can speak of a poverty trap if and only if there is a threshold level of capital, which we call $\widehat{K_i}$, such that those below $\widehat{K_i}$ converge to a low stable steady-state level of capital and those above converge to a high stable steady-state level of capital. In the vicinity of $\widehat{K_i}$, this implies that for households with $K_{i,t} < \widehat{K_i}$ we expect $K_{i,t+1} < K_{i,t}$, whereas for households with $K_{i,t} > \widehat{K_i}$ we expect $K_{i,t+1} > K_{i,t}$. The next step of

[18]The concave transition equation in Figure 3a also has a steady state at exactly zero. However, note that this is not a stable steady state – small shocks suffice to set households onto a path of convergence towards K^* – and hence we wouldn't expect to find a large mass of households there.

[19]The test makes use of the fact that concavity restrictions can be written as a set of linear inequality constraints when using an approximation by B-splines. Imposing those restrictions yields a constrained sieve estimator taking a B-splines base. The constrained residuals, adjusted for heteroscedasticity, are used to calculate Kolmogorov-Smirnov, Cramer-Von Mises and Anderson-Darling test statistics after applying a Khmaldaze transformation to eliminate the dependence induced by the use of the non-parametric estimator. Critical values for these tests are obtained by bootstrap using the unconstrained residuals. See Hidalgo and Komarova (2019) for further details.

the analysis is, therefore, to construct several estimates of the transition equation and identify a candidate threshold level, $\widehat{K}$.

The sample we use to trace out the transition equation consists of the group of ultra-poor households in treatment villages which are followed for a period of four years after receiving the transfer. Households with initial post-transfer assets above 3 are dropped, since these were erroneously targeted as beneficiaries of the program. This leaves us with a total of 3,276 households in the treatment sample.

We use the following notation. Let $k_{i,0} = \ln K_{i,0}$ denote log productive assets (in thousands of BDT) of household i without the transfer at baseline (in 2007), $k_{i,1} = \ln(K_{i,0} + T_i)$ log productive assets including the value of the transfer T_i at baseline (in 2007),[20] and $k_{i,3} = \ln K_{i,3}$ log productive assets at survey wave 3 four years after the transfer (in 2011). This is the first time we observe the beneficiaries after they were free to dispose of the asset. The evolution of households' asset stock after the transfer allows us to estimate an empirical transition equation

$$k_{i,3} = \phi(k_{i,1}) + \varepsilon_i, \tag{2}$$

where we should think of $\phi(k_{i,1}) = \mathbb{E}[k_{i,3} \,|\, k_{i,1}]$ as a transition equation in logs averaged across households.

A key challenge in estimating the transition equation is that, if there is indeed a threshold level at which asset dynamics bifurcate, with those above and below moving in different directions, then in the absence of large shocks there would be no observations close to that threshold. As discussed above, such large shocks are rare (Appendix Figure B1).

Three features, therefore, make our setting ideal to test for the existence of poverty traps and all three relate to our ability to exploit the large asset transfer and to trace effects over the short and long-run. First, the program moves over 3,000 households to the hollow part of the distribution of assets in treatment villages as shown in Figure 1b. Pushing poor households into this (much higher) range of assets enables us to test for the divergence that defines a poverty trap. Second, randomization yields a control group where this does not happen so that we can estimate the shape of the transition equation for a range of asset values that are typically observed (control) and compare this to estimates in ranges that are typically not observed (treatment). This comparison should reveal the inherent difficulty of trying to identify poverty traps in observational data where we cannot observe households around the threshold. Third, by following beneficiaries over eleven years we can test whether households experience different asset, occupation and poverty trajectories depending on whether the one off transfer places them above or below the threshold. This long-run analysis is critical to revealing whether or not small differences in initial assets can result in large differences in living standards as would be predicted by poverty trap theory.

[20] BRAC distributes the same asset bundles in all villages, hence their value depends on local prices. Since most households chose a cow bundle, we value this using the median cow prices within the catchment area of their BRAC branch.

3.3 Identification

The variation in $k_{i,1}$ that we use to identify the transition equation is induced by initial differences in $k_{i,0}$. Since the transfer program was targeted at households without significant productive assets, all eligible households own close to zero assets at baseline and initial differences in assets are therefore small. Nevertheless, as Figure 1b illustrates, there is some variation which we can exploit. When estimating the transition equation (Equation (2)), we impose the identifying assumption that the variation in $k_{i,0}$ at baseline is orthogonal to unobservable determinants of changes in productive assets after the program. This assumption might fail for two reasons. First $k_{i,0}$ might be systematically correlated with shocks that affect capital accumulation independently of the program. Second, $k_{i,0}$ might be correlated with unobservables that shape the response to the program. For instance, baseline capital might be correlated to latent talent for livestock rearing or to the effect of the training component of the program. In this case, post-transfer asset dynamics might be driven by individuals' transitions to the new steady state rather than by poverty trap dynamics.

3.3.1 Controls as counterfactual

First, consider the case of shocks to households' capital stock that are correlated with their baseline capital. Concretely, this can take various forms. For example, households with more baseline assets might be better connected and, hence, more likely to receive windfall inheritances or gifts, or may be able to take greater advantage of some other economic opportunity that may arise independently of the asset-transfer program. Similarly, households with less baseline assets may suffer more from weather or health shocks (Burgess et al., 2017).[21] We use the random allocation of the program and estimate a difference-in-differences model using potential beneficiaries in control villages as a counterfactual for actual beneficiaries in treatment villages. Randomization ensures that, in expectation, these two groups are identical in every respect, including unobservable determinants of capital accumulation correlated with $k_{i,0}$.

3.3.2 Individual thresholds

Second, baseline capital might be correlated with unobserved livestock rearing talent or the effect of the training that accompanies the asset transfer. In terms of the latter, training might increase households' productivity, A_i, and shift the steady state(s). Appendix Figure B2 shows that if the effect of the training component is larger for individuals with a higher level of baseline capital,

[21] This also covers the scenario in which households with a concave production technology receive random productivity shocks prior to our study but haven't converged to their new steady states when we observe them at baseline. Those with a high productivity draw have started to converge to a high steady state and will be measured with a high k_0. Over the study period, they will then continue to accumulate assets. If this could explain our results, we should see the same pattern in the treatment and control group. In particular, $I(\widetilde{k}_{i,1} > \widehat{k})$ should be a strong positive predictor of Δ_i also in the control group.

we can build a scenario where there is a level of k_0 that looks like a poverty threshold even if the production technology is globally concave.

As these concerns arise because of potentially different responses to treatment, they cannot be addressed using the control group. Instead, we use variation in the parameters that shift the transition equation to estimate different thresholds for different groups. This will allow us to test for poverty traps exploiting the differences in thresholds conditional on baseline capital. Consider the transition equation,

$$K_{i,t+1} = s_i A_{iv} f\left(K_{i,t}\right) + \left(1 - \delta\right) K_{i,t}.$$

There are two factors that determine the rate at which capital is accumulated. The first is the saving rate s_i: for a given level of capital and earnings, individuals who can save more will have more capital the next period. The second is the productivity parameter A_{iv}, which depends both on individual traits such as entrepreneurship and village level characteristics such as access to markets and the quality of infrastructure. Individuals who are able to save a large fraction of income, or to generate more income for the same level of capital will be able to accumulate more assets at a given point in time, other things equal. Under the assumption of a poverty trap, this then implies that their threshold will be lower, that is, a smaller transfer will be sufficient to push them out of the trap. This means that two households with the same endowment but different savings rate or earnings potential, might experience different asset dynamics, allowing us to hold k_0 fixed and thus rule out differential response to treatment correlated with $k0$ (Figure B2)

To test whether individuals with a higher saving rate face a lower threshold we use the dependency ratio as an instrument for savings. The rationale for this is that a larger share of earnings can be saved when there are fewer household members who consume but do not earn.[22] To test for differences due to earning potential we use a village measure of excess livestock earnings for non-beneficiaries at baseline. To do so, we regress livestock earnings on the number of cows, both linear and squared, and take the mean residuals at the village level. Intuitively, villages where individuals earn more than predicted from their livestock holdings must have the right infrastructure for livestock businesses.

The next two sections present our main results. Section 4 looks at the four-year response to the asset transfer by estimating the transition equation and identifying the poverty threshold (Section 4.1 and providing evidence in support of our identification strategy (Section 4.2). The following section 5 tests whether the poverty threshold creates persistent differences in the long run.

[22]The fact the median age of respondents is 35 at baseline implies that we can assume that fertility is exogenous to asset accumulation.

4 Short-Term Responses

4.1 The transition equation

Figure 4 panel (a) shows our main estimate of Equation (2) in the treatment group, using a kernel-weighted local polynomial regression.[23] Alternative specifications are presented in Appendix Figure B3. Panel (a) of Figure B3 reports the fitted values of a third order polynomial[24] and panel (b) reports the B-spline estimator.[25]

All three specifications show that the transition equation is S-shaped. The Hidalgo-Komarova shape test indeed rejects the null of global concavity with $p < 0.01$ and, in line with that, we also reject the null that the cubic term of the polynomial shown in Panel (a) of Figure B3 is zero.

All three estimation methods impose continuity of the transition equation. This implies that any poverty threshold will appear as an unstable steady state, with $\phi(\widehat{k}) = \widehat{k}$ and $\phi'(\widehat{k}) > 1$, such as shown in Figure 3b. Working for now under the assumption of continuity, we find this threshold level of $\widehat{k}$ by numerically approximating the intersection of $\widehat{\phi}(\cdot)$ with the 45° line. For example, for the local polynomial regression (Figure 4, panel (a)) this is done by finding a point in the smoothed graph just above and just below the 45° line and averaging their coordinates. Adjusting the number of smoothing points allows us to approximate this point with arbitrary precision. Using this method, we find $\widehat{k} = 2.333$ with a bootstrapped standard error of 0.015.[26] At this threshold, assets are worth 9,308.82 BDT (504 USD). For comparison, the median value of a cow for the ultra-poor in treatment villages is around 9,000 BDT (488 USD). Alternatively we can use the parametric estimates to compute the crossing point analytically, this yields a value of $\widehat{k} = 2.339$ (bootstrapped standard error 0.194), which corresponds to 9,379.14 BDT (508 USD).[27] Note that both the transition equation and the poverty threshold which it implies are averages of the individual transitions equations and thresholds. Some households lose assets even if they are above $\hat{k}$ and vice versa. Some observable dimensions of individual heterogeneity are exploited further in section 4.2.2. Importantly, the S-shape in the average transition equation rules out that all individual transition equations are concave, as the average of concave functions should itself

[23] Local polynomial regression estimates the conditional expectation $\mathbb{E}[k_3 \,|\, k_1 = k]$ at each smoothing point k of a pre-specified grid as the constant term of a kernel weighted regression of $k_{i,3}$ on polynomial terms $(k_{i,1} - k), (k_{i,1} - k)^2, \ldots, (k_{i,1} - k)^p$. For more details, see Fan and Gijbels (1996)

[24] This specification is similar to those in Antman and McKenzie (2007), Jalan and Ravallion (2004), and Lokshin and Ravallion (2004). However, these authors analyze the dynamics of household income instead of productive assets.

[25] A regression spline is a nonparametric smoothing method that uses spline functions as a basis. In general, an Mth order spline is a piecewise $M-$ degree polynomial with $M-2$ continuous derivatives at a set of pre-selected points (called the knots). B-splines are a particular type of splines. For more details, see Wasserman (2006).

[26] Due to the bootstrap sampling variation, there are cases where the poverty threshold is not unique, i.e. there is more than one point at which the transition equation crosses the 45° line from below. In these cases we record the lowest of the estimated thresholds. However, across all 1,000 bootstrapped samples, we always find at least one unstable crossing point.

[27] We compute this threshold as the second root of the polynomial $76.9 - (96.9 + 1)k + 41k^2 - 5.7k^3$, which is shown in Appendix Figure B3.

be concave.

If this level of assets is indeed unstable, individuals just to the left should slide back into poverty and those just to the right should accumulate assets over time, hence we should not find anyone with that level of assets in equilibrium. This is indeed the case as the estimated threshold falls exactly in the low-density range of the baseline distribution of assets in the full population (Figure 1a). The multiple equilibrium model is thus consistent with the bimodal distribution of assets. By contrast, a bimodal asset distribution does not arise naturally under a concave production technology. While possible in theory, it requires a bimodal distribution of the savings rate or individual productivity, neither of which we observe in the data (see Appendix Figure B4).

The same exercise replicated in control villages yield a transition equation with only one stable steady state at 0.7 (panel (b) of Figure 4). Remarkably, this corresponds to the low mode in Figure 1a. The transition equation is consistent with a pattern of transitory shocks or mean reversion, as higher initial asset levels predict a loss of assets over the consecutive four years. Note also that in the absence of credit markets, the productive asset measure is bounded at zero. Households starting with nothing can only experience positive shocks. Finally, recall that without the transfer there are few households close to the poverty threshold of $\widehat{k} = 2.333$, which is particularly true for the ultra-poor. This illustrates the difficulty in identifying poverty traps with observational data: to prove the existence of an unstable steady state we need to observe how people behave around it but we never do precisely because it is unstable.[28]

Returning to the treatment group, we note that the poverty threshold is such that about 60% of treatment households are placed above. Those who remain below do so by a small margin. The difference between the median transfer value and the threshold is only about 300 BDT (16 USD). This value is close to the median unit value of ploughs (250 BDT), carts (300 BDT), or sheds for keeping livestock (300 BDT) owned by the poor in our sample - assets that are complementary in maintaining and generating income from a cow. As assets are combined with labor to generate income, the picture that emerges is one where poor people cannot afford to purchase indivisible productive assets and remain employed in low wage, insecure casual jobs that pay little relative to the price of the asset and keep them in a poverty trap. This raises several key questions for policy: can a one-off transfer reduce poverty permanently? Do poverty traps create misallocation and if so, how much do we lose in terms of aggregate output because of this?

We will address these questions in Sections 5 and 6, after having provided evidence in support of our identifying assumptions in what follows.

[28]Those control households whom we nevertheless encounter close to this asset level at baseline have not, as a group, been placed there by an exogenous shock. We do not observe the same poverty trap dynamics for this group; either because they are too few for us to detect a pattern statistically or simply because they systematically differ from our treatment sample, e.g. in terms of their asset accumulation behavior.

4.2 Evidence on identifying assumptions

4.2.1 Controls as counterfactual

To investigate potential differences on unobservables we use households in control villages as counterfactual. Table 2 compares asset accumulation above and below the threshold in treatment and control villages. Start by defining Δ_i as the asset accumulation in the four years after the transfer over and above the value transferred by BRAC, that is $\Delta_i = k_{i,3} - k_{i,1}$. The bottom panels of Figures 3a–3c illustrate the close relation between Δ_i and the transition equation. As is evident from these figures, if $\widehat{k}$ indeed has the characteristics of a poverty threshold, one would expect $\Delta_i > 0$ for individuals whose baseline level of capital is large enough that, in combination with the transfer, it exceeds the threshold ($k_{i,1} > \widehat{k}$), whereas $\Delta_i < 0$ for those whose baseline level of capital is not large enough ($k_{i,1} < \widehat{k}$). The first column of Table 2 reports the estimates of:

$$\Delta_i = \alpha + \beta I(k_{i,1} > \widehat{k}) + \varepsilon_i \tag{3}$$

where $I(k_{i,1} > \widehat{k}) = 1$ if $k_{i,1} > \widehat{k}$ for households in the treatment villages. The estimates suggest that beneficiaries who stay below the threshold despite the transfer lose 14% of the assets over the next four years whilst those who are pushed past the threshold grow their assets by 16%. Column 2 reports the same results for households in control villages. Since these households do not receive a transfer, we define $I(k_{i,1} + \tilde{T} > \widehat{k}) = 1$ to identify households who would be above the threshold had they received a hypothetical transfer, $\tilde{T}$, of the same size. Here, $\hat{\beta}$ is close to zero, which supports the identifying assumption that households above and below the threshold would not have been on different accumulation trajectories in the absence of the transfer and are not differently affected by systematic shocks. It might seem surprising that the constant in the control group is large, both in absolute terms and relative to treatment. This is because control households own close to zero assets at baseline. They cannot lose much and small absolute changes appear large in percentage terms (Figure B1). Column 3 puts together treatment and control to estimate the difference-in-difference between treatment and control above and below the threshold. Under the assumption that, had it not been for the program, ultra-poor households in treatment villages would have experienced the same pattern of capital accumulation as their counterparts in control, this measures how much treatment households gain from being to the right of the poverty threshold. The estimate is similar to that in column 1, reflecting the fact that the pattern of capital accumulation is not significantly different around the (placebo) threshold for control households. Columns 4-6 of Table 2 repeat the exercise allowing the pattern of capital accumulation to depend on baseline assets, we estimate:

$$\Delta_i = \alpha + \beta_0 I(k_{i,1} > \widehat{k}) + \beta_1 k_{i,1} + \beta_2 I(k_{i,1} > \widehat{k}) \times k_{i,1} + \varepsilon_i.$$

This specification allows for a different slope of Δ_i in $k_{i,1}$ on each side of $\hat{k}$. Therefore, $k_{i,1}$ is

centered at $\hat{k}$, so that β_0 directly measures any discontinuity in Δ_i at $\hat{k}$. Our null hypothesis is $H_0 : \beta_0 = 0$, i.e., there is no discontinuity. Column 4 rejects the null and shows a discontinuity at $\widehat{k}$, where the change in capital goes from -0.28 to 0.20. To account for shocks that would have occurred in the absence of the program, Column 5 estimates the above regression in the control group. As before, we set $I(k_{i,1} + \tilde{T} > \widehat{k}) = 1$ if the baseline level of assets is such that control households would be past the threshold had they received the transfer. Here, there is no discontinuity at the (placebo) threshold as β_0 is close to zero. Column 6 pools treatment and control villages together and yields the same results, albeit less precisely estimated.

The pattern of column 4 is interesting because it shows that even when controlling for baseline assets, beneficiaries' asset change "jumps" above zero at $\hat{k}$. In addition, they lose increasingly more as they approach $\hat{k}$ from below and - as the positive interaction term suggests - gain increasingly once above $\hat{k}$. This pattern of change is consistent with the transition equation shown in Figure 3c but, depending on the time horizon, it could also be generated by a continuous transition equation as in Figure 3b.[29] These results, therefore, do not distinguish Figure 3c from Figure 3b. However, the pattern is reassuring for our identification assumptions: it seems unlikely that an unobserved correlate of baseline assets would affect asset dynamics in the specific way shown in column 4 with a large discontinuity exactly at $\hat{k}$.

4.2.2 Heterogeneous thresholds

Figure 5, panel (a) reports non-parametric estimates of the transition equation for households above and below the median saving rate, instrumented by the dependency ratio, while panel (b) splits households into those above and below the median earnings potential. Both panels show that the transition equation for households above the median is vertically above that for households below the median. The threshold for households with larger savings (earnings) potential is 2.29 (2.24), while that for households below the median is 2.36 (2.39). For inference, we randomly split the sample into two equal sized sub-samples, either using the individual or the village as unit, estimate the thresholds in each and take the difference between the two. Across 1000 repetitions of this procedure the frequency of a random sample split yielding the observed differences is less than 0.01 for both.

The fact that differences in savings and earnings potential imply different thresholds allows us to identify the effect of being above or below the threshold on asset accumulation for the same level of baseline capital. Table 3 estimates three regressions for each of the two dimensions. Columns 1 and 4 estimates the change in capital stock above and below the individual threshold, i.e. the high threshold if the household is below the median and vice versa. In line with the earlier

[29] We observe households at discrete points in time. Households initially closer to k have, on average, a larger distance to converge to their respective steady states than those already further away. At a sufficiently large time horizon relative to the speed of convergence, a discontinuity might thus appear in the empirical transition equation even if the underlying mechanism is continuous.

findings, we see that individuals for whom the transfer is not large enough to bring them past the earnings-specific threshold lose 16% of asset value in four years, whilst those who pass the threshold accumulate 14%. Similarly, individuals for whom the transfer is not large enough to bring them past the savings-specific threshold lose 15% of asset value in four years, whilst those who pass the threshold accumulate 17%. Columns 2 and 5 control for the level of baseline capital. Strikingly the coefficients remain stable, which is consistent with the fact that neither savings nor potential earnings are correlated with baseline capital. More importantly, and in line with the analysis in the previous section, these results reassure us that different patterns of accumulation above and below the threshold are not due to unobservables correlated with baseline capital.

Finally, columns 3 and 6 test whether it is the relevant individual thresholds that bind. To implement this test we restrict the sample to individuals with *high* thresholds and estimate:

$$\Delta_i = \alpha + \beta_L I(k_{i,1} > k_L^u) + \beta_H I(k_{i,1} > k_H^u) + \varepsilon_i,$$

here β_L measures the effect of being past the low threshold while β_H measures the effect of being past the high threshold. The results show that these individuals lose capital regardless of whether they are above the low threshold but they start accumulating once they go above the high threshold, which further allays the concern that results are driven by unobservables related to baseline capital.

5 Long-Run Dynamics

A key implication of poverty traps is that households experience different poverty trajectories depending on whether they are above or below the poverty threshold. In this section, we address the question of whether the threshold we identified from short run (4-year) asset dynamics generates persistent and sizable differences in outcomes in the long run. Our data allows us to explore these dynamics over the course of 11 years from 2007 to 2018. First, in Section 5.1, we track several outcomes for households above and below the poverty threshold. Guided by the theory of an occupational poverty trap, we test whether households above the threshold accumulate productive assets, take on better occupations and grow out of poverty. Second, we note that due to the long time horizon, life-cycle savings effects can substantially impact asset accumulation. Section 5.2 provides evidence for such effects and accounts for them in the analysis of long-run asset, occupation and welfare dynamics.

5.1 Long-run outcomes above and below the poverty threshold

Figure 6 plots estimates of the following panel specification:

$$Y_{it} = \beta_0 I(k_{i,1} > \widehat{k}) + \sum \beta_{1t} I(k_{i,1} > \widehat{k}) S_t + \sum (S_t) + \eta_{it} \tag{4}$$

where S_t are dummies for the 2009, 2011, 2014, 2018 survey waves and all other variables are as defined above. The outcomes of interest, Y_{it}, are productive assets in levels and total annual household consumption. We control for sub-district fixed effects. The coefficients of interest reported in Figure 6 are β_{1t}, which measure the additional difference between beneficiaries above and below the threshold at date t relative to this difference just after the transfer. Panel a) of Figure 6 shows that the initially small and insignificant difference in productive assets between households above and below $\hat{k}$ continues to rise over the consecutive survey waves and becomes significant in 2011 and 2018. By 2018, households that were initially above the threshold have on average 10,000 BDT more in productive assets compared to the difference at baseline, indicating large divergence over time. Panel b) shows a steadily increasing gap in household consumption between households above and below $\hat{k}$ relative to baseline, indicating an increase in resources available to the household and household welfare. We interpret this as further evidence that these households indeed escape a poverty trap and are better off in the long run than those who do not.

Table 4 contains the estimated β_0 and β_{1t} coefficients of equation 4. In addition to assets and consumption, it reports the asset composition (columns 2 and 3), net earnings (column 5), net earnings from self employment using assets (column 6) and working hours (columns 7 and 8). The decomposition of asset types reveals that the overall increase is driven by additional accumulation of cows and, particularly in 2018, land. This diversification towards an asset - land - which both differentiates the poor and non-poor in the villages we study and which is not any part of the program shows those above the threshold are on a different trajectory relative to those below. At the same time, ownership of less valuable assets shrinks (not shown), bringing the asset composition of beneficiaries above the threshold closer to their richer counterparts in the same villages (Figure 2a).

Reviewing column 5, it is interesting to note that consumption of households above $\hat{k}$ initially declines and stays negative until four years after the transfer. However, by 2018 the difference turns positive and significant.[30] Two things can be learned from this pattern. First, this result shows that assessing the long run is crucial when drawing welfare conclusions. Had we only considered effects up to 4 years after the transfer, we would have falsely concluded that households trapped in poverty by their low initial asset endowment appeared better off in terms of consumption. Similarly, the results cautions against the use of short-term consumption statistics as a measure of household poverty. Second, the consumption result can be seen as suggestive evidence that even

[30] Table C1 in the appendix shows that this result holds for alternative measures of welfare such as per-capita expenditure, food consumption and poverty headcount.

the poorest engage in forward looking behavior. Those most likely to escape the poverty trap are able and willing to forego current consumption in order to make investments which will only yield returns some years later. In line with this, columns 5 and 6 show an initial relative decline in net earnings as households aspiring to escape poverty re-invest more of their income directly into their asset stock - an investment that is rewarded by higher earnings only 7 years later.[31] Column 6 highlights that this pattern is almost entirely driven by net earnings in self-employed work. Finally, Columns 7 and 8 show that total hours worked and hours worked in livestock and land cultivation (self-employed) also increase. In the long run, we therefore see greater earnings being derived from livestock and land cultivation, as beneficiaries above the threshold shift into these new occupations that they had been excluded from. We also see beneficiaries above the threshold increasing labor supply particularly in these new occupations. Households above the threshold were thus not only able to sustain and expand their livestock asset stock, they were also able to work more and shift into more productive labor market activities.[32]

Our interpretation of the results in table 4 is that an occupational shift induced by the asset transfer is at the core of the poverty trap. All changes in both earnings and hours worked are driven by self-employment - a pattern that makes sense given that assets such as livestock or land are required to engage in the more productive occupations in the villages that we study. This interpretation is also consistent with the fact that the shortfall of those who remain below the poverty threshold is similar in value to typical complementary assets such as carts and sheds. However, we cannot rule out that alternative mechanisms also underlie and reinforce the trap. The difficulty is that those people who escape poverty improve many aspects of their lives. For example, they might consume more food (Table C1) or be less stressed.[33] It is possible that low nutrition or high levels of stress initially made people less productive and poorer and that these constraints where also released as a consequence of BRAC's program. On the other hand, improvements in these variables might merely be a consequence of people now being richer. Future research would have to exploit exogenous variation in both wealth or income and the hypothesized mechanism in order to make progress on this question. Our results suggest that an asset transfer large enough to induce occupational change for many households was sufficient to break potential nutritional or psychological effects that might have also trapped them in poverty.

[31] We do not have a direct measure of income as respondents are asked to report the total earnings from each business activity in the past year and presumably report these net of costs and investments.

[32] The results of tables 4 and 5 are largely robust to the following alternative specifications: holding prices constant at baseline levels to rule out that changes are driven by price effects or inconsistent deflation, controlling for individual fixed effects, restricting the sample to a balanced panel so that only households for which we have data in all survey waves are included, and restricting the sample to households within a small interval of baseline assets (2.24, 2.44) around $\hat{k}$ - a specification akin to a regression discontinuity design.

[33] See e.g. Dasgupta and Ray (1986) and Dasgupta (1997) for discussions of a nutritional poverty trap. See e.g. Shah, Mullainathan, and Shafir (2012), Mani et al. (2013), and Ridley et al. (2020) for evidence on the relationship between poverty and attention, cognitive function or mental health.

5.2 Life-cyle effects

Over the 11 year study period, life-cycle savings behavior might affect households' asset stock. As people get older, they work less with productive assets and instead dissave to maintain consumption. This section provides additional results on whether the effects of being above or below the threshold vary with age.

Figure 7 shows the cross-section of assets by age in the last four survey rounds for other poor, middle class and rich households in control villages. Life-cycle effects seem to play an important role, with respondents accumulating assets until their late 40s and then decumulating. Note that, while there is some variation in asset levels across survey rounds, the curve does not seem to shift to the right as we plot consecutive rounds, indicating that this is indeed an age and not a cohort effect. As respondents age, there will be a tendency to decumulate assets, irrespective of the poverty trap dynamics. For those above the poverty threshold, the two effects - convergence to a high steady state of productive assets and aging - will counteract each other. At baseline, the median age of beneficiaries is 35. Hence, in 2018 half of them will be above 46, suggesting that such life-cycle effects will be at play.

To account for potential life-cycle effects, the following analyses split the sample at the median baseline age of 35 and report results separately for those below ("young") and above ("old"). Figure 8 plots the deciles of the asset distributions above and below $\hat{k}$ over time. The same exercise is done for young (panel A) and old (panel B) beneficiaries separately. The horizontal red line indicates the average transfer value. Several findings are of note. First, there is increasing variation in asset holdings in all groups as the distributions fan out over time. This illustrates, as was noted above, that the poverty threshold is an average with some households above nevertheless losing assets and some of those initially below accumulating. Importantly, productive assets of those initially above $\hat{k}$ are higher than for those below at every decile of the distribution and every survey wave. If we restrict our attention to younger beneficiaries where life-cycle effects are muted (panel A), we indeed find that almost half of those who start above the threshold end up at least retaining the value of the transfer in 2018 while only 30% of those below do. Finally, the comparison of old and young beneficiaries reveals that the young accumulate assets faster and until the end of the study period. Beneficiaries above the median age start to show a pronounced decline in assets relative to their younger counterparts in 2014 - At this point, most of the old are 56 years or older - and this decline continues in almost all parts of the distribution in 2018. While even among the old, those who are initially above $\hat{k}$ seem to fare better in the long run, the asset accumulation effect is muted by the countervailing effect of aging.

The same pattern that emerges from Figure 8 is confirmed in the first column of Table 5, which repeats the analysis of Table 4 but splitting the sample into young (panel A) and old (panel B). The results suggest that the divergence in assets documented in Table 4 was mostly driven by young beneficiaries. While the older beneficiaries above $\hat{k}$ maintain an advantage in terms of

cows, they don't start to accumulate land as the young beneficiaries do. As they don't invest in land, the old generate much less income from self-employed activities throughout the study period. Does this imply that the old fall back into poverty? Column 5 of Table 5 suggests otherwise. The differences in consumption follow similar patterns in both age groups and by year 11 the households of old beneficiaries consume 3,304 BDT per year above the baseline difference if they are above $\hat{k}$. This is consistent with the view that old households save less or even sell assets as they approach the end of their (working) life which allows them to maintain a relatively higher living standard. Finally, it is interesting to note that the coefficient on consumption for old beneficiaries already turns positive in year 4, while young beneficiaries postpone consumption for more than four years. While suggestive, this is again consistent with a model of forward looking behavior. Possibly as a consequence of more asset accumulation and deferred consumption, the young experience a large additional increase in net earnings from year 7 onwards, again driven by self-employed work. By contrast the old see little differential change in net earnings in the long run, even though they they increase their labor supply to a similar extent as the young, if above $\hat{k}$.

6 Structural Estimation

The results of the previous two sections provide evidence of a poverty trap. People engaged in wage labor could have been engaged in more productive livestock rearing had they started with enough assets. This indicates that the overwhelming concentration of the ultra-poor in wage labor at baseline is unlikely to reflect those individuals' first-best choice of occupation given their productivity and preference parameters. In other words there is misallocation - money is being left on the table - people are trapped in low return occupations not because of a deficiency of ability but because of a deficiency in assets. A natural question that follows then is what is the extent of this misallocation? This is what we try to discover in this section.

To do this, we use a simple model of occupational choice to estimate individual-level parameters, determine the optimal occupation for each individual in the absence of capital constraints and hence quantify the extent of misallocation at baseline. Identifying individual-level parameters across occupations is typically challenging given that individuals are generally only observed in the occupation they do best. We overcome this challenge using the fact that almost all beneficiaries are engaged in wage labor at baseline, but that we also observe them all undertaking livestock rearing as a result of the program's requirement that beneficiaries keep the transferred asset for at least two years. Using these results, we simulate the implied total value and distribution of transfers necessary for all households to escape the poverty trap and consider the effects of a series of policy counterfactuals.

6.1 Simple model of occupational choice

Consider a simple environment where individuals allocate their time endowment R between self-employment in livestock rearing (l) and wage labor (h). We allow individuals to mix occupations and allow for overall labor supply to be elastic. We also consider the possibility of hiring in external labor (h') for livestock rearing, so that the total labor input in that activity is $l + h'$. The wage rate for hired-in labor is w'.

Let the individual production function for livestock rearing be given by (we drop subscript i for simplicity):

$$q = AF(\bar{k}, l + h').$$

We assume that the capital stock $\bar{k}$ is given and there is no possibility of borrowing or depositing money in a bank and earning interest. [34]

Since $\bar{k}$ is a constant, this is effectively a one-input production function that depends on $l + h'$. We will restrict attention to production functions that are multiplicatively separable in capital and labor:

$$F(\bar{k}, l + h') = f(\bar{k})g(l + h')$$

Notice that therefore, even if the production function may be S-shaped with respect to k when k is not given, so long as it is concave with respect to $l + h'$ we can use standard maximization techniques. Since we are mostly concerned with properties of $f(k)$ relating to convexity or non-convexity, we will assume that $g(l + h')$ is strictly concave.

For a wage laborer, the wage rate is w. We assume $w > w'$, to capture the fact that hired-in workers are usually members of the farmer's own family, and generally they are paid less than what the farmer earns by supplying wage labor herself. There is an exogenous demand constraint in the labor market, and so $h \leq \overline{H}$ where $0 < \overline{H} < \overline{R}$. Similarly, there is a constraint on the maximum hours of labor a farmer can hire in, $h' \leq \overline{N}$.

[34] The production function we propose can have several microfoundations. The one we develop in the paper is a general version of the following simple model: suppose individuals have an indivisible unit of labor which can be supply labor as a worker and earn w, or they can be self-employed and produce $f(k)$, but they cannot do both. If people have to depend on their own savings and are credit-constrained, then their payoff from self-employment is $f(k)$ and so individuals will choose to be workers until the k they own exceeds a certain level $f(k) \geq w$, i.e., their income is $y = \max\{f(k), w\}$. In the model, we allow for divisible labor that can be allocated in one's own enterprise as well as in the labor market, plus the possibility of hiring in labor.

Alternatively, suppose that the cost function has a fixed cost element: $C(y) = F + c(y)$ where variable cost, $c(y)$, has standard properties. If we interpret cost as working capital, then the production function is simply the inverse of the cost function. Let K denote total capital needed for production, i.e., fixed costs plus variable costs. Let Y and y denote gross and net output with $y \equiv Y - K$. Let $y = f(c)$ the inverse of the function $c(y)$. Then for net output we have: $y = 0$ for $K < F$ and $y = f(K - F)$ for $K \leq F$. Similarly, for gross output: $Y = K$ for $K < F$ and $Y = f(K - F) + K$ for $K \leq F$.

We assume that the (disutility) cost of supplying labor takes the form

$$\frac{1}{2}(\sqrt{\psi_l}l + \sqrt{\psi_h}h)^2$$

where $\psi_h > 0$ and $\psi_l > 0$.

As a result, the static optimization problem becomes:

$$\max_{l\geq 0, h\geq 0, h'\geq 0} Af(\bar{k})g(l+h') + wh - w'h' - \frac{1}{2}(\sqrt{\psi_l}l + \sqrt{\psi_h}h)^2 \tag{5}$$

subject to

$$h \leq \overline{H} \qquad \text{[H]}$$

$$h' \leq \overline{N} \qquad \text{[N]}$$

$$h + l \leq \overline{R} \qquad \text{[R]}$$

Assuming a fully interior solution, the first-order conditions for the maximization are:

$$\begin{aligned} Af(\bar{k})g'(l+h') &= \psi_l l + \sqrt{\psi_l \psi_h}h \\ w &= \sqrt{\psi_l \psi_h}l + \psi_h h \\ Af(\bar{k})g'(l+h') &= w' \end{aligned}$$

In the case of corner solutions, some of the equalities above need not hold. The full solution with all possible cases is characterized in Appendix A.

6.2 Model calibration

The first step in the estimation is to calibrate individual-level parameters for productivity in livestock rearing A and disutility of supplying wage labor and livestock rearing hours, ψ_h and ψ_l respectively. These parameters are identified from baseline and year 2 data by assuming that, in these years, individuals choose the hours that they devote to each occupation[35] and hire in optimally given their capital endowment, production technology, prevailing wage rates and exogenous hours constraints. The assumptions used to determine each of these is described below.

The production function assumed is

$$f(k_i)g(l_i + h_i') = (ak_i^2 + bk_i)(l_i + h_i')^\beta.$$

[35] These are self-reported and checked for consistency.

It represents the latent quadratic production function which, when combined with flat wage income that dominates at low capital levels, yields the characteristic S-shape described in Section 3.1. The parameters a, b and β of this function are estimated by non-linear least squares. The prevailing market wage and wage paid for hired in labor are means at the branch level in each survey wave. We set the time endowment constraint $\overline{R}$ to be 3,650 hours per year and drop from the estimation the three ultra-poor individuals who report total hours higher than this at baseline or year 2. The labor demand constraint $\overline{H}$ is set at the 90th percentile of wage labor hours worked at baseline by BRAC branch. The constraint $\overline{N}$ on how much labor can be hired in is set at the 95th percentile across all households and survey rounds, equal to 1,400 hours per year.

The optimization problem described in Section 6.1 yields first order conditions for several cases according to the occupation(s) in which the individual works, whether they hire in labor and whether each of the exogenous hours constraints binds. For the majority of ultra-poor beneficiaries, these first order conditions can be combined with data on capital and occupational choice at baseline and year 2 to calibrate the values of the parameters A, ψ_h and ψ_l that are consistent with the observed hours worked in livestock rearing and wage labor, and hours of labor hired in, being chosen optimally.

In particular, 16% of ultra-poor individuals mix occupations and hire in labor at year 2 (case 1 in Appendix A), such that the three year 2 first-order conditions can be solved for the three parameters of interest for these individuals. For those individuals in other cases at year 2, there are fewer first-order conditions than parameters so this method cannot be used. However, in many of these cases, first-order conditions from year 2 and baseline can be combined to calibrate the parameters. In our data 24% of individuals specialize in wage labor without hiring in labor at baseline, and at year 2 either mix occupations without hiring in labor or specialize in livestock rearing with hired in labor. In these cases, the baseline and year 2 first-order conditions again yield three equations that can be solved for the three parameters. Parameters can be calibrated for a further 23% of individuals by assigning ψ_h to be the maximum observed value for those individuals who do not work at baseline.[36]

This method yields estimated individual-level parameters for 64% of ultra-poor individuals. In all other combinations of cases at baseline and year 2, there are either very few individuals or the combination of cases does not permit calibration of all parameters (for instance, if an individual specializes in livestock rearing at baseline and year 2, it is not possible to pin down their disutility of wage labor hours). Plotting the baseline productive assets distribution for the 64% of households for whom we can conduct estimation and the 36% for whom we cannot reveals a high degree of overlap, with the latter distribution slightly rightward shifted. This suggests that those for whom we cannot conduct estimation are more likely to engage in livestock rearing and, therefore, less

[36] We abstract from the labor demand constraint and constraint on hired in labor in the parameter calibration since the choice of hours across occupations will be uninformative about underlying parameters where these constraints bind.

likely to be constrained in their choice of occupation (though not necessarily hours worked in each occupation).

Figure B5 plots the calibrated values of A, ψ_h and ψ_l against post-transfer baseline capital and shows that there is no systematic correlation between baseline wealth and any of these parameters, and no evidence of a discontinuity at the threshold capital level. The fact that A is not correlated with k_0 provides further support for our identification assumptions in the reduced form estimation. Moreover we find that, in line with the fact that wage labor carries social stigma, the disutility of wage labor hours ψ_h is higher than the disutility of livestock rearing hours ψ_l, as shown in Figure B6. The median value of ψ_h is more than 50% higher than the median ψ_l value. The distribution of the calibrated A parameters, shown in Figure B4c, is unimodal.

6.3 Model estimation

With estimated values for each individual's productivity in livestock rearing and disutility of labor hours in hand, we can use the model structure to solve for each individual's optimal hours in wage labor and livestock rearing, their optimal hours of hired in labor, and their implied payoff at any level of capital. In a first simulation exercise of this nature, we calculate these at each individual's year 4, 7 and 11 capital level in order to assess how well the model matches non-targeted moments in the data. In a second, we estimate the value of misallocation at baseline by comparing each individual's optimal occupational choice and payoff at the steady state capital level of the middle and upper classes (i.e. in the absence of capital constraints) to those observed at their baseline capital level.

6.3.1 Testing model fit using year 4, 7 and 11 data

We test the predictive power of the model by using the model to simulate each individual's optimal choice of hours in each occupation at their year 4, 7 and 11 capital levels and comparing these to the choice of hours observed for that individual at year 4, 7 and 11 respectively.

Figure 9 shows local polynomial predictions of model-predicted and actual hours in livestock rearing and wage labor respectively, as a function of the level of capital in the relevant year. As the left panels of Figure 9 makes evident, there is a close fit between the model-predicted and observed hours in livestock rearing in all three years. The right panels of Figure 9 repeat the same for wage labor hours and reveal a reasonable fit between model-predicted and observed hours in all years, although this appears to be strongest in year 4. In years 7 and 11, the model predicts slightly higher wage labor hours than are observed in the data at most capital levels. This pattern may be consistent with unmodelled effects such as individuals reducing the hours that they allocate to more physically-demanding wage labor occupations as they age.

6.3.2 Quantifying misallocation

In order to quantify misallocation, we estimate the payoff that the model suggests would be available to each ultra-poor individual were they to have the steady state capital level of the middle and upper classes, and compare this to the payoff available to them at their baseline capital level.

The steady state capital level of the middle and upper classes is estimated to be the level corresponding to the upper mode of the distribution across all wealth classes of productive assets excluding land, which occurs at 43,701 BDT.[37] This is higher than the baseline capital level of the vast majority of ultra-poor individuals, so in extrapolating to this higher capital level it is necessary to account for the income effect in the demand for leisure suggested by the observed negative correlation between income and hours worked at baseline. We achieve this by scaling up the labor disutility parameters ψ_h and ψ_l by the ratio of the median ψ_l for richer classes versus the median ψ_l for the ultra-poor.[38]

The model yields an expression for the optimal hours worked in each occupation and hired in, and respective payoffs, in each of the cases outlined in Appendix A. We use these expressions, together with the calibrated values of each individual's livestock-rearing productivity and disutility of labor hours, to calculate the occupational choice, hours worked and hours hired in that would yield the highest payoff for each individual at the steady state capital level of the middle and upper classes.

The results of this exercise reveal that, at the steady state capital level of the middle and upper classes, 90% of ultra-poor households for whom we can conduct the structural estimation should optimally specialize in livestock-rearing, 8% should mix and just 2% should specialize in wage labor. This contrasts starkly to the observed distribution across occupations at baseline, as shown in Figure 10. At their baseline capital level, only 1% of working ultra-poor households specialize in livestock rearing, with 97% specializing in wage labor and 2% mixing occupations. As such, the model suggests that 96% of individuals for whom we can conduct the structural estimation have non-zero misallocation.

The model also yields the total value of misallocation across all households for which the estimation is conducted as the sum of the differences between the payoff available to each individual at the steady state of the middle and upper classes and at their baseline capital level. The estimation suggests that the total value of misallocation thus quantified is 15 USD million.[39] The estimated total value of transfers required to bring all of these individuals to the average threshold

[37] Land is excluded in choosing this level since women across wealth classes rarely cultivate land; the ultra-poor possess little land across survey rounds; and land is a very expensive asset, the purchase of which is not endogenized in our model. The distribution of productive assets excluding land is also bimodal as shown in Figure B7.

[38] For five households, this scaling up of the disutility of labor is sufficient to result in negative estimated misallocation. For these households, the estimated value of misallocation is set to zero.

[39] This is the implied gain each period once the steady state has been reached. Here and in all simulations we top-code the top 5% of individual misallocation values at the 95th percentile to reduce the effect of outliers.

capital level identified in Section 4.1 — from which they are able to escape the poverty trap[40] — is an order of magnitude smaller at 1 USD million.

6.4 Simulating policy counterfactuals

The structure of the model allows us to simulate the effect of counterfactual changes in the model's parameters. We use this to consider how the results are influenced by potential general equilibrium effects of the intervention and to study the effects of a series of counterfactual policy interventions.

The central simulation exercise above aims to quantify the effects of propelling large numbers of the ultra-poor to higher capital levels. The scale of this change is such that it might influence the returns to livestock rearing, for instance due to falling produce prices. This would hurt all those engaged in livestock rearing including the ultra-poor themselves. Spillovers need not be negative, however; for instance Advani (2017) shows that in villages where many beneficiaries were treated, other households also increased their asset holdings after four years, which is consistent with a model of risk sharing between households in the same village. Here we focus on the potentially negative effect and we re-simulate the results reducing livestock income $Af(k)g(l+h')$ by a fixed factor. We find that, even in a case where this is reduced by 50%, 71% of ultra-poor households should specialize in livestock rearing, though the estimated value of misallocation falls by 57%. In order for the value of misallocation to fall to the estimated cost of eliminating the poverty trap, the simulations suggest that livestock income would need to be reduced by 89%. These results suggest that general equilibrium price effects may attenuate the estimated value of misallocation but are unlikely to overturn the central finding that the value of implied misallocation far exceeds the cost of eliminating the poverty trap.

In a second set of counterfactual simulations, we consider the effects of a series of alternative policy interventions that might be considered to tackle occupational inequality in this setting. In the first of these, we simulate the effect of increasing the wage available for wage labor activities. Even with a doubling of the wage rate, the simulations suggest that the share of households optimally specializing in livestock rearing at the steady state capital level of the middle and upper classes is 60%. An alternative policy counterfactual considers the effect of reducing the disutility of wage labor hours, ψ_h, for instance through increasing availability of occupations that do not bear the social status costs of agricultural or domestic service occupations. The simulations suggest that reducing all individuals' disutility of wage labor hours by 50% would reduce the share of the ultra-poor that should optimally specialize in livestock rearing to 79%. In the simulations that increase the wage rate or reduce the disutility of wage labor hours, the estimated value of misallocation falls much less than in the simulation that reduces livestock income (less than 10%

[40] Beyond this point, the transition equation is concave and the individual can accumulate towards the high stable steady state. As such, the transfers required to set individuals on a stable trajectory out of poverty need only elevate them to the capital level of the unstable steady state, from where they can continue to save towards convergence.

in both cases). This is because the former simulations influence marginal individuals in the left tail of the misallocation distribution, while the latter shifts the entire misallocation distribution to the left.

While the share optimally specializing in livestock rearing in both policy counterfactual simulations is lower than the share in the central simulations, these are still an order of magnitude higher than the 1% observed among ultra-poor households at baseline.

7 Implications for Policy

Our results point to the existence of a poverty threshold, so that households with a starting level of productive assets below that threshold are trapped in poverty, while households who are able to get past that threshold accumulate capital and approach the level of the richer classes. That allows them to switch occupations from casual laborers to the more productive business activity of livestock rearing, which in turn facilitates further asset accumulation. The existence of such a poverty threshold has important implications for policy design. Transfer programs that bring a large share of households above the threshold will see large effects on average, while transfers that fall short of this might have small effects in the long run.

As a simple illustration, we can compute the share of households in our sample that would have been moved above the threshold as a function of the transfer size. The black line in Figure 11 shows this. To construct this graph, we compute the difference between the threshold value and the initial value of productive assets for ultra-poor households. When computing this gap, it is necessary to account for the fact that some households would move above the threshold through positive shocks even without a transfer. We account for that by drawing random shocks from ultra-poor, poor, and middle-class households in the control group and adding those to the initial assets. To allow comparability with alternative policies, we express the transfer value relative to average annual per capita consumption. As the figure shows, around 6% of households would reach the threshold even without a transfer. Consistent with the fact that most ultra-poor households own close to zero assets, small transfers only slightly increase the share of households that pass the threshold. At a transfer just above 80% of annual per capita consumption all households, even those with zero baseline assets get moved past the poverty threshold.

The vertical line in Figure 11 shows the size of the actual transfer, which we can compare to alternative transfer schemes such as income support (NREGA) and microfinance. Assuming the household works each of the 100 days they are entitled to, the value of NREGA is .13 of annual PCE.[41]. BRAC typically offers entry microloans between 100 USD and 200 USD. These correspond to .18 and .3 of the average PCE. Thus, two of the main programs designed to tackle poverty are too stingy to make a difference for the majority: our simulation illustrates that they

[41] The transfer size of India's National Rural Employment Guarantee Act (NREGA) is computed based on Imbert and Papp (2015)

would allow fewer than 20% of households to escape poverty. This is consistent with evidence suggesting a negligible average impact of microfinance (Banerjee et al., 2015a; Meager, 2019) but a large effect on a small group of households that already run a successful business (Banerjee et al., 2019).[42]

We then turn to our structural model to to estimate the value of transfers needed to reduce misallocation to zero. In a first set of simulations, we resimulate the model under the assumption that all households are given a transfer equal to an increasing percentage of annual per capita consumption expenditure, until the point at which misallocation equals zero. This exercise suggests that the value of misallocation — measured as before against the maximum payoff available at the upper mode of the distribution of productive assets excluding land — would be zero if all ultra-poor households were given a transfer equal to 3.95 times the average level of baseline per capita consumption expenditure among ultra-poor households. The trajectory of the total value of misallocation as the transfer value is increased is shown in Figure 12a. The total cost of transferring 3.95 times the average level of baseline per capita consumption expenditure to each of the 2,283 ultra-poor households in the estimation, 5.7 USD million, remains much lower than the total value of estimated misallocation (15 USD million).

In a second set of simulations, we consider the possibility that misallocation could be measured not against the upper mode of the distribution of productive assets excluding land, but instead versus the maximum payoff available at the unstable steady state — from where the theory suggests individuals can accumulate towards the high steady state along the concave part of the transition equation. The results in this case are shown in Figure 12b and suggest that the value of misallocation would be zero if all ultra-poor households received a transfer equal to 1.05 times the average level of baseline per capita consumption expenditure.

8 Conclusions

Poverty traps are one of the most fundamental concepts in development economics. The contribution of this paper has been to provide evidence for their existence using the combination of a randomized asset transfer and an 11-year panel in rural Bangladesh. Our key finding is that people stay poor because they lack opportunity. It is not their intrinsic characteristics that trap people in poverty but rather their circumstances. This has three implications for how we think about development policy.

The first is that big pushes that enable occupational change will be needed to address the global mass poverty problem. Small pushes will work to elevate consumption but will not get people out of the poverty trap. The magnitude of the transfer needed to achieve occupational

[42]These authors also use a structural model that includes a poverty trap. They do find substantial average impacts on businesses at the 6-year horizon, but they show that these results are exclusively driven by the 30% of households with a pre-existing business.

change may be much larger than is typical with current interventions, though importantly it can be time-limited. Therefore, the fiscal cost of permanently getting people out of poverty through a large, time-limited transfer might actually be lower than relying on continual transfers that raise consumption but have no effect on the occupations of the poor.

The second is that big push policies can have long-lasting effects. Our analysis of long-run dynamics indicates that the asset, occupation and consumption trajectories of above threshold beneficiaries diverge from those of below threshold beneficiaries over time. This finding is important as it indicates that, by engendering occupational change, one-time pushes can have permanent effects.

The third is that poverty traps create mismatches between talent and jobs. We have shown that misallocation of labor is rife amongst the poor in rural Bangladesh. Indeed, we show that the vast majority of the poor in rural Bangladesh are not engaged in the occupations where they would be most productive. They are perfectly capable of taking on the occupations of the richer women but are constrained from doing so by a lack of resources. The value of eliminating misallocation is an order of magnitude larger than the cost of moving all the beneficiaries past the threshold. This is important as it implies that poverty traps are preventing people from making full use of their abilities and indeed it is the mass squandering of people's abilities that is the key tragedy of mass poverty.

We are now in the process of probing how generalizable this finding is, given that it comes from a specific intervention in a specific context. This involves two new strands of research, one focusing on other contexts and another on other interventions.

On other contexts, we are assembling and and harmonizing, for a whole range of countries, nationally representative IPUMS-DHS surveys that contain information on the holdings of productive assets of rural households. This enables us to look for bimodalities in the distribution of productive assets that might be consistent with existence of a poverty trap. We begin by looking at rural surveys for Bangladesh, Pakistan, India, Nepal, Myanmar and Afghanistan - settings with similar agrarian systems, large numbers of itinerant, casual laborers and high levels of rural poverty and asset inequality[43] - where the type of asset transfer transfer program studied here may be relevant.[44]

Figure 13 plots kernel density estimates of an index of productive assets for rural households in these six South Asian countries.[45] Consistent with the argument of this paper, in panel (a) of Figure 13, we see a clear bimodality in the distribution of productive assets for rural Bangladesh using this separate, nationally representative sample. Strikingly, we also see bimodal distributions in Afghanistan, Myanmar, Pakistan and Nepal in panels (d), (f), (c) and (e). Only in India do we

[43]See Bardhan (1984), Dreze and Sen (1990), and Kaur (2019)

[44]All these countries except Afghanistan and Nepal were part of British India.

[45]The wealth index is constructed from the first component of a principle component analysis on all agricultural assets, using harmonized IPUMS-DHS survey data for each country and year.

see rural households concentrated around a single mode (panel (b)). For five of the six countries there is a distinct low-density range between the largely assetless lower mode (bottom quintile) and asset-rich upper mode (third quintile). As discussed above these bimodalities can arise for various reasons and future research will bear down on whether different modes of the asset distribution are associated with different occupations and on examining the effects of interventions that move individuals past the threshold.

On other interventions, it is clear that a range of these may be effective in getting people out of poverty traps, as long as they shift people into occupations that leverage their talent. There might, for example, be other indivisible investments that are too large for the poor to afford and which exclude them from more profitable jobs. These need not be physical capital but can also be large investments in human capital such as a training, a college degree, or the cost of migration. Similarly, investments in infrastructure or other policies which encourage occupational change and raise individual productivity might also be effective.

In urban settings, where there is a larger variety of occupations, using large investments in human capital to shift people from subsistence self-employment into salaried employment might be critical to escaping poverty. We are engaged in a series of experiments looking at this intriguing possibility. For example, in Alfonsi et al. (2020) we find that significant investments in six months of vocational training can have large impacts on employment and earnings of disadvantaged youth in Uganda.[46] The fact that training costs ($400) are several multiples of annual incomes ($140) show how indivisible and unaffordable this human capital investment might be for target youth just as a cow is for poor women in rural Bangladesh.

Ending mass poverty is the central focus of development economics and policy. This paper points to the importance of expanding opportunity for the poor. It highlights the need to rethink our approach to tackle the problem of global poverty, and in particular, the critical importance of focusing on welfare policies that change the employment activities of the poor. This is distinct from traditional consumption-focused policies which have characterized welfare support both in developed and developing countries. It is only by expanding opportunities for the poor that we will be able to tap into the productive capacity of a large cross-section of humanity.

[46]The fact that we observe these effects documented in this paper for largely assetless and illiterate women whose median age is 35 is striking. Part of the logic of looking at younger populations - for example for young women and men transitioning into the labor force - is that occupational change might be more feasible for them.

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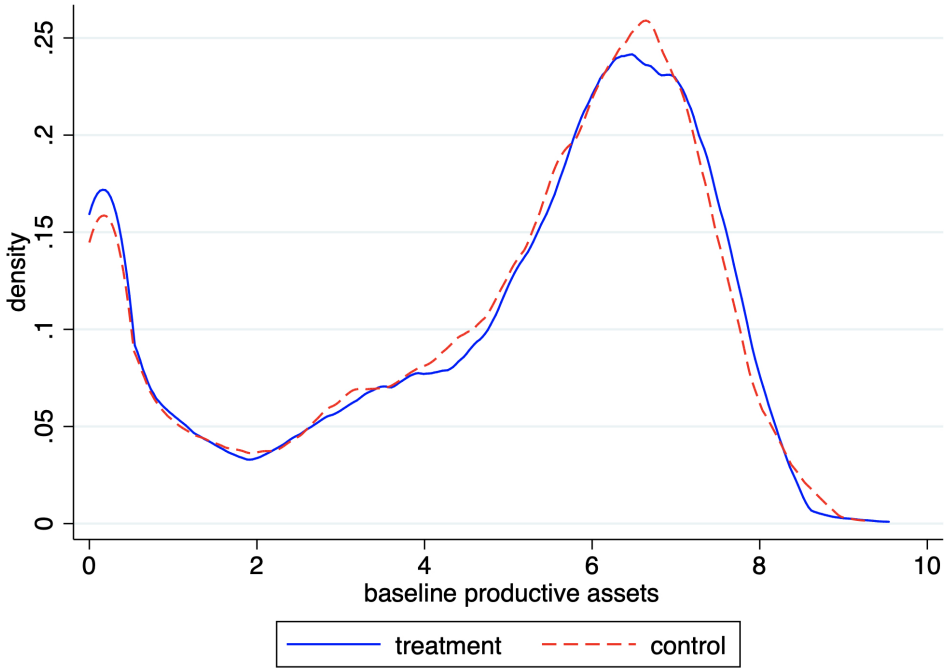
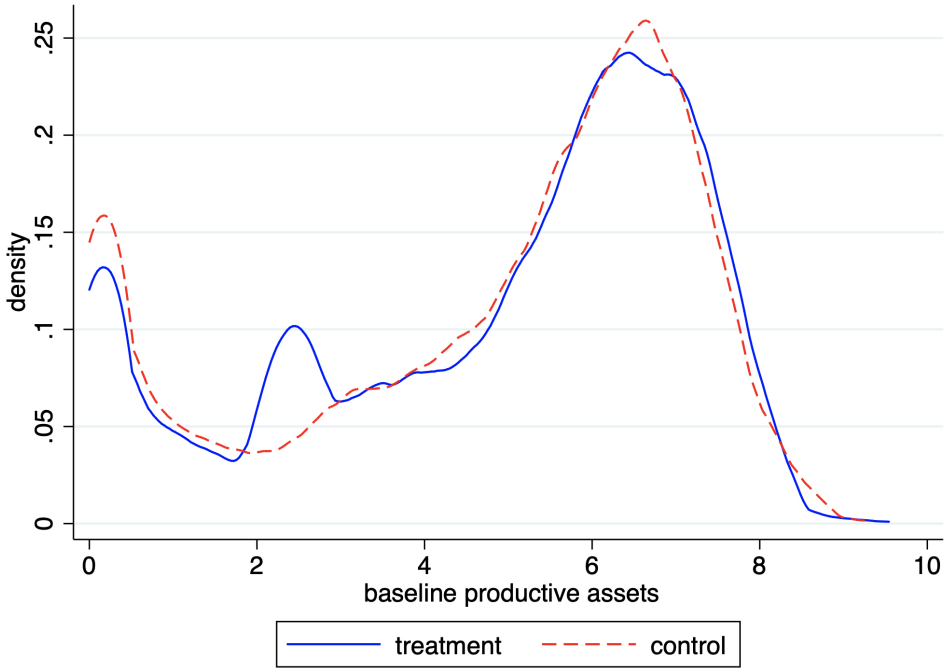
Figure 1: Distribution of Productive Assets in Bangladeshi Villages: all Wealth Classes

(a) Distribution of Productive Assets at Baseline



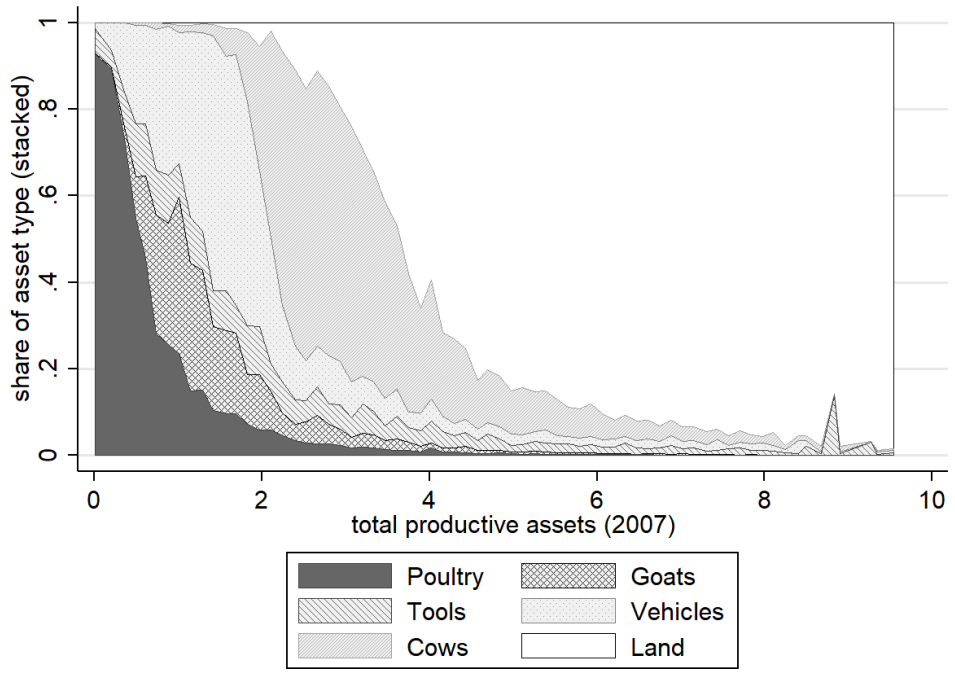
(b) Distribution of Productive Assets at Baseline after Transfer



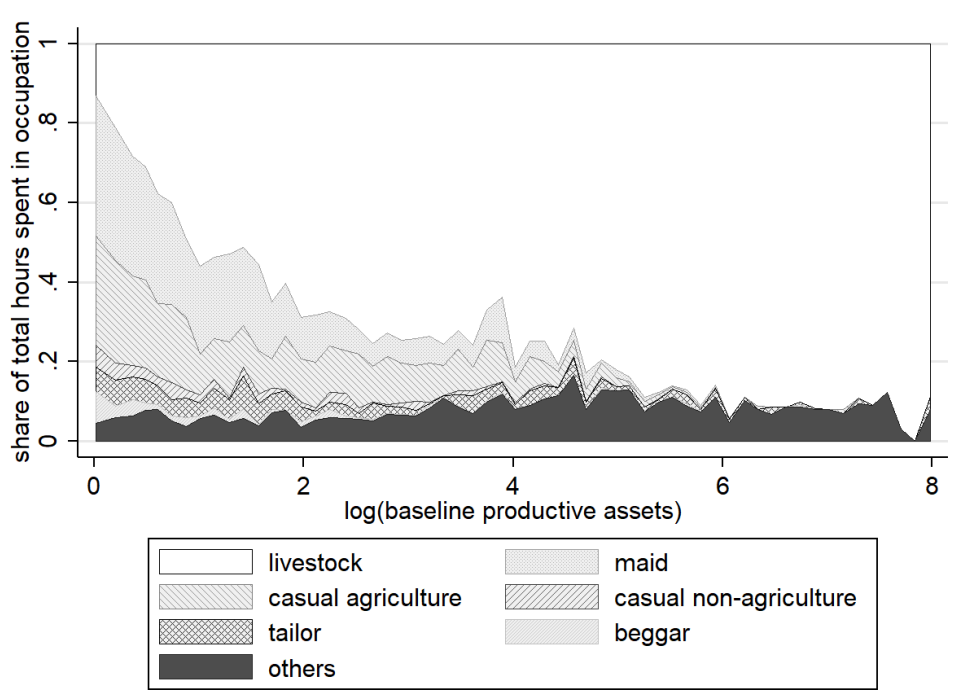
Notes: The graph shows kernel density estimates of the distribution of baseline productive assets in the full sample of 21,839 households across all wealth classes in treatment and control villages. Productive assets are measured as the natural logarithm of the total value, in 1,000 Bangladeshi Taka, of all livestock, poultry, business assets, and land owned by the households. Sample weights are used to account for different sampling probabilities across wealth classes. The weights are based on a census of all households in the 1,309 study villages. Panel b) shows the post-transfer distribution. Transfers for treatment households are imputed as the median value of a cow within the catchment area of a household's BRAC branch.

Figure 2: Asset Composition and Occupation by Baseline Productive Assets

(a) Asset Composition

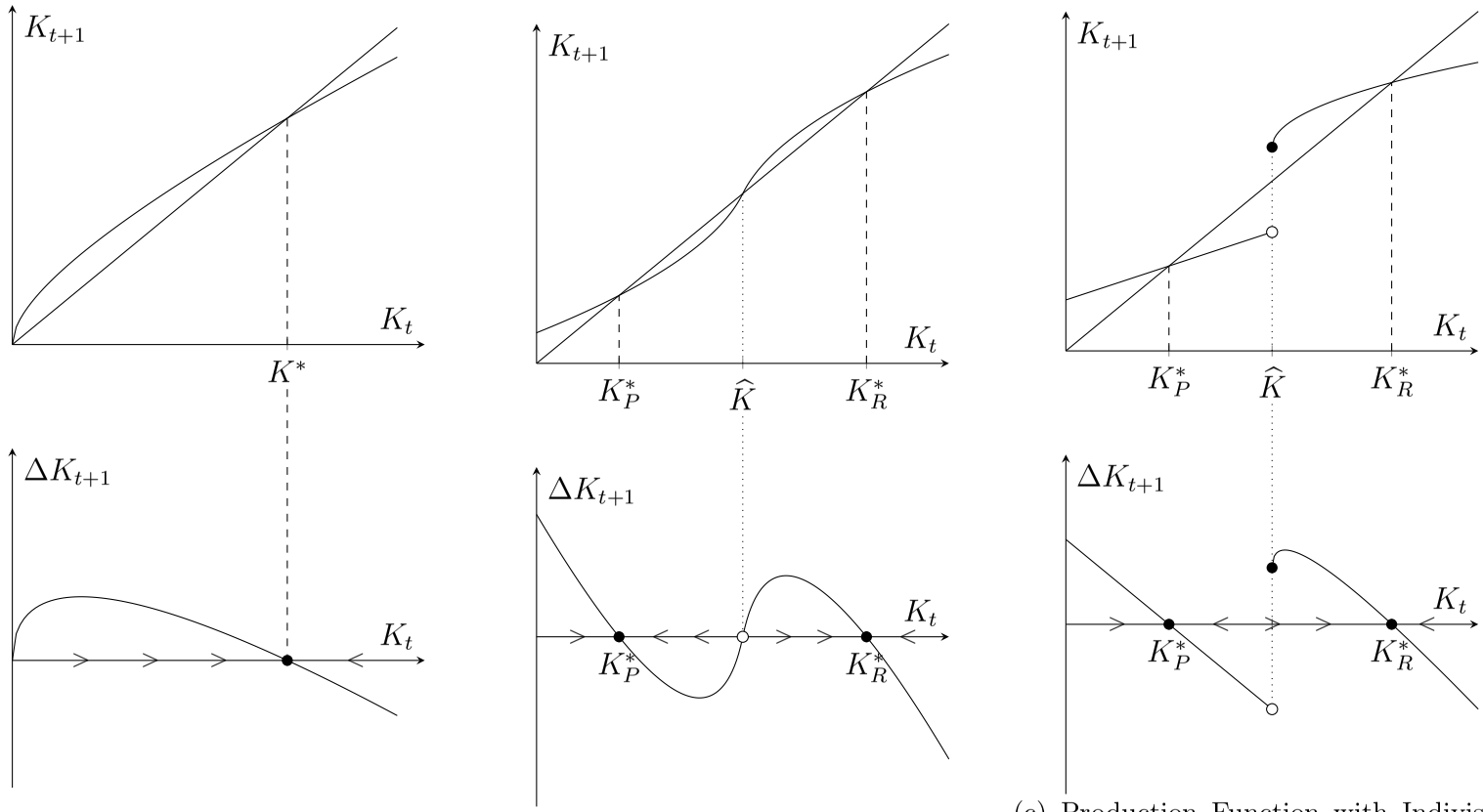


(b) Occupation and Productive Assets



Notes: The graph shows the composition of productive assets and hours spent in different occupations against baseline productive assets in the full sample of 21,839 households across all wealth classes. Productive assets are measured as the natural logarithm of the total value, in 1,000 Bangladeshi Taka, of all livestock, poultry, business assets, and land owned by the households. Panel a) splits livestock into goats and cows, and business assets into tools and vehicles. In panel b), hours reportedly spent on rearing poultry are excluded. All occupations with a population average of less than 10 hours are summarized in 'others'.

Figure 3: Three Transition Equations and Implied Asset Dynamics

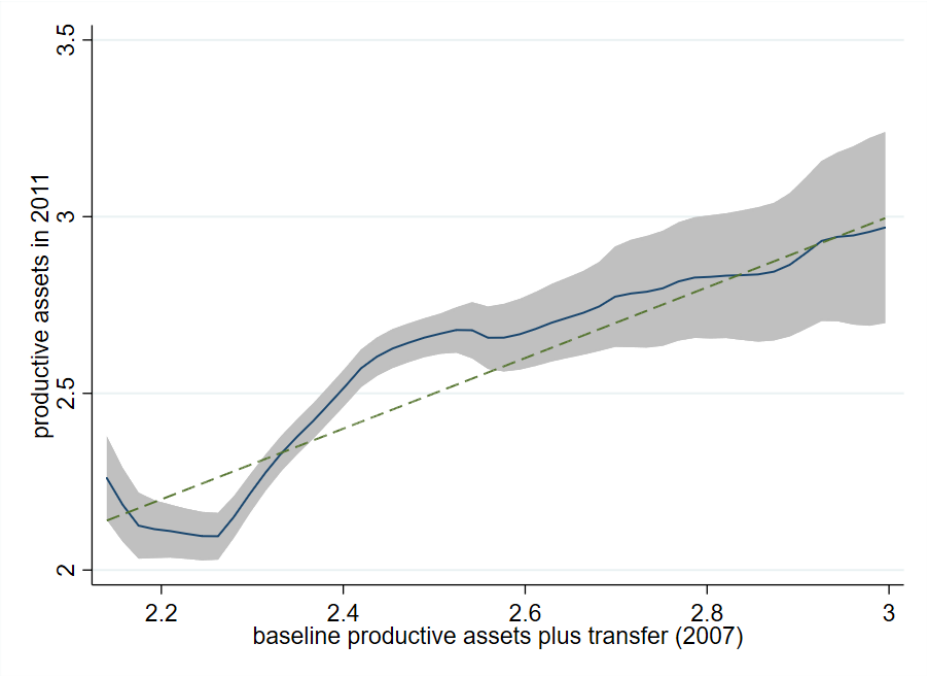


(a) Globally Concave Production Function

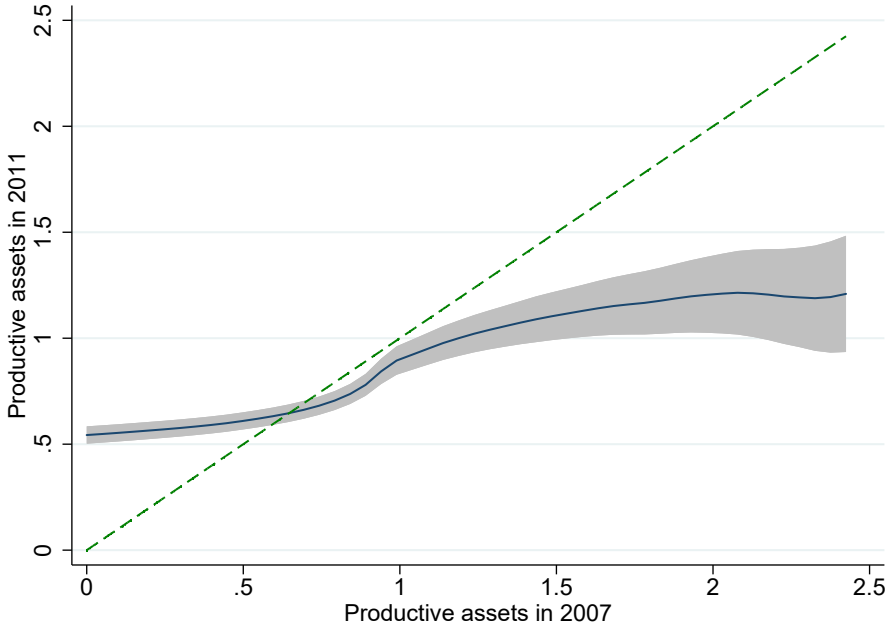
(b) S-shaped Production Function

(c) Production Function with Indivisibilities

Figure 4: Local Polynomial Estimates of the Transition Equation



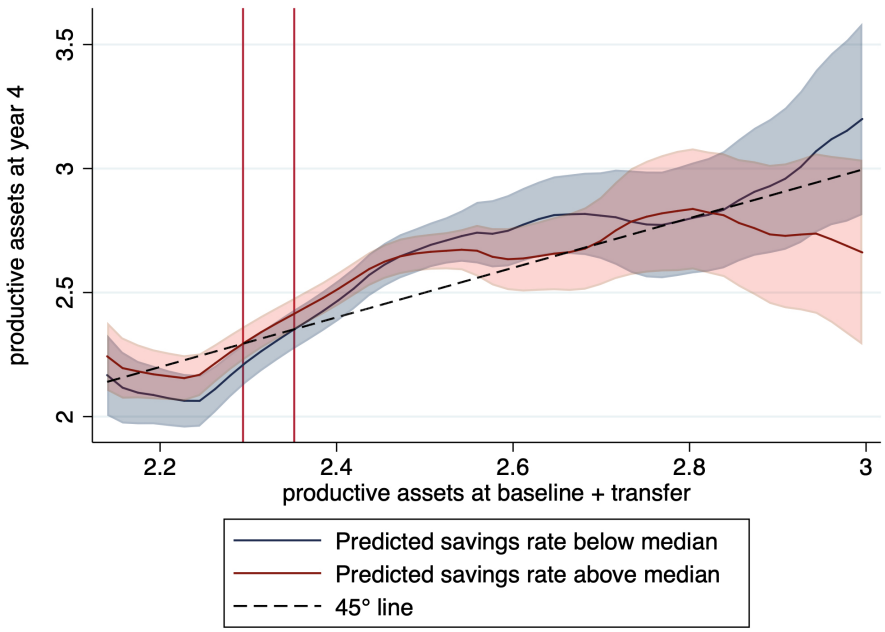
(a) Treatment villages



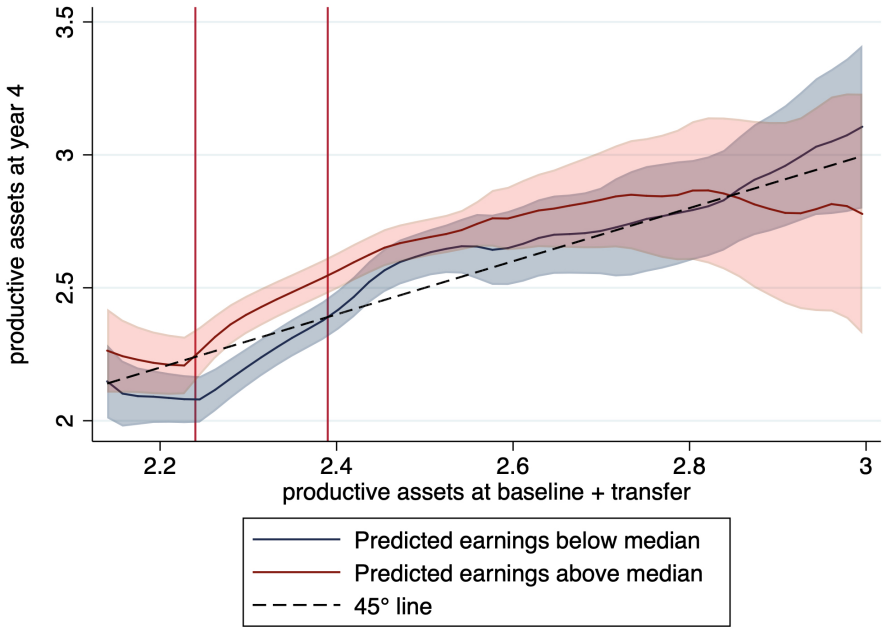
(b) Control villages

Notes: The sample is restricted to ultra-poor households with log baseline productive assets below 3 in treatment (panel a) and control (panel b) villages. Productive assets are measured as the natural logarithm of the total value, in 1,000 Bangladeshi Taka, of all livestock, poultry, business assets, and land owned by the households. Post-transfer assets are imputed by adding to each household's baseline assets the median value of a cow within the catchment area of a household's BRAC branch. The blue line plots the smoothed values of a local polynomial regression with an Epanechnikov kernel of optimal bandwidth. The grey area depicts 95 percent confidence bands. The dashed line represents the 45° line at which assets in 2011 equal initial assets in 2007.

Figure 5: Heterogeneous Empirical Transition Equations by Savings and Earnings Potential



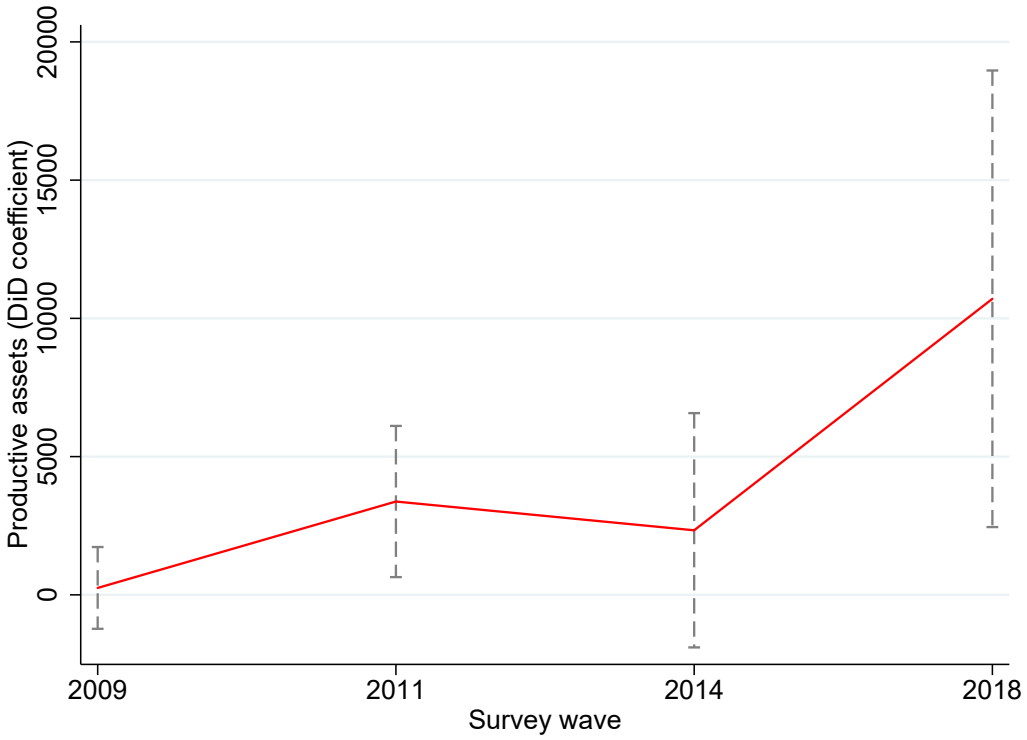
(a) Savings Potential



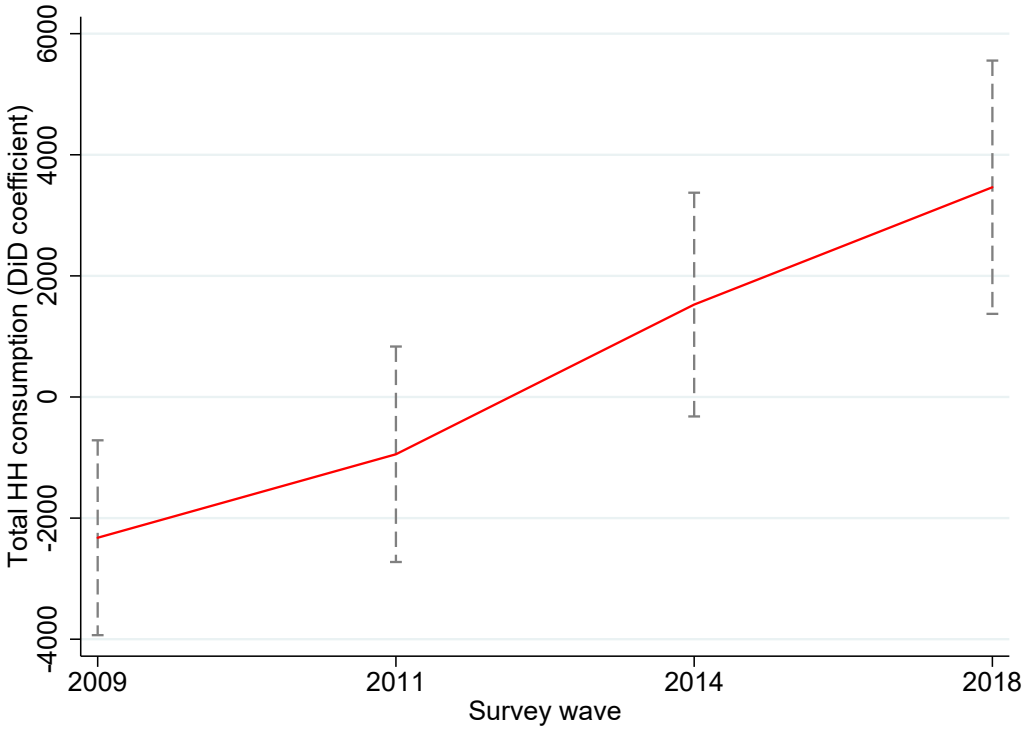
(b) Earnings Potential

Notes: The sample and estimation method are the same as in figure 4. Panels a) and b) split the sample respectively at the median of households' predicted savings rate and earnings potential. The predicted savings rate is computed as the predicted values from regressing the observed savings rate on a constant and a fourth order polynomial of the household's dependency ratio. The latter is the ratio of children (below 10), elderly (above 65), and chronically ill to total household members. Earnings potential is computed by as the residual (averaged at the branch level) from regressing livestock earnings on a constant and a second-order polynomial of the number of cows owned. The vertical red lines indicating unstable steady states are at 2.29 and 2.36 in panel a), and at 2.24 and 2.39 in panel b).

Figure 6: Difference in Differences Estimates of Long Run Dynamics in Productive Assets and Consumption



(a) Productive Assets



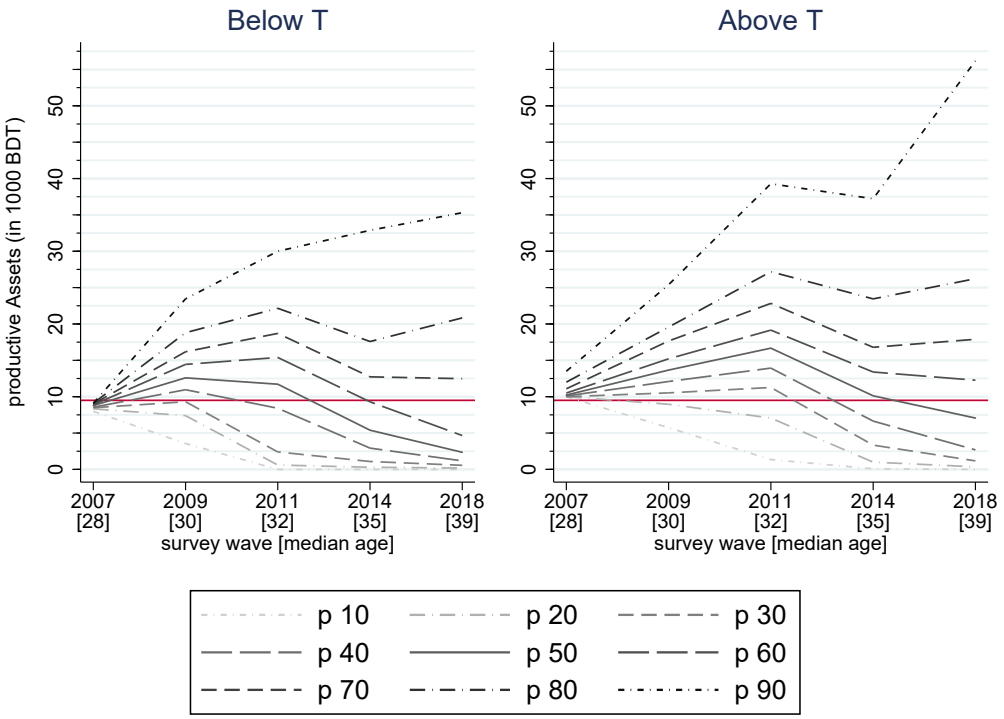
(b) Total Consumption

Notes: The figure plots the coefficients $\hat{\beta}_{it}$ from estimation equation 4. The sample consists of ultra-poor households with log baseline productive assets below 3 in treatment villages. The grey bars denote 90% confidence intervals.

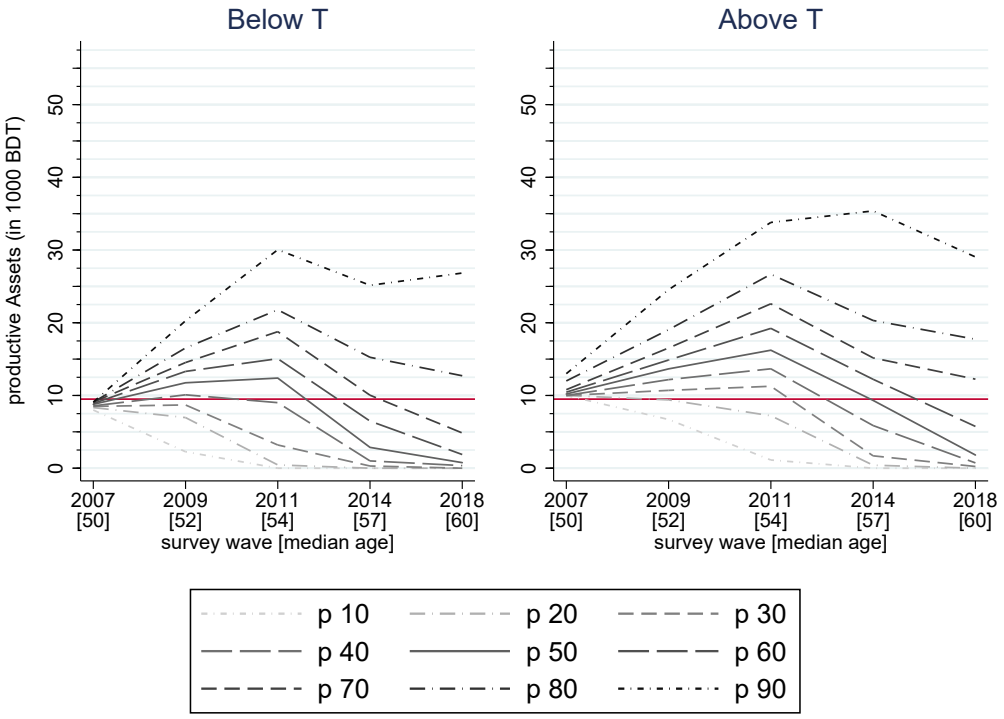
Figure 7: Asset stock over the life-cycle: control villages

Notes: The figure plots local polynomial plots of log productive assets against respondents' age. The sample consists of all households in control villages except the targeted ultra-poor (who receive BRAC's TUP program in 2014) and is trimmed at 80 years of age. Each line represents a different survey wave.

Figure 8: Productive Asset Dynamics in the Long Run above and below Poverty Threshold by Age



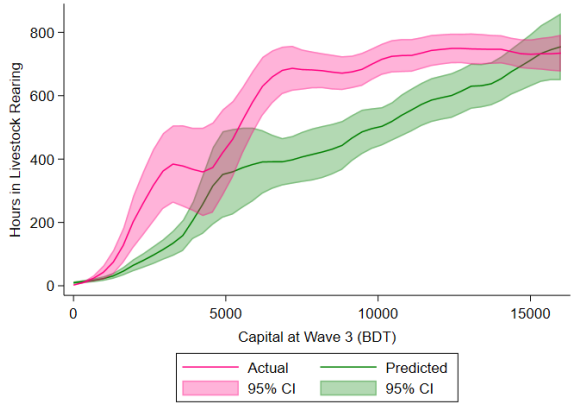
(a) Below median age (35)



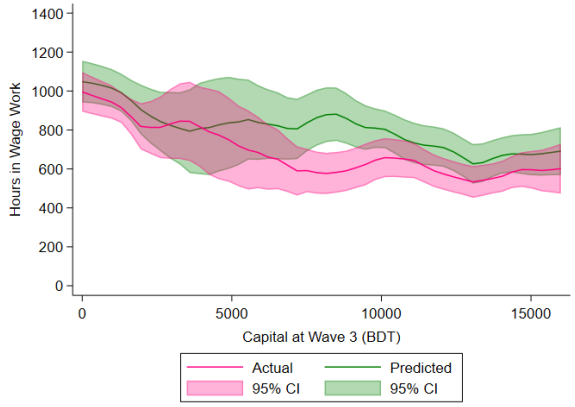
(b) Above median age (35)

Notes:

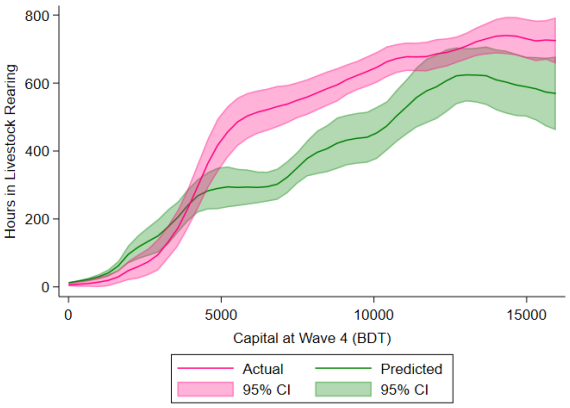
Figure 9: Hours Worked in Livestock and Wage Labor: Actual vs. Model Predictions



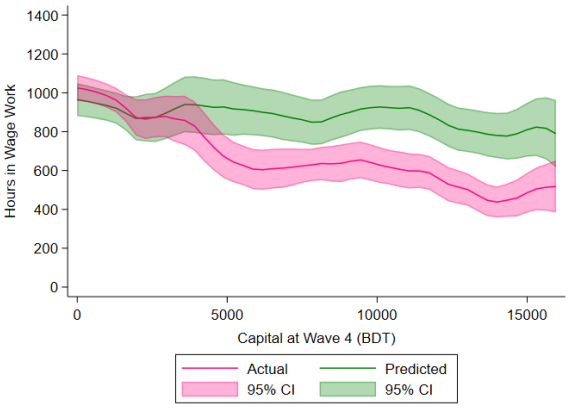
(a) Livestock: Year 4



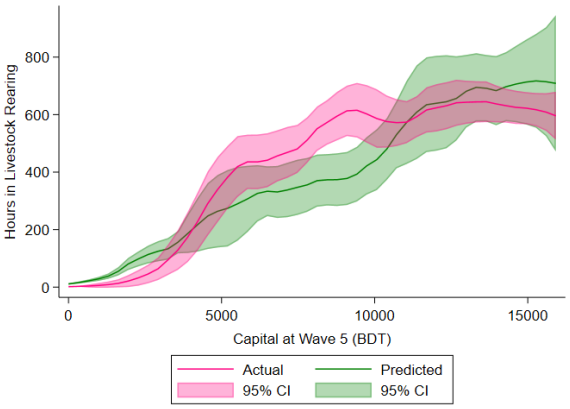
(b) Wage: Year 4



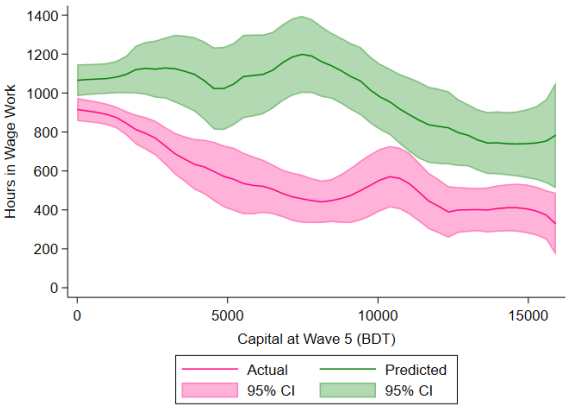
(c) Livestock: Year 7



(d) Wage: Year 7



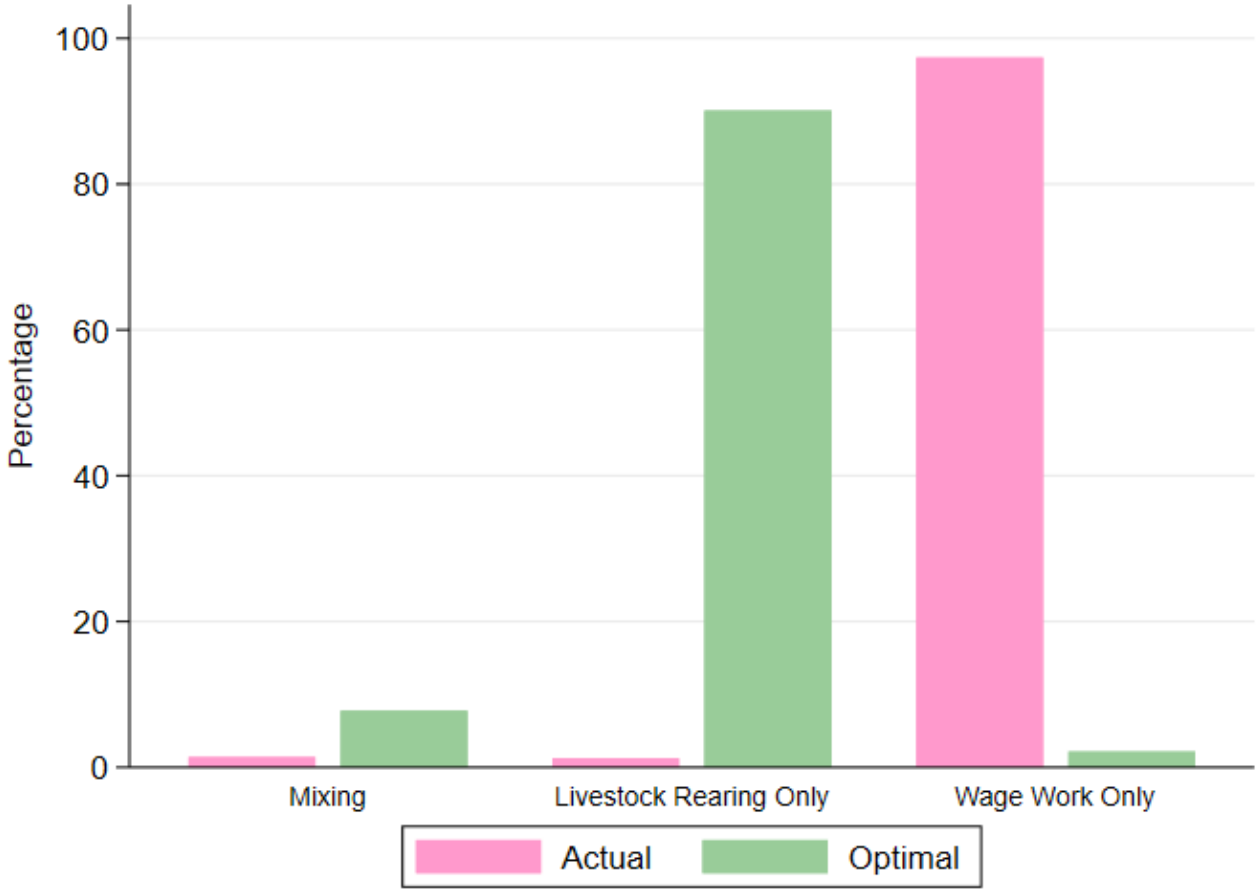
(e) Livestock: Year 11



(f) Wage: Year 11

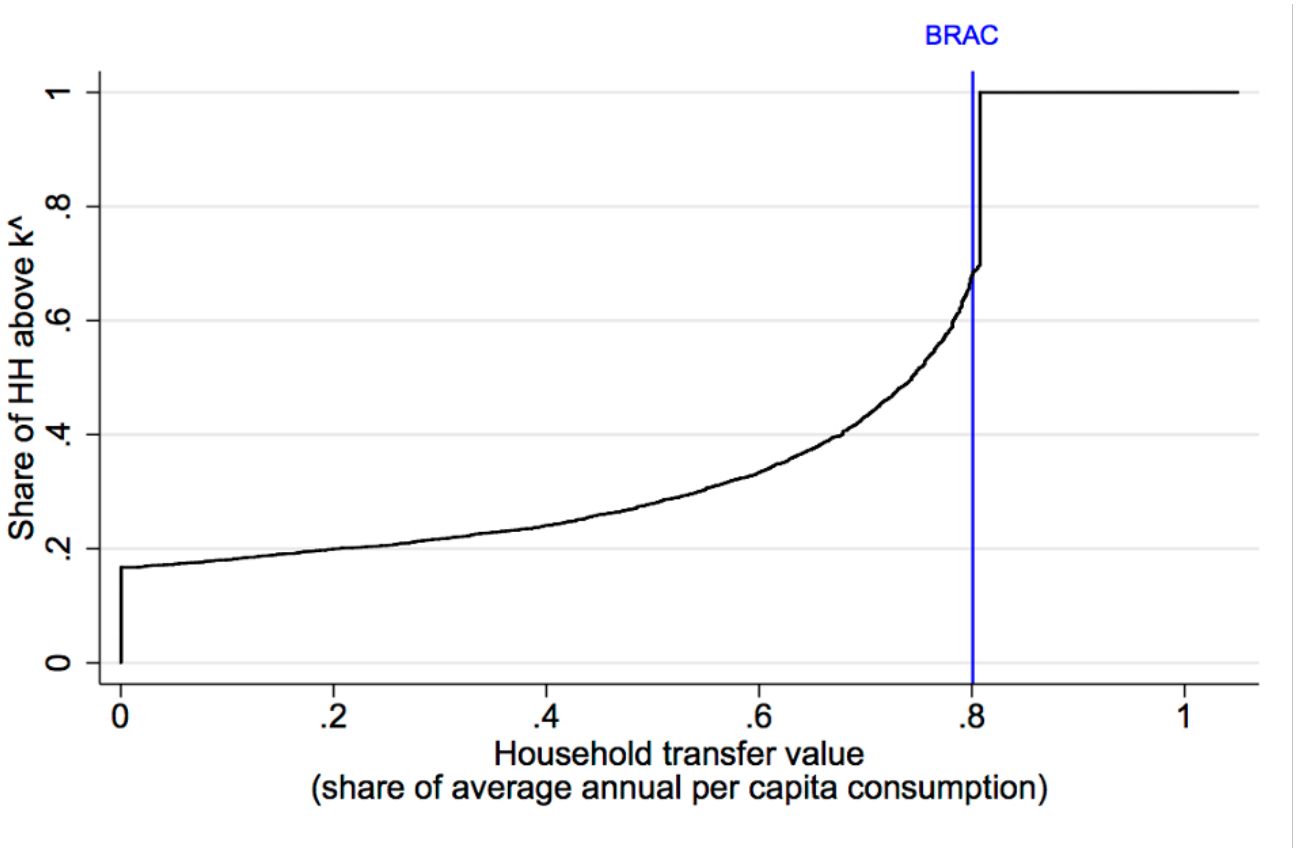
Notes: The pink graphs show local polynomial predictions of the observed hours worked in livestock rearing (left column) or wage labor (right column) in year 4, 7 and 11, as a function of year 4, 7 and 11 capital (respectively), for those of the 64% of ultra-poor individuals for whom individual-level parameters can be calibrated using baseline and/or year 2 data (as described in the text) who report positive labor hours in each year. The green graph shows, for the same individuals, local polynomial predictions of model-implied optimal hours worked as a function of observed year 4, 7 or 11 capital level. Ninety-five percent asymptotic confidence intervals for the local polynomial regressions are shown.

Figure 10: Occupational Choice: Actual vs. Model Prediction in the Absence of Capital Constraints



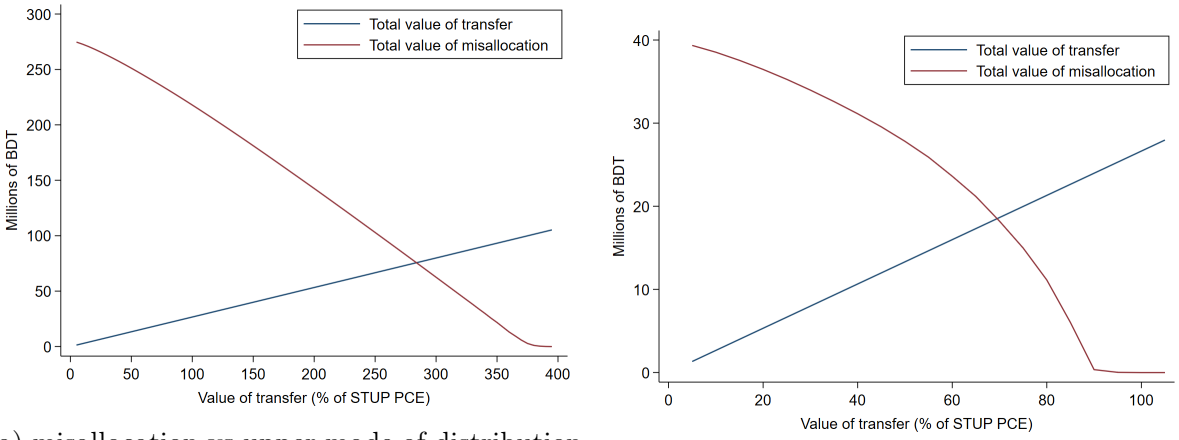
Notes: The green bars show the model-implied optimal distribution across occupations at the capital level corresponding to the upper mode of the distribution across all wealth classes of productive assets excluding land (43,701 BDT), for the 64% of ultra-poor individuals for whom individual-level parameters can be calibrated using baseline and/or year 2 data (as described in the text). The pink bars show the observed baseline distribution across occupations of those of these individuals who report positive labor hours at baseline.

Figure 11: Share of Ultra-Poor Households Above the Poverty Threshold as a Function of the Transfer Size



Notes: The sample includes ultra-poor households in treatment villages at baseline. The black line shows the empirical cumulative density of of the difference between the poverty threshold of $\hat{k} = 2.333$ and household's productive asset at baseline plus a shock randomly drawn from control households. Vertical lines depict different transfer sizes. The blue line shows the actual transfer, which is computed as the average of the imputed transfers we use in the main analysis.

Figure 12: Model Based Estimates of Misallocation as a Function of Transfer Value

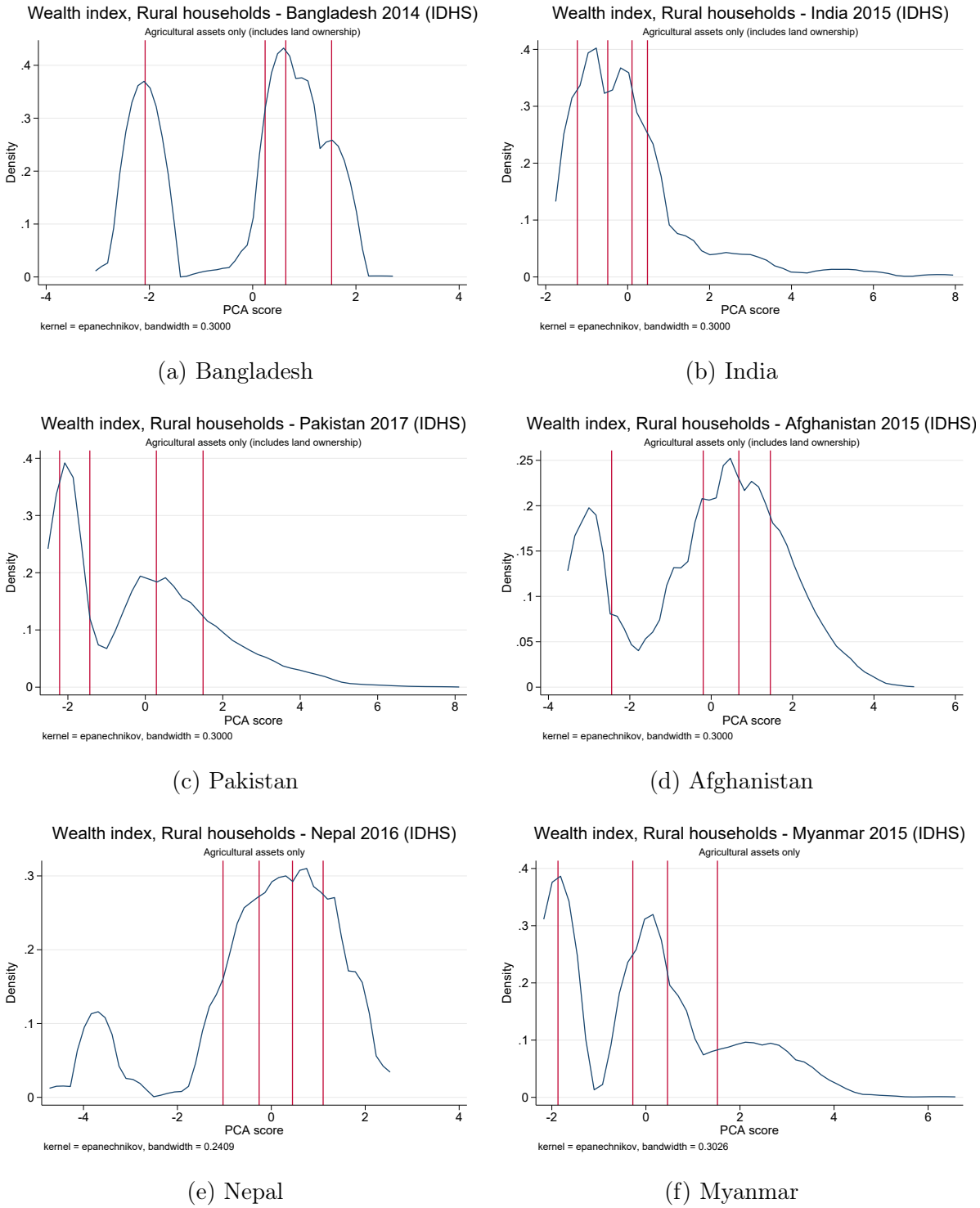


(a) misallocation vs upper mode of distribution of productive assets minus land

(b) misallocation vs unstable steady state

Notes: The graph shows the model-implied total value of misallocation (red) as transfers given to all households (blue) increase in increments of percentage of annual per capita consumption expenditure. In (a) Misallocation is measured against the maximum model-implied payoff available at the capital level corresponding to the upper mode of the distribution across all wealth classes of productive assets excluding land (43,701 BDT). In (b) misallocation is measured against the maximum model-implied payoff available at the unstable steady state capital level. The top 5% of individual misallocation values are top-coded at the 95th percentile in the simulations.

Figure 13: Distribution of Agricultural Assets for Rural Households across South Asia



(a) Bangladesh

(b) India

(c) Pakistan

(d) Afghanistan

(e) Nepal

(f) Myanmar

Notes: The graphs show kernel density plots of wealth scores for 6 South Asian countries, based on microdata from harmonized IPUMS-DHS household surveys. The wealth scores are constructed by performing a principle component analysis (PCA) at the individual level using a full list of agricultural assets. The first component of the PCA is used to compute the wealth index. The vertical red lines denote quintiles of the wealth distribution.

Table 1: The Economic Lives of Women in Bangladeshi Villages at Baseline

	(1) ultra-poor	(2) near poor	(3) middle class	(4) upper-class
A) Labour Outcomes				
In labour force	0.84	0.81	0.87	0.91
	(0.36)	(0.39)	(0.34)	(0.29)
Total hours worked per year	1134.31	938.53	819.82	820.79
	(888.38)	(821.22)	(639.08)	(549.77)
Total days worked per year	252.06	265.07	303.55	325.62
	(136.74)	(141.27)	(122.21)	(102.25)
Hourly income (BDT)	4.65	4.27	5.98	12.55
	(19.35)	(7.37)	(17.69)	(40.61)
B) Human and Physical Capital				
Years of formal education	0.56	1.26	1.99	3.72
	(1.63)	(2.43)	(2.99)	(3.74)
Literate	0.07	0.17	0.27	0.51
	(0.26)	(0.37)	(0.44)	(0.50)
Body mass index (BMI)	18.25	18.58	19.17	20.53
	(2.27)	(2.25)	(2.28)	(3.02)
Household Savings (1000 BDT)	0.15	0.40	1.62	8.61
	(0.83)	(1.24)	(10.62)	(29.29)
Productive assets (1000 BDT)	9.92	12.94	145.38	801.77
	(30.63)	(71.59)	(310.49)	(945.29)
Productive assets + Loans (1000 BDT)	10.53	14.83	150.23	812.83
	(31.10)	(72.47)	(312.50)	(947.65)
Observations	6732	7340	6742	2215

Notes: Standard deviations are reported in brackets. All statistics are constructed using baseline household data from both treatment and control villages. Wealth classes are based on the participatory rural assessment (PRA) exercise conducted by BRAC: the ultra-poor are ranked in the bottom wealth bins and meet the TUP program eligibility criteria, the near-poor are ranked in the bottom wealth bins and do not meet the program eligibility criteria, middle-class are ranked in the middle wealth bins, and the upper classes are those ranked in the top bin.The number of households in each wealth class at baseline is reported at the bottom of the table. All outcomes, except household savings, productive assets and loans, are measured at the individual level (for the ultra-poor women in the household). The recall period is the year before the survey date. The BMI statistics trim observations with BMI above 50.

Table 2: Short-Term Responses to the Asset Transfer

	Dependent variable: Δ_i					
	(1) Treatment	(2) Control	(3) Both	(4) Treatment	(5) Control	(6) Both
above $\hat{k}$	0.297***	-0.020	-0.020	0.475***	-0.097	-0.097
	(0.043)	(0.052)	(0.057)	(0.070)	(0.598)	(0.669)
Treatment			-0.483***			0.398
			(0.059)			(0.664)
above $\hat{k}$ × Treatment			0.318***			0.571
			(0.070)			(0.672)
Baseline assets				-2.199***	-0.463*	-0.463
				(0.698)	(0.266)	(0.298)
above $\hat{k}$ × Baseline assets				1.969***	-0.097	-0.097
				(0.729)	(0.269)	(0.301)
Treatment × Baseline assets						-1.737**
						(0.716)
above $\hat{k}$ × Treatment × Baseline assets						2.067***
						(0.744)
constant	-0.138***	0.345***	0.345***	-0.282***	-0.680	-0.680
	(0.033)	(0.046)	(0.050)	(0.057)	(0.592)	(0.662)
N	3292	2450	5742	3292	2450	5742

Notes: *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$. Standard errors in brackets. Sample: ultra-poor households in treatment and control villages with log baseline productive assets below 3 (Observations from control households are excluded if their baseline productive assets were above 3 if they had received the transfer). The dependent variable is the difference between log productive assets in 2011 and log of productive assets in 2007, where productive assets are defined as the total value of livestock, poultry, business assets (e.g. tools, vehicles and structures), and land. Above $\widehat{k}$ equals 1 if the baseline asset stock plus the imputed transfer is larger than 2.333, and 0 otherwise. In treatment, this represents households' actual post-transfer asset stock. In control, where no transfer was received, above $\widehat{k}$ indicates if the household would be above 2.333 if it had received a transfer. Baseline assets always refers to the actual level of assets, i.e. without the imputed transfer in control. Treatment was assigned at the village level. Baseline assets are centered at 2.333, i.e. the value reflects the log of household's productive assets in 2007 minus 2.333.

Table 3: Exploiting Individual Thresholds in Estimating Short-Term Responses to the Asset Transfer

	Earnings Potential			*Savings Potential*		
	Baseline (1)	FE (2)	Placebo (3)	Baseline (4)	FE (5)	Placebo (6)
Above $\widehat{k}_i$	0.301*** (0.044)	0.307*** (0.047)		0.319*** (0.045)	0.357*** (0.048)	
Above $\widehat{k}_L$			−0.268** (0.104)			0.172 (0.878)
Above $\widehat{k}_H$			0.474*** (0.072)			0.484*** (0.102)
Constant	−0.157*** (0.038)	−0.161*** (0.038)	−0.012 (0.09)	−0.154*** (0.035)	−0.177*** (0.037)	−0.262*** (0.07)
Baseline $\ln K_0$ FE	N	Y	Y	N	Y	Y
N	3,292	3,292	1,656	3,135	3,135	1,352

Notes: *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$. Robust standard errors in parentheses. Sample: ultra-poor households in treatment villages with log baseline productive assets below 3. The dependent variable is the difference between log productive assets in 2011 and log of productive assets in 2007, where productive assets are defined as the total value of livestock, poultry, business assets (e.g. tools, vehicles and structures), and land. Above $\widehat{k}_i$ equals 1 if the baseline asset stock plus the imputed transfer is larger than the individual specific threshold value based on earnings potential in columns 1-3 and savings in columns 4-6. For those with below median savings (earnings potential), the individual specific threshold is at 2.36 (2.39) and for those above the median it is 2.29 (2.24) (SeeFigure 5). $\widehat{k}_{L/H}$ equals 1 if the capital stock plus the transfer is larger than the thresholds for individuals below/above the median of earnings potential in columns 1-3 and savings in columns 4-6. Columns 3 and 6 restrict the sample to households for which the high threshold applies, that is, those with below median earnings potential or savings rate, respectively.

Table 4: Difference in Differences Estimates of Long-Run Dynamics

	(1) Productive assets	(2) Cows	(3) Land	(4) Cons.	(5) Net Earnings	(6) Net Earnings self-empl.	(7) Total hours	(8) Hours self-empl.
above $\hat{k}$	1,706	-1,076***	771	5,266***	-292	-179	-73**	46***
	(2,212)	(195)	(2,147)	(800)	(379)	(175)	(33)	(12)
Year 2 × above $\hat{k}$	251	495	1,024	-2,324**	-1,889***	-807***	-212***	-109***
	(896)	(365)	(770)	(975)	(329)	(253)	(39)	(15)
Year 4 × above $\hat{k}$	3,376**	3,329***	1,193	-946	-481	-282	84**	100***
	(1,657)	(452)	(1,530)	(1,078)	(346)	(265)	(41)	(18)
Year 7 × above $\hat{k}$	2,335	2,529***	845	1,526	2,162***	1,827***	19	-14
	(2,568)	(408)	(2,468)	(1,120)	(426)	(353)	(42)	(19)
Year 11 × above $\hat{k}$	10,708**	2,245***	9,775**	3,464***	1,457**	862**	86**	74***
	(5,004)	(374)	(4,880)	(1,268)	(703)	(425)	(41)	(17)
N	15713	15713	15713	14988	15713	15713	15713	15713

Notes: *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$. Sample: ultra-poor households in treatment villages with log baseline productive assets below 3. Coefficients report the difference in outcomes between those above vs. below the threshold, relative to this difference at baseline. Assets are measured in levels by their reported value and deflated to 2007 using the Bangladesh rural CPI. Other assets comprise of poultry, goats, machines, tools, and vehicles. Consumption refers to total annual household expenditure in 2007 BDT. Income from assets refers to income generated through self-employed work such as livestock rearing. Total hours and self-employed hours worked are measured annually. All regressions control for sub-district fixed effects. Robust standard errors in parentheses.

Table 5: Life Cycle Effects and Long-Run Dynamics

	(1) Productive assets	(2) Cows	(3) Land	(4) Cons.	(5) Net Earnings	(6) Net Earnings self-empl.	(7) Total hours	(8) Hours self-empl.
Panel A: Below median age								
above $\hat{k}$	4,137	-1,287***	3,493	3,596***	-850	-900***	-53	42***
	(2,736)	(270)	(2,640)	(1,021)	(586)	(245)	(43)	(16)
Year 2 × above $\hat{k}$	309	255	1,460	-1,693	-1,295***	-562	-195***	-102***
	(1,481)	(532)	(1,314)	(1,236)	(468)	(348)	(51)	(20)
Year 4 × above $\hat{k}$	6,769***	3,872***	3,993*	-1,639	-209	-406	98*	82***
	(2,441)	(717)	(2,244)	(1,392)	(506)	(391)	(54)	(24)
Year 7 × above $\hat{k}$	4,002	2,656***	2,600	3,340**	3,582***	3,093***	23	-18
	(2,485)	(417)	(2,283)	(1,489)	(659)	(588)	(55)	(26)
Year 11 × above $\hat{k}$	18,345**	2,482***	16,608*	4,191**	3,483***	2,079***	111**	91***
	(8,687)	(551)	(8,505)	(1,684)	(1,317)	(741)	(53)	(24)
N	8000	8000	8000	7689	8000	8000	8000	8000
Panel B: Above median age								
above $\hat{k}$	-2,163	-843***	-3,359	6,222***	-92	388	-142***	49**
	(3,593)	(294)	(3,505)	(1,226)	(352)	(259)	(50)	(19)
Year 2 × above $\hat{k}$	526	778	814	-2,758*	-2,298***	-942**	-198***	-121***
	(997)	(535)	(769)	(1,484)	(458)	(369)	(56)	(22)
Year 4 × above $\hat{k}$	79	2,730***	-1,470	845	-563	-9	103*	118***
	(2,379)	(577)	(2,220)	(1,555)	(460)	(349)	(59)	(26)
Year 7 × above $\hat{k}$	747	2,389***	-879	303	966*	707*	64	-7
	(4,655)	(739)	(4,530)	(1,598)	(544)	(402)	(63)	(29)
Year 11 × above $\hat{k}$	3,960	2,145***	3,551	3,304*	-151	-169	135**	68***
	(5,340)	(499)	(5,176)	(1,830)	(551)	(410)	(60)	(24)
N	7713	7713	7713	7299	7713	7713	7713	7713

Notes: *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$. Sample: ultra-poor households in treatment villages with log baseline productive assets below 3. The median age of this sample at baseline is 36. Coefficients report the difference in outcomes between those above vs. below the threshold, relative to this difference at baseline. Assets are measured in levels by their reported value and deflated to 2007 using the Bangladesh rural CPI. Other assets comprise of poultry, goats, machines, tools, and vehicles. Consumption refers to total annual household expenditure in 2007 BDT. Income from assets refers to income generated through self-employed work such as livestock rearing. Total hours and self-employed hours worked are measured annually. All regressions control for sub-district fixed effects. Robust standard errors in parentheses.

A Solution of the Structural Model

In this appendix we characterize the full solution of our structural model:

$$\max_{l\geq 0, h\geq 0, h'\geq 0} Af(\bar{k})g(l+h') + wh - w'h' - \frac{1}{2}(\sqrt{\psi_l}l + \sqrt{\psi_h}h)^2 \tag{1}$$

subject to

$$h \leq \overline{H} \tag{H}$$

$$h' \leq \overline{N} \tag{N}$$

$$h + l \leq \overline{R} \tag{R}$$

Case 1 Mixed occupational choice with hired-in labour ($l > 0, h > 0, h' > 0$).

Case 1a All [H], [N] and [R] slack.
In this case, the optimal solution must satisfy:

$$\begin{aligned} Af(\bar{k})g'(l+h') &= \psi_l l + \sqrt{\psi_l \psi_h} h \\ w &= \sqrt{\psi_l \psi_h} l + \psi_h h \\ Af(\bar{k})g'(l+h') &= w' \end{aligned}$$

Note that this is possible under the assumption that $w > w'$ and $\psi_h > \psi_l$. We can interpret the left-hand side of the first order conditions as the marginal benefit of increasing the amount of self-employment or wage labour supplied or the amount of labour hired in (in terms of additional production or earnings), whereas the right-hand side represents the respective marginal cost. Because the agent is choosing an interior solution for these three variables, it must be that the marginal benefit is equal to the marginal cost.

Case 1b [H] binding, [N] and [R] slack.
If $h = \overline{H}$, then the optimal solution is characterised by:

$$\begin{aligned} Af(\bar{k})g'(l+h') &= \psi_l l + \sqrt{\psi_l \psi_h}\, \overline{H} \\ h &= \overline{H} \\ Af(\bar{k})g'(l+h') &= w' \end{aligned}$$

Moreover, because [H] is binding, we have that

$$w \geq \sqrt{\psi_l \psi_h} l + \psi_h \overline{H},$$

i.e. in the optimum the marginal benefit of wage work could be greater than the marginal cost. This might mean that the agent would like to supply more hours of paid labour, but cannot do so because of the labour demand constraint.

Case 1c [H] and [N] slack, [R] binding.

If $h < \overline{H}$ but $h + l = \overline{R}$, letting λ denote the Lagrange multiplier on the time endowment constraint, the optimal solution must satisfy

$$\begin{aligned} Af(\bar{k})g'(l + h') &= \psi_l l + \sqrt{\psi_l \psi_h} h + \lambda \\ w &= \sqrt{\psi_l \psi_h} l + \psi_h h + \lambda \\ Af(\bar{k})g'(l + h') &= w' \\ h + l &= \overline{R} \end{aligned}$$

The multiplier $\lambda \geq 0$ represents the value of relaxing the binding constraint [R] at the optimum. It appears in the right-hand side of the first order conditions because, when the time endowment constraint binds, increasing the hours worked in livestock rearing implies decreasing the hours in wage labour (and vice versa). Combining the first two equations, we can characterise the solution as:

$$\begin{aligned} Af(\bar{k})g'(l + h') - \psi_l l - \sqrt{\psi_l \psi_h}(\overline{R} - l) &= w - \sqrt{\psi_l \psi_h} l - \psi_h(\overline{R} - l) \\ h &= \overline{R} - l \\ Af(\bar{k})g'(l + h') &= w' \end{aligned}$$

Case 1d [H] and [R] binding, [N] slack.

In this case the optimal solution is:

$$\begin{aligned} l &= \overline{R} - \overline{H} \\ h &= \overline{H} \\ Af(\bar{k})g'(\overline{R} - \overline{H} + h') &= w' \end{aligned}$$

As before, at the optimum we have

$$\begin{aligned} Af(\bar{k})g'(\overline{R}-\overline{H}+h') &\geq \psi_l(\overline{R}-\overline{H})+\sqrt{\psi_l\psi_h}\,\overline{H} \\ w &\geq \sqrt{\psi_l\psi_h}(\overline{R}-\overline{H})+\psi_h\overline{H} \end{aligned}$$

i.e. the marginal benefits of self-employment and wage labour could be greater than the respective marginal costs.

In all the sub-cases where [N] is binding, in the optimum we will have

$$Af(\bar{k})g'(l+\overline{N}) \geq w',$$

meaning that, because the farmer is hiring in the maximum amount of labour she can, it is possible that the marginal benefit of hiring in is still bigger than the marginal cost of doing so.

Case 1e [H] and [R] slack, [N] binding.
The optimal solution is characterised by:

$$\begin{aligned} Af(\bar{k})g'(l+\overline{N}) &= \psi_l l+\sqrt{\psi_l\psi_h}h \\ h &= \sqrt{\psi_l\psi_h}l+\psi_h h \\ h' &= \overline{N} \end{aligned}$$

Case 1f [R] slack, [H] and [N] binding.
The optimal solution is given by:

$$\begin{aligned} Af(\bar{k})g'(l+\overline{N}) &= \psi_l l+\sqrt{\psi_l\psi_h}\,\overline{H} \\ h &= \overline{H} \\ h' &= \overline{N} \end{aligned}$$

Case 1g [H] slack, [R] and [N] binding.
The optimal solution must satisfy:

$$\begin{aligned} Af(\bar{k})g'(l+\overline{N})-\psi_l l-\sqrt{\psi_l\psi_h}(\overline{R}-l) &= w-\sqrt{\psi_l\psi_h}l-\psi_h(\overline{R}-l) \\ h &= \overline{R}-l \\ h' &= \overline{N} \end{aligned}$$

Case 1h All [H], [N] and [R] binding.

The optimal solution is:

$$
\begin{aligned}
l &= \overline{R} - \overline{H} \\
h &= \overline{H} \\
h' &= \overline{N}
\end{aligned}
$$

Case 2 Mixed occupational choice without hired-in labour ($l > 0, h > 0, h' = 0$).

In all the sub-cases below, because $h' = 0$, necessarily we have

$$Af(\bar{k})g'(l) \leq w'$$

This means that, as no labour is being hired in, the marginal benefit of doing so must be less than the marginal cost. Also, [N] is slack because $\overline{N} > 0 = h'$.

Case 2a Both [H] and [R] slack.

In this case, the optimal solution must satisfy:

$$
\begin{aligned}
Af(\bar{k})g'(l + h') &= \psi_l l + \sqrt{\psi_l \psi_h} h \\
w &= \sqrt{\psi_l \psi_h} l + \psi_h h \\
h' &= 0
\end{aligned}
$$

Case 2b [H] binding, [R] slack.

The optimal solution is characterised by:

$$
\begin{aligned}
Af(\bar{k})g'(l + h') &= \psi_l l + \sqrt{\psi_l \psi_h}\, \overline{H} \\
h &= \overline{H} \\
h' &= 0
\end{aligned}
$$

with

$$w \geq \sqrt{\psi_l \psi_h} l + \psi_h \overline{H}$$

Case 2c [H] slack, [R] binding.

By the same argument as above, in the optimum we must have:

$$\begin{aligned} Af(\bar{k})g'(l+h') - \psi_l l - \sqrt{\psi_l \psi_h}(\overline{R} - l) &= w - \sqrt{\psi_l \psi_h} l - \psi_h(\overline{R} - l) \\ h &= \overline{R} - l \\ h' &= 0 \end{aligned}$$

Case 2d Both [H] and [R] binding. The optimal solution is:

$$\begin{aligned} l &= \overline{R} - \overline{H} \\ h &= \overline{H} \\ h' &= 0 \end{aligned}$$

with

$$\begin{aligned} Af(\bar{k})g'(\overline{R} - \overline{H}) &\geq \psi_l(\overline{R} - \overline{H}) + \sqrt{\psi_l \psi_h}\,\overline{H} \\ w &\geq \sqrt{\psi_l \psi_h}(\overline{R} - \overline{H}) + \psi_h \overline{H} \end{aligned}$$

We turn now to cases where the agent does only livestock rearing (self-employment) and no wage labour. Because $h = 0$, it must be the case that

$$w \leq \sqrt{\psi_l \psi_h} l + \lambda$$

at the optimum, where λ is again the Lagrange multiplier on the time endowment constraint (and $\lambda = 0$ if the constraint is slack). This mean that, even at $h = 0$, the marginal cost of supplying hours of paid work is higher than the marginal benefit. Also, note that the labour demand constraint [H] will always be slack, as $h = 0 < \overline{H}$.

Case 3 Livestock rearing only with hired-in labour ($l > 0, h = 0, h' > 0$).

Case 3a Both [R] and [N] slack.
The optimal solution must satisfy:

$$\begin{aligned} Af(\bar{k})g'(l+h') &= \psi_l l \\ h &= 0 \\ Af(\bar{k})g'(l+h') &= w' \end{aligned}$$

Case 3b [R] binding, [N] slack.

The optimal solution is given by:

$$l = \overline{R}$$
$$h = 0$$
$$Af(\bar{k})g'(\overline{R} + h') = w'$$

with

$$Af(\bar{k})g'(\overline{R} + h') \geq \psi_l \overline{R}$$

Case 3c [R] slack, [N] binding.
At the optimum we must have:

$$Af(\bar{k})g'(l + \overline{N}) = \psi_l l$$
$$h = 0$$
$$h' = \overline{N}$$

Case 3d Both [R] and [N] binding.
The optimal solution is:

$$l = \overline{R}$$
$$h = 0$$
$$h' = \overline{N}$$

Case 4 Livestock rearing only without hired-in labour ($l > 0, h = 0, h' = 0$).
Again, because $h' = 0$, we must have

$$Af(\bar{k})g'(l) \leq w'$$

at the optimum.

Case 4a [R] slack.
The optimal solution must satisfy:

$$Af(\bar{k})g'(l) = \psi_l l$$
$$h = 0$$
$$h' = 0$$

Case 4b [R] binding.

The optimal solution is:

$$l = \overline{R}$$
$$h = 0$$
$$h' = 0$$

with

$$Af(\bar{k})g'(R) \geq \psi_l \overline{R}$$

Next, we examine the cases where the agent does only wage labour but no livestock rearing herself. Because $l = 0$, we necessarily have that

$$Af(\bar{k})g'(h') \leq \sqrt{\psi_l \psi_h} h$$

Notice also that, since $h \leq \overline{H} \leq \overline{R}$, the time endowment constraint [R] is automatically slack.

Case 5 Wage work only with hired-in labour ($l = 0, h > 0, h' > 0$).

Case 5a Both [H] and [N] slack.

The optimal solution is given by:

$$l = 0$$
$$w = \psi_h h$$
$$Af(\bar{k})g'(h') = w'$$

Case 5b [H] binding, [N] slack. The optimum must satisfy:

$$l = 0$$
$$h = \overline{H}$$
$$Af(\bar{k})g'(h') = w'$$

with

$$w \geq \psi_h \overline{H}$$

Case 5c [H] slack, [N] binding. The optimum must satisfy:

$$l = 0$$
$$w = \psi_h h$$
$$h' = \overline{N}$$

Case 5d Both [H] and [N] binding. The optimum must satisfy:

$$l = 0$$
$$h = \overline{H}$$
$$h' = \overline{N}$$

In the last possible case, we have that $l + h' = 0$. Under standard regularity conditions (in particular, if we assume $g'(0) = +\infty$) this would never be an optimal choice. This is because the marginal return of starting any livestock rearing (either through self-employment or by hiring in external labour) is arbitrarily large, whereas the marginal cost is only finite.

However, to allow for this case, we consider the possibility of liquidating the physical capital stock, which would yield a profit of $\rho\bar{k}$ with $\rho \leq 1$. Hence, the problem that the agent faces is just a choice of hours of paid work:

$$\max_{h \geq 0} \rho\bar{k} + wh - \frac{1}{2}\psi_h h^2 \tag{2}$$

subject to

$$h \leq \overline{H} \tag{H}$$

Case 6 Wage work only without hired-in labour ($l = 0, h > 0, h' = 0$).

Case 6a [H] slack.

The optimality condition is

$$w = \psi_h h$$

Case 6b [H] binding. In this case we must have

$$h = \overline{H}$$

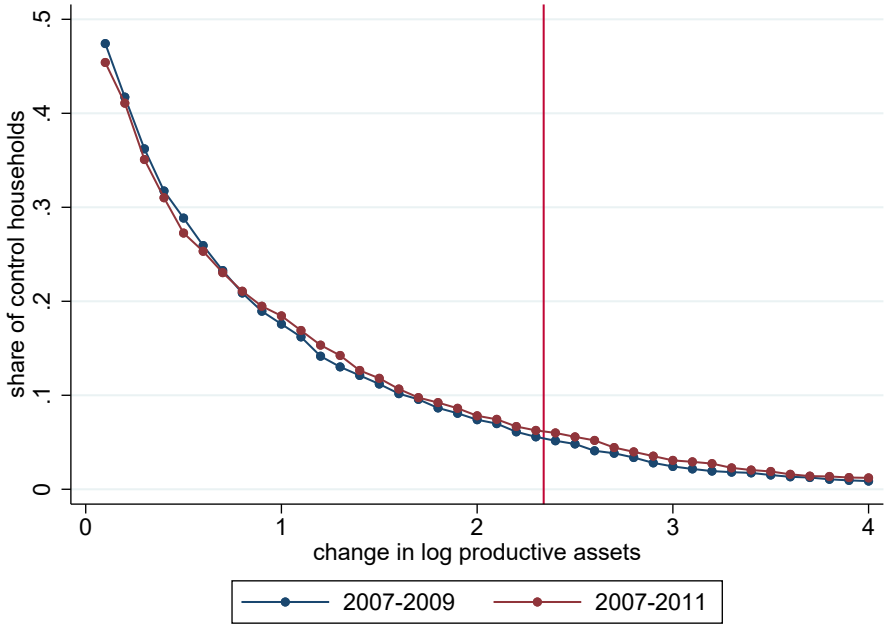
and $w \geq \psi_h \overline{H}$.

The above will be optimal when the solution to the maximization problem in (2) yields a higher payoff than the outcome of (1).

Finally, we note that with this parametrisation it is not possible to have $l = 0$ and $h = 0$ at the same time, because at those levels, the marginal cost of supplying wage labour is 0, whereas the marginal benefit is $w > 0$. However, this case seems to be empirically relevant.

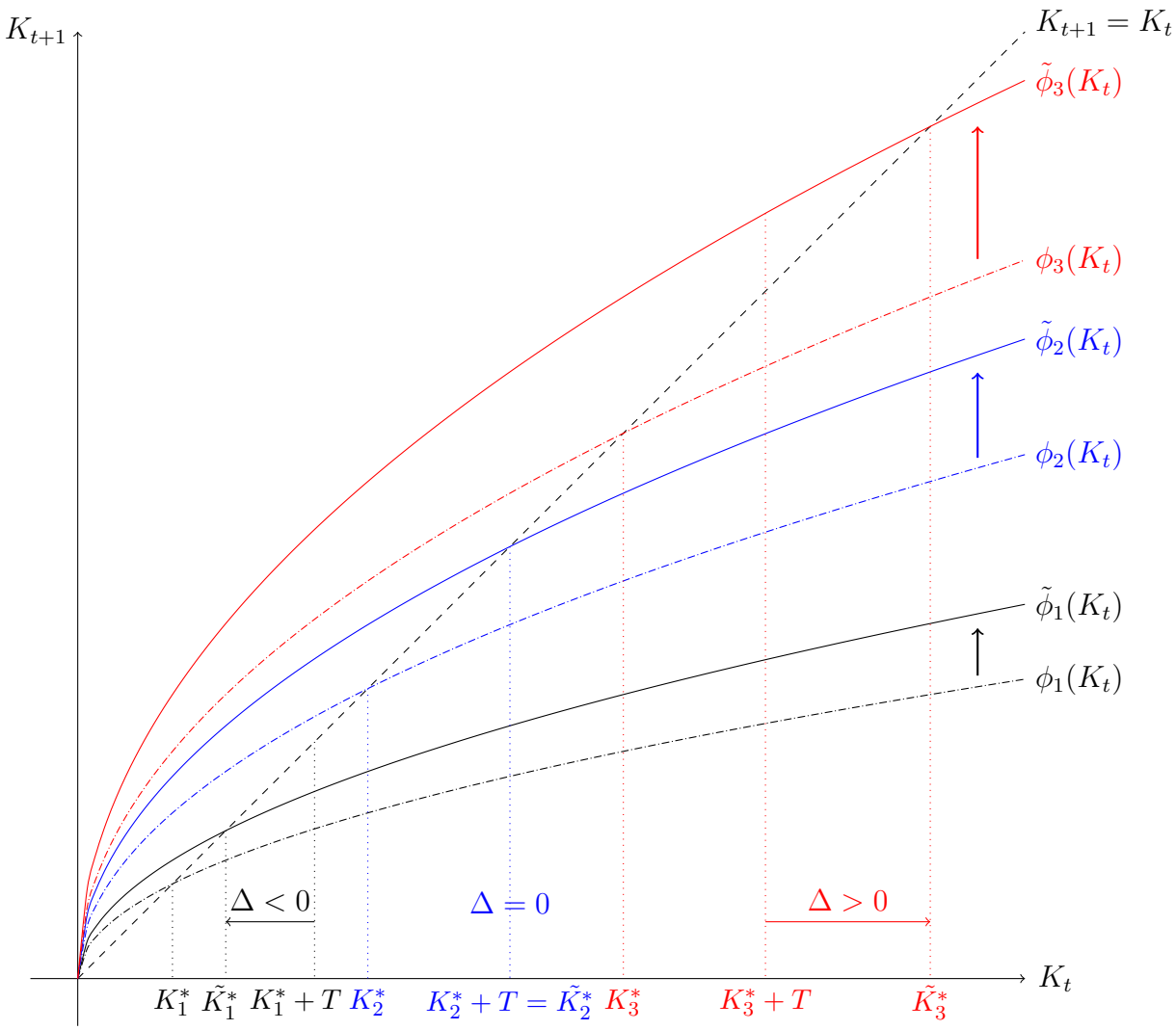
B Appendix Figures

Figure B1: Positive Asset shocks for control households



Notes: The figure reports the share of control households that experience a change in log productive assets larger that X between 2007 and 2009 (blue line) or 2007 and 2011 (red line), where X varies between 0 and 4 in increments of 0.1. The horizontal red line indicates the proximate size of asset transfer provided by BRAC to households in treatment villages.

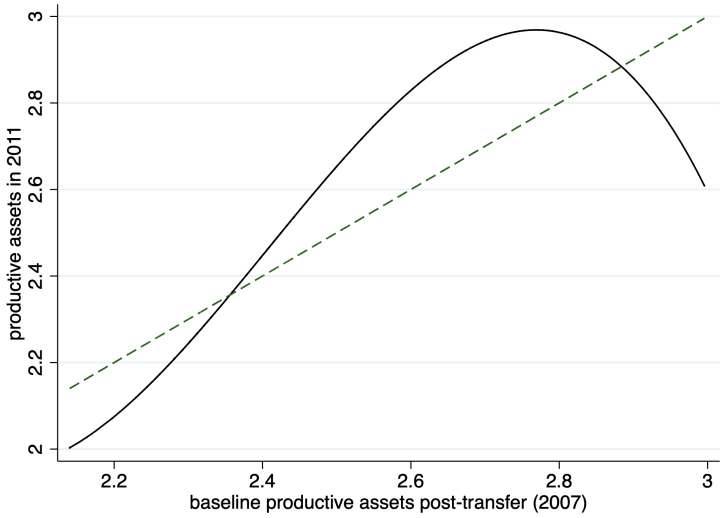
Figure B2: Unstable Steady State in the Empirical Transition Equation can emerge from Endogenous Response to Training under Concave Individual Transition Equations



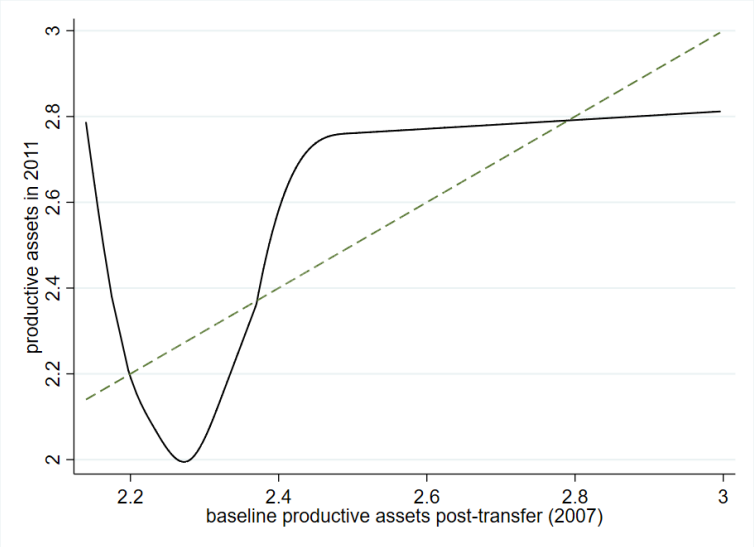
Notes: The figure illustrates the case in which the effect of the training is increasing in K_0. There exists level of capital, K_2^* such that $K_2^* + T = \widetilde{K_2^*}$. Individual $i = 1$ with $K_1^* < K_2^*$ gains less from the training which means that their new steady state is below their initial steady state plus the transfer, that is $K_1^* < \widetilde{K_1^*} < K_1^* + T$, which implies $\Delta_1 < 0$. Conversely, individual $i = 3$ with $K_3^* > K_2^*$ gains more from the training, raising their new steady state above their post-transfer asset value, that is $K_3^* < K_3^* + T < \widetilde{K_3^*}$, which implies $\Delta_3 > 0$

Figure B3: Alternative Estimates of the Transition Equation

(a) 3rd Order Polynomial

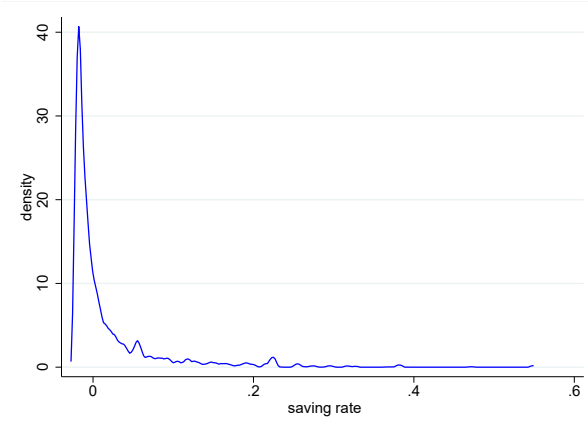


(b) B-splines

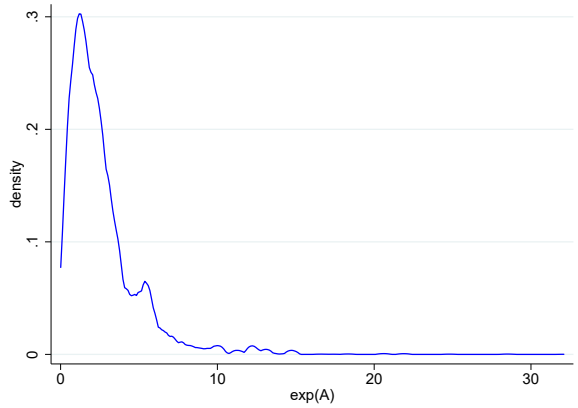


Notes: The sample is restricted to ultra-poor households in treatment villages with log baseline productive assets below 3. Productive assets are measured as the natural logarithm of the total value, in 1000 Bangladeshi Taka, of all livestock, poultry, business assets, and land owned by the households. Post-transfer assets are imputed by adding to each household's baseline assets the median value of a cow within the catchment area of a household's BRAC branch. The dashed line represents the 45° line at which assets in 2011 equal initial assets in 2007. Panel a) plots the predicted values of a regression of log productive assets in 2014 on a third order polynomial of log productive assets including the transfer in 2011. Panel b) shows a B-spline estimate of the same relationship.

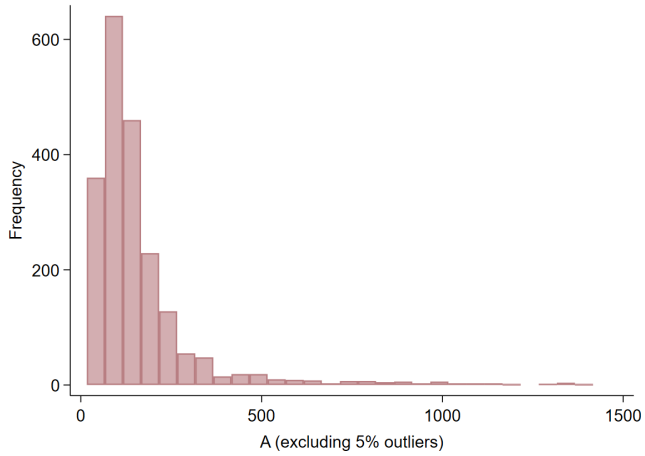
Figure B4: What explains Bimodal Distribution of Assets? Savings Rate and Individual Productivity in Livestock Rearing among the Ultra-Poor



(a) Distribution of savings rate



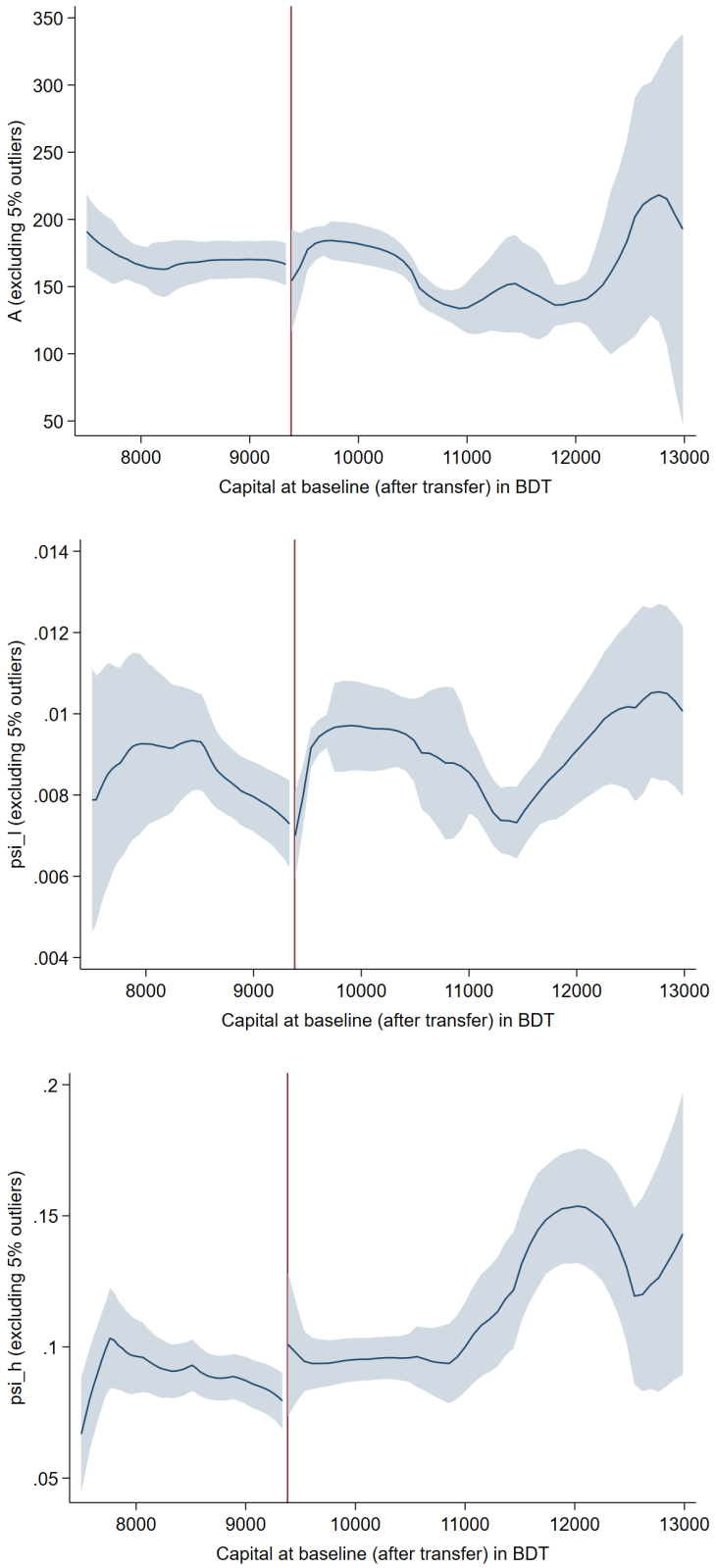
(b) Distribution of Productivity, panel regression



(c) Distribution of Productivity, structural estimation

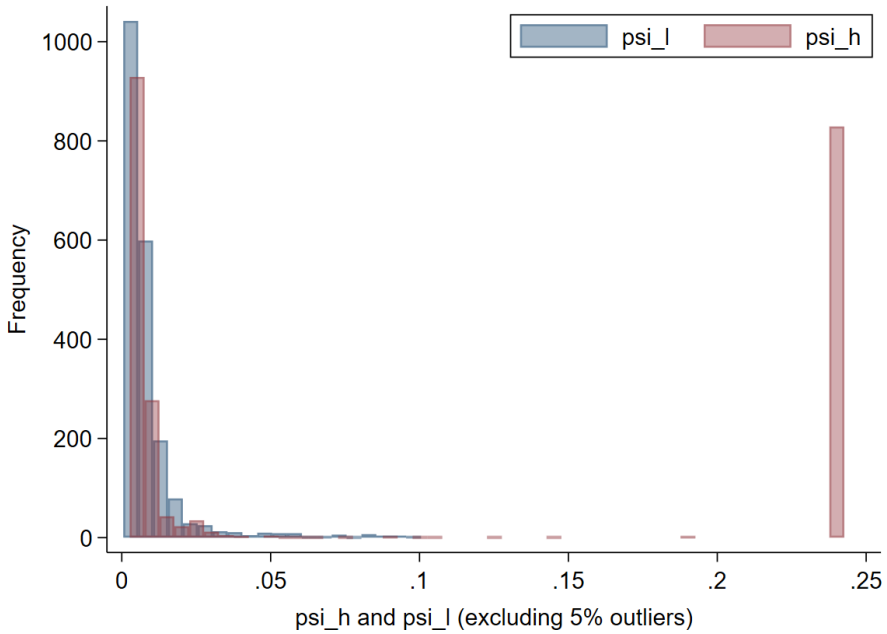
Notes: The graph shows density estimates of the distribution of households' savings rate (panel (a)) and livestock rearing productivity (panel (b)) for all surveyed households in treatment villages. The savings rate is net of survey wave and branch fixed effects. Household level productivity estimates are obtained by regressing log livestock income on log hours worked in livestock rearing, and the log of the number of cows, controlling for survey round, BRAC branch, and household fixed effects in a panel over the survey rounds 2007, 2009, 2011, 2014, and 2018. The graph (panel (b)) plots $A_i = exp(\hat{\mu}_i)$ of the household fixed effects $\hat{\mu}_i$, which we interpret as a measure of household TFP. One outlier at 124.8 is excluded. The distribution of the product of savings rate and productivity, $s_i \times A_i$, is also unimodal (not shown). The last figure (panel (c)) shows the density of household-level calibrated parameters for productivity in livestock rearing from the structural model. The sample are the 64% of ultra-poor individuals for whom individual-level parameters can be calibrated using baseline and/or year 2 data (as described in section 6.2).

Figure B5: Calibrated productivity, disutility livestock rearing and disutility of wage labor as a function of baseline capital.



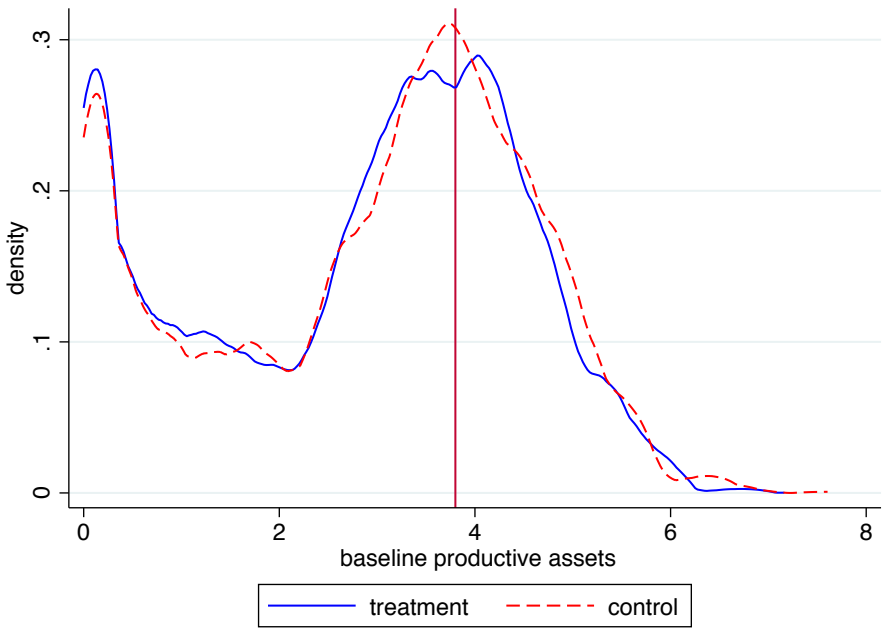
Notes: The graphs show calibrated values of individual-level parameters as a function of post-transfer baseline capital. The calibrated parameters shown are productivity in livestock rearing A (panel A), disutility of labor hours in livestock rearing (panel B), and disutility of wage labor hours (panel C). Five percent outliers are excluded. The vertical lines show the threshold level of capital. Local polynomial regressions are estimated separately on either side of the threshold. Ninety five percent asymptotic confidence intervals for the local polynomial regressions are shown.

Figure B6: Frequency distribution of calibrated disutility of labor parameters



Notes: The frequency distributions shown are of calibrated individual-level parameters for disutility of livestock rearing hours (blue) and wage labor hours (red), excluding 5% outliers, for the 64% of ultra-poor individuals for whom individual-level parameters can be calibrated using baseline and/or year 2 data (as described in the text). The upper mode in the latter frequency distribution reflects the fact that individuals who do not work at baseline are assigned the maximum calibrated value of the disutility of wage labor hours parameter.

Figure B7: Distribution of Productive Assets excluding Land



Notes: The graph shows kernel density estimates of the distribution of baseline productive assets excluding land in the full sample of 21,839 households across all wealth classes in treatment and control villages. Productive assets without land include all livestock, poultry, and business assets owned by the household. Sample weights are used to account for different sampling probabilities across wealth classes. The weights are based on a census of all households in the 1,309 study villages.

C Appendix Tables

Table C1: Difference in Differences Estimates of Long-Run Dynamics: Additional Outcomes

	(1) Productive assets (constant prices)	(2) Other Assets	(3) Per-capita expenditure	(4) Per-capita food expenditure	(5) Below 1.90 USD/day
Year 2 X above $\hat{k}$	665	-1,268***	-423	-268	0.0292
	(771)	(154)	(281)	(242)	(0.0224)
Year 4 X above $\hat{k}$	3,595***	-1,146***	-119	64	0.0265
	(733)	(155)	(267)	(209)	(0.0235)
Year 7 X above $\hat{k}$	3,045**	-1,039***	354	-135	-0.0316
	(1,340)	(227)	(269)	(198)	(0.0238)
Year 11 X above $\hat{k}$	2,370*	-1,312***	795***	912***	-0.0689***
	(1,256)	(330)	(256)	(202)	(0.0246)
N	15713	15713	14988	14993	14988

Notes: *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$. Sample: ultra-poor households in treatment villages with log baseline productive assets below 3. Coefficients report the difference in outcomes between those above vs. below the threshold, relative to this difference at baseline. assets are constantly valued at the median prices withing BRAC branch at baseline. For the difference-in-differences estimates, we still determine whether a household is considered above or below the poverty threshold based on the reported asset value at baseline, as in all previous specifications). Other assets are defined as all productive assets minus livestock and land. Consumption is measured per-capita using adult-equivalent household size. Below 1.90 USD/ day is a household-level dummy equal to one if annual per capita expenditure converted to USD at PPP is below 1.90 * 365. All regressions control for sub-district fixed effects. Robust standard errors in parenthesis.