WHY DO PEOPLE STAY POOR?*

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There are two broad views as to why people stay poor. One emphasizes differences in fundamentals, such as ability, talent, or motivation. The poverty traps view emphasizes differences in opportunities that stem from access to wealth. To test these views, we exploit a large-scale, randomized asset transfer and an 11-year panel of 6,000 households who begin in extreme poverty. The setting is rural Bangladesh, and the assets are cows. The data support the poverty traps view—we identify a threshold level of initial assets above which households accumulate assets, take on better occupations (from casual labor in agriculture or domestic services to running small livestock businesses), 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 large transfers, which create better jobs for the poor, are an effective means of getting people out of poverty traps and reducing global poverty. *JEL Codes:* I32, J22, J24, O12.

I. Introduction

Why do people stay poor? This is one of the most important questions in the social sciences because of its implications for human welfare. Understanding what causes poverty and its potential persistence is what motivated early contributors to

*We are grateful to BRAC and particularly to Fazle Abed, Shameran Abed, Mushtaque Chowdhury, Narayan Das, Mahabub Hossain, W. M. H. Jaim, Imran Matin, Anna Minj, Muhammad Musa, Munshi Sulaiman, Atiya Rahman, and Rabeya Yasmin for the collaborative research over the past 15 years that underpins this article. We thank the editor, Larry Katz, and four anonymous referees for detailed and helpful comments. We also thank Abhijit Banerjee, Michael Carter, Esther Duflo, Marcel Fafchamps, Javier Hidalgo, Chang-Tai Hsieh, Supreet Kaur, Joe Kaboski, Dean Karlan, Tatiana Komarova, Michael Kremer, Ben Moll, Víctor Quintas-Martínez, Jonathan Old, Debraj Ray, Alejandro Sabal-Bermúdez, Alwyn Young, and several seminar participants for comments. Bandiera and Burgess thank BA grant EC170232, and Ghatak acknowledges ESRC-DFID Grant ES/L012103/1 for financial support. All errors are our own.

The Quarterly Journal of Economics (2022), 1–59. https://doi.org/10.1093/qje/qjab045.
Advance Access publication on December 7, 2021.

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 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, particularly so in light of the current pandemic that has reversed most of the progress made since then.[1] Finding answers ultimately requires us to understand why people stay poor and then 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 take low-earning jobs because they are born poor. That is, there is a wealth threshold below which people are stuck in a poverty trap, where their initial wealth (rather than their abilities or traits) keeps them in poverty. 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]

The core objective of this article is to distinguish between these two views empirically. Distinguishing them is as important as it is difficult. It is important because they have dramatically different policy implications. In the presence of poverty traps, policies that help move people past the wealth threshold and into more productive forms of employment can have large and

1. Lakner et al. (2020) estimate that the COVID-19 pandemic pushed an additional 79 million people into extreme poverty, increasing the total headcount estimate from the non-COVID-19 scenario of 635 million to 732 million in 2020.

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; Myrdal 1957, 1968; Rostow 1960; Nurkse 1961). Typical poverty trap models generally focus on the combination of a fixed investment coupled with external frictions, such as borrowing constraints (Banerjee and Newman 1993; Galor and Zeira 1993), or on scarcity-driven behavior, leading to either nutritional (Dasgupta and Ray 1986; Ray and Streufert 1993; Dasgupta 1997) or behavioral (Banerjee and Mullainathan 2008; Bernheim, Ray, and Yeltekin 2015; Ridley et al. 2020) poverty traps.

persistent effects in reducing poverty, as opposed to various forms of income and consumption support policies that provide short-term relief. This suggests "big push" policies—analogous to those in models of industrialization displaying multiple equilibria (Hirschman 1958; Murphy, Shleifer, and Vishny 1989) but focusing on asset transfers to the poor in our context as opposed to coordinated industrial investment—might constitute a powerful means of addressing the global poverty problem. 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 the two explanations produce the same outcome in equilibrium, and hence to tell them apart we need to observe the behavior of those who cross the threshold. If poverty is due to differences in traits, they will return to where they started; conversely, if poverty is due to differences in opportunities, they will be elevated out of poverty forever. But in practice we rarely see anyone crossing the threshold or know where the threshold is. In their recent review of the poverty traps literature, 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 the problems of observational data, such as unobserved heterogeneity and the fact that one would expect few observations in the sample around a poverty threshold.[3]

Our data and setting allow us to overcome the difficulty of distinguishing differences in individual characteristics and asset dynamics that create a poverty trap that arise in the case of observational data. The main contribution of this article 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

3. Indeed, the empirical literature on poverty traps finds very mixed results. 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 (Jalan and Ravallion 2004; Lokshin and Ravallion 2004; Naschold 2013; Arunachalam and Shenoy 2017). In contrast, Adato, Carter, and May (2006) find evidence of S-shaped dynamics in an asset index for a population in South Africa, and Barrett et al. (2006) identify multiple equilibria consistent with a poverty trap in detailed panel data from several remote sites in Kenya and Madagascar. A number of studies on Ethiopian rural pastoralist communities generating income from a single asset, cattle, also find dynamics consistent with poverty traps where 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 sizes (Lybbert et al. 2004; Santos and Barrett 2011, 2016).

studying the effect of a large randomized asset transfer program in rural Bangladesh, BRAC's Targeting the Ultra-Poor Program (Bandiera et al. 2017). This is part of a larger survey effort we conducted covering 23,000 households across the wealth distribution in over 1,309 villages. These villages are situated in the poorest districts of Bangladesh. We track 6,000 poor households across 2007, 2009, 2011, 2014, and 2018, half of which are randomly selected to receive a large asset transfer in 2007, mainly in the form of livestock (cows).[4] Being able to track the long-run dynamics of assets, occupations, and poverty across 11 years is important because a central prediction of poverty trap models is that one-time policies can have permanent effects if they lift people out of the trap.

We begin by showing that the distribution of productive assets for all individuals in these villages is bimodal. 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 and the more productive ones (livestock rearing and land cultivation) do, helps 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.

What makes our setting exceptional is that, fortuitously, the program 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.[5] Tracing how assets evolve after the transfer allows us to test for poverty traps.

As livestock (cow) rearing is the main occupation of richer women, while largely assetless poor women work in casual labor, the program can be seen as an attempt for the latter to engage in the occupations of the former. Given that the value of the asset transfered is equal across beneficiaries, the value of the productive assets (e.g., whether they have or can afford carts, sheds,

4. Control households are offered the program after 2011.

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

rickshaws) that the poor already own at baseline may influence how successful they are at running a livestock business. To illustrate this, consider two beneficiaries, one who has—or can afford—an asset, say, a cart, which is complementary to the livestock transfer by BRAC, and one who has nothing. If the market can only be reached by cart, the value of the threshold would be the value of the livestock plus cart. In this case, we would observe that only the beneficiaries who can afford a cart escape poverty. We use this intuition to trace the evolution of assets for each level of assets at baseline (encapsulating both the preowned assets and the livestock transfer) to seek a threshold such that those above successfully operate a livestock business and grow out of poverty whereas those below fall back into poverty.

Our main results are as follows. First, we find that the dynamics of asset accumulation follow the S-shaped pattern characteristic of a poverty trap—those with limited initial assets lose them and those above a certain threshold accumulate more. We estimate the level of this poverty threshold to be at 9,309 Bangladeshi taka (BDT, US$504 PPP), which is slightly more than the median cow value of 9,000 BDT (US$488 PPP). The threshold matches closely with 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 would be expected to push those near it outward in either direction. The fact that two different methods applied independently on different samples yield the same threshold increases our confidence in the results.

Second, we show that the path of asset accumulation for beneficiaries is consistent with poverty trap dynamics 4 years and 11 years after the transfer. After four years, treated households whose baseline assets were so low that the transfer was not enough to bring them past the threshold are more likely to slide back into poverty, and those who manage to go past the threshold escape poverty. Following the same households over the 11-year period, we find that the two groups diverge further over time—beneficiaries who start above the threshold accumulate assets (including land), move into more productive occupations, and increase consumption, relative to those below. The divergence is even starker if we account for the underlying pattern of asset accumulation over the life cycle.

Our identification exploits differences in asset ownership before the transfer, like the cart in the example above, which are small relative to the size of the transfer. Nonetheless, because the asset transfer 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. We provide three pieces of evidence to allay this concern. First, we show that among households in control villages who have the same range of baseline assets as our beneficiaries but receive no transfer, the correlation between assets at baseline and future assets is actually negative, that is, households with more assets are more likely to lose them as they revert to the mean. Second, we control directly for an array of human capital variables and show that the characteristic S-shape is robust to these controls. This rules out that initial differences in observable measures of human capital account for the heterogeneous program response.

Third, we use the intuition that households with different human capital, saving rates, and earnings potential have different poverty thresholds to identify the poverty trap by comparing households with the same level of initial assets. Indeed, we find that individuals with higher earnings potential and savings rates have lower thresholds, and that individuals escape poverty only if the transfer brings them above their individual-specific thresholds. Both these checks support our identifying assumption that variations in baseline assets are orthogonal to unobservable determinants of postprogram changes in assets.

The reduced-form results present evidence that the average poor household is trapped in poverty. The next step is to quantify the misallocation caused by this. We do this by constructing a structural model of occupational choice that allows us to quantify 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 specializing in wage labor, while 98% of households are exclusively reliant on such work at baseline. Conversely, only 1% specialize in livestock rearing while 90% would do so if they had access to the same asset wealth as the middle and upper classes. Overall, this implies that 97% of households misallocate their labor at baseline. 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 an order of magnitude larger than the one-off cost of taking households across the poverty threshold.

Overall, a picture emerges where the poorest lack livestock and complementary assets, both of which are needed to take on more productive occupations but neither of which can be acquired through loans. This means that the poor are excluded from taking on these occupations and their labor and talent is wasted on less productive and more irregular occupations. The low wage and unreliable nature of those jobs prevents them from saving enough to fund the purchase of indivisible assets needed to run these businesses. As a result, the poor remain poor not because they are only suited to irregular, unproductive work but because they cannot access the better jobs. This situation creates significant misallocation of talent.

The implications of the existence of occupational poverty traps for development policy are profound. In this case, 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 because of the inadequacy of the transfer to effect this. In the last part of the article, we compare different poverty alleviation policies through the lens of a poverty trap framework. How many lives will be permanently affected 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.[6]

Our evidence 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, in which case this may be a more powerful and cost-effective route to improving long-run

6. 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. 2015a, 2019; Meager 2019).

welfare than continuous consumption support. The emerging literature suggests that although 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, 2020; Banerjee et al. 2015b; Bandiera et al. 2017; Haushofer and Shapiro 2018; Araujo, Bosch, and Schady 2019; Millán et al. 2020; Banerjee, Duflo, and Sharma 2020). Our article makes precise the conditions under which transfers can have a permanent effect by lifting people out of an occupational poverty trap. This suggests that very similar programs can have strikingly different effects depending on how many people they push past the threshold.

The rest of the article proceeds as follows. Section II details the context, data, and intervention we study. Section III describes the framework, methods, and identification strategy we use to test for poverty traps. Section IV uses short-term responses to the program after four years to distinguish between the two views of why people stay poor. In Section V, 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 VI, we outline and estimate our structural model of occupational choice, which allows us to quantify the extent of misallocation in the work that people do. In Section VII, we draw out the key policy implications from our findings. Finally, Section VIII concludes.

II. Background and Data

We test for the existence of a poverty trap using data collected to evaluate BRAC's Targeting the Ultra-Poor (TUP) Program in Bangladesh (Bandiera et al. 2017). The data cover 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.[7] Beneficiaries are offered a choice of several asset bundles, all of which are valued at around 9,045 BDT (US$490) and can be used

7. 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.

for income-generating activities.[8] Out of all eligible women, 91% chose 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 ineligibles (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, and 2014; and the initially ultra-poor were interviewed again in 2018. This enables us to track occupation, asset, and welfare dynamics over an 11-year period. Attrition between 2007 and 2018 is 14%.[9]

To evaluate the program, we randomize its rollout 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 have a control group of 700 villages. Although 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 to examine the distribution of productive assets across all wealth classes and in the structural model to determine what occupations the ultra-poor would engage in if they had a higher endowment of productive assets.

Table I 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 in total and per hour worked. Panel B illustrates

8. Throughout, we use the 2007 PPP-adjusted exchange rate of 18.46 BDT to US$1.

9. Migration is rare in our sample, as the median age of targeted 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 in Section V, attrition is balanced above and below the poverty threshold and the results remain unchanged when using the balanced panel of households that are observed in every survey wave.

TABLE I
THE ECONOMIC LIVES OF WOMEN IN BANGLADESHI VILLAGES AT BASELINE

	Ultra-poor (1)	Near poor (2)	Middle class (3)	Upper class (4)
In labor force	0.74	0.67	0.69	0.71
	(0.44)	(0.47)	(0.46)	(0.46)
Total hours worked per year	990.91	767.62	555.83	496.83
	(893.68)	(811.72)	(596.80)	(493.42)
Total days worked per year	252.06	265.07	303.55	325.62
	(136.74)	(141.27)	(122.21)	(102.25)
Hourly income (BDT)	5.61	5.63	9.83	21.67
	(21.22)	(10.93)	(38.09)	(69.95)
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)	18.38	18.96	19.49	20.60
	(2.40)	(2.56)	(2.82)	(3.40)
Household savings (1,000 BDT)	0.15	0.40	1.62	8.61
	(0.83)	(1.24)	(10.62)	(29.29)
Productive assets (1,000 BDT)	5.03	12.87	145.36	801.77
	(30.43)	(71.59)	(310.50)	(945.29)
Productive assets + loans (1,000 BDT)	5.64	14.77	150.22	812.83
	(30.92)	(72.47)	(312.51)	(947.65)
Observations	6,732	7,340	6,742	2,215

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, the middle class are ranked in the middle wealth bins, and the upper classes are those ranked in the top bin. The number of observations (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 main respondent in the household). The recall period is the year before the survey date. The BMI statistics trim observations with BMI above 50.

how differences in labor outcomes are correlated with differences in human and physical capital. Human capital is very low in these villages, and although there are differences across classes, even the richest women have only 3.7 years of education on average, and 49% of them are illiterate. Ownership of physical capital is what sets apart richer 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.[10] The last row of Table I shows that loans constitute a small fraction of total wealth in all wealth classes, consistent with imperfect credit markets.

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 I, Panel A which shows a kernel density estimate of the distribution of productive assets pooling all wealth classes. The distribution is bimodal, with one mass of households around 280 BDT (US$15) and one around 650,000 BDT (US$35,000), and hardly anyone in between.[11] Households in these village economies either own a lot of productive assets or have almost none. Differences in asset ownership relate directly to differences in consumption. For example, households at the low mode with assets of less than 650 BDT (US$35) have an average annual per capita expenditure of 11,760 BDT (US$637). For those at the high mode with assets between 370,000 BDT (US$20,000) and 1,107,600 BDT (US$60,000), this number is 20,454 BDT (US$1,108). Figure I, Panel B 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 3,000 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.

10. In detail, the list of productive assets comprises land, cows, goats, sheep, chickens, ducks, power pump, plough, tractor, mowing machine, unit for keeping livestock, shop premises, boat, fishnet, rickshaw/van, trees, and 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).

11. 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 use the simulation-based dip test by Hartigan and Hartigan (1985). The test rejects the null hypothesis of a unimodal distribution with $p < .01$.

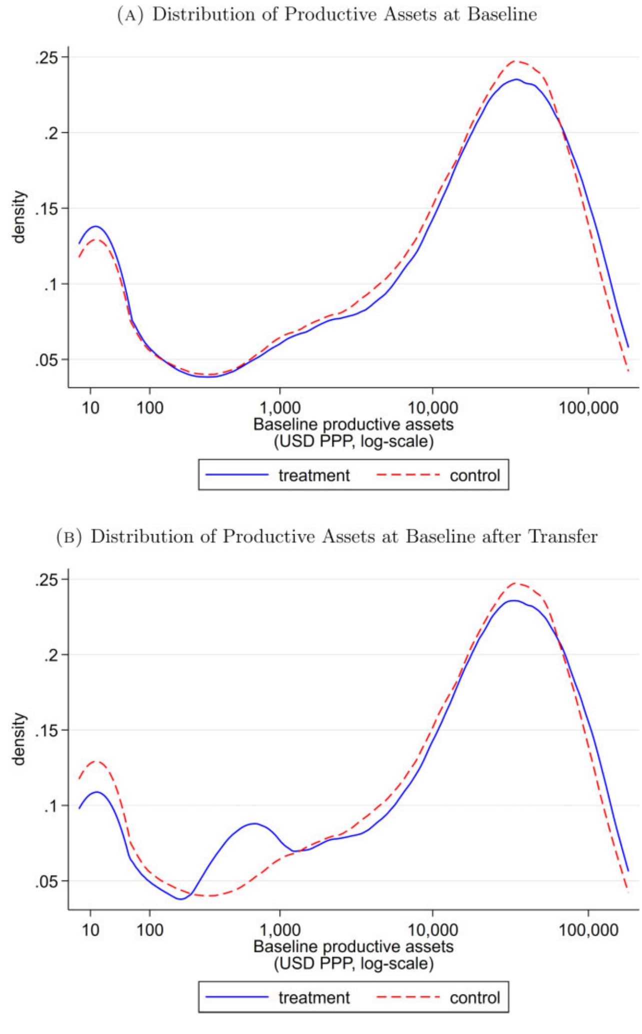


FIGURE I

Distribution of Productive Assets in Bangladeshi Villages: All Wealth Classes

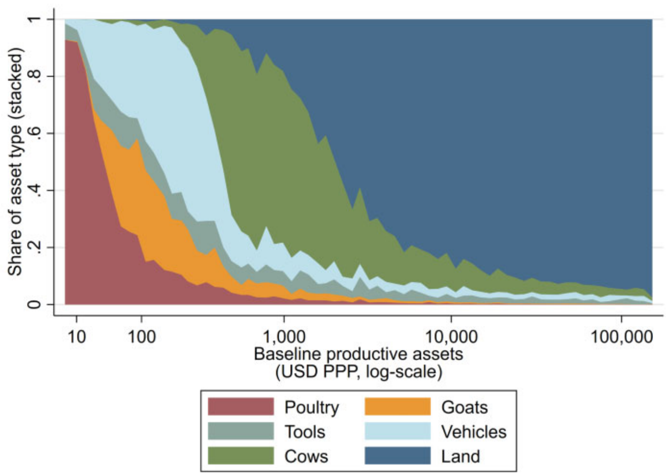
The graph shows kernel density estimates of the distribution of baseline productive assets in the full sample of 21,839 households across all wealth classes in treatment and control villages. Productive assets are measured as the natural log of the total value, in 1,000 Bangladeshi taka, of all livestock, 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 posttransfer distribution. Transfers for treatment households are imputed as the median value of a cow in the catchment area of a household's BRAC branch.

Richer households do not just own more assets, they also own more expensive assets. Figure II, Panel A shows that the program beneficiaries, 75% of whom own assets valued less than 1,000 BDT (US$54) at baseline, own mostly poultry and goats, while 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 II, Panel B shows how hours allocated to different occupations vary with the value of a household's productive assets. Casual employment in agriculture or domestic services prevails at low levels of productive assets, while self-employment in livestock rearing and land cultivation gradually takes 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 richer counterparts. It is key to note that this opportunity would not have arisen without the program. Online Appendix Figure B.1 plots, for control villages, the share of households that experience a positive shock of a certain size against the size of the shocks in log changes. 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 frequency is almost identical over the two-year and four-year horizon, indicating that shocks are mostly transitory.[12] Indeed, in control villages, only 3% of the households that are poor at baseline reach the asset stock of a median middle-class household within four years. The probability of catching up with

12. In the control group, log changes in assets between 2007 and 2009 are negatively correlated with changes between 2009 and 2011. An OLS regression of changes in the latter period on the first yields a coefficient of −0.44 (std. err. = 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.

(A) Asset Composition



(B) Occupation and Productive Assets

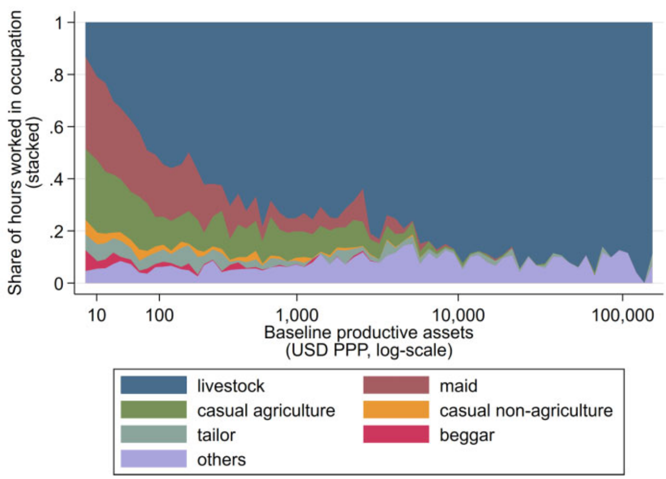


FIGURE II

Asset Composition and Occupation by Baseline Productive Assets

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 log 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."

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 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 the two views.

III. Framework and Method

III.A. Framework

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

As mentioned earlier, the notion of an individual poverty trap on which we focus 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 $Y_i = A_{i,v}f(K_i)$, where $f(\cdot)$ is the production function[13] and $A_{i,v}$ captures all 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 this special case, the transition equation can be expressed as:[14]

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

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 $K_i^* =$

13. 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 VI.

14. Note that we are also assuming 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. Given the low observed prevalence of loans in our setting (Table I), this seems to be a plausible assumption.

$\Phi_i(K_i^*)$. In the above example, this is a point where the amount of savings exactly offsets the amount of depreciation.

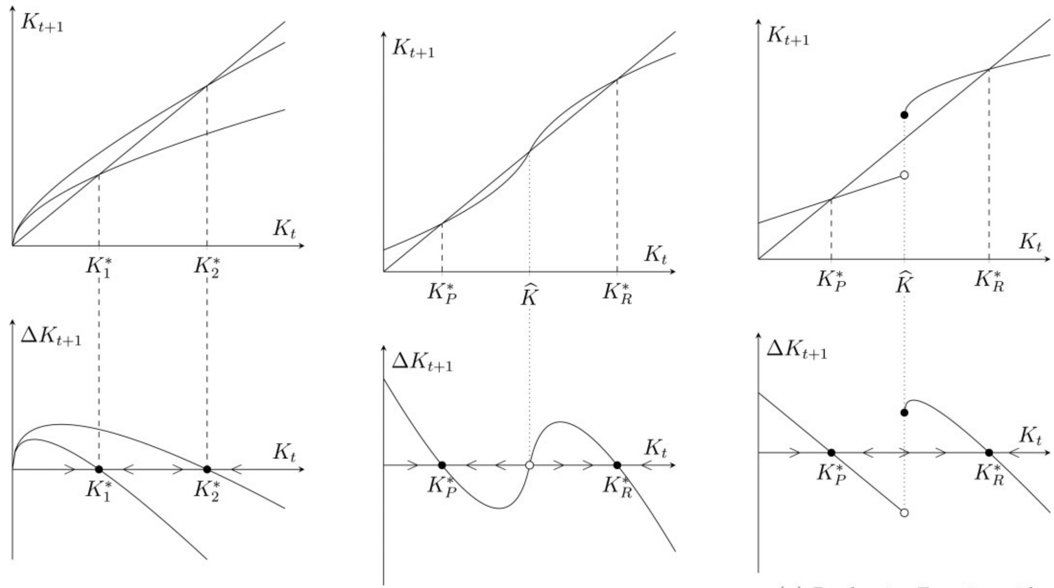
This framework allows us to precisely define a poverty trap. For illustration consider the transition equations depicted in the top panels of Figure III, Panels A and B. In each graph, the diagonal 45° line represents the set of points such that $K_{i,t+1} = K_{i,t}$. The transition equations in Figure III, Panel A are globally concave. They represent two households, each with a unique steady state, K_1^* and K_2^*. This transition equation could arise in the example under the assumption that s_i, $A_{i,v}$, and δ are constant in K, 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 $A_{i,v}$ 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 (K_1^*), and hence low income.

Another example of a transition equation is given in the top panel of Figure III, Panel B. Here, even among identical households, there are three steady states: two stable steady states, K_P^* and K_R^*, and an unstable steady state, $\widehat{K}$, 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 $\widehat{K}$ lose capital over time and converge toward the low steady state, K_P^*. Two households with identical productivity, preferences, and demographics will end up at different steady states and hence different income levels if only one of them had access to an initial endowment above $\widehat{K}$. The poor stay poor simply because they have no wealth—a poverty trap. 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), such a shape could, for example, arise because of increasing returns to scale in $f(\cdot)$ or if s_i is an increasing function of $K_{i,t}$.[15]

The S-shaped transition equation is not the only way there can be a poverty trap. Figure III, Panel C shows a transition equation with a discontinuity.[16] There are again two stable steady

15. For a review of different microfoundations underpinning these kinds of transition equations, see Ghatak (2015).

16. Such transition equations can have different microfoundations. They can result from indivisibility of labor supply even when the production function is



(A) Globally Concave Production Function

(B) S-shaped Production Function

(C) Production Function with Indivisibilities

FIGURE III

Three Transition Equations and Implied Asset Dynamics states, K_P^* and K_R^*, but now there is no steady state between them. Instead, households at and above the discontinuity point $\widehat{K}$ accumulate capital, whereas those just below $\widehat{K}$ 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 occupations, with a threshold capital level, $\widehat{K}$, required to access the more profitable occupation. While this is a plausible story in this setting, it is empirically challenging to distinguish Figure III, Panel C from Panel B, as we discuss below.

The bottom panels of Figure III, Panels A–C 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 transition equation. We 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.

This framework points to different interpretations of the baseline distribution of productive assets shown in Figure I, Panel A. 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 III, Panel A, then the final distribution of assets is independent of the initial allocation. The bimodal distribution of Figure I, Panel A therefore suggests that there are two groups of inherently different households. The poor who congregate at the low mode must by implication be unable, myopic, or lazy, while those at the high mode possess

well-behaved. For example, suppose individuals can either work as an 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 $f(k)$. Individuals will choose to be workers until the k they own exceeds a certain level $f(k) \geqslant w$, that is, their income is $y = \max\{f(k), w\}$. An alternative microfoundation can be derived from a standard cost function $C(y)$ consisting of a variable cost $c(y)$ component that depends on output y with standard properties, plus a fixed-cost component F. Interpreting variable cost as working capital k, let $y = f(k)$ be the production function, which is the inverse of the function $c(y)$. Given the presence of the fixed-cost component, let $K \equiv F + k$ be total capital. Then we have $y = 0$ for $K < F$ and $y = f(K - F)$ for $K \geqslant F$.

superior productivity or patience.[17] By contrast, if asset dynamics are better described by Figure III, Panels B or C, then a bimodal distribution of assets can arise simply from differences in starting positions. Though differences in household characteristics might still play a role—as discussed in Section IV.A—they are not necessary to explain long-run outcomes. Differential initial access to productive assets is sufficient to explain persistent differences in wealth and income. An S-shaped transition equation with an unstable poverty threshold will naturally generate a bimodal asset distribution, even among identical households.

III.B. Method

The foregoing discussion reveals two important insights. First, if the transition equation, $\Phi_i(K_{i,t})$ is globally concave, there cannot be multiple stable equilibria in the capital accumulation process, and hence no poverty trap as we have defined it. The first step of the empirical analysis therefore formally tests the concavity of $\Phi_i(K_{i,t})$ using the nonparametric shape test developed by Komarova and Hidalgo (2019).[18]

Second, we can speak of a poverty trap if and only if there is a threshold level of capital, which we call $\widehat{K}$, such that those below $\widehat{K}$ 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 $\widehat{K}$, this implies that for households with $K_{i,t} < \widehat{K}$ we expect $K_{i,t+1} < K_{i,t}$, whereas for households with $K_{i,t} > \widehat{K}$ we expect $K_{i,t+1} > K_{i,t}$. The next step of the analysis is to construct several estimates of the transition equation and identify a candidate threshold level, $\widehat{K}$.

17. The concave transition equation in Figure III, Panel A 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 toward K^*—and hence we would not expect to find a large mass of households there.

18. 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 P-splines. Imposing those restrictions yields a constrained sieve estimator taking a P-splines base. The constrained residuals, adjusted for heteroskedasticity, 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 nonparametric estimator. Critical values for these tests are obtained by bootstrap using the unconstrained residuals. See Komarova and Hidalgo (2019) for further details.

The sample we use to trace out the transition equation consists of the group of ultra-poor households in treatment villages that are followed for a period of 11 years after receiving the transfer. We estimate their transition between baseline, in 2007, and four years later, in 2011, which is the first time we observe the beneficiaries after they are free to sell the assets provided by BRAC. Households with initial posttransfer assets above 19,000 BDT (US$1,029) are dropped, since these were erroneously targeted as beneficiaries of the program. This leaves us with a total of 3,292 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), and $k_{i,3} = \ln K_{i,3}$ log productive assets at survey wave 3 four years after the transfer (in 2011).[19] 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 $\phi(k_{i,1}) = \mathbb{E}[k_{i,3} \mid k_{i,1}]$ 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, such large shocks are rare (Online Appendix Figure B.1).

Three features 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 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 I, Panel B. 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 we can estimate the shape of the

19. BRAC distributes the same asset bundles in all villages, hence their value depends on local prices. Since 91% of households chose a cow bundle, we value the transfer at the median cow price in the catchment area of each BRAC branch.

transition equation for a range of asset values that are typically observed (control) and compare this with estimates in ranges that are typically not observed (treatment). Third, by following beneficiaries over 11 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 small differences in initial assets can result in large, permanent differences in living standards as would be predicted by poverty trap theory. The first two features are explored in Section IV. The long-run analysis is in Section V.

When estimating the transition equation from $k_{i,1}$, we rely on nonexperimental variation in baseline assets that is potentially endogenous to the asset accumulation process. A causal interpretation of the transition equation would fail if, for example, $k_{i,1}$ was systematically correlated with asset shocks or with unobservable characteristics that shape the response to the program. We address such concerns in detail in Section IV.B after presenting our main results.

IV. Poverty Traps in the Short Run

We we can use the dynamics of capital accumulation following the asset shock to test between the two views of poverty. Figure IV, Panel A shows our main estimate of equation (2) in the treatment group, using a kernel-weighted local polynomial regression.[20] Alternative specifications are presented in Online Appendix Figure B.2. Panel A of Figure B.2 reports the fitted values of a third-order polynomial,[21] and Panel B reports the P-spline estimator.[22]

20. Local polynomial regression estimates the conditional expectation $\mathbb{E}[k_3 \mid k_1 = k]$ at each smoothing point k of a prespecified 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).

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

22. 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 preselected points (called the knots). P-splines are a particular type of splines. For more details, see Wasserman (2006).

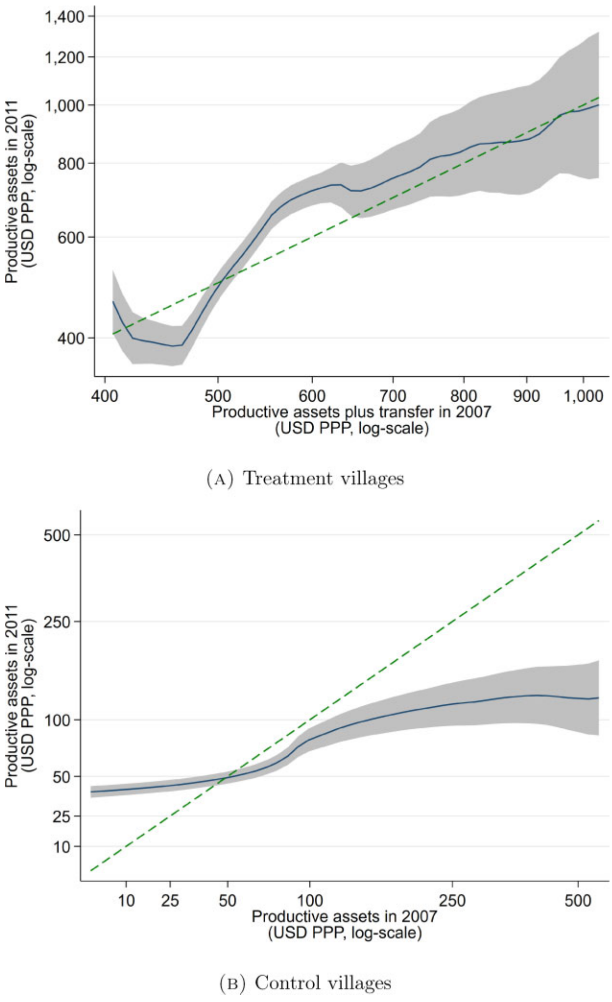


FIGURE IV

Local Polynomial Estimates of the Transition Equation

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 log of the total value, in 1,000 Bangladeshi taka, of all livestock, poultry, business assets, and land owned by the households. Posttransfer assets are imputed by adding to each household's baseline assets the median value of a cow in the catchment area of a household's BRAC branch. The solid line plots the smoothed values of a local polynomial regression with an Epanechnikov kernel of optimal bandwidth. The gray area depicts 95% confidence bands. The dashed line represents the 45° line at which assets in 2011 equal initial assets in 2007.

All three specifications show that the transition equation is S-shaped. The shape test (Komarova and Hidalgo, 2019) indeed rejects the null of global concavity with $p < .01$ and, in line with that, we reject the null that the cubic term of the polynomial shown in Panel A of Online Appendix Figure B.2 is zero. These results support the poverty traps view of the world—people who cannot get above the threshold end up in the low-asset holding mode in Figure I, Panel A and engage in irregular and unproductive wage labor. In contrast, those who are elevated above the threshold move toward the high-asset holding mode of Figure I, Panel A and participate in more-remunerative occupations that require capital.

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 III, Panel B. We find this threshold level of $\widehat{k}$ by numerically approximating the intersection of $\widehat{\phi}(\cdot)$ from the local polynomial regression with the 45° line (Figure IV, Panel A). Specifically, 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. This yields $\widehat{k} = 2.333$ in log BDT with a bootstrapped standard error of 0.014.[23] At this threshold, assets are worth 9,308.82 BDT (US$504). For comparison, the median value of a cow for the ultra-poor in treatment villages is around 9,000 BDT (US$488). With the parametric estimate, the threshold can be computed analytically, which yields $\widehat{k} = 2.34$ (bootstrapped standard error 0.284), or 9,379.14 BDT (US$508).[24]

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 find few households with this level of assets in equilibrium. This is indeed the case as the estimated threshold falls exactly in the low-density

23. Due to the bootstrap sampling variation, there are cases where the poverty threshold is not unique, that is, 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. Across all 1,000 bootstrapped samples, we always find at least one unstable crossing point.

24. 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 Online Appendix Figure B.2.

range of the baseline distribution of assets in the full population (Figure I, Panel A). 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. Although possible in theory, it requires a bimodal distribution of the savings rate or individual productivity, neither of which we observe in the data (see Online Appendix Figure B.3).

Having identified what appears to be a poverty threshold, we try to quantify its importance by comparing the asset accumulation trajectories above and below it. Denote by $\Delta k_i = k_{i,3} - k_{i,1}$ asset accumulation in the four years after the transfer over and above the value transferred by BRAC. The bottom panels of Figure III, Panels A–C illustrate the close relationship between Δk_i and the transition equation. If $\widehat{k}$ indeed has the characteristics of a poverty threshold, one would expect $\Delta k_i > 0$ 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 $\Delta k_i < 0$ for those whose baseline level of capital is not large enough ($k_{i,1} < \widehat{k}$). The following regression specification allows us to test this hypothesis:

(3)

$$\Delta k_i = \alpha + \beta_0 \mathbb{I}[k_{i,1} > \widehat{k}] + \beta_1 (k_{i,1} - \hat{k}) + \beta_2 \mathbb{I}[k_{i,1} > \widehat{k}] \times (k_{i,1} - \hat{k}) + \varepsilon_i .$$

This specification allows for a break in the asset dynamics at $\hat{k}$ and for different slopes of Δk_i in $k_{i,1}$ on each side of $\hat{k}$.

The results for the treatment group are reported in Table II, Panel A. Column (1) reports a simplified specification including only the indicator for above $\hat{k}$. On average, beneficiaries who stay below the threshold despite the transfer lose 14% of assets over the next four years while those who are pushed past the threshold grow their assets by 16%. Column (2) estimates the full equation (3). Allowing for a discontinuous slope in $k_{i,1}$ reveals a discontinuity in asset dynamics at $\hat{k}$ with those closest to the threshold experiencing the most extreme changes. One might be tempted to interpret this result of a discontinuous “jump” as evidence that the true transition equation behind the poverty trap is discontinuous as depicted in Figure III, Panel C and not like Figure III, Panel B. While the pattern of change is certainly consistent with the transition equation shown in Figure III, Panel C, this is not the case since, depending on the time horizon, it could also be

TABLE II

SHORT-TERM RESPONSES TO THE ASSET TRANSFER

	Dependent variable: log change of productive assets 2007–2011				
	Panel A		Panel B		
	Treatment (1)	Treatment (2)	Control (3)	Control (4)	Both (5)
Above $\hat{k}$	0.297***	0.475***	– 0.020	– 0.097	– 0.020
	(0.043)	(0.070)	(0.052)	(0.598)	(0.057)
Baseline assets		– 2.199***		– 0.463*	
		(0.698)		(0.266)	
Above $\hat{k}$ × baseline assets		1.969***		– 0.097	
		(0.729)		(0.269)	
Treatment					– 0.483***
					(0.059)
Above $\hat{k}$ × treatment					0.318***
					(0.070)
Constant	– 0.138***	– 0.282***	0.345***	– 0.680	0.345***
	(0.033)	(0.057)	(0.046)	(0.592)	(0.050)
N	3,292	3,292	2,450	2,450	5,742

Notes. * $p < .1$; ** $p < .05$; *** $p < .01$. Standard errors are 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 had they 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 $\hat{k}$ 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 posttransfer asset stock. In control, where no transfer was received, Above $\hat{k}$ indicates whether the household would be above 2.333 if it had received a transfer. Baseline assets always refers to the actual asset stock, that is, in control without the imputed transfer. Baseline assets are centered at 2.333, such that the coefficient on Above $\hat{k}$ reflects the log change at the threshold. Treatment was assigned at the village level.

generated by a continuous transition equation as in Figure III, Panel B.[25]

The average poverty threshold amounts to only slightly more than the typical value of a cow. Nevertheless, only about 66% of treatment households are placed above by the transfer. Those who remain below do so by a small margin. Most of them have zero assets at baseline. The difference between the median transfer value and the threshold is only about 300 BDT (US$16). This value is close to the median unit value of ploughs (250 BDT),

25. We observe households at discrete points in time. Households initially closer to $\hat{k}$ 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.

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.

One plausible interpretation consistent with these results is that there is a minimum scale of operation required for profitable and sustainable livestock production and that this scale is slightly higher than just the value of the animal. Carts and sheds are complementary inputs into the process of generating income from a cow. For example, a household who already owns a cart will be able to sell livestock products, such as milk and manure, at distant markets at better prices, thus generating higher income. Indeed, the composition of baseline assets around the threshold reveals that what sets households just above $\hat{k}$ apart from those below is their ownership of complementary assets like vehicles, which raise the returns to livestock rearing (Online Appendix Figure B.4). The additional income can be reinvested in expanding the business by raising calves or diversifying into different assets such as agricultural land (we provide evidence for the latter in Section V). It will also cushion households against shocks, for example, if animals fall sick.

Households below the threshold lack such complementary assets and in this context cannot obtain them through trade or loans. A particular problem is posed by the indivisibility of many complementary production inputs. Absent rental markets, it is impossible to rent a cart for one day of the week. Those without initial access to these inputs are therefore prevented from gradually saving their way out of poverty. Operating without complementary inputs, these households do not generate sufficient income to keep the cow well-fed and healthy, or they simply sell it because they deem the occupation unprofitable. As they lose livestock and other assets, they move further away from the minimum feasible scale of self-employed production and are again forced to take up low-wage, insecure, casual jobs that pay little relative to the price of productive assets. Thus, the combination of indivisible complementary inputs and the absence of rental or credit markets generates a poverty trap that locks the poorest in the worst occupations.

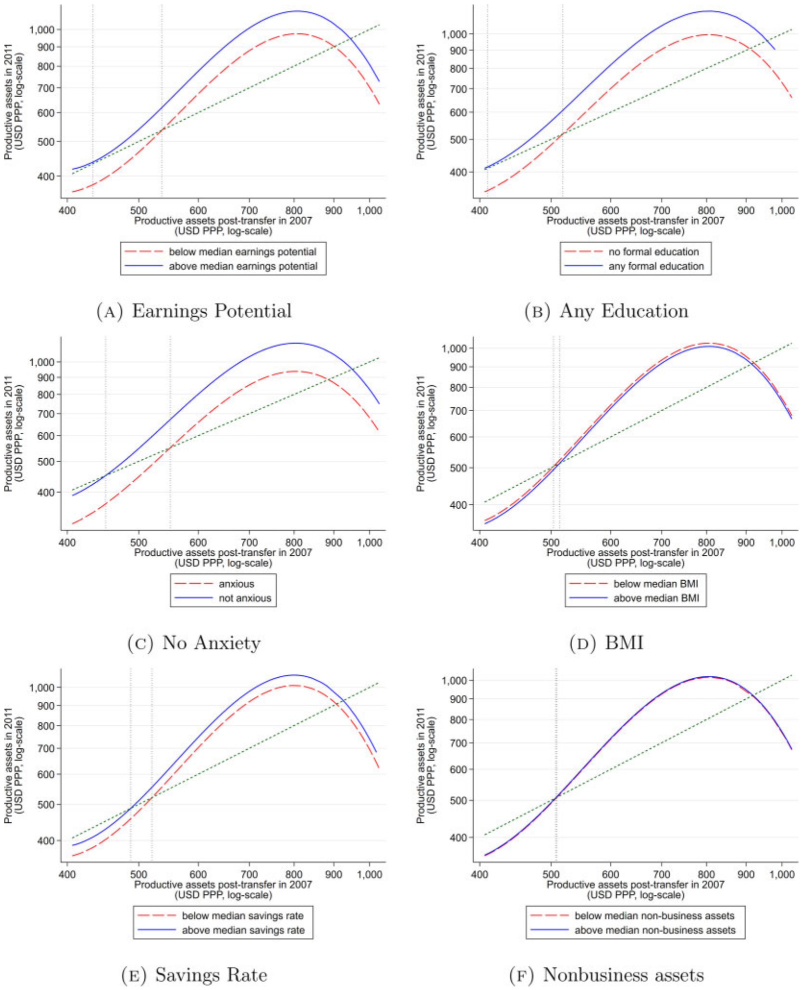
Although we believe this to be the most plausible mechanism underlying the poverty trap, we cannot rule out that alternative mechanisms also reinforce it. The difficulty in distinguishing these mechanisms is that those who escape poverty improve many aspects of their lives. For example, they consume more food (as will be seen in Section V). They might also be healthier or experience less stress. Without additional exogenous variation in these variables, we cannot know whether they are causes or consequences of poverty, or both.

IV.A. Heterogeneous Thresholds

The transition equation of Figure IV and the poverty threshold are averages of individual trajectories. As the poverty trap operates at the individual level, these averages conceal some interesting heterogeneity. Some households lose assets even if they are above $\hat{k}$ and vice versa. Consider equation (1) again, which, if true, can explain the sources of this heterogeneity. Above, we have provided evidence that the S-shape of the transition equation is generated by increasing returns to scale in the production function, $f(K_t)$. But equation (1) reminds us that asset accumulation also depends on $A_{i,v}$ and s_i. At a given level of current assets, future assets will be higher if the household produces more income (high $A_{i,v}$) or saves a larger share of it (high s_i). This implies an upward shift in the household's transition equation, such that it faces a lower poverty threshold. This heterogeneity also provides an additional source of identification, as described in the next section.

This prediction can be tested by allowing the poverty threshold to differ across subsamples with low and high $A_{i,v}$ or s_i. To maintain sufficient power, we estimate the nonlinear transition equation as a third-order polynomial, allowing the constant term to differ across the two groups. The estimated transition equations are depicted in Figure V. Panels A–D test for heterogeneity by productivity, $A_{i,v}$. Productivity can vary at the village or the individual level. A village-level proxy for livestock productivity, or earnings potential, is derived from observed livestock returns in the full population.[26] This measure captures any factors of a household's environment favorable to livestock production. Figure V, Panel A plots the transition equations of ultra-poor treatment households allowing for a vertical shift if the household is in a village with above-median earnings potential. The vertical dotted lines indicate the unstable steady state or, if there

26. Here, the sample includes all wealth classes. We regress the household's net livestock earnings on a constant and a second-order polynomial of the number of cows owned. Earnings potential is then defined as the average, at the village level, of the residuals from this regression.



(A) Earnings Potential

(B) Any Education

(C) No Anxiety

(D) BMI

(E) Savings Rate

(F) Nonbusiness assets

FIGURE V

Heterogeneity of Transition Equations

The sample is restricted to ultra-poor households with log baseline productive assets below 3 in treatment villages. The graphs show predicted values of third-order polynomial regressions of the productive assets in 2014 on productive assets in 2011. The sample is split into two groups by the variable indicated in each panel. Earnings potential is computed as the residual (averaged at the village level) from regressing livestock earnings on a constant and a second-order polynomial of the number of cows owned. Any education is an indicator equal to 1 if the respondent spent a positive number of years in formal schooling. Anxiety is an indicator equal to 1 if the respondent reports having mental anxiety that hampered daily activities. Nonbusiness assets comprise radio, television, electric fan, refrigerator, cellphone, bicycle, motorcycle, sewing machine, furniture, jewelry, and ceremonial saree.

is no intersection, the point closest to the 45° line. In line with the prediction, households who live in a village with higher average returns to cow rearing can generate more income at a given asset level. Their transition equation is shifted upward, resulting in a lower poverty threshold. Conversely, living in a low-productivity village increases the threshold relative to the population average.

Individual traits and human capital will also affect livestock productivity. Figure V, Panels B–D report proxies for education, mental health, and physical health, respectively. In Panel B the sample is split into respondents who report at least one year of formal education (13%) and those who do not, indicating that the former face a much lower poverty threshold. The same result appears when the sample is split by whether the respondent has experienced some mental anxiety that hampered daily activities (54%), with an above-average threshold for those who do (Panel C). Interestingly, there is no heterogeneity when the sample is split at the median body mass index (BMI), a proxy for physical health (Panel D).

Including measures of human capital as proxies for productivity warrants some additional discussion. In theory, human capital should not be treated as an immutable trait but as something people can accumulate, in the same way as physical, productive assets. We do not have comprehensive measures of how human capital changes over our study period, so we cannot test for a human capital poverty trap. The finding that these variables shift the poverty threshold in the expected direction is consistent with a complementarity between human and physical capital. Recall that while BRAC offers asset-specific training as part of the TUP program, the present experiment was not designed to separate the effect of the training from that of the asset transfer.[27] The above results also serve as a reminder that our poverty threshold must be interpreted as a posttraining threshold. In the absence of the training, which presumably increased livestock productivity, households might have faced an even higher threshold. Note that this does not affect our main conclusion that there is a poverty threshold, as long as the effect of the training is not heterogeneous with a jump at $\hat{k}$.[28]

27. See Karlan et al. (2018) for such an experiment.

28. Heterogeneous response to the training is discussed in Section IV.B.

Households' ability and willingness to save is measured by the ratio of cash savings over cash savings plus total household expenditure in 2009.[29] As expected, households that manage to save a larger fraction of their income require a lower asset stock to escape poverty (Panel E).[30]

Finally, we note that the stock of nonbusiness assets does not seem to be associated with the poverty threshold (Panel F). If it was, it might indicate that nonproductive wealth is used to buffer the productive asset stock against shocks.

IV.B. Identification Checks

Identification of the transition equation relies on initial differences in baseline capital, $k_{i,0}$. For a causal interpretation of our main results, we need to impose the assumption that the variation in $k_{i,0}$ at baseline is orthogonal to other determinants of posttransfer asset changes.

Initial differences in asset levels are small relative to the size of the transfer, since the program was targeted at the asset poor. But this only partly alleviates identification concerns. Broadly speaking, there are two reasons for concern: correlation between baseline assets and asset shocks, and correlation between baseline assets and program response. Let us consider them in turn.

First, causal identification fails if $k_{i,0}$ is systematically correlated with individual characteristics or specific shocks that affect a household's chances at asset accumulation. For example, households with more baseline assets might be better connected and, hence, more likely to receive windfall inheritances or gifts. They also may be able to take greater advantage of some economic opportunity that arises independently of the asset transfer program. Conversely, households with fewer baseline assets may

29. Measuring savings behavior in a theory-consistent way is complicated. Our survey records cash savings at two-year intervals. Earnings that are reinvested between survey rounds will not be recorded as savings but as an increase in assets. Conceptually, this reinvestment is exactly what s_i in equation (1) captures. Our empirical measure of the savings rate is therefore not equivalent to s_i but a proxy for the household's ability to save.

30. A potential concern with interpretation of this result is that savings may be endogenous to potential asset trajectories. Such concerns may be less pertinent to earnings potential and formal education, since the former is defined at the village level and the latter fixed throughout the study period. Overall, the consistency of results across the different variables in this analysis suggests model-consistent heterogeneity in thresholds.

suffer more from weather or health shocks (Burgess et al. 2017). Concerns of this nature can be addressed by comparing asset dynamics in the treatment group with the control group. Randomization ensures that in expectation, these two groups are identical in every respect, including unobservable determinants of capital accumulation correlated with $k_{i,0}$.

When the nonparametric estimation method for the transition equation is applied in control villages, the S-shaped pattern we found in the treatment group is absent (Figure IV, Panel B). The transition equation of control households 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. There is only one stable steady state, which falls close to the low mode in Figure I, Panel A. From this graph, it does not seem that the S-shape in the treatment group was generated by a systematic pattern of shocks.

This conclusion is corroborated when we look at asset accumulation. Table II, Panel B repeats the analysis of Panel A with households in control villages. Since these households do not receive a transfer, we define $I[k_{i,1} + \tilde{T} > \widehat{k}]$ to identify households who would be above the threshold had they received a hypothetical transfer, $\tilde{T}$, of the same size as their counterparts in treatment villages. Columns (3) and (4) indicate no change in asset dynamics at this placebo threshold. The same result holds in column (5), which combines the treatment and control sample in a difference-in-differences specification. In the absence of the transfer, households with high and low assets would not have been on divergent accumulation trajectories and are not differentially affected by shocks. It is only when some households are lifted above $\hat{k}$ by the transfer that they diverge on to a new accumulation trajectory.[31]

The second major concern for causal identification is that households with more baseline assets respond differently to some aspect of the TUP program. Phrased differently, the heterogeneity

31. Comparison with the control group also covers another problematic scenario. Suppose households with a concave production technology receive random productivity shocks prior to our study but have not fully 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 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 Δk_i also in the control group.

in outcomes that we attribute to initial differences in assets may instead be due to some other form of heterogeneous program response. For instance, baseline capital might be correlated with latent talent for livestock rearing, which is only revealed once the household receives a cow. Similarly, those who already own some livestock could benefit disproportionately more from the training component of the program. To illustrate, suppose that the training effect is larger for households with more baseline assets. This generates a scenario where some k_0 appears like an unstable steady state even if all individual transition equations are concave (Online Appendix Figure B.5). In this case, posttransfer asset dynamics are driven by individuals' transitions to a new steady state in a way that appears similar to—but is not—a poverty trap. Here, the control group is of no help because it did not receive the program. Absent experimental variation in k_0, our strategy must be to provide additional evidence against the most plausible alternative explanations.

To start, note that an alternative explanation based on heterogeneous program responses cannot easily explain the shape of the transition equation. Online Appendix Figure B.5 makes clear that to explain the S-shaped transition equation, the relationship between baseline assets and program response must also follow an S-shape. Also recall the pattern discovered in Table II, column (4): those below $\hat{k}$ lose more assets the more they initially own. Asset accumulation then jumps and becomes positive at $\hat{k}$. If this pattern should be explained, for example, by differential treatment effects of the training, it must be that below $\hat{k}$ richer households benefit less from the training. The training effect must then increase discontinuously at $\hat{k}$. While possible, it seems implausible to posit such a pattern in the relationship between baseline assets and training response or latent talent for livestock rearing.[32]

Next we consider the particular concern that it is human capital which is underlying heterogeneous responses to the program, that is, that households with more human capital benefit

32. The discontinuity in Δk_i at $\hat{k}$ is robust to more flexible specifications than the one reported in Table II. Online Appendix Figure B.6 estimates the relationship between asset accumulation and baseline assets nonparametrically, allowing for a break at $\hat{k}$, and yields the same conclusion. We estimated the relationship between baseline assets and a large set of observable baseline characteristics and do not find a similar discontinuity at $\hat{k}$ for any of them. The only exception is the share of vehicles in total assets, which increases discontinuously at $\hat{k}$ (See Online Appendix Figure B.4 for examples).

more from the program (training or transfer) but are also likely to own more productive assets at baseline. In a setting where rates of formal education and literacy are extremely low (Table I), it is not straightforward to construct a single, reliable measure of human capital. Our approach is, instead, to control for a host of observables in the hope that they proxy for relevant dimensions of human capital. In particular, we compute residualized productive assets as

$$\tilde{k}_{i,t} = k_{i,t} - \tilde{\alpha} - \tilde{\beta}' H_{i,t}$$

for the years $t = 2007$ and $t = 2011$, where $\tilde{\alpha}$ and $\tilde{\beta}$ are coefficients from an OLS regression of assets on a set of control variables, $H_{i,t}$.[33] The relationship between these residuals displays the same S-shape as we saw in the raw data (Online Appendix Figure B.7). Even after all observable variation related to human capital has been muted, asset dynamics show a pattern indicative of a poverty trap.

The final approach to alleviate concerns regarding endogeneity of baseline assets is to control for k_0 directly by including k_0 fixed effects. It is impossible to do this when estimating the transition equation or the asset accumulation regression (equation (3)), since it would leave no variation to identify the parameters of interest. But evidence from Section IV.A suggests that different subpopulations face different poverty thresholds depending on their earnings potential, individual ability, and savings rate. These differences in individual poverty thresholds can be exploited for an identification check where k_0 is held constant. We use a variant of equation (3):

$$\Delta k_i = \alpha + \beta \mathbb{I}[k_{i,1} > \hat{k}_i] + \delta_{k_0} + \varepsilon_i, \tag{4}$$

where now the indicator $\mathbb{I}[k_{i,1} > \hat{k}_i]$ is equal to 1 if household i is above its individual poverty threshold, $\hat{k}_i$. The individual threshold is computed for different subpopulations as described above and as shown by the vertical lines in Figure V. Splitting the

33. Human capital controls are all defined at baseline and include age, age squared, BMI, a health index constructed from the number of physical activities the respondent struggles to perform, a dummy for each year of formal education completed, literacy, numeracy, an indicator for whether the respondent reports being happy or very happy, and an indicator for whether the respondent reports having mental anxiety that hampered daily activities.

sample into two, for example by median earnings potential, we get a high and a low poverty threshold. Between these, there lies a range where households with identical baseline capital k_0 can be either above or below the poverty threshold relevant to them, depending on their earnings potential. This allows us to control for a baseline asset fixed effect, δ_{k_0}. Of course, the exercise is only meaningful for variables that shift the poverty threshold. Table III reports estimates of equation (4) for sample splits by earnings potential, education, anxiety, and the savings rate, corresponding to Figure V, Panels A–C and E, respectively. For each variable, the first column reports estimates without k_0 fixed effects (columns (1), (3), (5), and (7)). These columns reproduce the main result of Table II, Panel A: households below the individual threshold lose between 10% and 18% of assets, and those above accumulate an additional 14% to 18%. When k_0 fixed effects are included in columns (2), (4), (6), and (8), the coefficients change only marginally and, if anything, become more pronounced. This is reassuring: if baseline capital was systematically correlated with other factors driving posttransfer asset accumulation, controlling for it should affect these coefficients. Further, the sample splits induce variation in poverty thresholds along quite different dimensions, yet yield surprisingly similar results. If one was particularly concerned, for example, about endogeneity of the savings rate, one should be comforted by the identical result for earnings potential. This conclusion holds in the last two columns of Table III, where the sample is split into 16 groups covering all possible combinations of the previous four variables and an individual poverty threshold is computed for each. Finally, we can reassure ourselves that it is indeed the relevant threshold that binds. Among those who should face the high threshold (those with low earnings potential and savings rate, who report having anxiety and no education), we find no effect of being above the low threshold (Online Appendix Table C.1).

This set of findings cannot be explained in the scenario of heterogeneous program response that was constructed to motivate this discussion (Online Appendix Figure B.5). If an unobserved relationship between baseline assets and training effects, or latent talent for livestock rearing, was generating the results on asset accumulation, these results should disappear once we control for baseline assets.

TABLE III

EXPLOITING INDIVIDUAL THRESHOLDS IN ESTIMATING SHORT-TERM RESPONSES TO THE ASSET TRANSFER

	Earnings potential		Savings rate		No anxiety		Any education		Combined	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Above $\hat{k}_i$	0.319***	0.325***	0.345***	0.381***	0.245***	0.238***	0.302***	0.336***	0.264***	0.284***
	(6.75)	(6.31)	(7.66)	(7.76)	(5.57)	(4.84)	(6.56)	(6.57)	(6.14)	(6.01)
Constant	−0.176***	−0.180***	−0.169***	−0.191***	−0.106**	−0.102**	−0.152***	−0.174***	−0.107**	−0.119***
	(−4.34)	(−4.19)	(−4.45)	(−4.79)	(−2.99)	(−2.71)	(−3.90)	(−4.19)	(−3.16)	(−3.32)
Baseline k FE	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
N	3,292	3,292	3,292	3,292	3,292	3,292	3,292	3,292	3,292	3,292

Notes. * $p < .1$; ** $p < .05$; *** $p < .01$. Robust standard errors are 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 $\hat{k}_i$ equals 1 if the baseline asset stock plus the imputed transfer is larger than the individual-specific threshold value based on the variable indicated at the top of each column (see Figure V). Earnings potential is computed 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. Any education is an indicator equal to 1 if the respondent spent a positive number of years in formal schooling. Anxiety is an indicator equal to 1 if the respondent reports having mental anxiety that hampered daily activities. For the last two columns (Combined) the sample is split into 16 ($= 2^4$) groups covering all possible combinations of the previous four variables. An individual threshold is computed for each of the 16 groups and used in the regression.

V. Poverty Traps in the Long Run

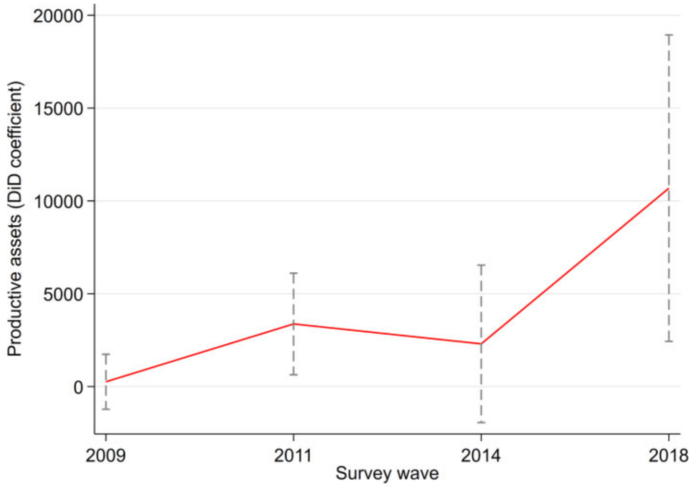
A key implication of a poverty trap is that households experience different long-run trajectories depending on their initial circumstances. In this section, we address the question of whether the threshold we identified from short-run (four-year) asset dynamics generates persistent and sizable differences in outcomes in the long run. Our data allow us to explore these dynamics over the course of 11 years from 2007 to 2018. We start by tracking several outcomes for households above and below the poverty threshold and show persistent differences in productive assets, occupations, and poverty. Then we provide evidence that due to the long time horizon, life cycle savings effects substantially affect asset accumulation, and show that once these effects are accounted for the divergence of assets, occupations, and poverty becomes more pronounced.

Figure VI plots estimates of the following panel specification:

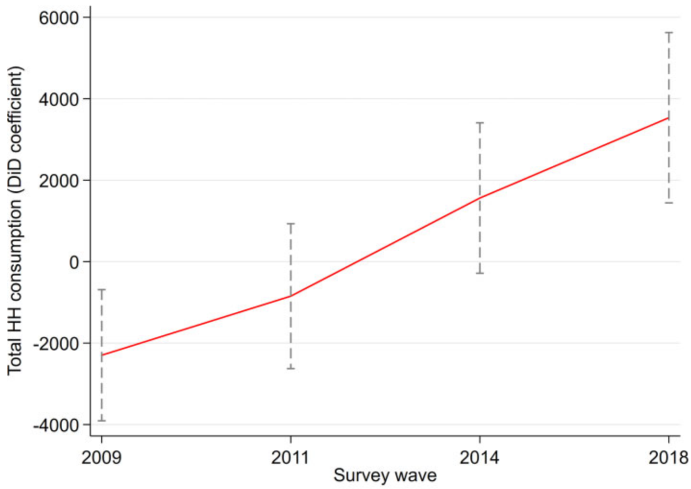
$$Y_{i,t} = \beta_0 I(k_{i,1} > \widehat{k}) + \sum_t \beta_{1,t} I(k_{i,1} > \widehat{k}) S_t + \sum_t \beta_2 S_t + \eta_{i,t}, \quad (5)$$

where S_t are indicators for the 2009, 2011, 2014, and 2018 survey waves and all other variables are as defined previously. The outcomes of interest, $Y_{i,t}$, are productive assets in levels and total annual household consumption. We control for subdistrict fixed effects. The coefficients of interest are the $\beta_{1,t}$. They measure the additional difference between beneficiaries above and below the threshold at date t relative to this difference just after the transfer. Figure VI plots these coefficients for assets and consumption. Panel A shows that the initially small 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 (US$542) more in productive assets compared to the difference at baseline, indicating substantial 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 IV contains the estimated $\beta_{1,t}$ coefficients of equation (5). In addition to assets and consumption, it reports



(A) Productive Assets



(B) Total Consumption

FIGURE VI

Difference-in-Differences Estimates of Long-Run Dynamics in Productive Assets and Consumption

The figure plots the coefficients $\hat{\beta}_{i,t}$ from estimation equation (5). The sample consists of ultra-poor households with log baseline productive assets below 3 in treatment villages. The dashed bars denote 90% confidence intervals.

TABLE IV

DIFFERENCE-IN-DIFFERENCES ESTIMATES OF LONG-RUN DYNAMICS

	Productive assets (1)	Cows (2)	Land (3)	Cons. (4)	Net earnings (5)	Net earnings self-empl. (6)	Total hours (7)	Hours self-empl. (8)
Year 2 × above $\hat{k}$	260	514	1,018	−2,298**	−1,878***	−803***	−211***	−110***
	(897)	(365)	(770)	(976)	(329)	(253)	(39)	(15)
Year 4 × above $\hat{k}$	3,374**	3,346***	1,178	−847	−443	−242	84**	99***
	(1,658)	(452)	(1,531)	(1,078)	(346)	(265)	(41)	(18)
Year 7 × above $\hat{k}$	2,302	2,522***	821	1,561	2,151***	1,817***	21	−15
	(2,570)	(408)	(2,470)	(1,120)	(426)	(353)	(42)	(19)
Year 11 × above $\hat{k}$	10,686**	2,239***	9,758**	3,534***	1,462**	864**	87**	74***
	(5,003)	(374)	(4,878)	(1,267)	(703)	(424)	(41)	(17)
N	15,713	15,713	15,713	14,988	15,713	15,713	15,713	15,713
p-value year 2 vs. 4	.092	< .01	.924	.232	< .01	.097	< .01	< .01
p-value year 2 vs. 7	.448	< .01	.939	< .01	< .01	< .01	< .01	< .01
p-value year 2 vs. 11	.040	< .01	.076	< .01	< .01	< .01	< .01	< .01

Notes. * $p < .1$; ** $p < .05$; *** $p < .01$. Sample: ultra-poor households in treatment villages with log baseline productive assets below 3. Coefficients report the difference in outcomes between those above versus below the poverty threshold of 9,379 BDT (US$508), 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 subdistrict fixed effects. Robust standard errors are in parentheses.

results on 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 in asset divergence is driven by additional accumulation of cows and (particularly in 2018) land. The diversification toward land, which was not offered in the program by BRAC, is remarkable. Land is the asset that sets apart rich from poor in this context (Figure II, Panel A). 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.

Reviewing column (4), we find it interesting 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.[34] Two things can be learned from this pattern. First, assessing the long run is crucial when drawing welfare conclusions. Had we only considered effects up to four years after the transfer, we would have falsely concluded that households trapped by their low initial asset endowment appeared better off in terms of consumption. Similarly, the results caution 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 the poorest engage in forward-looking behavior. Those most likely to escape the poverty trap are able and willing to forgo current consumption to make investments that 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 reinvest more of their income directly into their asset stock—an investment that is rewarded by higher earnings only seven years later.[35] 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,

34. Online Appendix Table C.2 shows that this result holds for alternative measures of welfare, such as per capita expenditure, food consumption, and poverty headcount.

35. 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.

we 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, they were also able to work more and shift into more productive labor market activities.[36]

Our interpretation of the results in Table IV is that an occupational shift induced by the asset transfer was at the core of breaking the poverty trap. All changes in earnings and hours worked are driven by self-employment—a pattern that is intuitive 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 completes the narrative of the previous section. Once the constraint on assets is released, the poor are able to change occupation. It was not their ineptness that previously excluded them from taking up a better occupation but their inability to make a large enough initial investment. Households with initial access to sufficient complementary assets can, however, permanently take up a more profitable and reliable occupation.

Over the 11-year study period, the median age of beneficiaries increases from 35 to 46. Over such a time horizon, life cycle savings behavior might affect households' asset stocks. As people get older, they work less with productive assets and instead use savings to maintain consumption. When plotting the cross section of assets by age in the last four survey rounds for other poor, middle-class, and rich households in control villages, we indeed see an inverse U-shaped pattern that peaks at around 48 (Online Appendix Figure B.8). As respondents age, they decumulate assets irrespective of poverty trap dynamics. For those above the poverty threshold, the two effects—convergence to a

36. The results of Table IV 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 (Online Appendix Table C.2, column (1)); controlling for individual fixed effects (Online Appendix Table C.3); restricting the sample to a balanced panel so that only households for which we have data in all survey waves are included (Online Appendix Table C.4); and restricting the sample to households within a small interval of baseline assets ($k_{i,1} \in [2.233, 2.433]$) around $\hat{k}$—a specification akin to a regression discontinuity design (Online Appendix Table C.5).

high steady state of productive assets and aging—will counteract each other.

To account for these life cycle effects, in the Online Appendix, we split the sample at the median baseline age of 35 and report results separately for those below ("young") and above ("old"). If we restrict our attention to younger beneficiaries where life cycle effects are muted, 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 (Online Appendix Figure B.9). The comparison of old and young beneficiaries reveals that the young accumulate assets faster and until the end of the study period. In contrast, among the old, the asset accumulation effect is muted by the countervailing effect of aging. Nevertheless, those who are initially above $\hat{k}$ fare better in the long run in all age groups.

In Online Appendix Table C.6, we report the different trajectories of asset types, consumption, earnings, and hours worked for households above and below the threshold, accounting for the life cycle. This reveals that it is the young who accumulate land, which allows them to generate more income from self-employed activities. However, consumption evolves similarly. This implies that old households save less or sell assets as they approach the end of their (working) life, which allows them to maintain a relatively higher living standard. Finally, we find that young beneficiaries postpone increasing consumption for longer than the old. This is consistent with a view of poor households that, as permitted by their circumstances, engage in forward-looking behavior and plan strenuous escapes from poverty over multiple years.

VI. Quantifying Misallocation

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 as 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 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 people 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 we also observe them 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.

VI.A. 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.

Since $\bar{k}$ is a constant, this is effectively a one-input production function that depends on $l + h'$. We 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, as 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 nonconvexity, we 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 paid less than what the farmer earns by supplying wage labor herself. There is an exogenous demand constraint in the labor market, $h \leqslant \overline{H}$ where $0 < \overline{H} < \overline{R}$, and on the maximum hours of labor a farmer can hire in, $h' \leqslant \overline{N}$.

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:

$$\max_{l\geqslant 0, h\geqslant 0, h'\geqslant 0} Af(\bar{k})g(l+h') + wh - w'h' - \frac{1}{2}(\sqrt{\psi_l}l + \sqrt{\psi_h}h)^2 \tag{6}$$

subject to

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

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

$$h + l \leqslant \overline{R}. \tag{R}$$

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 Online Appendix A.

VI.B. 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-two data by assuming that in these years, individuals choose the hours they devote to each occupation[37] 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

$$f(k_i)g(l_i + h'_i) = \left(ak_i^2 + bk_i\right)(l_i + h'_i)^{\beta}.$$

This 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 III.A. The parameters a, b, and β of this function are estimated by nonlinear 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 a 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 a year.

The optimization problem described in Section VI.A 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 exogenous hours constraint binds. For the majority of beneficiaries, these can be combined with data on capital and occupational choice at baseline and year 2 to calibrate the values of A, ψ_h, and ψ_l that are consistent with the observed hours worked and hired in being chosen optimally. In particular, 17% of ultra-poor individuals mix occupations and hire in labor at year two (case 1 in Online Appendix A), such that the three year-2 first-order conditions can be solved for the three parameters of interest. For those individuals in other cases at year 2, there are fewer first-order conditions than parameters. However, for a further 25% of individuals that 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, the baseline and year-2 first-order conditions can be combined to yield three equations that can be solved for the three parameters. Parameters can be calibrated for a further 23% by assigning ψ_h to

37. These are self-reported and checked for consistency.

be the maximum observed value for those individuals who do not work at baseline.[38]

This method yields estimated individual-level parameters for 65% 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 households for whom we can and cannot conduct estimation reveals a high degree of overlap, with the latter slightly rightward shifted. This suggests that those for whom we cannot conduct estimation are more likely to engage in livestock rearing and therefore are less likely to be constrained in their choice of occupation (though not necessarily hours worked in each occupation).

Online Appendix Figure B.10 plots the calibrated values of A, ψ_h, and ψ_l against posttransfer 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, providing 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 median disutility of wage labor hours ψ_h is higher than the median disutility of livestock rearing hours ψ_l (Online Appendix Figure B.11). The distribution of the calibrated A parameters (Online Appendix Figure B.3c) is unimodal.

VI.C. Model Estimation

With estimated values for each individual's parameters in hand, we can use the model structure to solve for each individual's optimal hours in wage labor and livestock rearing, optimal hours of hired-in labor, and implied payoff at any level of capital. In a first simulation exercise, we calculate these at each individual's year-4, -7, and -11 capital level to assess how well the model matches nontargeted moments in the data. We then estimate the value of misallocation at baseline by comparing each individual's optimal occupational choice and payoff at the steady-state capital

38. We abstract from the constraints on labor demand and hired-in labor in the parameter calibration because the choice of hours across occupations will be uninformative about underlying parameters where these constraints bind.

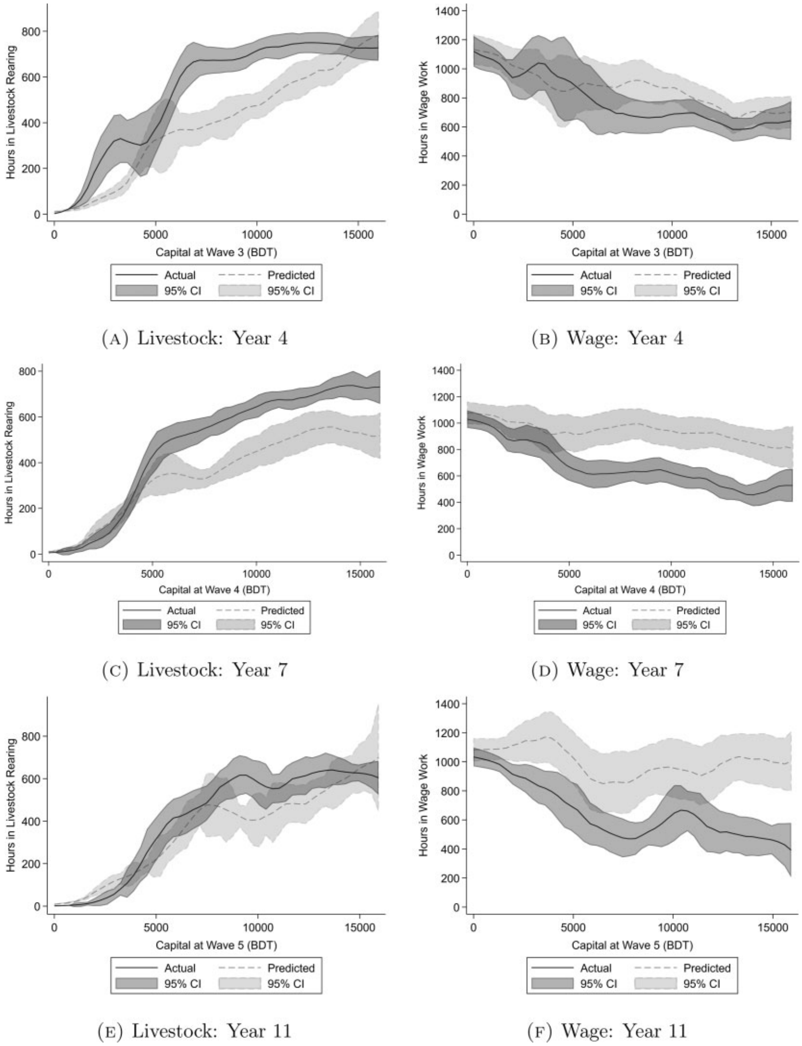
level of the middle and upper classes (i.e., in the absence of capital constraints) to those observed at their baseline capital level.

1. *Testing Model Fit Using Year-4,-7, and -11 Data.* We test the predictive power of the model by simulating each individual's optimal hours in each occupation at their year-4, -7, and -11 capital levels and comparing these with the observed choice of hours in each year. Figure VII shows local polynomial predictions of model-predicted and actual hours in livestock rearing and wage labor, as a function of capital in the relevant year. There is a close fit between the model-predicted and observed hours in livestock rearing in all three years, and a reasonable fit for wage labor hours in all years, although this appears to be strongest in year 4 while in years 7 and 11 the model predicts slightly higher wage labor hours than are observed at most capital levels. This pattern may be consistent with unmodeled effects, such as individuals reducing the hours they allocate to more physically demanding wage labor occupations as they age.

2. *Quantifying Misallocation.* 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 with 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 (US$2,367).[39] This is higher than the baseline capital level of the vast majority of ultra-poor individuals, so in extrapolating 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 ψ_h and ψ_l by the ratio

39. 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 Online Appendix Figure B.12.



(A) Livestock: Year 4

(B) Wage: Year 4

(C) Livestock: Year 7

(D) Wage: Year 7

(E) Livestock: Year 11

(F) Wage: Year 11

FIGURE VII

Hours Worked in Livestock and Wage Labor: Actual versus Model Predictions

The solid, dark gray 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 65% 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 dashed, light gray 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 levels. Ninety-five percent asymptotic confidence intervals for the local polynomial regressions are shown.

of the median ψ_l for richer classes versus the median ψ_l for the ultra-poor.[40]

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 Online Appendix A. We use these, together with the calibrated parameters for each individual, 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 VIII. At their baseline capital level, only 1% of working ultra-poor households specialize in livestock rearing, with 98% specializing in wage labor and 1% mixing occupations. As such, the model suggests that 96% of individuals for whom we can conduct the structural estimation have nonzero 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 US$16 million.[41] The estimated total value of transfers required to bring all of these individuals to the average threshold capital level identified in Section IV—from which they are able to escape the poverty trap—is an order of magnitude smaller at US$1 million. This comparison may be influenced by general-equilibrium effects of the intervention, which we investigate in the next section.

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

41. 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.

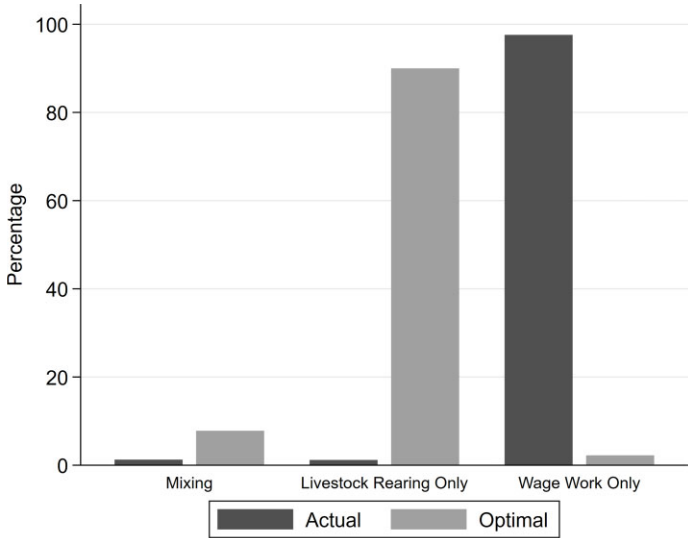


FIGURE VIII

Occupational Choice: Actual versus Model Prediction in the Absence of Capital Constraints

The light gray 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; US$2,367), for the 65% 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 dark gray bars show the observed baseline distribution across occupations of those of these individuals who report positive labor hours at baseline.

VI.D. 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 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 which would hurt all those engaged in livestock rearing including the ultra-poor themselves. Spillovers need not be negative, however; Advani (2019) shows that in villages where many beneficiaries were treated, other households also increased their asset holdings, consistent with a model of risk sharing. Here we focus on the potentially negative effect by resimulating where livestock income $Af(k)g(l + h')$ is reduced by a fixed factor. We find that even in a case where this is reduced by 50%, 69% of ultra-poor households should specialize in livestock rearing, though the estimated value of misallocation falls by 57%. 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.

We simulate the effect of increasing the wage available for wage labor activities, given that dramatic occupational change away from casual wage labor may result in general equilibrium effects on wages in these occupations. Indeed, Bandiera et al. (2017) find that agricultural and maid wages paid to ineligible women in treatment villages are 9% and 11% higher, respectively, than in control villages after four years. 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%. The estimated value of misallocation falls by 8% in this case, suggesting that even with significant general-equilibrium wage effects, the value of misallocation still exceeds the total value of transfers required to bring all individuals to the average threshold capital level by a considerable margin.

In a second set of counterfactual simulations, we consider the effects of alternative policy interventions that might be considered to tackle occupational inequality in this setting. The previous simulation of increasing the wage available for wage labor activities is one such policy. 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%.[42] While the share optimally specializing in livestock

42. In the simulations that increase the wage rate or reduce the disutility of wage labor hours, estimated misallocation falls much less than in the simulation

rearing in these 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.

VII. Implications for Policy

Our results point to the existence of a poverty threshold such that households with a starting level of productive assets below that threshold are trapped in poverty and households who are able to get past the threshold accumulate capital and approach the asset level of the richer classes. This 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 solid line in Figure IX 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 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 IX shows the size of the actual transfer, which we can compare to alternative transfer schemes such as income support (NREGA) and microfinance. Assuming

reducing livestock income (less than 10% in both cases) since these influence marginal individuals in the left tail of the misallocation distribution rather than shifting the entire misallocation distribution to the left.

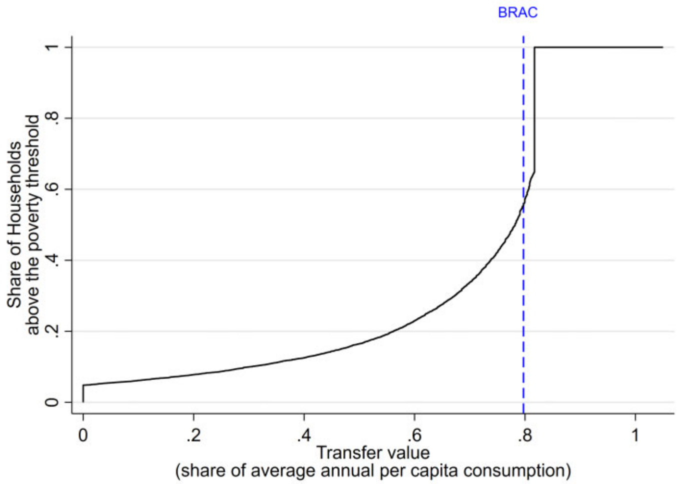


FIGURE IX

Share of Ultra-Poor Households above the Poverty Threshold as a Function of the Transfer Size

The sample includes ultra-poor households in treatment villages at baseline. The solid line shows the empirical cumulative density of the difference between the poverty threshold of $\hat{k} = 2.333$ and households' productive assets at baseline plus a shock randomly drawn from control households' four-year asset changes. The vertical dashed line shows the actual transfer, which is computed as the median of the imputed transfers we use in the main analysis.

the household works each of the 100 days they are entitled to, the value of NREGA is 0.13 of annual per capita expenditure.[43] BRAC typically offers entry microloans between US$100 and US$200, which correspond to 0.18 and 0.3 of average annual per capita expenditure. Thus, two of the main programs designed to tackle poverty are too small-scale to make a long-term difference for the majority: our simulation suggests that they would allow fewer than 20% of households to escape poverty. This is consistent with evidence suggesting a negligible average effect 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).[44]

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

44. These authors also use a structural model that includes a poverty trap. They do find substantial average effects on businesses at the six-year horizon, but

We turn to our structural model 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 Online Appendix Figure B.13a. 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, US$5.7 million, remains much lower than the total value of estimated misallocation (US$16 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 toward the high steady state along the concave part of the transition equation. The results 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 (Online Appendix Figure B.13b).

VIII. Conclusions

Poverty traps are one of the most fundamental concepts in development economics. The contribution of this article 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 their circumstances. This has three implications for how we think about development policy.

they show that these results are exclusively driven by the 30% of households with a preexisting business.

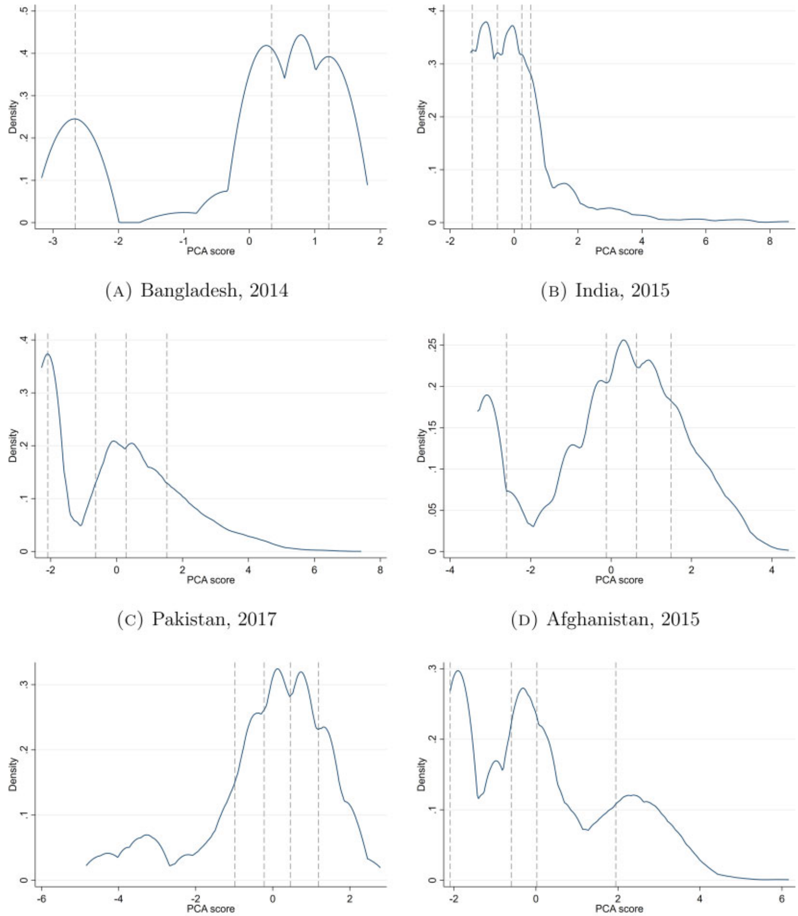
The first is that big pushes that enable occupational change will be needed to address the global poverty problem. Small pushes will work to elevate consumption but will not free people from the poverty trap. The magnitude of the transfer needed to achieve occupational change may be much larger than is typical with current interventions, though importantly it can be time limited. The fiscal cost of permanently getting people out of poverty through a large, time-limited transfer might therefore 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 because 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 among 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 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 because it implies that poverty traps are preventing people from making full use of their abilities and indeed, the mass squandering of people's abilities is the key tragedy of poverty.

Future research should probe the generalizability of these results to other contexts and interventions. At a first pass, bimodal asset distributions, which are symptomatic of poverty traps, can be found in several South Asian countries with similar agrarian systems; large numbers of irregular, casual laborers; and high levels of rural poverty and asset inequality where the type of asset transfer program studied here may be relevant.[45] Figure X plots kernel density estimates of an index of productive assets for rural households from nationally representative IPUMS and

45. See Bardhan (1984), Dreze and Sen (1990), and Kaur (2019).



(A) Bangladesh, 2014

(B) India, 2015

(C) Pakistan, 2017

(D) Afghanistan, 2015

(E) Nepal, 2016

(F) Myanmar, 2015

FIGURE X

Distribution of Agricultural Assets for Rural Households across South Asia

The graphs show kernel density plots of wealth scores for six South Asian countries, based on microdata from harmonized IPUMS and DHS household surveys. The wealth scores are constructed by performing a principal component analysis (PCA) at the household level using a full list of agricultural assets. The list of specific assets varies across countries. The first component of the PCA is used to compute the wealth index. All kernel density estimates use an Epanechnikov kernel with a bandwidth of 0.3. The vertical dashed lines denote quintiles of the wealth distribution.

DHS surveys. Strikingly, bimodal distributions are present in five of these six countries.

Regarding generalizability to other interventions, it is clear that those that shift people into occupations which leverage individuals' talent may be effective in helping them to escape poverty traps. One area where there has been a lot of experimentation in this regard is in varying the design of the graduation program. For example, Karlan et al. (2018) look at unbundling the training from the asset transfer component. There might, however, be other indivisible investments that remain too large for the poor to afford and that exclude them from more profitable jobs. These need not be physical capital but can be large investments in human capital, such as training, a college degree, or the cost of migration. Similarly, investments in infrastructure or other policies that 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 effects 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 poverty is the central focus of development economics and policy. This article 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 consumption-focused policies, which have traditionally characterized welfare support both in developed and developing countries. It is only by expanding opportunities for the poor that we will be

46. The fact that we observe these effects 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.

able to tap into the productive capacity of a large cross-section of humanity.

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Supplementary Material

An Online Appendix for this article can be found at *The Quarterly Journal of Economics* online.

Data Availability

Data and code replicating the tables and figures in this article can be found in Balboni et al. (2021) in the Harvard Dataverse, https://doi.org/10.7910/DVN/PPMEIR.

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