Do Asset Transfers Build Household Resilience?*

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Abstract

Can anti-poverty interventions help small-scale farm households withstand economic shocks and stressors, and reduce the chances of falling into poverty? This paper estimates the impact of one such anti-poverty project on household resilience, where resilience is measure as the probability that a household will sustain at least the threshold level of assets required to support consumption above the poverty line. Using six rounds of data collected over 42 months on an asset transfer program in Zambia's rural Copperbelt province, and using estimates of households' conditional welfare distributions, we construct measures of resilience to poverty. We find that the program significantly increased resilience among participant households, with beneficiaries 44% less likely than control households to fall into poverty. The program both increased the mean and decreased the variance in household assets, signaling an upward shift in households' conditional asset distributions. Compared with a conventional impact assessments based on standard measures of asset poverty, our method demonstrates the added value of the resilience estimation; numerous households classified as non-poor show a low probability of remaining non-poor over time.

Keywords: Poverty Dynamics, Resilience, Livestock, Asset Transfers

JEL Classification: O12, O22

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1 Introduction

As households in the developing world are exposed to new or increasingly severe climate and economic shocks, anti-poverty programs have begun to prioritize building household resilience (World Bank, 2016; Hallegatte et al., 2017; Fernández-Gimenez et al., 2011, 2012; Venton et al., 2012). Even so, little attention has been paid as yet to a key question underlying these resilience-building initiatives: can anti-poverty programs alter the likelihood that a household will fall into poverty in the foreseeable future?

To date, the economic impact evaluation literature has mostly estimated programmatic effects under an assumption of full certainty. Retrospective evaluations have focused on the first moment of the household welfare distribution, rather than on changes in household ability to withstand shocks and maintain above-poverty levels of consumption. Forward-looking poverty evaluations are obviously critical for assessing the lasting effects of interventions, as well as for comparing households who have received a transient boost to welfare to those who have undergone structural transformations of their circumstances, changes likely to alter their future economic outcomes.

This paper applies Barrett and Constas's (2014) moment-based definition of development resilience, which draws together methods and theories related to poverty traps, vulnerability, and ecological resilience. Development resilience is a probabilistic and forward-looking concept quantifying the capacity of households to escape poverty or remain non-poor over time. We measure household resilience as a probability of accumulating and retaining a minimum level of assets required to remain non-poor over-time in the face of diverse shocks and stressors. We employ the econometric technique proposed by Cissé and Barrett (2016) to construct household-specific resilience scores, and we use these estimated resilience scores as an outcome variable in our analysis.

The integrated asset transfer program studied in this paper makes a one-time livestock transfer to participant households, provides training on livestock management and other livelihood skills, and also provides veterinary and agricultural extension services. We estimate the causal impacts of the program on the mean and variance of outcomes of interest and on development resilience itself by exploiting the program rollout to overcome problems related to endogenous household investment and production decisions. Contemporaneous with Cissé and Ikegami (2016), this research is among the first to estimate the impact of a development intervention on household resilience.

Reinforcing the results of other recent analyses of livestock transfer programs (Bandiera et al., 2017; Ahmed et al., 2009; Das and Misha, 2010; Emran et al., 2014; Banerjee et al., 2015; Rawlins et al., 2014; Jodlowski et al., 2016; Kafle et al., 2016), as well as Dercon (1998) who models livestock acquisition as a stochastic path out of poverty for households, our results show that this multifaceted "big-push" intervention decreased poverty rates, increased consumption expenditures, increased livestock production, and increased asset holdings and earnings from self-employment. These effects are found to continue three and half years after the initial round of the intervention, and to have increased over time. Assuming that such year-three benefits repeat through additional cycles, the ratio of program benefits to costs is approximately 4.5.[1]

Extending previous work, our results show that the integrated livestock transfer program significantly increased household development resilience. Households receiving both training and livestock at the baseline are 44% less likely to fall into asset poverty than the control households 42 months post-intervention. Moreover, we find that the program increased headcount resilience among participant households. While 80% or more of the households receiving livestock at the baseline are resilient at the endline, the comparable headcount resilience rate for controls is only 28.6%. Decomposing these effects into first (central tendency) and second (spread) moments reveals that the livestock transfer and training program has both increased mean household asset holdings and decreased the variance in asset holdings. The program has shifted the conditional transition asset distribution upward and truncated uncertainty in asset holdings.

Measurement of program impact on resilience is especially relevant to understanding the impact of asset transfers. Such programs are often motivated by an expectation that sufficiently large transfers can enable households trapped in poverty to move onto a different growth trajectory towards a non-poor steady state. Transitioning from a growth dynamic associated with a low-level equilibrium to one that leads to a non-poor equilibrium state may be impossible without asset transfers or other programs to enable sufficient fixed investment. While the theory of bifurcated growth dynamics justifies "big-push" interventions, impact evaluation that focuses only on the first moment of outcomes ignores the potential for shocks or stressors to move households who have received transfers back to

[1] Most of the early livestock transfer programs, however, were plagued by implementation and targeting problems and hence have been deemed largely to have failed (Ashley et al., 1999). India's Integrated Rural Development Program (IRDP), for example, is thought to be highly ineffective because of its poor targeting and design (Drèze, 1990; Pulley, 1989).

a low-level equilibrium. Development resilience, in contrast, both quantifies the probability that a beneficiary household might move back into poverty and allows an assessment of an intervention's effect on that probability.

By comparing resilience results with standard estimates of program impact on asset poverty, we demonstrate the added benefits of assessing program impacts on resilience. Though both resilience and the conventional impact measures show that the program improved the welfare of recipients, we find notable differences in magnitudes across the methods. The difference in the scale of the effect is most concerning for households observed around the asset poverty threshold. We find that while a substantial number of households who received partial treatment from the program gained sufficient assets to be classified as non-poor at the midline, they demonstrated too low a probability of remaining non-poor over time to be classified as resilient. This discrepancy points to the practical significance of failing to account for nonlinearities in welfare dynamics and limiting analysis to the first moment in the distributions of welfare outcomes. In this case, resilience measurement provides more insight about household status than conventional measures.

The next section of this paper discusses the theory of development resilience in multi-equilibrium and single-equilibrium poverty traps. In addition, section 2 also discusses a primary mechanism through which a transfer program is likely to affect poor households' livelihoods. Section 3 explains the empirical implementation of the development resilience concept. Section 4 describes the program setting, the intervention and the research design. Program treatment effects are presented in section 5; development resilience results and their comparison with impact evaluation results are presented in section 6. Section 7 explores the mechanism of program impacts by presenting evidence on reallocation of household labor. Section 8 compares program benefits relative to costs. Section 9 concludes by discussing the merits of estimating development resilience in impact evaluation and possible limitations and drawbacks to development resilience.

2 Development Resilience

Resilience as a development concept draws on ideas from ecology, engineering and economics. Resilience has roots in ecology focusing on the capacity of a system to maintain functionality when shocked (Holling, 1973) as well as the system's ability to persist, renew, and redevelop (Holling,

1996) in the face of uncertainty and perturbations.[2] The concept of vulnerability in economics is closely related to ecological resilience, and refers to a probabilistic ex-ante measure of the likelihood that future consumption will fall below a defined (normative) poverty threshold (Chaudhuri et al., 2002; Calvo and Dercon, 2007; Ligon and Schechter, 2003; Christiaensen and Subbarao, 2005).

Development resilience builds on vulnerability in two important ways. First, while vulnerability measurement is concerned with the immediate impact of shocks, resilience focuses on the longer-term ability to absorb them. Operationally, this difference means that analysis of vulnerability can be implemented using cross sectional or short term panel data while resilience measurement requires data collected over a longer time frame. Second, because it emphasizes the immediate impact of shocks, the vulnerability literature largely ignores welfare path dynamics. In contrast, development resilience incorporates the dynamics which are central to the microeconomics of poverty traps. Development resilience is a forward-looking measure that assesses a household's propensity to avoid poverty in the future given unpredictable and/or exogenous changes in circumstances. This paper follows Barrett and Constas's (2014) conceptualization of resilience based on a nonlinear welfare growth path: "the capacity over time of a person, household or other aggregate unit to avoid poverty in the face of various stressors and in the wake of myriad shocks. If and only if that capacity is and remains high over time, then the unit is resilient." The next two subsections detail the theory of development resilience.

2.1 Resilience in Multi-Equilibria Poverty Trap

Multi-equilibria poverty traps are characterized by the existence of multiple technologies associated with distinct growth paths and by the presence of structural barriers that prevent some households from accessing the more remunerative path. Poor households may be on a lower growth trajectory that leads to a steady state equilibrium below the poverty line and may lack capacity to switch to the technology that would allow them to reach the higher steady state equilibrium (Carter et al., 2007).[3] Figure 1 depicts this situation in space with current wealth (as proxy for welfare) on the horizontal axis and future wealth on the vertical axis. The S-shaped curve represents wealth

[2] See Folke (2006) for a review of resilience in the ecology literature.

[3] A classic example is a nutritional poverty trap in which workers lacking sufficient income to afford a threshold nutrient intake (Mazumdar, 1959; Dasgupta and Ray, 1986, 1987) and consumption level (Mirrlees, 1975; Stiglitz, 1976) are rationed out of the labor market making it even harder to achieve minimal levels of caloric intake and even harder to secure future employment.

dynamics and $\bar{W}$ represents both the static poverty line and the dynamic poverty threshold where wealth bifurcates. However, the static poverty line and the dynamic threshold need not coincide. It is possible to observe households in poverty but not in persistent poverty. In the figure, households with wealth below $\bar{W}$ at time t will be on a growth path tending towards point A, below the poverty line. Those with wealth above $\bar{W}$ will tend towards the non-poor steady state at point B. In this context, increasing resilience implies reducing the probability that a household will be on the section of the growth path leading to a low-level equilibrium.[4]

Barrett and Constas (2014) use a conditional moment function for wellbeing in a multiple equilibria poverty trap to represent resilience, $m^k(W_{t+s} \mid W_t, \varepsilon_t)$, where m^k is a kth moment of wellbeing at time $t+s$ and $s > 0$; with resilience a function of wellbeing W_t and random shock ε_t at time t. The deterministic relationship between W_t and W_{t+s} that is typically considered in the poverty trap literature is replaced with a conditional moment growth function and associated conditional dynamic transitional distribution functions. Barrett and Constas's (2014) notion of resilience is presented in Figure 1 by introducing conditional dynamic distributions -the vertical curves- to capture stochasticity in the transition between periods. A household's development resilience is the cumulative probability above the horizontal dynamic poverty threshold. Unless the entire vertical curve sits above $\bar{W}$, there exists some probability of falling onto a path toward a poverty trap. As less of the probability distribution falls below the poverty threshold, a household becomes more resilient.

The likelihood of falling into persistent poverty depends on the level of wellbeing at time t and the dispersion in the distribution of outcomes. As demonstrated by their respective vertical conditional transition curves, households H_1 and H_2 in the figure face drastically different probabilities of falling into persistent poverty, but either household could find itself in a poverty trap. Although H_1 is above the dynamic poverty threshold ($\bar{W}$) at time t, a negative shock could imply a draw below $\bar{W}$ and set it on a trajectory towards the lower level equilibrium A. As with negative shocks, large enough positive nudges have the potential to move the poor onto a path towards a non-poor state and higher resilience. For example, a wealth transfer to H_2 could imply a draw above $\bar{W}$ placing the household on the growth path towards the non-poor equilibrium. A shift in the

[4] Barrett et al. (2016) review theories of household poverty traps, their mechanisms, measurements and policy implications. Similarly, Kraay and McKenzie (2014) review the theory at the macro-level and describe the limited state of empirical evidence.

conditional dynamic transition curve that moves H_2 towards H_1 represents an improvement in the household's development resilience since a smaller share of the probability distribution will fall below $\bar{W}$. Similarly, reduction in the dispersion of the distribution for H_1 will increase its resilience.

2.2 Resilience in Single Steady-State Equilibrium

Although Barrett and Constas's (2014) resilience theory is explicitly based on nonlinear path dynamics with multiple steady-state equilibria, development resilience is also relevant in the case of the existence of a single steady-state equilibrium below the poverty line. Group characteristics that could lead to this outcome include geographic isolation as in Jalan and Ravallion (2002) or Ravallion and Wodon (1999); poverty reinforcing structural characteristics embedded in national institutions as in Acemoglu et al. (2001); or multiple other factors discussed in the literature.[5] Figure 2 depicts this "club-convergence" single equilibrium poverty trap with conditional transition distribution functions (gray vertical curves) and presents possible effects of a multifaceted asset transfer program on households' asset holdings and poverty status. In this scenario everyone in the population faces the same concave technology $G^o(W_t, \alpha_o, \varepsilon_t)$, where α is a group defining characteristic. This yields a steady state equilibrium A that is below the poverty threshold $\bar{W}$. Hence, all remain poor for the foreseeable future. No wealth transfer is sufficient to change the long-run living standards and resilience has little meaning as everyone is expected to be persistently poor. Imagine a poor family that owns wealth stock of X at time t. The family remains poor with wealth of X^o at time $t+s$ and in the long-run converges to equilibrium A – a poverty trap.

The resilience concept becomes relevant only if there is a change in the growth trajectory that can create an escape from poverty. For example, a skill improving training program can increase the per unit return to capital, shifting the growth path upwards. If the impact of such a program shifts the curve to $G'(W_t, \alpha_1, \varepsilon_t)$, a wealth level of X at time t now yields wealth of X' at time $t+s$, on average, and with some probability the household grows toward point D, an equilibrium above the poverty line. With zero uncertainty around the growth trajectory, the household inevitably moves to a non-poor steady state. In reality, dispersion around the average return can affect how quickly or whether a household actually remains out of poverty. As shown in Figure 2, there is some

[5] For example, a setting with poor health conditions could impose frequent negative shocks in utero that permanently limit abilities at birth and have significant effect on individuals' life-earning trajectories (Almond and Currie, 2011).

probability that this household will continue to draw outcomes from the distribution that are below $\bar{W}$. As the probability of such an outcome declines, the household's resilience rises. Additionally, training combined with wealth transfers can have even greater impact on households' resilience. For example, along with the training, wealth transfer of τ to the household with X amount of wealth in Figure 2 will set its growth trajectory to $G'(W_t, \alpha_1, \varepsilon_t)$, which yields X'' amount of wealth at time $t+s$ that is greater than the outcome under skill-only intervention X'. As shown in the figure, this is likely to decrease the the probability of falling into poverty even more and hence have greater impact on resilience development.

Resilience can be operationalized by defining it as the capacity to hold productive asset stock above a minimum critical asset poverty threshold over time. Increasing resilience therefore means increasing the probability of holding assets above the critical threshold. Such an improvement could be the result of increase in the conditional mean asset stock, a decrease in the conditional variance or both. Whether the multiple equilibria or single equilibrium scenario holds, theory implies that development policies and interventions should focus on increasing capital, decreasing downside risk and changing underlying structural characteristics at time t (Barrett and Constas, 2014). The intervention analyzed in this paper is focused on enacting precisely these sorts of changes: transferring improved breeds of livestock, providing livelihood skills through trainings, and providing agricultural and veterinary extension services.

3 Development Resilience Measurement

We construct resilience scores using the econometric technique proposed by Cissé and Barrett (2016) and applied to food security in Upton et al. (2016) and an assessment of the impact of livestock insurance in Cissé and Ikegami (2016). We then use the estimated resilience scores as outcome variables in the impact evaluation of the livestock transfer program. First, assuming a first-order Markov processes, the mean (indicated by the M subscript) stochastic asset level of household i at time t, (W_{it}), is modeled as a polynomial function of its lagged asset ($W_{i,t-1}$), a vector of household characteristics, X_{it}, and its exposure to random shocks ε_{it}:

$$W_{it} = \sum_{j=1}^{k} \beta_{Mj} W_{i,t-1}^{j} + \gamma_M X_{it} + \varepsilon_{Mit} \tag{1}$$

Included in the household characteristics are indicators for survey wave dummies and the interaction between each treatment assignment and survey wave dummy. The polynomial lagged asset measures are included to allow for S-shaped dynamics that are typical of multiple equilibria poverty traps, where $k = 3$ is its most parsimonious parametric specification (Barrett et al., 2006). Assuming $\mathbb{E}[\varepsilon_{Mit}] = 0$, the first conditional moment (μ_{1it}) is predicted as:

$$\hat{\mu}_{1it} = \mathbb{E}[W_{it}] = \sum_{j=1}^{k} \hat{\beta}_{Mj} W_{i,t-1}^{j} + \hat{\gamma}_M X_{it} \tag{2}$$

Following Just and Pope (1979) and Antle (1983), residuals from the first moment equation can be used to model the second moment (subscript V) as below:

$$\hat{\varepsilon}_{Mit}^{2} = \sum_{j=1}^{k} \beta_{Vj} W_{i,t-1}^{j} + \gamma_V X_{it} + \varepsilon_{Vit} \tag{3}$$

Again, assuming $\mathbb{E}[\varepsilon_{Vit}] = 0$, the predicted variance of a household i at time t (μ_{2it}) then is:

$$\hat{\mu}_{2it} = \sum_{j=1}^{k} \hat{\beta}_{Vj} W_{i,t-1}^{j} + \hat{\gamma}_V X_{it} \tag{4}$$

The first two moments are sufficient to describe household i's conditional transition distribution function of asset holding at time t if $W_{i,t-1}$ is distributed normally, lognormally or gamma. Once the function is identified either by assuming its distribution or through a moment generating function (MGF), the development resilience of a household i at time t (ρ_{it}) is the probability that the household will have asset holding above a critical asset poverty threshold ($\bar{W}$) at period t. Since the resilience measure increases with the upward shift of the conditional transitional distribution, greater resilience will be achieved by increasing the conditional mean, decreasing the conditional variance when mean is above the minimum threshold, $\bar{W}$, or both. The next section describes the intervention that is studied in the paper to assess its impact on development resilience.

4 Program Site, Intervention and Research Design

4.1 Program Setting and Intervention

The Copperbelt Rural Livelihoods Enhancement Support Project (CRLESP) was implemented by Heifer International with funding from Elanco Animal Health (USA). The project operated in 12 rural communities in Zambia's Copperbelt province. The region, which relied heavily on copper, has gone through a difficult economic transition since the collapse of the copper market over the last three decades resulting in the loss of employment and in rural areas loss of remittances (World Bank, 2007). Many dislocated workers turned to agriculture. Despite relatively good quality and availability of land, limited asset holdings, limited farming and livestock management skills, and credit and market constraints have contributed to low agricultural and economic productivity, food insecurity, and poor child nutrition (Heifer International, 2010).

The CRLESP encouraged poor households to engage in commercial livestock activities through livestock transfers, training on livestock management and basic household livelihood skills, and provision of agricultural extension and veterinary services. Further, the program attempted to mitigate poor health and raise awareness regarding HIV/AIDS, and the importance of improved hygiene and sanitation through various community health trainings. Communities and households had to pass a screening process and follow a set of guidelines to qualify for program participation. Community members first organized themselves into groups and submitted an application to one of Heifer's Zambia offices. Households in approved groups had to demonstrate their eligibility, which was contingent on commitment to participate in training activities, commitment to construct an animal shed, and payment into a community insurance fund. The screening excluded the poorest members of the community but the program participants were poor; about 60% of the households in our survey lived on less than USD 1.90 purchasing power parity (PPP) per person per day at baseline. Similarly, households with professional employment or sufficient assets to generate reliable income were screened out of the recipient pool.[6]

The program was implemented in phases due to agency capacity constraints. Groups earlier in

[6] Given that the program targeted poor households that were able to invest in an animal shed and contribute to the insurance fund, the group may not represent the population of Zambia or the Copperbelt. In addition, individuals self-selected into groups (and hence into the program) to have access to livestock. Participant households, therefore, may differ from a typical Zambian household in preferences and other unobservable factors.

a queue received support in the initial round, while other groups, referred to as "Prospectives", were wait-listed until a future date when resources become available. While all households in groups identified to receive treatment in the initial round received livelihood skill trainings and associated benefits of enhanced social capital, only a randomly selected subset of these households received livestock at the start of the project; we refer to these early recipients as "Originals". Depending on the ecological and market conditions of their location, Originals were given either a pregnant dairy cow, two pregnant draft cattle or one male and seven female meat goats. A bull was also given to each group that received draft or dairy cattle to service members' donated animals. Irrespective of animal type, the monetary value of the livestock transfer was similar across recipients, USD 1629 PPP on average. Originals were required to pass on a female offspring for each female animal they received through the program to the members of their groups that did not receive a transfer in the initial round. These second-phase recipients are referred to as a "Pass on the Gift" (POG) households. While Originals received full treatment (training and productive assets) and POGs received partial treatment (training at the baseline and a lower value asset transfer after a delay), Prospective households, which are spatially separate from other groups, received neither and serve as a "control" group in our analysis.

4.2 Research Design

The project collected six rounds of detailed demographic and socioeconomic information from sampled households. The baseline included 106 Original, 111 POG and 67 control households and was conducted in January and February of 2012, overlapping with the timing of the initial livestock transfer. Follow-up surveys began six months later and were conducted July/August 2012, January/February 2013, July/August 2013, January/February 2015 and July/August 2015. Figure 3 presents the timeline of the six survey rounds and the timing of treatment for participant households.

We exploit the rollout of the program to identify impacts. Since both the early recipients (Originals) and future recipients (Prospectives) passed identical screening and selection processes and have equivalent eligibility, we assume the two groups to be comparable on unobservables and treat the Prospectives as a pseudo control group. These two groups differ on timing of application to the program only. Correlation between unobservable group characteristics and application timing

could threaten identification, but observable data provide no evidence that such correlation exists. Furthermore, the Original and control households reside in different villages and spillover across communities is unlikely. Nonetheless, a challenge to our identification is that control households might alter their behavior in the anticipation of receiving the livestock transfer.[7] Jodlowski et al. (2016) find no such anticipatory behavior in the first four rounds of the panel.

POG households are likely to exhibit different spillovers and anticipatory behaviors than the controls, despite identical processes selecting them into the program. First, although neither the controls nor the POGs initially received the donated livestock, POG households initially received training which could affect management of farm animals they already own. Second, anticipatory behavior may be more likely among POGs than controls as the POGs start receiving immature female animals from the Original households as early as six months after the baseline. Third, POG households live in the same communities as the Originals and are more likely to experience project spillovers. Thus, we use the POG households in our analysis as a second treatment group, rather than as a control group.

Table 1 provides baseline balance tests for the treatment and control group characteristics. For each group of characteristics, we also report p-value of the F-test from the regression of treatment on all outcomes within the group. The Original and control samples are well balanced in all dimensions except for consumption and poverty status. The normalized differences for expenditure and poverty outcomes, nonetheless, are close to the threshold level of one fourth of the combined sample variance and we expect sensitivity to specification to be of little or no concern (Imbens and Wooldridge, 2009). The attrition rate of 13% (Online Appendix Table I) is comparable to other asset transfer program evaluations with similar durations and survey lags (Banerjee et al., 2015; Bandiera et al., 2017). POG households are less likely to be interviewed in all six rounds compare to the control households. Original households, on the other hand are as likely to be followed throughout the panel as the control households and we find no difference in attrition by baseline outcomes and characteristics. For our analysis we restrict the sample to the 247 households interviewed in all six survey rounds.

[7] For example, the control households might begin focusing on livestock and give up other activities in expectation of the arrival of the livestock. This kind of anticipatory behavior would bias the treatment effect downward if returns from livestock are at least as high as the other activities. An upward bias could emerge if households divest from some income generating activities or decrease total labor supply in advance of the transfer and and hence appear worse off than they otherwise would (Ashenfelter, 1978; Ashenfelter and Card, 1985)

4.3 Poverty Transition

We begin the data exploration with an assessment of poverty transitions which provides a simple framework to study changes in poverty status across the treatment groups and to examine the dynamics of poverty in the context of the project. However, the simple analysis does require understanding the differences in the pre-project baseline poverty rates between the groups. The share of treatment households that are poor and non-poor based on baseline per capita consumption expenditures are reported in Table 1. We note that at baseline significantly higher shares of Originals and POGs live under the USD 1.90 PPP poverty line relative to the controls. Baseline poverty rates among the Original and POG families are 62.3% and 62.2% respectively, compared to only 41.8% among control families.

Figure 4 shows poverty transitions between baseline, midline, and endline, according to baseline poverty status. Baseline poverty status (poor or not poor according to the USD 1.90 PPP poverty line) is reported on the horizontal axis in both Panel A and B. The vertical axis presents poverty status at endline and midline (Panel A) and at endline (Panel B). Panel A shows poverty transitions by treatment groups, both in 18 months and 42 months after the program implementation. We report p-values from tests of poverty rate equality between the two time periods for each group to check persistence in poverty reduction.

The top panel of Figure 4 suggests that poverty reduction among Original households is persistent and is increasing over time. Among baseline-poor households, greater shares of Original and POG households make a transition out of poverty into a non-poor state in both the time periods, as compared to control households. Poverty rates are statistically indistinguishable between 18 and 42 months after the intervention for both baseline poor and non-poor households in each treatment group. The exception is Original baseline-poor households; among this group the poverty headcount rate falls dramatically – from 55% in 18 months to 33% in 42 months.

In Panel B, we follow Jalan and Ravallion (1998) to assess poverty persistence by using the last three rounds (18, 36 and 42 months after the baseline) of the survey to classify households as chronically poor, transiently poor or never poor. Households whose average consumption over the three survey rounds is below the poverty line are defined as chronically poor. Given the definition, a chronically poor household may not be poor in all three survey periods. Imbedded in this group

are "persistent poor" – households that are observed below the poverty line in all three rounds. Similarly, we classify families into transient poor if their average consumption over the three survey periods is above the poverty threshold but they are observed below it at least once during that period. Never-poor are households that are observed above the poverty line in all three survey rounds.

Panel B suggests that the intervention has had a significant impact on reducing the persistence (or cessation) of poverty. Originals who were poor at baseline are significantly more likely to be classified as transient or never-poor based on their expenditures in the last three rounds: 17% of the Originals that are poor at the baseline are never-poor in the last three rounds compared to only 9% of POGs and 7% of the controls. While only 37% of the Originals households that are poor at the baseline fall into chronic poverty, 70% and 75% of poor POGs and controls fall into chronic poverty. The non-poor control families, however, are more likely to remain non-poor (49%) in the last three time-periods in comparison to the Original (33%) and POG (38%) families. Moreover, only 17% of the non-poor controls fall into chronic poverty, which is 8% less than the non-poor Originals. The negative effects among the baseline-non-poor Originals, nonetheless, are relatively small in sizes and are likely to be offset by the large gains among the baseline-poor Originals when calculating the program treatment effects.

5 Program Treatment Effects

We begin the program evaluation with the standard first-moment impact assessment both to motivate our resilience estimations and to demonstrate that measuring a positive asset change is a necessary but not sufficient component of determining changes in household development resilience. Exploiting the experimental variation caused by the rollout of the program into two treatment arms and a control group, we estimate the following difference-in-differences/fixed-effect specification:

$$y_{it} = \alpha + \sum_{t=1}^{2} \beta_t (T_t \times Original_i) + \sum_{t=1}^{2} \delta_t (T_t \times POG_i) + \sum_{t=1}^{2} T_t + Original_i + POG_i + \eta_i + \varepsilon_{it} \quad (5)$$

where y_{it} is an outcome of interest for household i at time t and t takes the values of 0, 1 and 2 for 2012 baseline, 2013 midline and 2015 endline respectively. T_t are indicator variables that refer

to survey waves. $Original_i$ and POG_i are indicators for two treatment arms – whether household i is in the full-treatment (Original) or partial-treatment, Pass on the Gift (POG), group. As the household's timing of application to the program determined the treatment status, we include household fixed effects η_i to control for unobserved heterogeneity and cluster the error term ε_{it} at the household level. As a result, the coefficients on $Original_i$ and POG_i in Equation (5) are not identified. The equation, nonetheless, can be treated as the garden variety difference-in-difference specification.

β_t and δ_t are the coefficients of interest, which under the assumptions of "parallel trends" and stable unit treatment value assumption (SUTVA) identify intent-to-treat (ITT) effects of the program on Original and POG groups respectively. As discussed in the research design, we expect both assumptions to hold. First, pre-randomization, the control (Prospective) group is identified through a process identical to that of the Original and POG groups; all three passed the same selection and screening processes and have equivalent eligibility. Second, Equation (5) controls for all household-specific time-invariant factors and time-varying factors that are equal across all groups. Third, we expect zero spillovers across treatment and control communities because of their relative geographical separation and hence SUTVA holds. SUTVA between the two treatment groups, however, may not hold as both Original and POG groups reside in the same communities. Hence, we cannot explicitly distinguish between the pure program effects and the general equilibrium responses induced by the program in the community and this is an important distinction. Nonetheless, the spillovers within the communities are due to the program itself; the coefficients, therefore, can be viewed as the overall program treatment effects. Similarly, complete compliance implies that the coefficients also identify treatment-on the treated (TOT) impact of the program.

5.1 Productive Assets and Household Durables

Table 2 presents the program impacts on household accumulation of productive and durable assets using Equation (5). Information on the full asset portfolio was collected in the baseline and in follow up survey waves of July/August 2013 and July/August 2015 (18 and 42 months after baseline); we refer to these follow up rounds as time 1 and 2 in the table. All monetary values are PPP-adjusted USD and deflated to 2012 prices using Zambia's CPI.

First we analyze whether beneficiary households in the Copperbelt region undertake the live-

stock activities prescribed by the program and measure the direct impact on livestock holdings and earnings. Table 2 reports impacts on herd size and quarterly income from livestock related activities. Originals received either a dairy cow, two draft cattle or eight goats; all are equivalent to 0.7 tropical livestock units (TLU). A one-unit TLU gain relative to the controls one year post-intervention represents an increase of 0.3 TLU above the transfer amount, meaning the recipients had begun to increase their holdings beyond the initial transfer. Consistent with the impact on herd size, within one year the value of livestock holding of the Originals increased by USD 460.6 relative to the control households. Half of the increase was due to the initial livestock gift.[8] Moreover, an increase of USD 64.6 in quarterly income from selling livestock and livestock products during that time-period implies that the transfers were productive within the first year of the intervention. Among POGs we find a small increase in herd size and herd value but no significant effect in livestock revenue in the first year, consistent with POGs receiving immature animals after the Originals' donated livestock produce offspring.

Three years after the baseline, intervention effects are large among both the Originals and POGs. Relative to the control group, the herd size of the Original households increases by 1.11 TLU or 92% of the baseline mean, and POGs' herd size increase by about one TLU unit. The gains in herd sizes are associated with increases in livestock-based revenue for both groups. The Originals experience an increase in livestock-based revenues of 821.6% (USD 110.7) relative to the baseline. POGs, meanwhile, see an increase of USD 72.1 (imprecisely estimated) in income from livestock. Comparing the Originals' 18 and 42 month impacts indicates that the program effects are sustained with continued growth in herd size and related earnings. After 42 months, the value of animals owned by Originals has increased by 261% (USD 497.1) relative to the baseline, which is 141% net of the transfer value. The 18 month and 42 month impacts on POG household livestock values are USD 173.8 and 305.5 respectively. Because the livestock transfers to POGs were spread over the period analyzed, we are unable to separate out the direct transfer value from the added value generated after the transfer.[9] Finding that the treatment effects grow after the initial transfer

[8] In the first wave of the transfers, the Original households receive livestock worth about USD 1629 in PPP (USD 229 per capita), which is not included in baseline asset value. Therefore, 49.8% of the first year rise in the value of livestock can be attributed to the transfer itself.

[9] We do not observe the amount, type and age of immature animals the POGs receive from the Originals; hence, we are unable to quantify and value the transfer amount. Figure 3 shows when POGs receive their gifts. Almost half of the POG households receive their livestock gifts after round 4, 18 months post-intervention.

suggests the transfers helped households sustain economic growth and perhaps provided a path out of poverty. The resilience estimations will test this hypothesis.

Aggregating across asset types, Table 2 shows that by three years post-intervention total household asset value increased by 124.6% (USD 495.7) among the Originals. The increment is robust relative to the first-year increment of USD 477.1 (with the p-value of 0.825 on the equality between the two periods' impacts). The impacts are significant among POG households as well, USD 279.3 and 294.5 after one and three years, respectively, of the intervention. The growth in livestock assets is the major component driving the aggregate change. Overall, these results suggest that the poor households in rural Copperbelt province are able take on and sustain livestock rearing activities that are likely to be more rewarding than the available alternatives.

5.2 Consumption Expenditure, Food Security, and Asset Poverty

We analyze program impacts on poverty status, consumption expenditures, a subjective food security measure and asset poverty status at 12 and 36 months after the intervention using Equation (5) and present the results in Table 3. These two survey rounds occurred in the same season as the baseline and are therefore more appropriate for analysis of consumption impacts than the later rounds used in analysis of assets in Table 2. Relative to the control group, the share of Original households with expenditure below the USD 1.90 poverty line drops by 22.0 percentage points (pp) after one year. The impact is even greater after three years: 31.4pp drop or 50.3% decrease from the baseline mean. The impact on the partially treated POG group is more modest and is statistically insignificant.

Relative to the controls, the weekly per capita total expenditure of the Originals increases by USD 7.47 or 58.8% of the baseline mean after three years. This is higher relative to the one-year effect of USD 3.34 indicating increase in gains over time. Although positive, gains of USD 0.45 and 1.64 after one and three years among POGs are not precisely estimated. Columns 2 and 3 decompose the total expenditures into food and nonfood expenditures. Three-year gains of 3.72 and 3.75 USD among the Originals in food and nonfood expenditures, respectively, relative to the controls are significantly greater than the one-year impacts. Consumption changes for POGs are statistically indistinguishable from zero. Because of the program design, all POG households received training but not every POG received animals early enough to be productive or affect consumption over the

observed time-period. These effects are comparable to Kafle et al. (2016) which analyzed data from the first 18 months of the same program. Although consumption expenditures show no evidence of impact for POGs, significantly higher shares of both Original and POG households consider themselves to be food secure compare to the controls. The share of Originals that report having enough food for their families increases by 18.2pp and 21.3pp after one and three years respectively. The impact among the POGs is 11.1pp after one year and 15.5pp after three years of the intervention.

Based on the relationship between consumption and assets, explored in the Online Appendix, we estimate an asset poverty line at USD 308 (PPP) per capita. This asset poverty line represents the per capita asset wealth that is associated with consumption at the expenditures poverty line. As the table shows, we find a significant reduction in the number of Original and POG households below this threshold, compared to the control group. While POGs show little change with respect to the expenditure poverty line, we find that the program has successfully moved some of them above the asset poverty line. The apparent decrease in the magnitude of the treatment effects on asset poverty over-time among the Original group raises concern about sustainability of impacts, however, the test of inequality of the treatment effects between the two periods is negative. Indeed, three-year impacts for both the treatment groups (Original and POG households) are statistically equal if not higher in magnitude than the one-year impacts for almost all the outcomes considered in this section. These findings suggests that program impacts do not dissipate and likely increase over time.

Given the differences in effects between the Originals and the POGs over time, we investigate whether POG impacts are merely delayed or whether we see evidence of general equilibrium responses to greater demand for livestock labor or increased local supply or milk, meat, or animal traction. Our results suggest that the differences are attributable to delayed impacts rather than to accrual of unique benefits to early Originals adopters. The differences in the scale of treatment effects between the Originals and POGs diminishes over time in almost all the outcomes considered in this section. In particular herd size, the outcome that is directly affected by the program and is most likely to be affected by the general equilibrium responses, we observe that compared to the controls the POGs hold herds of equivalent size to the Originals (1.03 vs 1.11) three years after the baseline. This suggests both that the Originals' head start does not crowd out others in the community from livestock rearing and that the treatment effects differences between the two groups

are likely to disappear over time.

5.3 Outcome Heterogeneity

Besides physical asset constraints, households may face ability constraints associated with managing animals. Although households select themselves into the program and receive basic training and veterinary extension support, the program effects are likely to be heterogeneous on innate ability for animal husbandry. Given substantially large livestock gifts, over five times the initial average asset level (Jodlowski et al., 2016), some families may be persuaded to engage in animal husbandry even if it makes them worse off than they otherwise would be from their usual alternatives. Hence, despite the positive average program benefits, this may be of concern. We use the following quantile treatment effects (QTE) specification to explore such heterogeneity in impacts.

$$Q_{\Delta y_i}(\tau) = \alpha(\tau) + \beta_1(\tau)Original_i + \beta_2(\tau)POG_i \tag{6}$$

where Δy_i is a the difference between the three year and baseline values of outcomes y for household i. The program impacts on distribution of outcomes are reported in Figure 5. Panel A shows the quantile treatment effects on distributions of total asset value. For both the treatment groups (Originals and POGs) the effects are more pronounced at higher centiles. While the impact on asset value is increasing on centiles for Originals, the treatment effects among POGs at the top centiles are statistically equivalent to zero. Panel B shows the treatment effect on consumption among the Originals at consistently higher level at each centile except at the extreme top and bottom centiles where the effects are imprecisely estimated. The distributional effect on POGs remain non-negative over all the centiles, however it is imprecisely estimated. It is reassuring to note that all the quantile treatment effects are non-negative which removes any concern related to the endowment effect.

6 Effects on Development Resilience

We model resilience explicitly in asset space because assets serve as an input for future household asset accumulation and hence welfare gains. Information on assets in the panel was collected at

baseline and 18 months, 36 months and 42 months after the baseline. Given the structure of the data and Markov first-order path dynamics, we can recover parameters only on the last three rounds in the regression setting. Equation (1), hence, reduces to:

$$W_{it} = \alpha + \sum_{j=1}^{k} \beta_j W_{i,t-1}^{j} + \sum_{l} \sum_{t=1}^{3} \gamma_{lt}(T_t \times D_l) + \sum_{t=2}^{3} \delta_t T_t + \theta Z_{it} + \varepsilon_{it} \tag{7}$$

where, W_{it} is asset value of household i at time t in natural log. Time period t takes the values of 0, 1, 2, and 3 for baseline, 18, 36 and 42 months after the baseline respectively. T_t are indicators for survey waves 18 months, 36 months and 42 months. D_l, where $l \in (Original_i, POG_i)$, are dummy variables for the two treatment arms. Z_{it} refer to family composition and other characteristics that influence asset accumulation, and ε_{it} are random shocks that household i faces. The originals received pregnant livestock during or soon after the baseline survey. The initial recipients are already reaping the benefits (milk, meat, ploughing, increase in herd size etc.) from the transfers by 18 months post-transfer. Therefore, we add transfer values to the Originals' baseline asset values, which serve as the lagged term for the survey round 4 (18 months) or $t = 1$ in the specification. Figure I in the Online Appendix, which provides discussion on model selection, shows that the cubic fit and locally weighted regression (Lowess smoothing) of asset values on lagged values follow each other closely. We choose cubic ($k = 3$) as our preferred functional form.

Asset values are non-negative for all the households in the sample.[10] Consequently, we assume the dependent variable to be distributed Poisson and fit a GLM log link using maximum likelihood on the mean Specification (7). Using the parameter estimates from (7), we predict the first moment of asset distribution of household i at time t as in Equation (2). Squared residuals from Equation (7) are used to estimate Equation (3),[11] which recovers parameters to predict the second moment (Equation 4). We calculate each household's probability density function (pdf) of asset holding for each period assuming the conditional transition distribution function to be gamma distribution.[12] We convert the poverty line of USD 1.90 PPP into an asset poverty line ($\bar{W}$) of USD 308 PPP as shown in Figure II of the Online Appendix. Using the calculated minimum asset threshold,

[10] To depict the program setting accurately we assume credit market to be absent as such households cannot borrow to buy asset. All the households in our sample own some asset hence the value is always greater than zero.

[11] Because variance must be nonnegative, we, again, assume the dependent variable to be distributed Poisson and fit GLM log link using maximum likelihood.

[12] The parameters (shape and scale) for Gamma distribution are: $W_t \mid W_{t-1} \sim \Gamma(\frac{\mu_{1t}^2}{\mu_{2t}}, \frac{\mu_{2t}}{\mu_{1t}})$.

we estimate each household's development resilience in each period, ρ_{it}, i.e. the probability of a household to achieve the minimum asset threshold $\bar{W}$.

6.1 Resilience Treatment Effects and Headcount Resilient Rate

In order to assess the program's impact on development resilience, we follow Cissé and Barrett (2016) that $\partial\hat{\rho}_{it}/\partial X_{it}$ is a characteristic X_i's impact on development resilience and estimate the following specification:

$$\hat{\rho}_{it} = \alpha + \sum_{j=1}^{k} \beta_j W_{i,t-1}^{j} + \sum_{l} \sum_{t=1}^{3} \gamma_{lt}(T_t \times D_l) + \sum_{t=2}^{3} \delta_t T_t + \theta Z_{it} + \varepsilon_{it} \tag{8}$$

$$\begin{aligned} \text{Note that:} \quad \frac{\partial \hat{\rho}_{it}}{\partial (T_t \times D_l)} &= \hat{\gamma}_{lt} \\ &= \mathbb{E}[\hat{\rho}_{it} \mid W_{i,t-1}^{j}, Z_{it}, T_t, D_l = 1] - \mathbb{E}[\hat{\rho}_{it} \mid W_{i,t-1}^{j}, Z_{it}, T_t, D_l = 0] \\ &\quad \text{where } t \in [1, 2, 3] \end{aligned} \tag{9}$$

which are the differences of the conditional means between the treatment and control groups at time t. The causal inference of the program's impacts, γ_{it}, is based on the conditional independence assumption:

$$\mathbb{E}[\hat{\rho}_{0it} \mid W_{i,t-1}^{j}, Z_{it}, T_t, D_l] = \mathbb{E}[\hat{\rho}_{0it} \mid W_{i,t-1}^{j}, Z_{it}, T_t] \tag{10}$$

As discussed in Section 4.2, the treatment assignment was quasi-randomized with each group having equal eligibility into the program. Pre-intervention, the treatment and control groups are balanced on observables, including mean assets (Table 1). We expect both the first and second moments of the asset holding to be equivalent between the treatments and control households prior to the intervention.

Panel A in Table 4 presents the estimated average marginal treatment effects on development resilience, measured as the share of the probability distribution of asset holding of a household that is above the asset poverty line.[13] Relative to the controls, both the Originals and POGs have a significantly lower probability of falling into asset poverty in all three rounds. The development

[13] Since the resilience outcome is measured in fractions i.e. $\hat{\rho}_{it} \in [0, 1]$, we assume the dependent variable is distributed binomially and fit the GLM logit link regression using maximum likelihood. We calculate the standard errors of the parameter estimates by bootstrapping the whole process (from mean specification to the resilience specification) and clustering at household level using 400 replications.

resilience score is 0.228 points or 87.7% higher for the Originals after 18 months of the treatment than the controls. Similarly, the Originals are 41.3% (0.145 points) and 44.1% (0.167 points) more asset resilient than the controls at 36 and 42 months post-intervention respectively. Among POGs, the program has increased household development resilience by 73.8% (0.192 points), 31.6% (0.111 points) and 29.0% (0.110 points) after 18, 36 and 42 months respectively. Although significantly higher in all rounds relative to the controls, the impact appears to decrease in magnitude over time for both the treatment groups. To provide evidence on this we test whether the 36 and 42 months impacts are equivalent to 18 months post-intervention impact. The tests of equality of impacts between rounds, however, show no such evidence (with all the p-values from the tests above 0.35). These results are consistent with the treatment effects in Table 2, where the program impacts on asset values are also robust over time. Both the resilience and the difference-in-difference results suggest that the program has improved households' welfare. Resilience results, in addition, show that the program has improved households' ability to remain non-poor into the future.

Household resilience increases if the conditional mean of asset values increases, if the conditional variance decreases when the conditional mean is above the minimum threshold $\bar{W}$, or both. Estimating Equation (8) using predicted conditional household-time specific mean and variance as the dependent variables reveals that the mean asset holding among the treated groups increases compared to the controls in all rounds (Panel B).[14] Moreover, the impacts on mean outcomes are similar for Originals and POGs. The impacts on the variance, are significant for the Originals but are statistically insignificant for POGs (Panel C). The conditional asset spread among the Originals drops significantly relative to the controls (except in round 5), but the POGs' assets are equivalently spread out (statistically) as the controls in all rounds. The limited impact of the treatment in terms of reducing the dispersion of outcomes for POGs explains the smaller estimated program impact on POGs' resilience compared to the Originals (Panel A).

Relating these results to the theoretical mechanism discussed in Section 2 suggests that the program shifted the first-moment dynamic growth path upward for both the treated groups. While the conditional transition distribution associated with the first-moment shrinks for the Originals, it remains unchanged for the POGs. Both cases, however, imply increase in resilience when the

[14] Because both the first and second moments are nonnegative, we assume the dependent variables are distributed Poisson and fit the GLM log link regression using maximum likelihood.

expected asset value is above the poverty line. In short, these results together with the difference-in-difference specification imply that the program has increased households' asset holdings and decreased their probability of falling into asset poverty. Among the Originals, the program has both increased mean household asset holdings and decreased the variance in holdings.

Figure 6 presents the headcount resiliency rate by treatment groups for each survey wave. We define household i to be resilient at time t if its probability of falling below the asset poverty line (i.e. its estimated resilience, $\hat{\rho}_{it}$) is greater than a minimum normative threshold ($\bar{R}$) at time t i.e. $R_{it} = 1$ if $\hat{\rho}_{it} > \bar{R}$; 0 otherwise.[15] Eighteen months after the initial treatment, most of the originals (77.1%) are resilient compared to only 18.2% and 17.5% of the POGs and controls respectively. The number increases slightly for the Originals after 36 and 42 months of the intervention – more than 80% become asset resilient. Similarly, the headcount resiliency rate among the POG and control households increases in later periods but more so for POGs. The gap between the number of resilient POG and control households widens noticeably over time. However, among POGs the resilience treatment effects (the difference of average resiliency scores between POGs and controls) presented in Table 4 Panel A decreases over time. The distribution of resilience scores among the control group, thus, is likely positively skewed in the later periods (few units with very high resilience scores), whereas the distribution among POGs is likely more symmetric.

6.2 Resilience vs Impact Evaluation Measures

To provide the direct comparison between resilience and standard impact evaluation methods, consider households that are asset non-poor based on having an asset value above the calculated asset poverty threshold of USD 308 (Table 3). While Originals are 47% less likely to be asset poor, the POGs are 24.3% less likely to be asset-poor 18 months post-intervention. 42 months post-intervention, however, the POGs are as likely to be asset non-poor as Originals (38.4% and 39% respectively). While significant and consistent in direction, these effects are noticeably different in magnitude from the effects on resilience headcount. The differences in headcount resilience rates

[15] The resilience threshold ($\bar{R}$) is comparable to poverty line used in headcount poverty calculation; a unit is classified as resilient if it is above the threshold and non-resilient if below. Unlike the poverty line, which is generally rooted to some necessary expenditure requirement for household's functioning, the resilience threshold is arbitrary. We set the initial resilience threshold at 0.5 ($\bar{R} = 0.5$) and present the headcount resiliency rate by treatment groups for each survey wave. The threshold of 0.5 is greater than the 0.25 used in Upton et al. (2016) but lower than 0.8 used in Cissé and Barrett (2016). However, we also calculate headcount resilience rate using 0.8 for sensitivity.

between the Original and control groups in Figure 6 are significantly higher in magnitude than the difference-in-differences treatment effects. We observe a similar pattern even after increasing the resilience threshold to 0.8 and changing distribution and functional form of the asset holding (Figure 8).

Although the POG households are significantly more likely (24.3%: Table 3) to be asset non-poor compared to the controls 18 months post-intervention, the resilience headcount rates between the two groups are almost identical (18.2% vs. 17.5%: Figure 6). This is likely happening because a relatively high number of POG households are observed just above the asset poverty threshold with sufficient assets to be classified as asset non-poor but with insufficient probability of holding onto assets above the threshold in the future to be classified as resilient. In order to investigate this possibility, we report Kernel density household asset distribution over time by treatment status in Figure 7 (Panel A). While more control households are likely to be observed above the threshold at the baseline compared to the POGs, the pattern reverses after 18 months, which is likely to generate significant positive treatment effects on POGs in the difference-in-difference estimations. However, we see no such clear pattern in resilience score distribution among control and POG households that are above the resilience threshold (Figure 7: Panel B). Moreover, among the asset non-poor households at 18 months post-baseline, significantly fewer POG households are development resilient compared to their control counterparts (37.0% vs 42.9% results not shown). In such scenarios, the standard static measurements such as asset poverty headcount might be misleading as they fail to incorporate households' level of vulnerability to poverty. The resilience measure, on the other hand, provides the likelihood of one's future outcome relative to the threshold given its present status. Hence, resilience measurement yields more insight about households' capacity to escape or remain out of poverty.

6.3 Robustness Check

In this subsection we re-estimate the program's marginal treatment effects on resilience using an alternative functional form, an alternative distributional assumption and an alternative estimation technique. We present these results in Table 5. Column 1 presents the program impacts assuming the polynomial lagged asset to be quadratic i.e. $k = 2$ to incorporate the single-steady- state equilibrium poverty trap discussed in Section 2.2. Column 2 presents the estimates assuming W_{t-1} to

be normally distributed. Both sets of the estimates are comparable (in significance and magnitude) to the initial results presented in Table 4. Additionally, we estimate effects on resilience using OLS and again find results to be consistent with the earlier estimates. Figure 8 presents headcount asset resilience rates using alternative resilience thresholds. Figure 8a and Figure 8d are resilience rate using $\bar{R} = 0.8$ as the resilience cutoff i.e. a household is development resilient only if its resilience measure is above 0.8 ($\rho_{it} > 0.8$) assuming W_{t-1} to be distributed gamma and normal respectively. As expected, the count of resilient households decreases across the treatment groups and over-time (about 20% less) in both methods. Originals, nonetheless, are the most resilient across all survey waves. Functional form and distribution assumptions appear to be of no significance in the resilience rate calculation for our estimations. While Figure 8b shows the headcount resilience rates using the quadratic functional form, Figure 8c shows the headcount rates assuming a normal distribution. Estimates of the number of asset resilient households across the treatment groups in both specifications are consistent with the initial estimates. The estimated program impacts on asset resilience are robust across the choices of threshold, functional form, distributional assumption and estimation technique.

7 Mechanism

We find that a time-limited integrated asset transfer program led to sustained gains in household consumption, income, asset holdings, and resilience. While we find no evidence of a bifurcated growth path inducing a poverty trap, the conditions in the research site suggest a single low-level equilibrium in absence of the intervention. In this setting, a large one-time asset and skill transfer is likely to ease households' capital and skill constraints and shift their growth curve in a northeast direction, which represents improvements both in wellbeing and resilience. Similarly, the program is likely to help households' transition to more remunerative technologies, which, again, improves wellbeing and resilience. Lack of access to capital alone, however, is not a sufficient condition to keep poor in persistent poverty if they can sell their labor optimally. While the poor are generally endowed with labor but few productive assets, imperfections in rural labor markets can prevent them from fully utilizing their labor resources and prompts them to accept low-paying casual jobs (Bardhan, 1984; Drèze, 1988; Rose, 2001; Banerjee and Duflo, 2007; Kaur, 2014; Bandiera et al.,

2017). A one-time productive asset transfer and training program, however, is likely to break the barriers the rural poor face in accessing capital, facilitating entry into higher return activities and moving them from a low-level growth path to a higher level one (Bandiera et al., 2017).

The program analyzed here intended to use livestock transfer and training to enable households to engage in more capital intensive self-employment. Analysis of adults' occupation choices and households' income from different streams can reveal whether change in labor allocation was actually part of the mechanism by which this program achieved impact. Table 6 shows that the program prompted households to take on self-employment activities and leave casual labor. Adult women in the Original households are 20.4% and 16.2% (23.6% increase relative to the baseline) more likely to be engaged in self-employment 36 and 42 months after the intervention. Additionally, three and half years after the baseline, Original households have decreased participation in casual labor employment by 7.5% – a decrease of 157.7% since the baseline relative to controls.

Three years after the baseline, quarterly income from selling livestock products and cattle increases by 821% among Originals - an increase of USD 111 relative to controls, which is significantly greater than the one-year increase of USD 64.6. Although statistically insignificant, POG households also experience increases in their quarterly income from livestock rearing (USD 72) in the three years since baseline relative to control households. In addition to increased income from livestock, the results show treated households shift out of paid employment – relative to the controls both the Originals' and POGs' paid income decreases in both the periods. The results for total revenue show, the shifts out of casual employment into livestock activities led to substantial increases in household revenues. Overall, these results suggest that the transfer of livestock and skills helped remove the barriers to entry into higher return labor activities which is consistent with a more stable asset base and greater resilience.

8 Cost-Benefit Analysis

A number of observers have called for increased attention to the costs of achieving impacts associated with asset transfers. Table 7 presents conventional benefit-cost measures for project assessment and extends them to indicate the cost of achieving increases in resilience. Details of cost-benefit calculation are presented in the Online Appendix. In total, the direct cost of the program

amount to USD 1853 per household – 1629 for livestock and 224 for equipment and supplies. Most of the program costs, however, are indirect and related to supervision and program implementation (USD 2474 per household), which are spread over the duration of the program. Costs include staff wages, and salary support for veterinarians and agricultural experts for the duration of the program. Additionally, indirect costs include training, evaluation, travel and vehicle operation and other office expenses. The total program cost is USD 5009 per household for the full duration of the program. Compared to similar programs, this cost is higher than the BRAC program, USD 1363 (Bandiera et al., 2017), but comparable to the six Graduation programs, ranging from USD 1455 to 5962 (Banerjee et al., 2015).

Following Banerjee et al. (2015) and Bandiera et al. (2017) gains in household nondurable consumption are the core benefit measure. Estimated changes in household consumption expenditures are calculated by multiplying the weekly treatment impacts with average household size (7.1 in year one and 6.3 in year three) times 52. Year two impacts are assumed to be equal to the gains in year one. Similarly, we assume year three consumption gains to persist after the third year through year 20 and we report net present value of future gains in year four and beyond. We add year 3 asset gains and the total benefits amount to USD 22299 over the 20 year time horizon. Additional indirect benefits such as gains in human capital through better nutrition, increase school expenditure on children etc., however, are not accounted for in the analysis. Similarly, the program promotes social cohesion and learning; the potential gains through these avenues are difficult to capture. Our benefit analysis, therefore, underestimates true program benefits.

Row 7 shows the benefit ratio of the program, which is obtained dividing the total benefit by the total program cost. On average the benefit from the program is 4.45 times higher than its cost. The ratio is comparable to the findings from other livestock transfer programs. It is slightly higher than the ratios reported in Banerjee et al. (2015) (ranges from 2.6 to -1.9) and in Bandiera et al. (2017), which is 3.21. The ratio of benefit to cost is robust to different values of the discount rate and different time horizons.

Row 8 presents the calculated internal rates of return (IRR), which are based on the estimated changes in household nondurable consumption expenditures and calculated as the discount rate at which the net present value of the benefits are equal to the program cost. We follow Bandiera et al. (2017) and assume these gains last for a period of 20 years. The IRR is 24% at the mean –

clearly exceeding the formal lending interest rate of 12.1% at the beginning of the project(World Development Indicators, 2017).[16] This implies that the household in rural Zambia can finance these high-return activities if provided the access to formal credit. The IRR is robust to different values of the social discount rate and different program benefit time-horizons.

Panel C in Table 7 focuses on the cost of improving the resiliency headcount by one percent at different resiliency cutoffs. Costs are calculated as total transfer value divided by the gains in resiliency headcount rate (see Online Appendix). The original transfer value of USD 2145 (USD 1853 inflated to year 3) helped increase headcount resiliency by 20.8% among the treated group (Original + POG) compared to the control group at the 0.8 resiliency cutoff 18 months post-intervention. If households are distributed uniformly over asset-holding, an investment of USD 103 into the program moves 1% of the non-resilient households into resiliency after 18 months of the investment, such that they have less than a 20% probability of falling into poverty in the future.[17] Consistent with the treatment effects (Table 2), the cost of increasing headcount resiliency by 1% decreases after three and half years (USD 84) – as transfers become more productive and/or higher number of the POGs receive transfers over-time, greater number of treated households become resilient. As expected, the cost is lower at the 0.5 resilience cutoff - USD 100 and USD 58 at 18 and 42 months post-transfer, respectively.

9 Discussion and Conclusions

This paper implements a quantifiable measure of household resilience and demonstrates its application and relevance in the context of an impact evaluation. Results from the impact evaluation find that a one-off transfer of assets and training increased household development resilience; the intervention shifted the conditional transition distribution of households' asset holdings upward, increasing expected asset holdings and decreasing conditional variance. Findings demonstrate that attention to conditional variance in impact on assets provides important insights into program

[16] Internal rates of return are heterogeneous across livestock transfer programs. While the rate varies from 6.9% to 23.4% in the six Graduation pilots (Banerjee et al., 2015),Bandiera et al. (2017) report the rate of 22% for BRAC program in Bangladesh. The IRR for cash transfer programs are similar to the livestock transfer programs.Blattman et al. (2016) report IRR of 24% for a cash transfer of USD 150 towards non-farm self-employment activities along with training and follow-up supervision to ultra-poor in post-war Uganda.

[17] For this to hold households either have equal livestock rearing abilities or the abilities are orthogonal to the baseline asset-holding. Since, all households (treated and control) self-select themselves into the program and quasi-random treatment assignment means, on average, livestock rearing abilities between the groups are equal.

effectiveness and persistence of estimated effects.

Resilience as a household outcome offers three important advantages for impact analysis. First, by estimating the impacts of interventions on the first moment of household welfare only, most analyses fail to countenance the possibility of changes in the higher moments, in particular the introduction of increased or diminished uncertainty in welfare outcomes. In contrast, the development resilience measure estimates the full distribution of household welfare, providing a more complete picture of intervention impacts and yielding insights into household capacity to mitigate future risks and avoid falling into poverty in the foreseeable future. These inferences are especially significant for households at or near the poverty threshold. Though such households may be classified as non-poor in measurements such as a poverty headcount, resilience quantifies the likelihood that they will stay out of poverty. Our finding that a substantial share of households in the analysis are asset non-poor and yet not resilient illustrates this point. Resilience measurement yields policy-relevant insights into household wellbeing that other measures miss.

Second, because conventional methods proxy inter-temporal variation in endline household status, they offer only limited insight into longer-term household welfare. In contrast, the resilience estimation implemented in this paper exploits inter-temporal variance in prior periods to predict future outcomes based on estimated poverty dynamics. Third, central to poverty traps theory is the possible existence of nonlinear welfare path dynamics. With regard to policy, such dynamics have important implications, most notably that one-time "big-push" interventions can indeed foster a sustainable trajectory out of poverty. While the impact evaluation literature largely ignores the possibility of such nonlinear dynamics, the concept of resilience, rooted in poverty trap theory, takes into account the potential importance of such nonlinearities, with vital relevance to intervention analysis and development policy design.

Even so, measurement of development resilience as proposed by Barrett and Constas (2014) and implemented here does have important limitations. First, the measure is sensitive to assumptions governing its estimation. Central to quantifying development resilience is the estimation of higher order moments of the welfare distribution using techniques from Just and Pope (1979) and Antle (1983) and the method relies on the goodness-of-fit of the first moment regression equation. The resilience estimate is therefore sensitive to the choice of explanatory variables. Moreover, the measure could have a perverse implication: for a household with a mean asset level just below

the poverty threshold, increasing variability would raise measured resilience. Finally, the method applied here is data intensive, as multiple rounds of follow-up data are required to estimate the probability distributions on wealth. Nonetheless, at different levels of population aggregation, the concept of development resilience and its measurement complement and in many cases serve as an improvement over conventional impact evaluations focused only on first-moments of outcomes.

Given the expectation of increasingly frequent natural disasters, unstable weather patterns, macroeconomic shocks, and other humanitarian emergencies, anti-poverty interventions will continue to focus on bolstering the capacity of poor households to mitigate risks and on encouraging the poor to shift to more secure and remunerative activities. Our resilience estimation results suggest that the multifaceted approach focused on improving wellbeing through transfers, decreasing downside risk and changing underlying structural barriers to economic progress, can have lasting impact on households' ability to accumulate and retain productive assets and to withstand covariate and idiosyncratic shocks. We argue, moreover, that resilience theory can serve to guide development practitioners in the design and evaluation of future anti-poverty programs. Our findings suggest that standard impact evaluation measurements are insufficient to establish households' resilience against future poverty spells and should be complemented, where possible, by estimation and evaluation of higher moments of the household welfare distribution. Researchers and practitioners interested in understanding and evaluating household will need to rethink their impact evaluation plans by, for example, shifting to the collection of high-frequency data over longer time periods. The contributions in terms of policy design and assessment could be considerable and are important areas of future work.

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Table 1: Baseline Characteristics and Balance

	Means (SD)			Test of equality of means [P-val]		Normalized differences	
	(1) Original	(2) POG	(3) Control	(4) Original= Control	(5) POG= Control	(6) Original - Control	(7) POG - Control
A. Household Characteristics							
Head is female	0.283	0.252	0.209	0.267	0.506	0.121	0.072
	(0.453)	(0.436)	(0.410)				
Head is illiterate	0.057	0.090	0.030	0.385	0.081	0.093	0.180
	(0.232)	(0.288)	(0.171)				
Joint F-test of treatment on all variables [P-val]				0.441	0.294		
B. Household Assets							
Herd size (TLU)	1.162	0.741	1.233	0.849	0.173	-0.022	-0.156
	(1.930)	(1.797)	(2.595)				
Total Asset (Per Capita)	382.054	222.757	460.133	0.453	0.013	-0.085	-0.294
	(551.714)	(346.283)	(728.025)				
Joint F-test of treatment on all variables [P-val]				0.586	0.009		
C. Poverty and Household Expenditure							
Total per capita expenditure	12.872	13.340	18.298	0.003	0.007	-0.341	-0.306
	(9.574)	(10.028)	(12.693)				
Below 1.90 USD PPP Poverty Line	0.623	0.622	0.418	0.008	0.008	0.294	0.293
	(0.487)	(0.487)	(0.497)				
Joint F-test of treatment on all variables [P-val]				0.006	0.012		
D. Household revenue and Saving							
Total Revenue	527.539	543.884	1083.991	0.103	0.114	-0.197	-0.191
	(724.437)	(768.995)	(2727.464)				
Bank account	0.113	0.054	0.149	0.502	0.052	-0.075	-0.224
	(0.318)	(0.227)	(0.359)				
Joint F-test of treatment on all variables [P-val]				0.133	0.029		

Notes: All data refers to the baseline survey. Columns 1, 2 and 3 report means with standard deviation in parentheses by household's treatment status. Columns 4 and 5 report the p-value of the test of equal means. Columns 6 and 7 report normalized differences computed as the difference in means in treatment and control villages divided by the square root of the sum of the variances. Household total assets refer to value of livestock, durables, agricultural tools, and livestock equipment divided by the household size. The poverty line threshold used is USD 1.90 PPP per person per day, as measured in 2012 prices. The household expenditure items covered are: food, clothing, household durables, schooling, medical, alcohol-tobacco, fuel and other home expenditures. Household revenue refers to the value revenue from livestock, agriculture, paid income and revenue from other micro enterprises. At the foot of each Panel we report the p-value associated with the average standardized difference, defined as in Kling et al. (2007). All monetary amounts are PPP-adjusted USD terms and are deflated using CPI to 2012 prices using PPP and CPI published by the World Bank. In 2012, 1 USD = 2.5 Kwacha PPP.

Table 2: Treatment Effects on Productive Asset

	(1) Herd size (TLU), per household	(2) Livestock value, per capita	(3) Total asset value, per capita	(4) Revenue from livestock, per capita per quarter
Time 1 Original (18 months post treatment)	0.99***	460.60***	477.12***	64.56*
	(0.24)	(73.04)	(99.95)	(34.53)
Time 1 POG (18 months post treatment)	0.46**	173.77***	279.29***	36.97
	(0.20)	(55.15)	(87.61)	(34.61)
Time 2 Original (42 months post treatment)	1.11***	497.10***	495.75***	110.74**
	(0.35)	(89.22)	(114.51)	(46.56)
Time 2 POG (42 months post treatment)	1.03***	305.45***	294.46***	72.09
	(0.35)	(59.62)	(89.79)	(46.42)
Baseline mean	1.201	190.4	397.9	13.48
Time 2 impact: % change Original	92	261.1	124.6	821.6
Time 1 impact = Time 2 impact [p-value]	0.738	0.601	0.825	0.0365
Adjusted R-squared	0.218	0.233	0.145	0.045
Observations	741	741	741	741

Notes: *** (**) (*) indicates significance at the 1% (5%) (10%) level. Treatment on the treated estimates are reported based on a difference-in-difference specification estimated using OLS. All outcomes are measured at the household level. All the estimation regress the outcome of interests for household i in survey wave T on a constant, dummies for two treatment groups, interaction between each treatment assignment dummy and each survey wave dummy, and set of household fixed effects. Standard errors are clustered at the household level. The coefficients shown are those on the treatment-survey wave interaction terms. Time 1 and time 2 refer to 18 and 42 months post-intervention except in column 4, where they refer to 12 and 36 months post-intervention. In Column 1, herd size is measured in tropical livestock units (TLU) which assigned value of 0.7 for adult cattle, 0.5 for immature cattle, and 0.1 for a sheep or a goat. Livestock value (Column 2) is the value of the household's herd size. Values in column 3 include herd, household durables, agricultural and livestock tools. All monetary amounts are PPP-adjusted USD terms and are deflated using CPI to 2012 prices using PPP and CPI published by the World Bank. In 2012, 1 USD = 2.5 Kwacha PPP.

Table 3: Treatment Effects on Consumption Expenditure, Food Security, and Asset Poverty

		Per Capita Consumption				
	(1) Below Poverty Line	(2) Food (last week)	(3) Nonfood (avg weekly)	(4) Total (avg weekly)	(5) Enough Food	(6) Asset Non-poor
Time 1 Original (12 months post treatment)	-0.220**	1.59	1.75	3.34	0.182***	0.470***
	(0.088)	(1.41)	(1.28)	(2.11)	(0.060)	(0.088)
Time 1 POG (12 months post treatment)	-0.029	-0.91	1.36	0.45	0.111*	0.243***
	(0.087)	(1.42)	(1.10)	(2.03)	(0.060)	(0.082)
Time 2 Original (36 months post treatment)	-0.314***	3.72***	3.75***	7.47***	0.213***	0.390***
	(0.086)	(1.40)	(1.27)	(2.11)	(0.075)	(0.091)
Time 2 POG (36 months post treatment)	-0.059	0.16	1.48	1.64	0.155**	0.384***
	(0.085)	(1.32)	(1.04)	(1.96)	(0.070)	(0.087)
Baseline mean	0.625	6.480	6.238	12.72	0.750	0.302
Time 2 impact: % change Original	-50.32	57.48	60.12	58.77	28.44	129.1
Time 1 impact = Time 2 impact [p-value]	0.299	0.282	0.0653	0.121	0.523	0.277
Adjusted R-squared	0.025	0.070	0.032	0.040	0.125	0.216
Observations	741	741	741	741	741	741

Notes: *** (**) (*) indicates significance at the 1% (5%) (10%) level. Treatment on the treated estimates are reported based on a difference-in-difference specification estimated using OLS. All outcomes are measured at the household level. All the estimation regress the outcome of interests for household i in survey wave T on a constant, dummies for each survey wave, dummies for two treatment groups, interaction between each treatment assignment dummy and each survey wave dummy, and set of household fixed effects. Standard errors are clustered at the household level. The coefficients shown are those on the treatment-survey wave interaction terms. Time 1 and time 2 refer to 12 and 36 months post-intervention except in column 6, where they refer to 18 and 42 months post-intervention. In Column 1, the poverty line threshold used is USD 1.90 PPP per person per day, as measured in 2012 prices. Column 2 is per person food expenditure in the last seven days from own production, purchased and gift. In Column 3, nonfood expenditure includes average weekly per person expenditures on clothing, household durables, schooling, medical, alcohol-tobacco and other home expenditures. Column 4 is total of food and nonfood weekly expenditures. Column 5 is an indicator variable for subjective food security, which takes the value of 1 if the survey respondent think the household usually or always have enough food to feed all the members. Asset non-poor in column 6 is an indicator variable that takes the value of 1 if total household asset value is above 308 USD PPP per person, 0 otherwise. The asset poverty threshold calculation is discussed in the Online Appendix. We report the baseline mean of each dependent variable of the Original group. In all columns we report the p-value on the null hypothesis that the impact on Original at time 1 and time 2 are equal. All monetary amounts are PPP-adjusted USD terms and are deflated using CPI to 2012 prices using PPP and CPI published by the World Bank. In 2012, 1 USD = 2.5 Kwacha PPP.

Table 4: Treatment Effects on Household Resilience

	Originals (OG)			Pass on the Gift (POG)			
	18 Months	36 Months	42 Months	18 Months	36 Months	42 Months	Observations
Panel A:							
Development resilience	0.228***	0.145***	0.167***	0.192***	0.111**	0.110*	741
	(0.0563)	(0.0512)	(0.0627)	(0.0536)	(0.0470)	(0.0564)	
Control group resilience mean	0.26	0.351	0.379				
Impact: % change	87.7	41.3	44.1	73.8	31.6	29.0	
Round impact = round 4 impact [p-value]	–	0.365	0.517	–	0.381	0.384	
Panel B:							
First Moment (Mean)	0.591***	0.350***	0.341***	0.490***	0.330**	0.289**	741
	(0.142)	(0.131)	(0.128)	(0.166)	(0.141)	(0.140)	
Panel C:							
Second Moment (Varience)	-0.365**	-0.0929	-0.404**	0.258	0.228	-0.175	741
	(0.161)	(0.159)	(0.179)	(0.198)	(0.160)	(0.192)	

Notes: *** (**) (*) indicates significance at the 1% (5%) (10%) level. Each panel in the table represents a separate regression. Panel A reports marginal treatment effects estimated using generalized linear model (GLM) with binomial family and logit link function. Panel B and C show marginal treatment effects for mean and variance respectively, which are estimated using GLM with Poisson family and log link function. Each estimation regresses the outcome of interest for household i in survey round t on a constant, dummies for each survey rounds, the interaction between each treatment assignment dummy and each survey wave dummy, cubic polynomial of a first-lagged outcome and time t household characteristics (head is female, household size, head is married head age, head education level and number of children under 5). The coefficients shown are those on the treatment-survey wave interaction terms, which is the difference between the treatment and control means for that survey wave. Bootstrapped household level cluster standard errors using 400 replications are in parenthesis. Development resilience in Panel A is the probability that the household's value of total assets is above the asset threshold of 308 USD PPP per capita. Expected asset in each period is assumed to follow gamma distribution with first and second moments estimated from path dynamic equations using GLM with Poisson family and log link function. Asset includes livestock, bicycle, radio, television, solar panel , motorbike, bed, hoes, sickle, shovel, slasher, pangas, mortar, sieve, wheel barrow, sprayer, maize sheller, grain mill, oil press, axe, ox yoke, ox plough, ox cart, livestock shed, feeder, chaff cutter, fencing, milking buckets and chairs, salt/mineral feeder and ripper/cultivator. In Panel A, we report the mean resilience of the control group for each survey wave and p-value on the null hypothesis that the later periods (36 and 42 months) are equal to the earlier period (18 months) impact. All monetary amounts are PPP-adjusted USD terms and are deflated using CPI to 2012 prices using PPP and CPI published by the World Bank. In 2012, 1 USD = 2.5 Kwacha PPP.

Table 5: Treatment Effects on Household Resilience - Robustness Checks

			OLS	
	Gamma ($k = 2$)	Normal ($k = 3$)	Gamma ($k = 3$)	Normal ($k = 3$)
Time 1 Original (18 months from baseline)	0.237***	0.226***	0.228***	0.225***
	(0.0567)	(0.0563)	(0.0573)	(0.0575)
Time 1 POG (18 months from baseline)	0.186***	0.198***	0.179***	0.185***
	(0.0534)	(0.0556)	(0.0518)	(0.0540)
Time 2 Original (36 monhts from baseline)	0.157***	0.143***	0.137***	0.136***
	(0.0514)	(0.0510)	(0.0516)	(0.0514)
Time 2 POG (36 monhts from baseline)	0.118**	0.116**	0.110**	0.114**
	(0.0469)	(0.0480)	(0.0476)	(0.0486)
Time 3 Original (42 months from baseline)	0.167***	0.162**	0.156***	0.151**
	(0.0629)	(0.0629)	(0.0600)	(0.0603)
Time 3 POG (42 months from baseline)	0.113**	0.108*	0.111**	0.110*
	(0.0561)	(0.0576)	(0.0563)	(0.0574)
Test of Equality of Impacts [p-value]				
Original: Time 1 = Time 2	0.381	0.368	0.000	0.000
Original: Time 1 = Time 3	0.456	0.496	0.000	0.000
POG: Time 1 = Time 2	0.460	0.373	0.000	0.000
POG: Time 1 = Time 3	0.437	0.342	0.000	0.000
Observations	741	741	741	741

Notes: *** (**) (*) indicates significance at the 1% (5%) (10%) level. Each column in the table represents a separate regression. Column 1 reports marginal treatment effects estimated using generalized linear model (GLM) with binomial family and logit link function with polynomial lagged asset to be quadratic ($k = 2$) in the path dynamics equation. Column 2 shows marginal treatment effects estimated using GLM with binomial family and logit link function assuming conditional transition distribution function to be normal. Columns 3 and 4 show treatment effects from OLS assuming conditional transitional distribution function to be gamma and normal respectively. Each estimation regresses the outcome of interest for household i in survey round t on a constant, dummies for each survey rounds, the interaction between each treatment assignment dummy and each survey wave dummy, cubic polynomial of a first-lagged outcome and time t household characteristics (head is female, household size, head is married head age, head education level and number of children under 5). The coefficients shown are those on the treatment-survey wave interaction terms, which is the difference between the treatment and control means for that survey wave. Bootstrapped household level cluster standard errors using 400 replications are in parenthesis. Development resilience refers to the probability that the household's value of total assets is above the asset threshold of 308 USD PPP per capita. First and second moments estimated from path dynamic equations using GLM with Poisson family and log link function. Asset includes livestock, bicycle, radio, television, solar panel , motorbike, bed, hoes, sickle, shovel, slasher, pangas, mortar, sieve, wheel barrow, sprayer, maize sheller, grain mill, oil press, axe, ox yoke, ox plough, ox cart, livestock shed, feeder, chaff cutter, fencing, milking buckets and chairs, salt/mineral feeder and ripper/cultivator. In each column, we report the p-value on the null hypothesis that the later periods (36 and 42 months) are equal to the earlier period (18 months) impact. All monetary amounts are PPP-adjusted USD terms and are deflated using CPI to 2012 prices using PPP and CPI published by the World Bank. In 2012, 1 USD = 2.5 Kwacha PPP.

Table 6: Treatment Effects on Employment and Income

			Per Capita Revenue and Income		
	(1) Self Employment	(2) Casual Labor	(3) Total Revenue	(4) Live-stock	(5) Paid Income
Time 1 Original (12 months post treatment)	0.204***	-0.043	541.23	64.56*	-2.52
	(0.070)	(0.041)	(332.63)	(34.53)	(7.97)
Time 1 POG (12 months post treatment)	0.107	0.003	429.10	36.97	1.79
	(0.076)	(0.039)	(333.68)	(34.61)	(8.84)
Time 2 Original (36 months post treatment)	0.162**	-0.075*	723.99*	110.74**	-16.85
	(0.068)	(0.039)	(368.88)	(46.56)	(14.04)
Time 1 POG (36 months post treatment)	0.122	-0.018	400.46	72.09	-24.56*
	(0.078)	(0.039)	(368.21)	(46.42)	(13.88)
Baseline mean	0.696	0.0476	523.1	13.48	0.536
Time 2 impact: % change	23.27	-157.7	138.4	821.6	-3147
Time 1 impact = Time 2impact [p-value]	0.560	0.470	0.199	0.0365	0.164
Adjusted R-squared	0.029	0.001	0.039	0.045	0.026
Observations	988	988	741	741	741

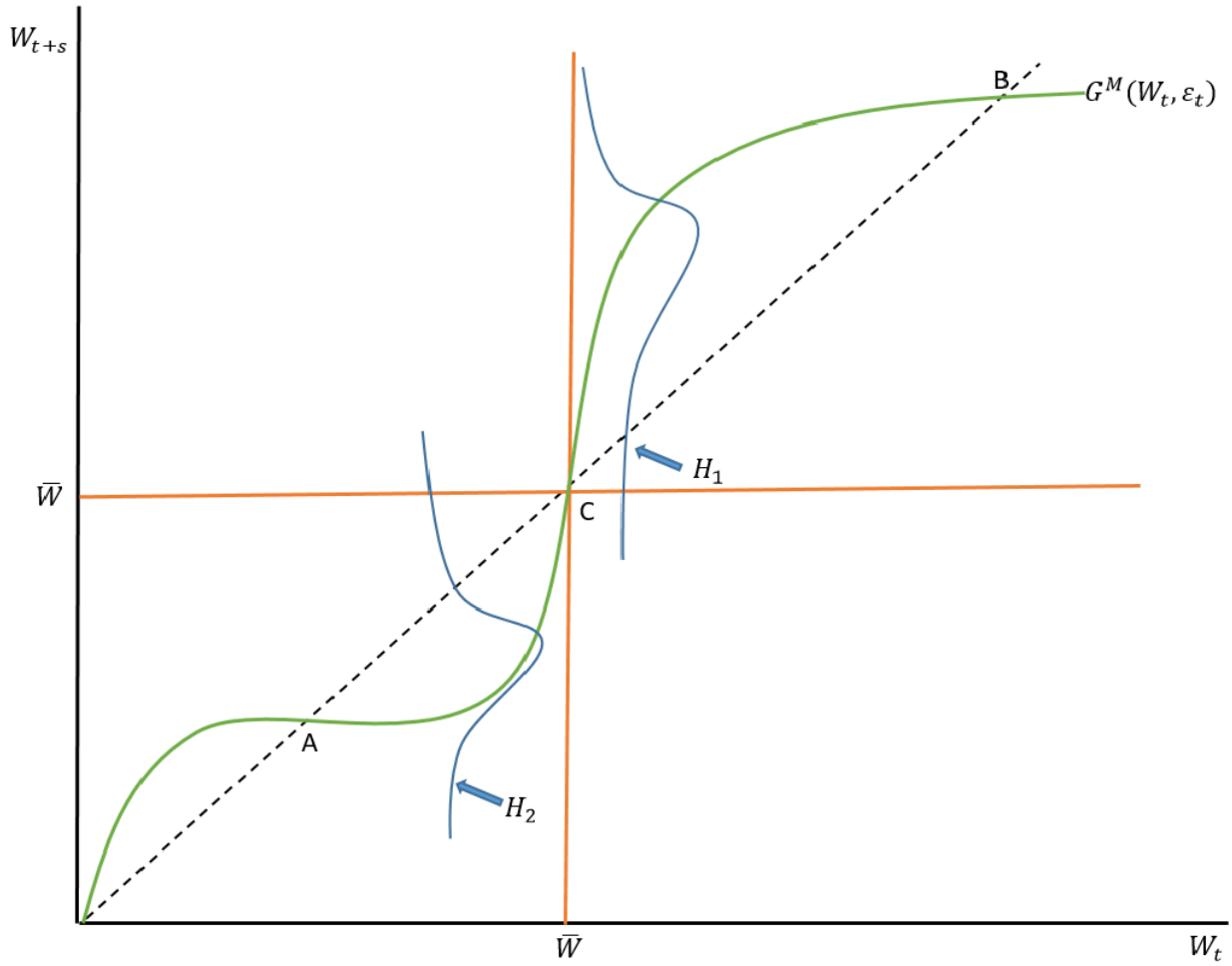
Notes: *** (**) (*) indicates significance at the 1% (5%) (10%) level. Treatment on the treated estimates are reported based on a difference-in-difference specification estimated using OLS. All outcomes are measured at the household level except (1) self employment and (2) casual labor, which are at individual level - women 18 to 65 years of age. All the estimation regress the outcome of interests for household h (or individual i living in household h) in survey wave T on a constant, dummies for each survey wave, dummies for two treatment groups, interaction between each treatment assignment dummy and each survey wave dummy, and set of household fixed effects. The coefficients shown are those on the treatment-survey wave interaction terms. Standard errors are clustered at the household level. Due to data limitation time 1 and 2 refer to 36 and 42 months post-intervention respectively in column 1 and 2. Self employment is defined as people reporting working on their own farms or non-farm enterprises as their main occupation. Casual laborers are those who reported selling their labor for farm or non-farm activities. Livestock revenue is the value of livestock and livestock products (milk, meat, eggs, hire out of draft animal, manure and other products) household sold in last 3 months. Paid income are wage income from labor (salaried or casual) in the last 3 months. Total revenue, column 3, is yearly income calculated adding yearly revenues from agriculture and livestock, paid income, micro-enterprise profits, remittance and other transfers last year. We report the baseline mean of each dependent variable of the Original group. In all columns we report the p-value on the null hypothesis that the impact on Originals at time 1 and time 2 are equal. All monetary amounts are PPP-adjusted USD terms and are deflated using CPI to 2012 prices using PPP and CPI published by the World Bank. In 2012, 1 USD = 2.5 Kwacha PPP.

Table 7: Cost-Benefit Analysis

Panel A. External parameters		
a Direct asset transfer costs at year 0		1853
b Training, salaries, supervision etc. at year 0		2474
c Total costs at year 0 (a+b)		4327
d Total costs discounted at year 3		5009
Social Discount = 5%		
Year 3 PPP Exchange = 2.94		
Panel B. Estimated Benefits		
1 Year 1 change in annual nondurable consumption expenditure		1293.9
2 Year 2 change in annual nondurable consumption expenditure, assuming treatment effect equal to year 1		1293.9
3 Year 3 change in annual nondurable expenditure		1418.3
4 From year 4 till year 20 NPV change in nondurable expenditure, assuming year 3 gains persist		15990.2
5 Year 3 change in asset value		2302.7
6 Total Benefits (1+2+3+4+5)		22299.0
7 **Benefits/Cost ratio** (assuming benefits last 20 years from transfer date)		**4.45**
Sensitivity to different time horizons/discount rates		
i *Benefits last 5 years post-intervention*		1.79
ii *Benefits last 10 years post-intervention*		2.90
iii *Social discount = 7%*		3.80
iv *Social discount = 10%*		3.07
8 **IRR** (assuming benefits last 20 years from transfer date)		**0.24**
i *Benefits last 5 years post-intervention*		0.10
ii *Benefits last 10 years post-intervention*		0.22
iii *Social discount = 7%*		0.23
iv *Social discount = 10%*		0.22
Panel C. Cost of increasing headcount resilient rate by 1%		
Resilience threshold cutoff	$\bar{R} = 0.5$	$\bar{R} = 0.8$
i Year 1 post-intervention	99.83	102.95
ii Year 3 post-intervention	58.22	83.64

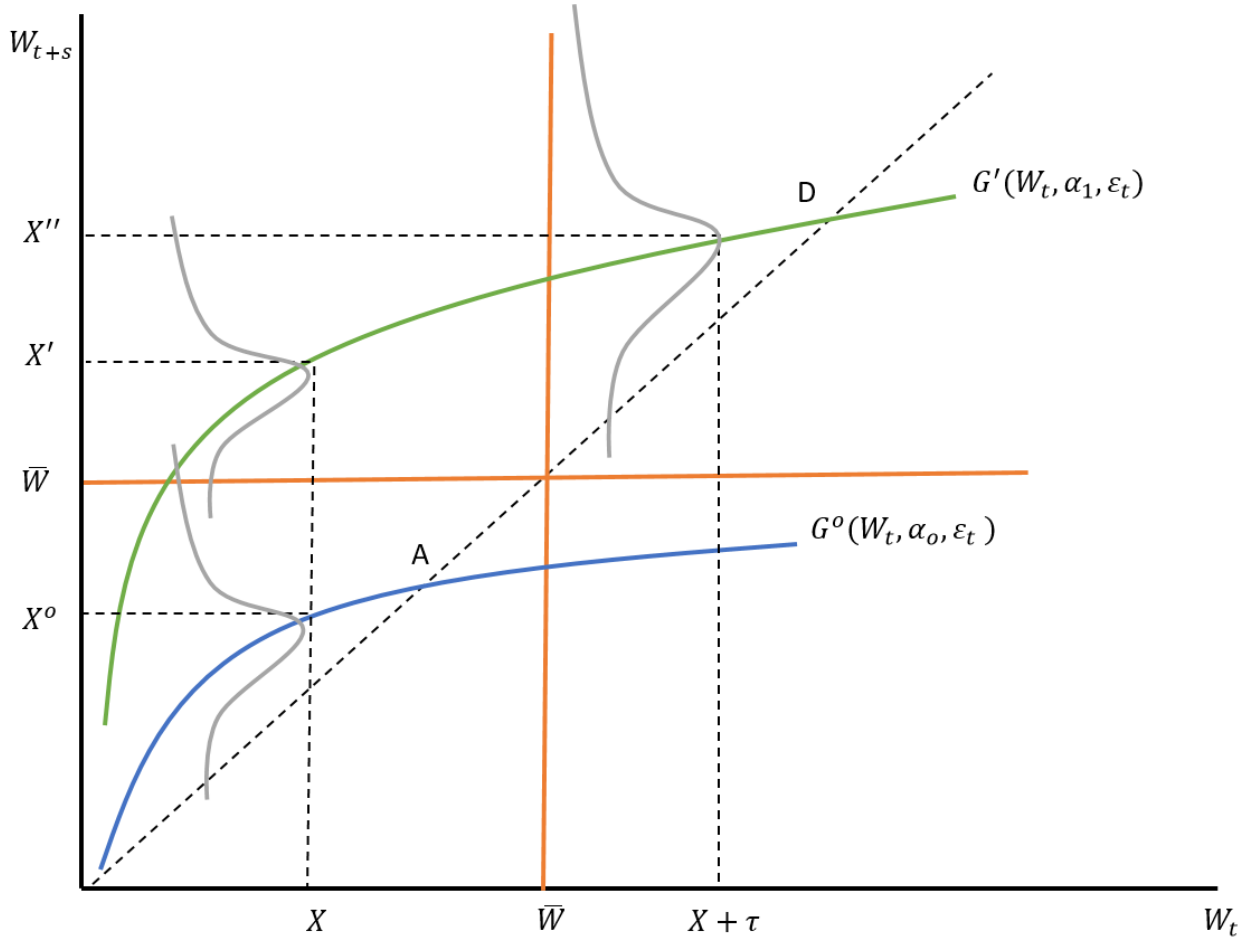
Notes: Panel A reports per household costs. Direct asset transfer cost equal to the value of livestock (1629 USD), horticulture (20 USD) and agricultural equipment and supplies (204 USD) transfers. Household nondurable consumption includes both food (own production and purchased) and nonfood expenditures (clothing, schooling, medical, alcohol-tobacco , transportation, cosmetics, fuel and other home expenditures). Annual changes in household consumption are calculated multiplying treatment effects with average household size in the year (7.1 in year one and 6.3 in year three) times 52. Assets equal the value of herd size, agricultural tools, durables and livestock equipment minus the value of transfer. Internal rate of return (IRR) is based on estimated nondurable consumption gains, assuming that these last for 20 years. Year 1 and year 3 in panel C refer to 18 and 42 months after the intervention respectively. Average cost of increasing head count resilience by a percent is the value of transfer divided by the gains in headcount resilient rate (see Online Appendix). All monetary amounts are PPP-adjusted USD terms and are deflated using CPI to 2012 prices using PPP and CPI published by the World Bank. In 2012, 1 USD = 2.5 Kwacha PPP.

Figure 1: Multiple Equilibria Wellbeing Dynamics with Conditional Transition Distributions



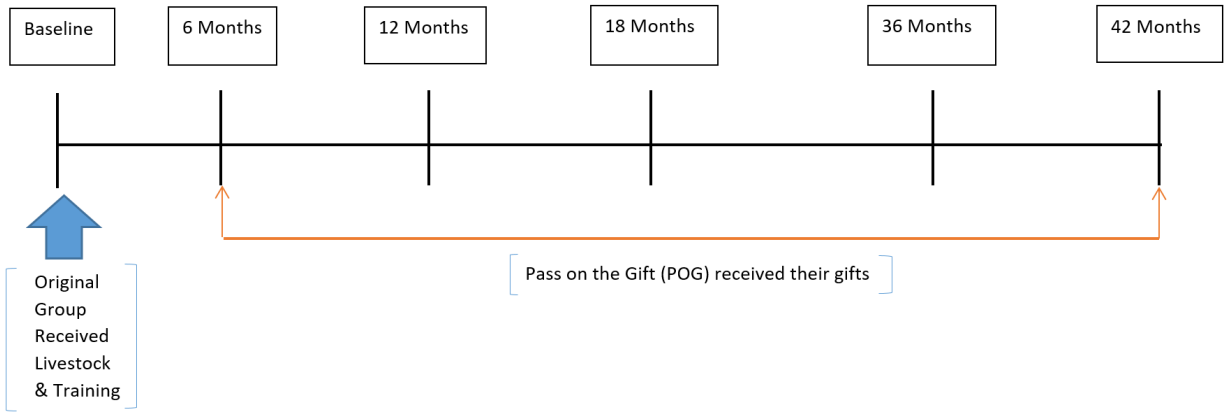
Notes: Adopted from Barrett and Constas (2014). Threshold, $\bar{W}$, represents both the dynamic poverty threshold and static poverty line. Point C is the point of inflection or the unstable dynamic equilibrium. Point A and B are long-run steady state poverty and non-poverty equilibrium respectively.

Figure 2: Single Equilibrium Wellbeing Dynamics with Conditional Transition Distributions



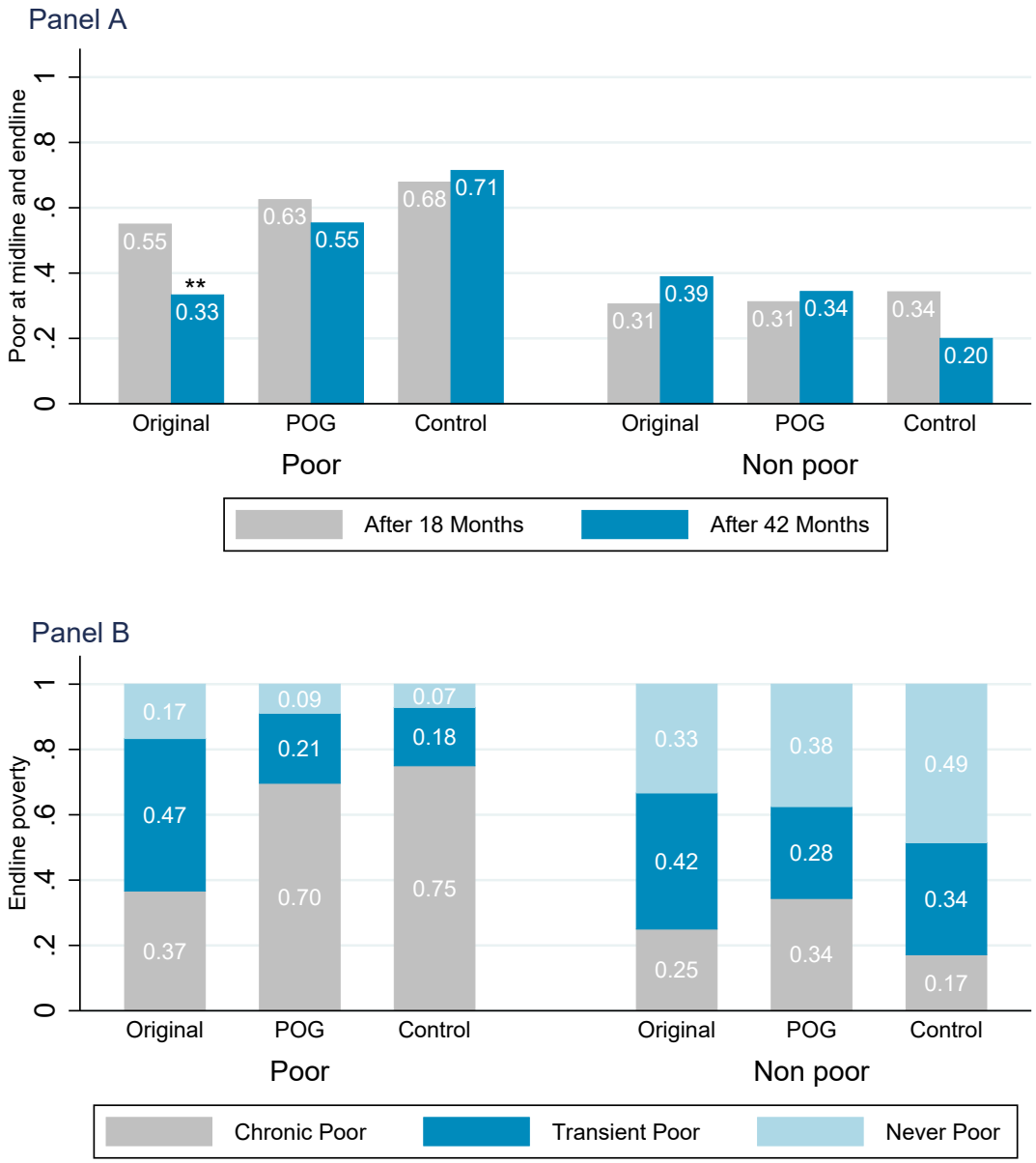
Notes: $\bar{W}$ is a minimum level of assets required to maintain consumption above the poverty line. Points A and D are long-run steady state equilibria associated with $G^o(W_t, \alpha_o, \varepsilon_t)$ and $G'(W_t, \alpha_1, \varepsilon_t)$ growth curves respectively.

Figure 3: Program and Survey Time Line



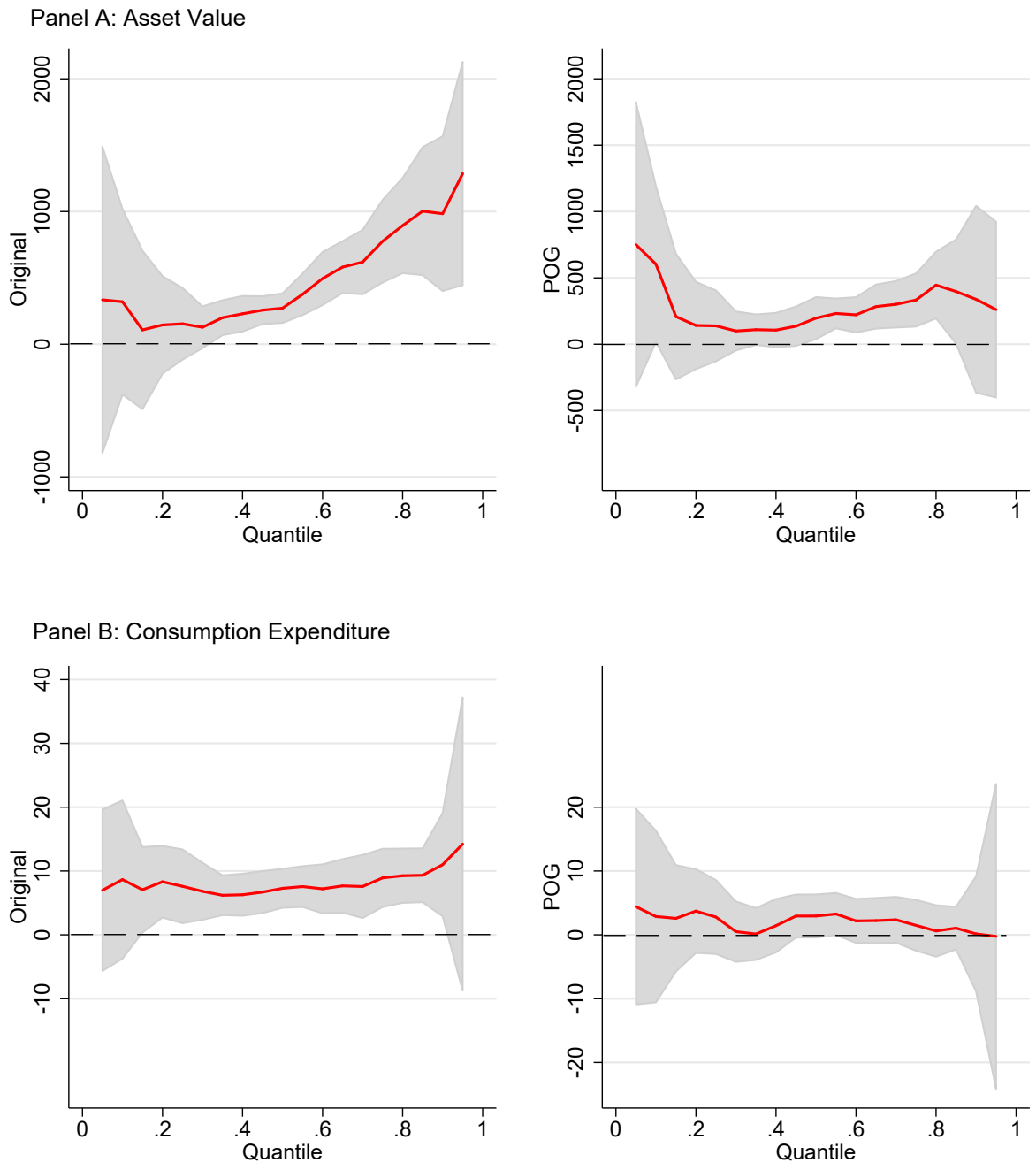
Notes: Baseline refers to January-February 2012. Timeline after the baseline represents the time when the follow-up surveys were conducted.

Figure 4: Poverty Transition



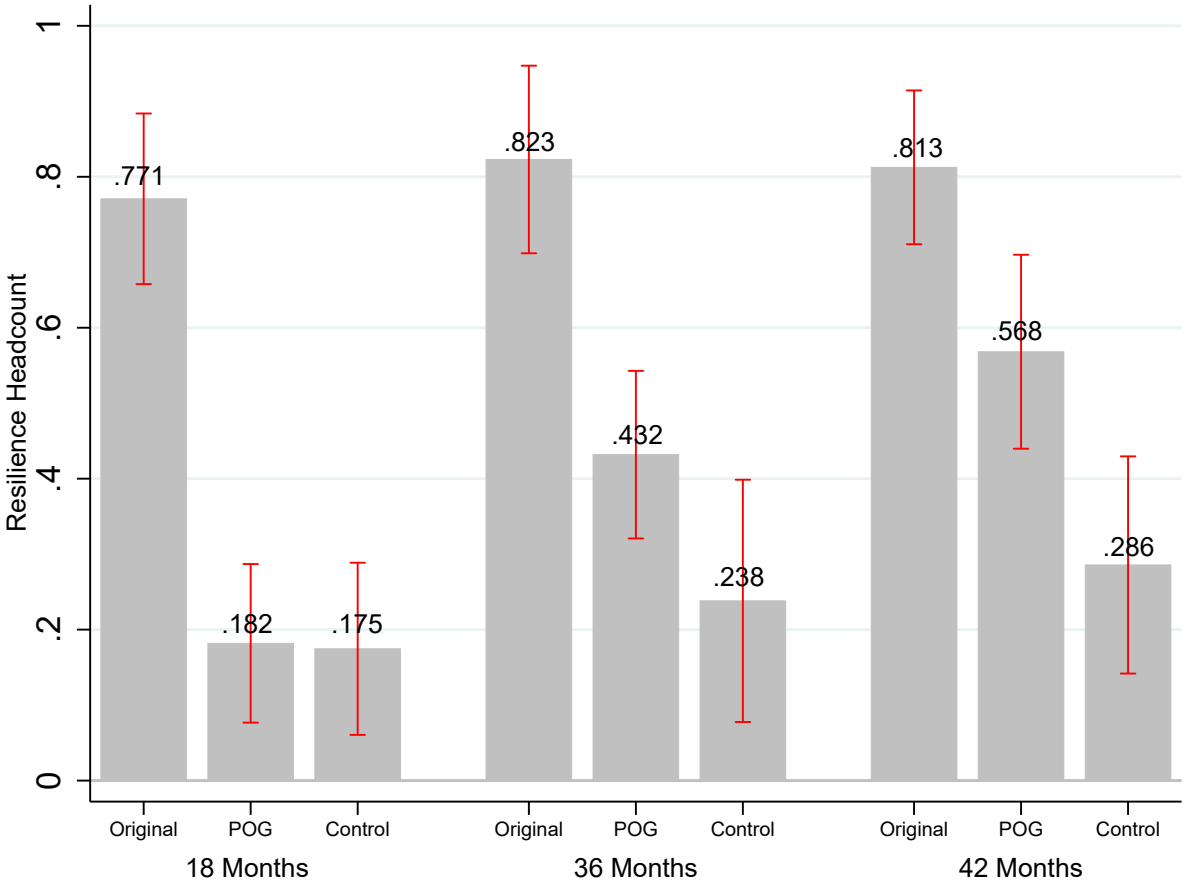
Notes: Figure shows endline poverty status (vertical-axis) conditioned on baseline poverty (horizontal axis) by treatment assignment. Baseline poverty status, poor or not poor on the the horizontal axis, is same for both panel A and B. Panel A shows headcount poverty rate for each baseline poverty-treatment assignment bean after 18 and 42 months. *** (**) (*) indicates significance at the 1% (5%) (10%) level for the test of equality of poverty rates between the two time periods. Poverty line threshold used is USD 1.90 PPP per person per day, as measured in 2012 prices. Panel B shows household's transition into chronic poor, transient poor or never-poor state for each baseline poverty-treatment assignment bean. While households with average expenditure in the last three waves of the survey (round 4,5 and 6) below the poverty line are define as chronic poor, transient poor are those whose average consumption over the three survey periods is above the poverty threshold but are observed below it at least once over that period. Never-poor are those who are observed above the poverty line in all three survey rounds. Expenditure includes both food (value of own production, purchased and gift in the last 7 days) and average weekly non-food expenditure (clothing, household durables, schooling, medical, alcohol-tobacco and other home expenditures). All monetary amounts are PPP-adjusted USD terms and are deflated using CPI to 2012 prices using PPP and CPI published by the World Bank. In 2012, 1 USD = 2.5 Kwacha PPP.

Figure 5: Three Year Quantile Treatment Effects



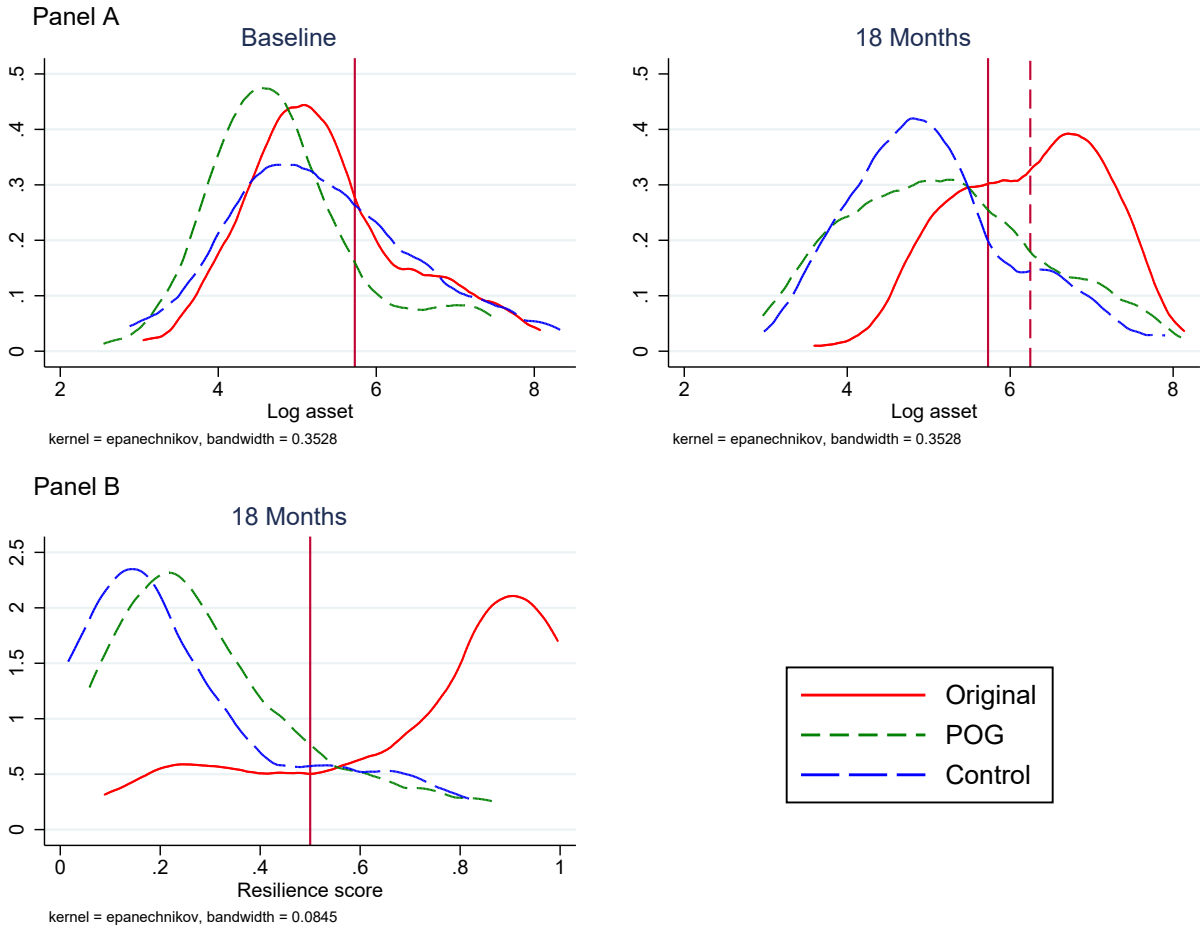
Notes: Quantile treatment effect (QTE) estimates of the differences in outcomes between three-year follow-up and baseline are presented in each panel. Bootstrapped 95% confidence intervals are using 400 replications. In Panel A,asset includes livestock, bicycle, radio, television, solar panel , motorbike, bed, hoes, sickle, shovel, slasher, pangas, mortar, sieve, wheel barrow, sprayer, maize sheller, grain mill, oil press, axe, ox yoke, ox plough, ox cart, livestock shed, feeder, chaff cutter, fencing, milking buckets and chairs, salt/mineral feeder and ripper/cultivato. In Panel B, consumption expenditures include both food (value of own production, purchased and gift in the last 7 days) and average weekly non-food expenditure (clothing, household durables, schooling, medical, alcohol-tobacco and other home expenditures). All monetary amounts are PPP-adjusted USD terms and are deflated using CPI to 2012 prices using PPP and CPI published by the World Bank. In 2012, 1 USD = 2.5 Kwacha PPP.

Figure 6: Headcount Resilience Rate (Gamma, $\bar{W} = 308$, $\bar{R} = 0.5$ and $k = 3$)



Notes: Bootstrapped 95% confidence intervals are calculated using 400 replications. Standard errors are clustered at household level. Household i at time t is classified as resilient if its probability of having asset value above the asset threshold of 308 USD PPP per capita ($\bar{W} = 308$) is greater than 0.5 ($\bar{R}$). Expected assets of each household in each round is assumed to follow gamma distribution with first and second moments estimated from path dynamic equations using GLM with Poisson family and log link function. Asset includes livestock, bicycle, radio, television, solar panel , motorbike, bed, hoes, sickle, shovel, slasher, pangas, mortar, sieve, wheel barrow, sprayer, maize sheller, grain mill, oil press, axe, ox yoke, ox plough, ox cart, livestock shed, feeder, chaff cutter, fencing, milking buckets and chairs, salt/mineral feeder and ripper/cultivato. We report the mean of the control group for each survey wave. All monetary amounts are PPP-adjusted USD terms and are deflated using CPI to 2012 prices using PPP and CPI published by the World Bank. In 2012, 1 USD = 2.5 Kwacha PPP.

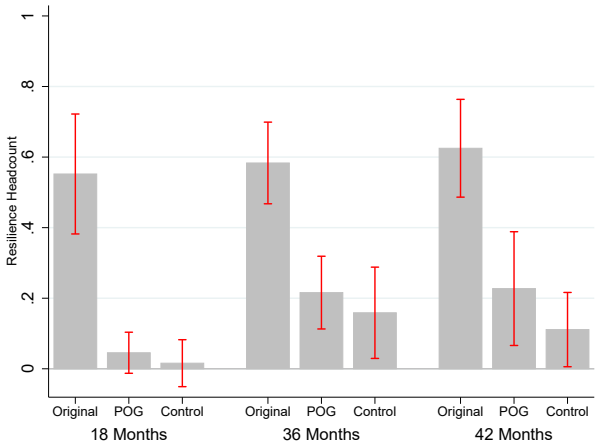
Figure 7: Kernel density estimate of asset and resilience



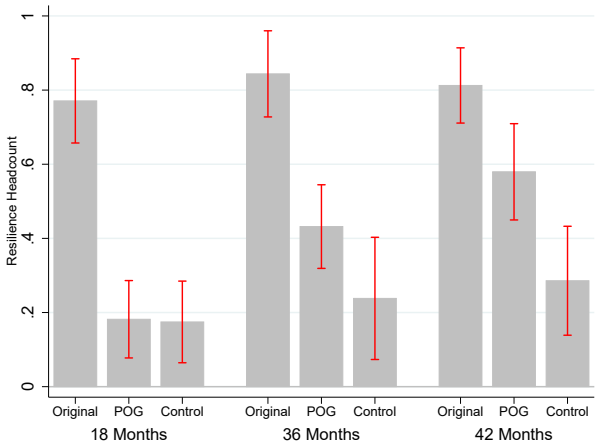
Notes: Panel A shows Kernel density household asset distribution by treatment groups at the baseline and 18 months post-intervention. The vertical solid line represents asset poverty threshold of 5.73 ($log(\bar{W}) = 5.73 \implies \bar{W} = 308$ USD PPP per person). Panel B shows Kernel density resilience distribution at 18 months after the baseline. The vertical solid line represents resilience threshold of 0.5. Assets include value of livestock, bicycle, radio, television, solar panel , motorbike, bed, hoes, sickle, shovel, slasher, pangas, mortar, sieve, wheel barrow, sprayer, maize sheller, grain mill, oil press, axe, ox yoke, ox plough, ox cart, livestock shed, feeder, chaff cutter, fencing, milking buckets and chairs, salt/mineral feeder and ripper/cultivator. All monetary amounts are PPP-adjusted USD terms and are deflated using CPI to 2012 prices using PPP and CPI published by the World Bank. In 2012, 1 USD = 2.5 Kwacha PPP.

Figure 8: Headcount Resilience Rate - Robustness Checks

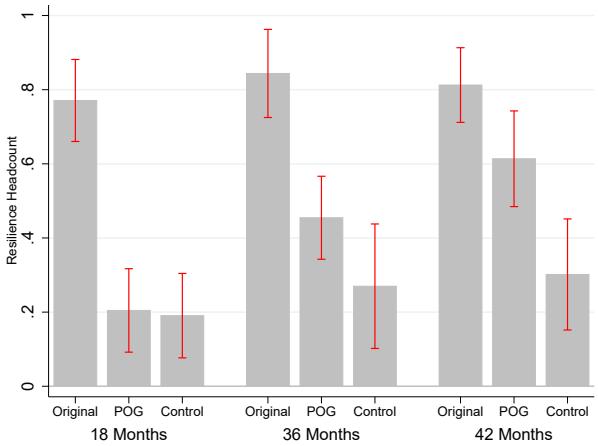
(a) Gamma, $\bar{W} = 308$, $\bar{R} = 0.8$ and $k = 3$



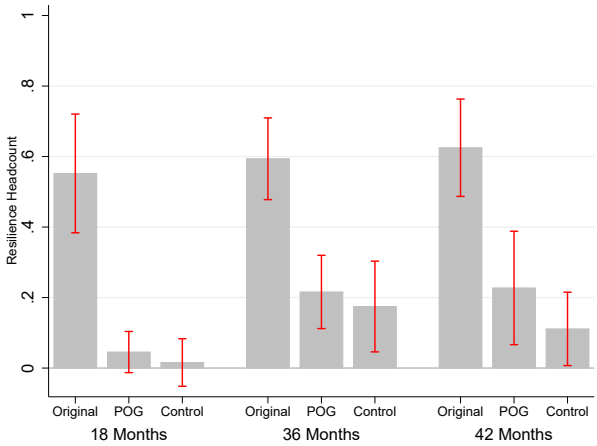
(b) Gamma, $\bar{W} = 308$, $\bar{R} = 0.5$ and $k = 2$



(c) Normal, $\bar{W} = 308$, $\bar{R} = 0.5$ and $k = 3$



(d) Normal, $\bar{W} = 308$, $\bar{R} = 0.8$ and $k = 3$



Notes: Bootstrapped 95% confidence intervals are calculated using 400 replications. Standard errors are clustered at household level. Household i at time t is classified as resilient if its probability of having asset value above the asset threshold of 308 USD PPP per capita ($\bar{W} = 308$) is greater than $\bar{R}$. While the expected assets of each household in each round is assumed to follow gamma distribution in Figure 8a and 8b, it is assumed to be normally distributed in Figure 8c and 8d. First and second moments estimated from path dynamic equations using GLM with Poisson family and log link function with polynomial lagged asset to be cubic i.e. $k = 3$ is a preferred functional form except Figure 8b where $k = 2$. Asset includes livestock, bicycle, radio, television, solar panel , motorbike, bed, hoes, sickle, shovel, slasher, pangas, mortar, sieve, wheel barrow, sprayer, maize sheller, grain mill, oil press, axe, ox yoke, ox plough, ox cart, livestock shed, feeder, chaff cutter, fencing, milking buckets and chairs, salt/mineral feeder and ripper/cultivato. We report the mean of the control group for each survey wave. All monetary amounts are PPP-adjusted USD terms and are deflated using CPI to 2012 prices using PPP and CPI published by the World Bank. In 2012, 1 USD = 2.5 Kwacha PPP.

ONLINE APPENDIX

I Attrition

Table I: Attrition

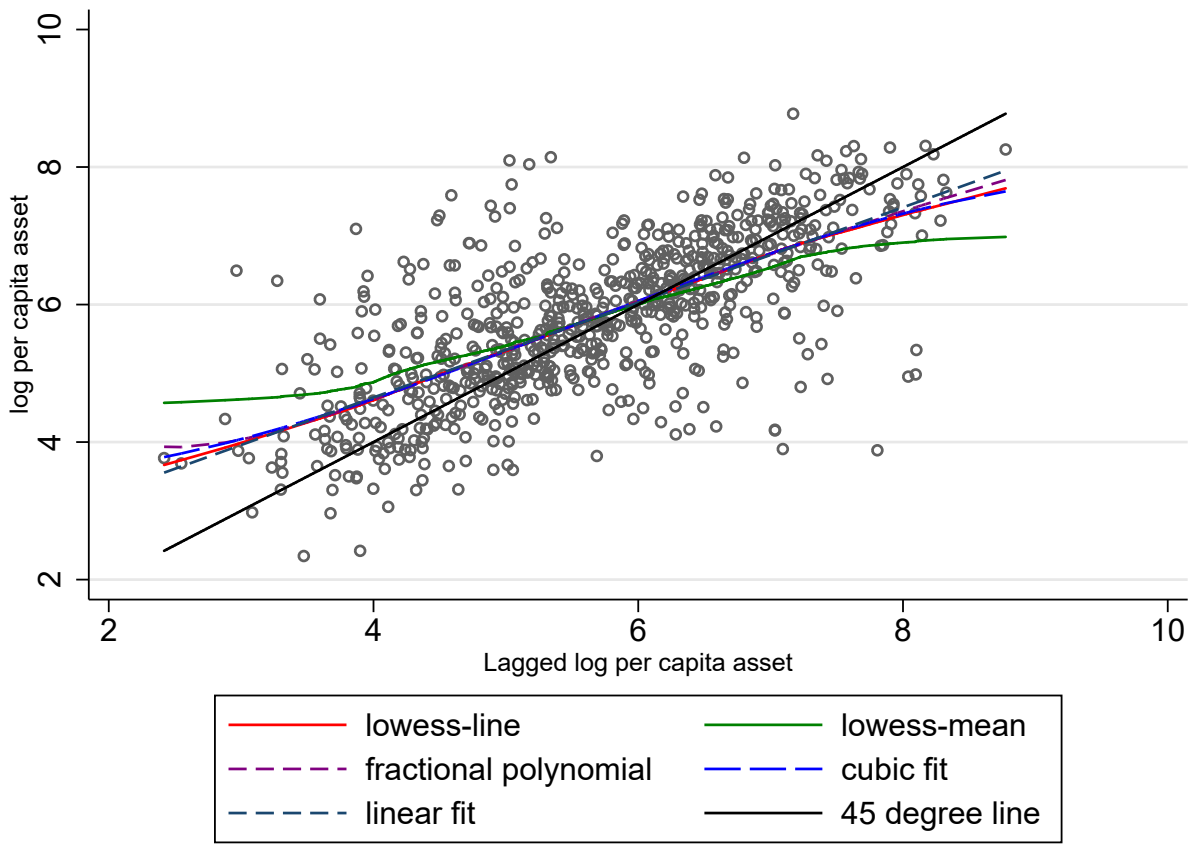
	(1)	(2)	(3)	(4)
Original	-0.035	-0.046	-0.021	-0.149
	(0.052)	(0.053)	(0.093)	(0.300)
POG	-0.148***	-0.151***	-0.094	-0.876***
	(0.051)	(0.053)	(0.091)	(0.279)
Total per capita expenditure		-0.003	0.001	
		(0.002)	(0.003)	
Herd size (TLU)		-0.000	-0.025	
		(0.014)	(0.031)	
Total per capita assets		0.000	0.000	
		(0.000)	(0.000)	
Total per capita expenditure × Original			-0.003	
			(0.005)	
Total per capita expenditure × POG			-0.008*	
			(0.005)	
Herd size (TLU) × Original			0.024	
			(0.039)	
Herd size (TLU) × POG			0.039	
			(0.038)	
Total per capita assets × Original			0.000	
			(0.000)	
Total per capita assets × POG			0.000	
			(0.000)	
Attrition Rate: Baseline to Endline	0.130			
Test: OG and all OG interacted jointly 0 [p-val]			0.738	0.0900
Test: POG and all POG interacted jointly 0 [p-val]			0.00502	9.76e-05
Baseline characteristics				Yes
Baseline characteristics interacted with Treatment				Yes
Adjusted R-squared	0.028	0.027	0.031	0.109
Observations	284	284	284	284

Notes: *** (**) (*) indicates significance at the 1% (5%) (10%) level. OLS estimates are reported based on the sample of households observed at baseline. The dependent variable is a dummy variable equal to one if the household is observed in all 6 survey waves (baseline, 6 months, 12 months, 18 months, 36 months, and 42 months post-intervention), and zero otherwise.

II Wellbeing Path Dynamics and Asset Threshold

Wellbeing Path Dynamics and Treatment (First Stage)

Figure I: Asset Dynamics



Notes: Asset includes livestock, bicycle, radio, television, solar panel , motorbike, bed, hoes, sickle, shovel, slasher, pangas, mortar, sieve, wheel barrow, sprayer, maize sheller, grain mill, oil press, axe, ox yoke, ox plough, ox cart, livestock shed, feeder, chaff cutter, fencing, milking buckets and chairs, salt/mineral feeder and ripper/cultivator. All monetary amounts are PPP-adjusted USD terms and are deflated using CPI to 2012 prices using PPP and CPI published by the World Bank. In 2012, 1 USD = 2.5 Kwacha PPP.

In order to choose the optimal functional form for the polynomial of lagged wellbeing use AIC, BIC, Log likelihood criteria or the LR test. Figure I reports different fits of the asset holding at time t on its lagged. The cubic fit and locally weighted regression (Lowess smoothing) of asset values on lagged values follow each other closely. From above tests and the graph, we choose cubic ($k = 3$)

as our preferred functional form.

$$y_{it} = \alpha + \sum_{j=1}^{3} \theta_j y_{i,t-1}^j + \lambda_t + \delta D_{it} + \beta X_{it} + \epsilon_{it} \tag{I}$$

$$y_{it} = \alpha + \sum_{j=1}^{3} \theta_j y_{it}^j + \sum_{j=1}^{3} \phi_j D_{it} \times y_{i,t-1} + \lambda_t + \delta D_{it} + \beta X_{it} + \epsilon_{it} \tag{II}$$

Estimate Equation (I), check if the cubic lagged term is significant i.e. $H_0 : \theta_3 = 0$, which will provide suggestion if the asset (asset value/income) dynamic growth is s-shaped (or inverted s). Now to check whether the treatment has altered the path dynamics we will estimate Equation (II) and perform following tests:

$$H_0 : \phi_1 = \phi_2 = \phi_3 = 0 \tag{III}$$

$$H_0 : \phi_2 = \phi_3 = \delta = 0 \tag{IV}$$

$$H_0 : \delta = 0 \tag{V}$$

where, Test (III) will check if the treatment has altered the rate of change of the curvature. Hypotheses (IV) and (V) will test if the treatment shifted the growth curve horizontally or vertically respectively.

Transforming Consumption Threshold to Asset Threshold

We map the income/consumption poverty line, above which one is considered non-poor, to asset levels and create asset base threshold as below:

$$Log(C_{it}) = \alpha + \gamma Log(W_{it}) + \beta X_{it} + \epsilon_{it} \tag{VI}$$

where, C_{it} is per capita per day consumption of household i at time t, W_{it} is per capita value of total asset at time t of household i and X_{it} is vector of controls affecting household consumption. We limit analysis to baseline data only. We subtract the value of asset transfers made to households in baseline and estimate equation 7 using OLS strategy. Using the estimated coefficients and median characteristics of the sample, we map 1.90 USD PPP $\bar{P}$ consumption to household per capita asset

level as below:

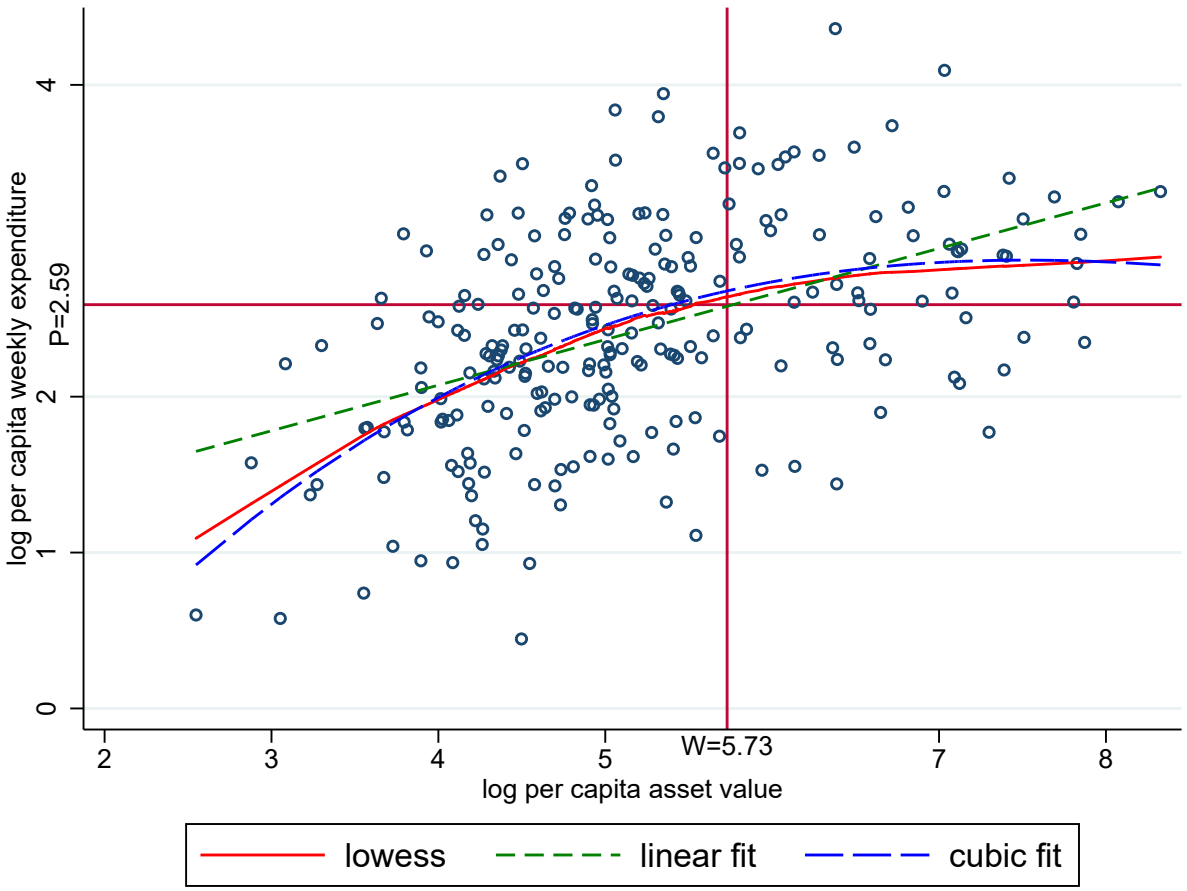
$$Log(\bar{W}) = \frac{Log(\bar{P}) - \hat{\alpha} - \hat{\beta} X_m}{\hat{\gamma}} \tag{VII}$$

where, $\bar{P}$ is a consumption poverty line. The hat, $(\hat{})$, caret refers to estimated coefficients, m subscripts represents the median value of the sample and $\bar{W}$ is the asset threshold, below which households will be considered as being vulnerable to poverty. Figure II presents the consumption poverty line mapping to asset threshold using round 1 data. As shown in Figure II the asset baseline in natural log is 5.73 ($= Log(\bar{W}) \implies \bar{W} = \exp 5.73 \approx 308$ USD PPP).[18]

Alternative two strategies: first, using rounds 4, 5 and 6 data and adding round fixed effects in estimation of Equation (VI) and second, median asset value of the wealthiest third households at the baseline, coincidently, yield very similar asset poverty line.

[18] All monetary amounts are PPP-adjusted USD terms and are deflated using CPI to 2012 prices using PPP and CPI published by the World Bank. In 2012, 1 USD = 2.5 Kwacha PPP.

Figure II: Asset Poverty Line ($\bar{W}$)



Notes: Asset includes livestock, bicycle, radio, television, solar panel , motorbike, bed, hoes, sickle, shovel, slasher, pangas, mortar, sieve, wheel barrow, sprayer, maize sheller, grain mill, oil press, axe, ox yoke, ox plough, ox cart, livestock shed, feeder, chaff cutter, fencing, milking buckets and chairs, salt/mineral feeder and ripper/cultivator. All monetary amounts are PPP-adjusted USD terms and are deflated using CPI to 2012 prices using PPP and CPI published by the World Bank. In 2012, 1 USD = 2.5 Kwacha PPP.

III Cost-Benefit Calculation

We exploit estimated ITT treatment effects of the program to perform the cost-benefit analysis. As discussed in the research design section, while the Original households received both the livestock and training at the baseline, pass on the gift (POG) households received only training. The Originals, however, are required to pass on the first female offspring from every female animal they received through the program. Therefore, the POGs also benefit from the initial asset transfer, the Originals, however, do not fully reap the benefits from the initial livestock transfer. Thus, to evaluate the full program benefits we need to incorporate the benefits POGs enjoy as well. We use following strategy to calculate the specific program benefit $\hat{B}$:

$$\hat{B} = B^O \times S^O + B^P \times S^P \tag{VIII}$$

where, B^O is the ITT treatment effect for Original households and B^P is the ITT treatment effect on POGs. S^O and S^P are the shares of Original and POG program participants respectively. Overall, 35% of the beneficiaries are Original households while the rest 65% are POGs. We include changes in household nondurable consumption, household asset accumulation and estimated future consumption gains as the program benefits. Following, Banerjee et al. (2015), we do not include household expenditure on durable goods as they will be captured in the asset accumulation. We include only third year changes in asset accumulation in the total benefits. To calculate future gains in household consumption, we assume the consumption gains observed in year three last in perpetuity. Household second year gains are assumed to be same as the first-year gains.

Following the joint guideline set by the World Bank Group (2013), we set the initial social discount rate of 5% but also calculate benefits/cost ratios using 7% and 10% for sensitivity.

The total project costs was USD 1 million. The program implementing partner, provided us with the detailed budget and the number of beneficiaries. Although, the costs are spread-out over the duration of the program, we assume all the costs exist at year 0 and inflate to year three net present value given by:

$$C_3 = C_0 \times (1.05)^3 \tag{IX}$$

where, C_0 is the per household total program cost, which includes the value of direct transfers, trainings costs, staff salaries, and all other program implementing, monitoring and supervision costs at year 0. All the costs are converted to purchasing power parity (PPP) for cross-country comparison purposes.

Calculating Cost of Increasing Resiliency Headcount by 1%

Given the first-order Markov process in estimating households' development resilience, we cannot estimate resilience at the baseline. However, given the quasi-randomize program design, control and treatments groups are likely be balance, on average, at the baseline. Assuming balance baseline we calculate gain in headcount development resilient rate, $\hat{R}_t$, at time t is follow:

$$\hat{R}_t = R_t^O \times S^O + R_t^P \times S^P - R_t^C \tag{X}$$

where, R_t^O, R_t^P and R_t^C, are the headcount resilient rate among Original, POG and control households at time t, where $t \in [18, 33, 42 \text{ months}]$. Again S^O and S^P are the shares of Original and POG program participants respectively. Cost of increasing resilient rate by 1% at time t, $\hat{C}$ is calculated as follow:

$$\hat{C}_t = \frac{\text{Total value of transfers at year 3}}{\hat{R}_t} \tag{XI}$$

Transfer values are inflated from year 0 to year 3 using Equation (IX).