Journal of Development Economics 138 (2019) 205–227

Contents lists available at ScienceDirect

Journal of Development Economics

journal homepage: www.elsevier.com/locate/devec

# Do asset transfers build household resilience?

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ARTICLE INFO

*JEL classification:*
O12
O22

*Keywords:*
Poverty dynamics
Resilience
Livestock
Asset transfers

ABSTRACT

We estimate the impact of an asset transfer program on household resilience. We measure resilience as the probability that a household will sustain at least the threshold asset level required to support consumption above the poverty line. Using six rounds of data collected over 42 months in rural Zambia, we construct a measure of resilience based on households' conditional welfare distributions to estimate program impacts. We find that the program increased household resilience; beneficiaries' likelihood of being non-poor in future periods increased by 44%. The program both increased mean assets and decreased variance, signaling an upward shift in households' conditional asset distributions. Our method demonstrates the added value of the resilience estimation compared with a conventional impact assessment; numerous households classified as non-poor are unlikely to remain non-poor over time and the relationship between wealth and resilience is driven by changes in both the conditional mean and the conditional variance.

## 1. Introduction

In response to perceived increases in the severity of climate and economic shocks in developing countries, anti-poverty programs have begun to prioritize household resilience (World Bank, 2016; Hallegatte et al., 2017; Fernández-Gimenez et al., 2011, 2012; Venton et al., 2012). Despite considerable discussion of building resilience through development initiatives, the question of whether an initiative can alter the likelihood that a household will fall into poverty in the foreseeable future has rarely been examined empirically.

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 consumption above a poverty threshold. Forward-looking poverty evaluations are obviously critical for assessing the lasting effects of interventions, as well as for distinguishing between households that have received a transient welfare boost and those that have experienced a structural change likely to alter their future economic circumstances.

This paper applies Barrett and Constas's (2014) moment-based definition of development resilience: "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." Drawing together the methods and theories related to poverty traps, vulnerability, and ecological resilience, development resilience is a probabilistic and forward-looking concept that takes into account both the first and second moments of the household welfare distribution and quantifies 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 in the face of diverse shocks and stressors. We employ the econometric technique proposed by Cissé and Barrett (2018) 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 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;

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https://doi.org/10.1016/j.jdeveco.2019.01.003
Received 1 August 2017; Received in revised form 30 April 2018; Accepted 9 January 2019
Available online 19 January 2019
0304-3878/

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 the program's benefits at year 3 are repeated through the 20th year of the intervention, 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. The program increases beneficiaries' likelihood of being non-poor in future periods; households receiving both training and livestock at the baseline are 44% more likely to be non-poor than Control households 42 months after the intervention. Moreover, we find that the program increased headcount resilience among participant households. While more than 80% of the treatment households are resilient at the endline, the comparable endline 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 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 a low-level equilibrium. Development resilience, in contrast, quantifies the probability that a beneficiary household might move back into poverty and permits 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 value of measuring resilience in the context of impact assessment. 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. Differences are most striking 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 presents the theory of development resilience and 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 on 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 the concept of vulnerability in two important ways. First, the vulnerability measurement literature is predominantly concerned with the immediate impacts of shocks and does not account for exposure to stressors. Resilience, on the other hand, focuses on the longer-term impacts of both shocks and stressors. The emphasis on stressors is important in light of studies such as Rockmore's (2017) study of conflict in Northern Uganda, which finds that aggregate welfare losses from insecurity are larger than the realized violence. Second, the emphasis of the vulnerability literature on the immediate impact of shocks largely ignores welfare path dynamics. In contrast, development resilience is the study of well-being dynamics incorporating the possibility of nonlinear welfare growth paths. Operationally, these differences mean that while analysis of vulnerability can be implemented using cross sectional or short term panel data exploiting heterogeneity among the households or individuals within a sample, resilience measurement requires data collected over a longer time frame to exploit the inter-temporal variation of a household or individual.

This paper follows Barrett and Constas's (2014) conceptualization of resilience: "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."

Barrett and Constas (2014) use a conditional moment function for well-being in a multiple equilibria poverty trap to represent resilience, $m^k(W_{t+s} \mid W_t, \varepsilon_t)$, where $m^k$ is a $k$th moment of well-being at time $t+s$ and $s > 0$; with resilience a function of well-being $W_t$ and random shock $\varepsilon_t$ at time $t$. The deterministic relationship between $W_t$ and $W_{t+s}$ typically employed in the poverty trap literature is replaced with a conditional moment growth function and associated conditional dynamic transitional distribution functions. Although demonstrated using a multiple equilibria poverty trap, Barrett and Constas's (2014) resilience concept does not require a nonlinear path dynamic with multiple steady-state equilibria and is equally relevant in the case of the existence of a single steady-state equilibrium below the poverty line. A household's development resilience can be measured as the cumulative probability above the dynamic poverty threshold in the case of multiple equilibria and as the cumulative probability above the static poverty line $\overline{W}$ in the case of a single equilibrium. Unless the entire probability distribution sits above $\overline{W}$, there exists some probability that the household will fall into poverty. As less of the probability distribution falls

[1] Most 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 have been highly ineffective because of flaws in targeting and design (Drèze, 1990; Pulley, 1989).

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

below the poverty threshold, a household becomes more resilient. The likelihood of falling into poverty therefore depends on the household's level of well-being at time $t$ and the dispersion in the distribution of outcomes.

As a simple descriptor, this resilience measure provides a consistent estimate of the true population conditional poverty level. However, a simple conditional mean of poverty status should provide a similar result. For example, if there were a single asset type or uniform asset types and *iid* shocks and stressors, a non-parametric regression of poverty status in time $t$ on treatment should provide the same answer as the resilience calculation based the conditional moment functions. Nonetheless, estimating the conditional moment functions offers additional value in two ways. First, estimation of the value of the polynomial on lagged wealth allows for nonlinear persistence, which can enhance both forecasting and identification of heterogeneous response to common wealth shocks. The practical significance of this is suggested by studies such as Jalan and Ravallion (2001) and Lokshin and Ravallion (2004), which demonstrate that the same negative shocks have more persistent effects on poorer households than wealthier ones. The second advantage of the method is that it allows distinguishing whether the estimated relationship between wealth and resilience is driven by effects on conditional mean or on conditional variance. Simple theory and the prior literature (Rosenzweig and Binswanger, 1993) would suggest the effect of an asset transfer program is likely to be mainly in the conditional mean as decreasing absolute risk aversion should lead wealthier households to pursue higher return, higher variance strategies. Estimation of the conditional moment functions permits one to test that theory directly; a simple descriptive of the conditional poverty rate cannot provide these insights. For example, we find that numerous households are non-poor based on their mean asset holdings but are not resilient to remain non-poor over time once we account for the estimated asset holding variance (Section 6.1).

Resilience theory implies that development policies and interventions should focus on increasing household capital, decreasing downside risk and changing underlying development-impeding 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 training, and providing agricultural and veterinary extension services. To reflect the program, we define resilience exclusively in asset space and understand it as the capacity of a household to hold productive asset stock above a minimum critical asset poverty threshold (either dynamic or static) over time. Increasing resilience therefore means increasing the probability of holding assets above the defined threshold. Such an improvement could be the result of increases in the conditional mean asset stock, a decrease in the conditional variance or both. Given potential stochastic welfare outcomes related to uncertainty in herd dynamics and to the variety of risks households are exposed to, assessing the programmatic effects beyond the first moment of the outcomes of interest may provide greater insight about the status of the program recipients. This is especially true in the presence of bifurcating dynamics (Carter et al., 2007; Barrett et al., 2016). For example, a negative shock could imply a draw below the dynamic asset poverty threshold, setting the household on a trajectory towards a lower level equilibrium. As with negative shocks, large enough positive nudges have the potential to move the poor onto a path towards a non-poor, higher resilience state. Limiting the analysis to the first moment in the distributions of welfare outcomes, however, will not provide such insights.

## 3. Development resilience measurement

We construct resilience scores using the econometric technique proposed by Cissé and Barrett (2018) and applied in different contexts by Upton et al. (2016) and Cissé and Ikegami (2016). We then use the estimated resilience scores as outcome variables in an 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 $\varepsilon_{it}$:

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

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 $(\mu_{1it})$ is predicted as:

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

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:

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

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

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

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, the development resilience of a household $i$ at time $t$ $(\widehat{\rho}_{it})$ is the probability that the household will hold assets above a critical asset poverty threshold $(\overline{W})$ at period $t$:

$$\widehat{\rho}_{it} \equiv P\left(W_{it} \geq \overline{W}\right) = \overline{F}_{W_{it}}\left(\overline{W}; \widehat{\mu}_{1it}(W_{it}, X_{it}), \widehat{\mu}_{2it}(W_{it}, X_{it})\right) \tag{5}$$

where $\overline{F}(.)$ is the assumed cumulative distribution function. 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, $\overline{W}$, or both. The next section describes the intervention studied in the paper.

## 4. Program intervention and research design

The Copperbelt Rural Livelihoods Enhancement Support Project (CRLESP) was implemented by Heifer International with funding from Elanco Animal Health (USA). The project operated in twelve rural communities in Zambia's Copperbelt province. The region, which relied heavily on copper, has gone through a difficult economic transition over the last three decades resulting in the loss of employment and loss of remittances in rural areas (World Bank, 2007). Many dislocated mine workers have turned to agriculture. Despite the availability of good quality farm land, limited asset holdings, limited farm 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).

### 4.1. The intervention

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.[3]

Due to the implementer's capacity constraints, the program was implemented in phases based on a queue that was established using date of application. Communities earlier in the queue received support in the initial round, while other qualified communities, referred to as "Prospectives", were wait-listed until a future date when resources would become available. However, every community in the target district had equal opportunity to apply at the same time. Heifer Zambia advertised the program intensively through the local media and through the government agricultural extension agents working in the region. The information dissemination across the communities regarding the program and application process was consistent in timing and content. Geographically, there is no significant disparity in distance to Heifer's regional office in Ndola, Zambia from these communities. Applications were primarily submitted by women-led self-help groups. Groups based in twelve different communities qualified for the program. The sample for this study consisted of groups from the three communities scheduled to receive services around the time of the planned baseline survey plus groups from communities that were slated to receive services in the next opportunity. The communities that had already begun to receive services and those that were further down in the queue were excluded from the study. While all households in groups identified to receive treatment at the baseline received livelihood skill trainings and associated benefits of enhanced social capital, resource constraints meant only a randomly selected subset of these households could 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.

### 4.2. Data and 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.[4]

We exploit the rollout of the program to identify the program impacts. Since both the early recipients (Originals) and future recipients (Prospectives) passed identical screening, self-selected for participation, 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.[5] Jodlowski et al. (2016) find no such anticipatory behavior in the first four rounds of the panel. We acknowledge that the experimental design based on the heterogeneity in the application timing is not a pure RCT, however, the window between the call for application and choosing the program recipients was very narrow.[6] Given the rural setting with limited transportation and communication infrastructure, we believe the heterogeneity in application timing between the first three and the next two communities is random rather than systematic. Based on equal eligibility, the fact that Controls went through the same selection process as treated households, observation from our field visits, focus group meetings, and multiple discussions with the implementing staff and extension agents in the field, we believe that the Prospective household are appropriate counterfactuals.

Although the POGs were left out of the initial livestock transfer at random and come from the same groups as the Originals, we do not use POGs as a comparison group in the analysis for three reasons. First, the POGs received all the trainings regarding animal management, livelihood skills and health at the same time as the Originals, which could affect management of farm animals and other productive assets they already owned. Second, POG households started receiving immature animals from the Originals as early as six months after the baseline, therefore, anticipatory behavior among the POGs could be a factor.

[3] The screening process implies that 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.

[4] The household surveys collected household consumption and asset holdings. We utilize community-level food prices collected during the baseline survey to calculate households' food expenditures. Regarding asset values, for each household we calculated a per unit value for each asset owned. We used the median of the asset unit values in the community as the community level price/value for each asset. All monetary amounts in the paper 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 was equivalent to 2.5 PPP adjusted Zambian Kwacha.

[5] 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 hence appear worse off than they otherwise would (Ashenfelter, 1978; Ashenfelter and Card, 1985).

[6] Unfortunately, we do not have exact dates but Heifer Zambia staff report that applications were submitted within a short period of time - on the order of 1–2 weeks.

Third, POG households reside in the same communities as the Originals and are more likely to experience project spillovers. An additional complication is the significant heterogeneity in the timing of asset transfer to POG households; while some households received livestock as early as six months after the baseline, others waited up to 36 months. We normalize the timing of transfer and perform an event-study analysis on the outcomes of interest to check the appropriateness of POG households as a comparison group for Originals (Appendix C). The results suggest POG households are not a suitable comparison group for the Originals. Thus, we use the POG households in our analysis as a second treatment group.

Table 1 provides baseline balance tests for the Treatment and Control groups. The tests suggest no significant differences in means between the Control and Original households' asset and revenue and income variables (Panels B and D). We do see differences in household size (Panel A), poverty status (per capita), and per capita household expenditures (Panel C). All household characteristics in Panel A are balanced except the household size. Compared to the Controls, Original household have more nonelderly female adult members and children. In the presence of economies of scale, failure to adjust the consumption for household size may lead to overestimation of poverty for large households and underestimation for small households, driving the differences in per capita expenditures and poverty status. The household-level (as opposed to per capita) expenditures between the groups is balanced (Panel C: line 3). We assume that the variation in poverty and expenditure variables at the baseline (Panel C) does not reflect a systematic difference in groups' ability to organize, willingness to participate in the program, or capability to rear animals; rather, differences are likely due to relatively small sample sizes and differences in household size. As a robustness check, we adjust the household size using the OECD adult equivalency (ae) method and report adult equivalence adjusted poverty and expenditure variables in Panel E. The poverty rates between the groups using the adult equivalence correction are statistically equivalent. The differences in per capita expenditures between the groups are still significant but small in magnitude. Moreover, one may expect richer farmers to be better organized and apply earlier; however, this is not the case as Control households are less likely to be poor than the treated households. Similarly, if greater poverty reflects lesser livestock

**Table 1**
Baseline characteristics and balance.

| | Means (SD) | | | Test of equality of means [P-val] | |
|---|---|---|---|---|---|
| | (1)Original | (2)POG | (3)Control | (4) Original = Control | (5) POG = Control |
| **Panel A: Demography** | | | | | |
| Head is female | 0.283 | 0.252 | 0.209 | 0.267 | 0.506 |
| | (0.453) | (0.436) | (0.410) | | |
| Head is illiterate | 0.057 | 0.090 | 0.030 | 0.385 | 0.081 |
| | (0.232) | (0.288) | (0.171) | | |
| Head is married | 0.821 | 0.874 | 0.791 | 0.635 | 0.163 |
| | (0.385) | (0.333) | (0.410) | | |
| Household size | 7.377 | 6.928 | 5.627 | 0.000 | 0.000 |
| | (2.799) | (2.762) | (2.059) | | |
| Household size (Adult equivalence) | 4.862 | 4.491 | 3.807 | 0.000 | 0.002 |
| | (1.717) | (1.666) | (1.282) | | |
| **Panel B: Assets** | | | | | |
| Herd size (TLU) | 1.162 | 0.741 | 1.233 | 0.849 | 0.173 |
| | (1.930) | (1.797) | (2.595) | | |
| Total asset value (Per capita) | 382.054 | 222.757 | 460.133 | 0.453 | 0.013 |
| | (551.714) | (346.283) | (728.025) | | |
| Asset non-poor | 0.302 | 0.144 | 0.328 | 0.718 | 0.006 |
| | (0.461) | (0.353) | (0.473) | | |
| **Panel C: Poverty & Expenditure** | | | | | |
| Poverty status (Below USD 1.90) | 0.623 | 0.622 | 0.418 | 0.008 | 0.008 |
| | (0.487) | (0.487) | (0.497) | | |
| Total weekly expenditure (Per capita) | 12.872 | 13.340 | 18.298 | 0.003 | 0.007 |
| | (9.574) | (10.028) | (12.693) | | |
| Total weekly expenditure (HH level) | 86.384 | 80.834 | 88.731 | 0.787 | 0.335 |
| | (55.898) | (48.458) | (55.276) | | |
| **Panel D: Revenue & Income** | | | | | |
| Total revenue last year (Per capita) | 527.539 | 543.884 | 1083.991 | 0.103 | 0.114 |
| | (724.437) | (768.995) | (2727.464) | | |
| Livestock revenue last 3 months (Per capita) | 13.603 | 19.640 | 78.138 | 0.120 | 0.160 |
| | (40.139) | (54.555) | (336.992) | | |
| Crops revenue last year (Per capita) | 301.593 | 332.440 | 240.678 | 0.295 | 0.173 |
| | (475.180) | (602.685) | (287.585) | | |
| Other labor & non-labor income last 3 months (Per capita) | 32.015 | 26.666 | 106.658 | 0.250 | 0.214 |
| | (98.283) | (55.531) | (523.726) | | |
| **Panel E: Poverty & ExpenditurePer adult equivalence)** | | | | | |
| Poverty status (Below USD 1.90) | 0.349 | 0.333 | 0.239 | 0.117 | 0.172 |
| | (0.479) | (0.474) | (0.430) | | |
| Total weekly expenditure (Per adult equivalence) | 19.054 | 19.907 | 26.020 | 0.007 | 0.015 |
| | (13.893) | (13.466) | (17.622) | | |

Notes: All monetary amounts are measured in USD PPP-adjusted. Household assets refer to value of livestock, durables, agricultural tools, and livestock equipment. The expenditure items covered are: food, clothing, household durables, schooling, medical, alcohol-tobacco, fuel and other home expenditures. Other labor and non-labor income refers to paid income and micro-enterprise profits. Total revenue last year is calculated by adding yearly revenues from crops and livestock, paid income, micro-enterprise profits, remittance and other transfers (total revenue = 4 × livestock revenue last 3 months + 4 × other labor and non-labor income last 3 months + crops revenue last year + remittances and other transfers last year). Poverty status is a binary variable equal to 1 if per day per person (or per adult equivalence) expenditure is below the 1.90 USD poverty line, and 0 otherwise.

**Table 2**
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) | |
| Baseline characteristics | | | | Yes |
| Baseline characteristics interacted with Treatment | | | | Yes |
| 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 |
| 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 binary 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.

entrepreneurial ability, our strategy, should underestimate the program effects. To control for any unobserved individual heterogeneity, we use household fixed effects in our estimation.

The attrition rate of 13% (Table 2) 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 than the Control households to be interviewed in all six rounds. 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.

## 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:

$$y_{it} = \alpha + \sum_{t=1}^{2} \beta_t (T_t \times Original_i) + \sum_{t=1}^{2} \delta_t (T_t \times POG_i) + \sum_{t=1}^{2} T_t + Original_i + POG_i + \eta_i + \varepsilon_{it} \tag{6}$$

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. Although the project collected five rounds of follow-up surveys, the information collected was not identical across rounds. Depending on the availability of data on the outcome variable, we define 2013 midline (time 1) either as 12 months or 18 months, and 2015 endline (time 2) either as 36 months or 42 months post baseline. $T_t$ are indicator variables that refer to survey waves. $Original_i$ and $POG_i$ are indicators for two treatment arms. As the household's timing of application to the program determined the treatment status, we include household fixed effects $\eta_i$ to control for unobserved heterogeneity and cluster the error term $\varepsilon_{it}$ at the household level. As a result, the coefficients on $Original_i$ and $POG_i$ in Eq. (6) are not identified. The equation, nonetheless, can be treated as the garden variety difference-in-difference specification.

$\beta_t$ and $\delta_t$ 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-treatment, the Control (Prospective) group is identified through a process identical to that of the Original and POG groups. Second, Eq. (6) 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 comparison 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.

**Table 3**
Treatment effects on productive asset.

| | (1) Household herd size (TLU) | (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 (Original) | 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 [p-value] (Original) | 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, Eq. (6), specification. All outcomes are measured at the household level. 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 assign a 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.

### 5.1. Productive assets and household durables

Table 3 presents the program impacts on accumulation of productive and durable assets using Eq. (6). 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.

First we analyze whether beneficiary households undertake the livestock activities prescribed by the program and measure the direct impact on livestock holdings and earnings. Table 3 reports impacts on herd size and quarterly income from livestock related activities. Originals received an average of 0.88 tropical livestock units (TLU), which is not included in the baseline herd size. A one-unit TLU gain, 0.99 to be precise, relative to the Controls one year post-intervention represents an increase of 0.11 TLU above the transfer amount, meaning the recipients had begun to increase their holdings beyond the initial transfer. The Originals' gains are particularly notable since they are required to pass on female offspring to POGs. Within one year, the value of the Originals' livestock holdings increased by USD 460.6 per capita relative to the Control households. Half of the increase was due to the initial livestock gift.[7] 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 on 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 households' 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. Finding that the treatment effects grow after the initial transfer 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 3 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 post-intervention, respectively. 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 to 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 Eq. (6) and present the results in Table 4. 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 3. 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.

[7] In the first wave of the transfers, the Original households received livestock worth about USD 1629, about 229 per capita, which is not included in the baseline asset value. Therefore, 49.8% (= 229/460.6) of the first year rise in the value of livestock can be attributed to the transfer itself. The per capita change in the herd size may not directly reflect the change in the value of herd size because; first the value of the same type of livestock may change over time in the community - after seeing the benefits, livestock may become more valuable or the presence of too many livestock may decrease the price etc. Second, we calculate the value of herd size using the method described above and use country-level CPI to deflate the value to the baseline. However, if the increase in the price of animal is more than the CPI adjustment, we may face this discrepancy, which is exactly the case.

**Table 4**
Treatment effects on consumption expenditure, food Security, and asset poverty.

| | Per Capita Consumption | | | | | |
|---|---|---|---|---|---|---|
| | (1) BelowPoverty Line | (2) Food(last week) | (3) Nonfood(avg weekly) | (4) Total(avg weekly) | (5) EnoughFood | (6) AssetNon-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 (Original) | 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 [p-value] (Original) | 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, Eq. (6), specification. All outcomes are measured at the household level. 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 report the household usually or always has 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 Appendix B.2. Columns 1, 5, and 6 are linear probability models; nonlinear estimates using logistic regressions are reported in Table A.2.

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 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 compared to the Controls (Column 5).

Based on the relationship between consumption and assets, explored in Appendix B.2, 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 expenditure 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 equality 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.[8]

Given the sequence of program implementation, the possibility that the early entrants (Originals) may crowd out others in the community from livestock rearing activities is of concern. Our results show no evidence of such crowding out. Although we cannot entirely rule out the general equilibrium responses to greater demand for livestock labor or increased local supply of milk, meat, or animal traction, the differences in treatment effects between the Originals and the POGs are mostly attributable to delayed impacts rather than to accrual of unique benefits to early adopters. The differences diminish over time in almost all the outcomes considered in this section. In particular for herd size, the outcome that is directly affected by the program and is most likely to be affected by the Originals' head start, we observe that POGs experience the same impact as the Originals (1.03 vs 1.11) three years after the baseline. Rather than early adopters crowding out others, we see evidence that the differences in treatment effects between the two groups are likely to disappear over time.

## 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. Eq. (1) 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,

[8] Analyses of heterogeneity in impacts using quantile regression methods in Appendix E shows that these effects are consistent across quantiles, though weaker at the extremes.

**Table 5**
Treatment effects on household resilience.

| | Originals (OG) | | | Pass on the Gift (POG) | | | Observations |
|---|---|---|---|---|---|---|---|
| | 18 Months | 36 Months | 42 Months | 18 Months | 36 Months | 42 Months | |
| **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) | |
| Resilience mean (Control group) | 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 (Variance) | −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 average marginal treatment effects estimated using generalized linear model (GLM) with binomial family and logit link function. Panels B and C show average 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 round, 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. 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. 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.

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 $\varepsilon_{it}$ are random shocks that household $i$ faces. The originals received pregnant livestock during or soon after the baseline survey. The initial recipients reap benefits (milk, meat, ploughing, increase in herd size etc.) from the transfers well within 18 months. 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. Fig. B.1 in Appendix B, 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. Consequently, we assume the dependent variable to be distributed Poisson and fit a GLM log link using maximum likelihood on the mean. Using the parameter estimates from Eq. (7), we predict the first moment of the asset distribution of household $i$ at time $t$ as in Eq. (2). Squared residuals from Eq. (7) are used to estimate Eq. (3),[9] which recovers parameters to predict the second moment (Eq. (4)). We calculate each household's probability density function (pdf) of asset holdings for each period assuming the conditional transition distribution function to be gamma distribution.[10] We convert the poverty line of USD 1.90 PPP into an asset poverty line ($\overline{W}$) of USD 308 PPP as shown in Fig. B.2 (Appendix B.2). Using the calculated minimum asset threshold, we estimate each household's development resilience in each period ($\rho_{it}$).

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

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

### 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 (2018) that $\partial\hat{\rho}_{it}/\partial X_{it}$ is a characteristic $X_i$'s impact on development resilience and estimate the following specification:

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

Note that:

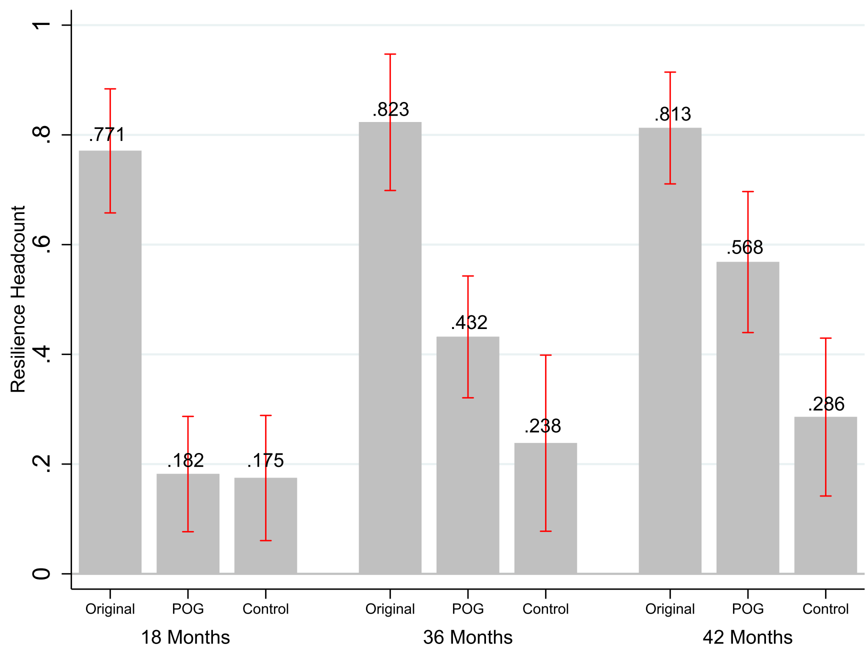
$$\begin{aligned} \frac{\partial \hat{\rho}_{it}}{\partial (T_t \times D_l)} &= \hat{\gamma}_{lt} \\ &= \mathbb{E}[\hat{\rho}_{it} \mid W_{i,t-1}^j, Z_{it}, T_t, D_l = 1] \\ &\quad - \mathbb{E}[\hat{\rho}_{it} \mid W_{i,t-1}^j, Z_{it}, T_t, D_l = 0] \\ &\text{where } t \in [1, 2, 3] \end{aligned} \tag{9}$$

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, $\gamma_{it}$, 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 5 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




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, $R_{it}$, if its resilience score is greater than 0.5 i.e. $R_{it} = 1$ if $\hat{\rho}_{it} > \bar{R}$; 0 otherwise; where ,$\bar{R} = 0.5$. 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.

**Fig. 1.** Headcount Resilience Rate (Gamma, $\overline{W} = 308$, $\overline{R} = 0.5$ and $k = 3$).

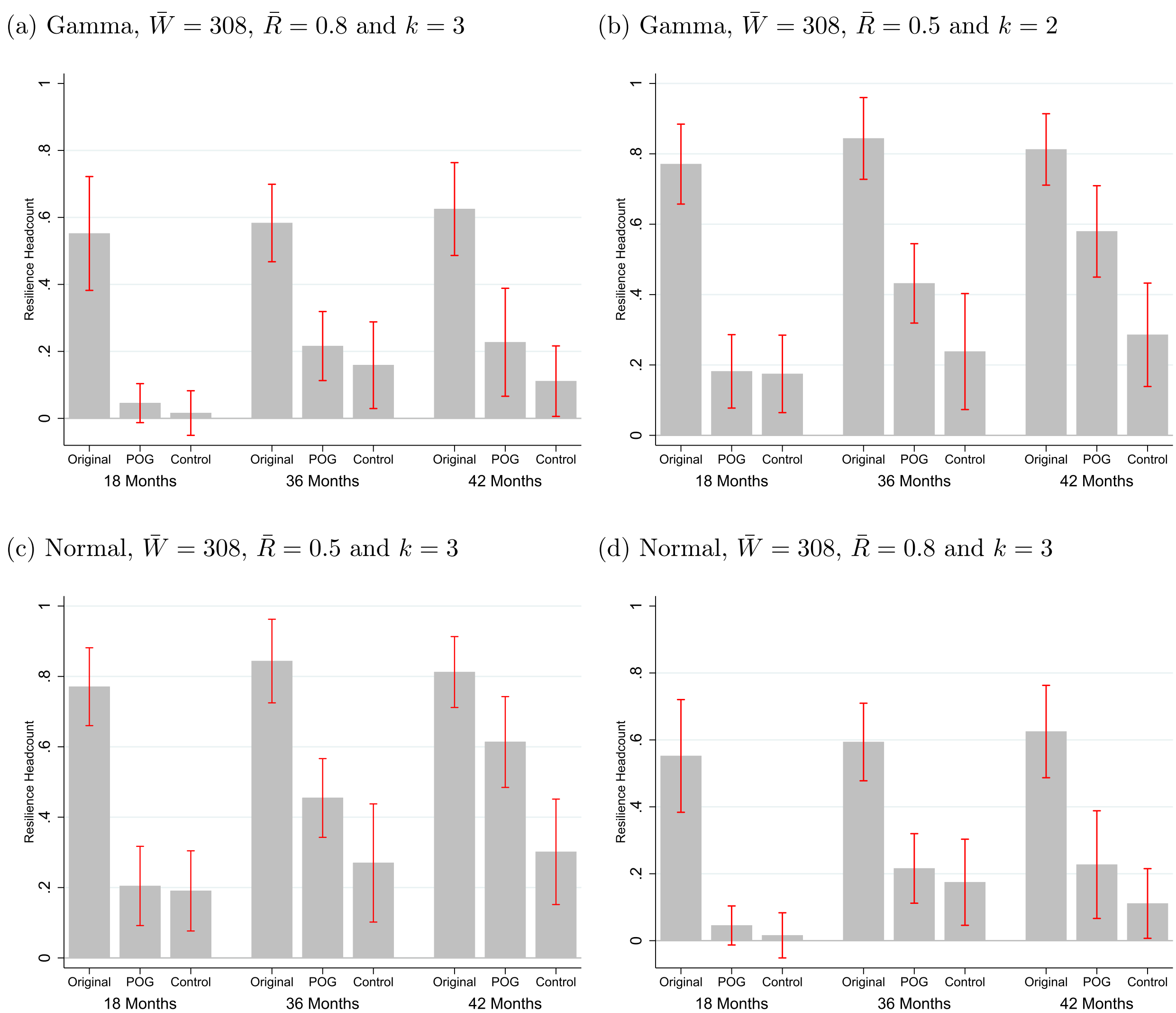
the asset poverty line.[11] Relative to the Controls, both the Originals and POGs have significantly higher resilience to poverty in all the three rounds. The development resilience score is 0.228 points or 87.7% higher for the Originals after 18 months of the treatment than the Controls. Similarly, the Originals are 41.3% (0.145 points) and 44.1% (0.167 points) more 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 treatment groups. To provide evidence on this we test whether the 36 and 42 months impacts are equivalent to impacts 18 months post-intervention. 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 3, 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 $\overline{W}$, or both. Estimating Eq. (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).[12] 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). While the conditional asset spread among the Originals drops significantly relative to the Controls (except in round 5), the asset spread for the POGs is equivalent to that of the Controls.

The absence of an effect on asset spread for the POGs likely reflects the heterogeneity in the timing of livestock transfer to the POGs, and the Just and Pope (1979) and Antle (1983) method we use to calculate variance, which depends on the predictive power of the explanatory variables (lagged assets) and does not distinguish between positive and negative shocks. While the transfer value is included in Originals' baseline assets, the delayed transfer to the POGs is not. Therefore, though positive, the transfer acts as a shock and is likely to increase residuals in Eq. (2) among POGs that receive the transfer. In the earlier rounds, because of the lower value asset transfer and the fact that only a few POGs had received transfers, there is no change in the estimated residuals compared to the Controls. The $\widehat{\beta}_V$'s for POGs in Eq. (3) are statistically equivalent to zero (not shown). Similarly, in the later rounds, although more POGs received their gifts, the immature animal early POG recipients received is likely to mature and stabilize in value. The difference in the transfer timing, therefore, is likely to lead to heterogeneous estimated residuals in Eq. (2). Fig. A.1 in Appendix A reports the relationship between assets and estimated variance in our sample. The U-shaped curves suggest households at the extremes face higher

[11] Since the resilience outcome is measured in fractions i.e. $\widehat{\rho}_{it} \in [0, 1]$, 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.

[12] 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.




Notes: Expected assets of each household in each round is assumed to follow a gamma distribution in Figure 2a and 2b, and a normal distribution in Figure 2c and 2d. 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 2b where $k = 2$.

**Fig. 2.** Headcount resilience rate - robustness checks.

asset volatility. Similarly, POGs, in general, face the highest level of variance in their asset holding 18 month post-intervention but as more and more POGs receive their transfer and for longer periods, the variance decreases and the distribution moves closer to that of Originals. In addition, 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 increasing resilience when the 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 poverty.

Fig. 1 presents the headcount resilience 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 ($\overline{R}$) at time $t$ i.e. $R_{it} = 1$ if $\hat{\rho}_{it} > \overline{R}$; 0otherwise.[13] 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.

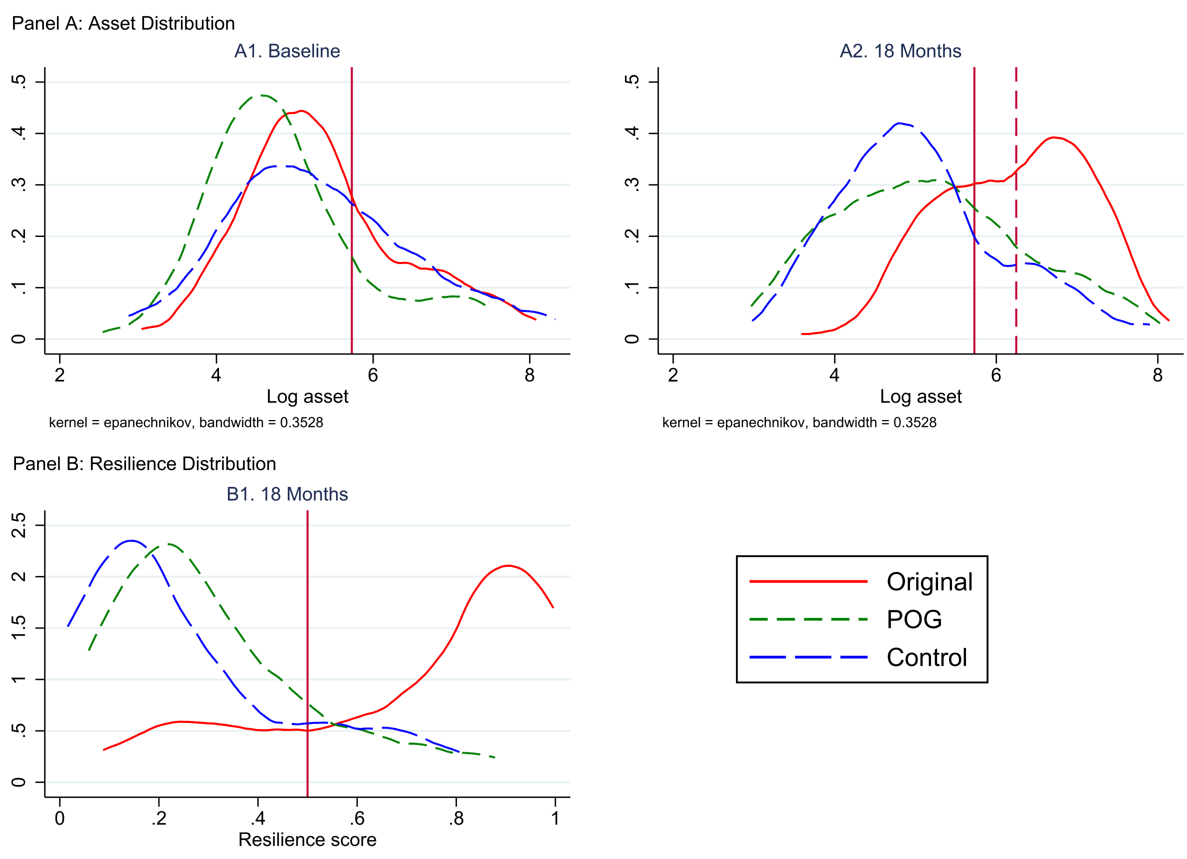
[13] The resilience threshold ($\overline{R}$) is comparable to poverty line used in headcount poverty calculation; a unit is classified as resilient if it is above the threshold and non-resilient if below. Unlike the poverty line, which is generally rooted to some necessary expenditure requirement for household's functioning, the resilience threshold is arbitrary. We set the initial resilience threshold at 0.5 ($\overline{R} = 0.5$) and present the headcount resilience 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 (2018). However, we also calculate headcount resilience rate using 0.8 for sensitivity.

The number increases slightly for the Originals after 36 and 42 months of the intervention – more than 80% become asset resilient. Similarly, the headcount resilience 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 resilience scores between POGs and Controls) presented in Table 5 Panel A decreases over time. The distribution of resilience scores among the Control group, thus, is likely to be positively skewed in the later periods, whereas the distribution among POGs is likely to be more symmetric.

### 6.2. Resilience vs impact evaluation measures

To provide the direct comparison between resilience and standard impact evaluation methods, we compare asset poverty rates and resilience rates. While households with an asset value above the calculated asset poverty threshold of USD 308 are defined as asset non-poor, households with estimated resilience score of 0.5 and above are classified as resilient. The treatment effects from the difference-in-difference specification for the two outcomes are reported in Table A.1 in Appendix A. While Originals are 47.0% less likely to be asset poor, they are 59.6% more resilient compared to the Controls 18 months post-intervention. Similarly, 42 months post-treatment Originals are more likely to be resilient than asset non-poor (52.7% vs 39.0%).

The difference in the effect size between the two outcomes is more pronounced among the POGs. Although the POG households are significantly more likely (24.3%) to be asset non-poor compared to the Controls at 18 months after intervention, there is no difference in resilience rates between the two groups. We observe a similar pattern even after increasing the resilience threshold to 0.8 and changing distribution and functional form of the asset holding (Fig. 2). This result emerges 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 inadequate 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 Fig. 3 (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




Notes: Panel A shows Kernel density estimate of household asset by treatment groups at the baseline and 18 months post-intervention. While the vertical solid lines represent asset poverty threshold of 5.73 ($log(\bar{W}) = 5.73 \implies \bar{W} =$ 308 USD PPP per person), the dash vertical line in A2 is the asset poverty threshold plus the half of standard deviation of asset distribution among the Controls 18 months post-intervention. Panel B shows Kernel density estimate of resilience at 18 months after the baseline. The vertical solid line represents resilience threshold of 0.5.

**Fig. 3.** Kernel density estimate of asset and resilience.

**Table 6**
Treatment effects on household resilience - robustness checks.

| | Gamma ($k = 2$) | Normal ($k = 3$) | OLS | |
|---|---|---|---|---|
| | | | 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 average 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 average 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.

POG households that are above the resilience threshold (Fig. 3: 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. The resilience measure, on the other hand, provides the likelihood of one's future outcome relative to the threshold given its present status. Hence, the resilience measurement yields more insight about households' capacity to escape or remain out of poverty.

### 6.3. Robustness check

We re-estimate the effects on resilience using an alternative functional form, an alternative distributional assumption and an alternative estimation technique. Column 1 of Table 6 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. 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 5. Additionally, we estimate effects on resilience using OLS and again find results to be consistent with the earlier estimates. Fig. 2 presents headcount asset resilience rates using alternative resilience thresholds. Fig. 2a and d are resilience rate using $\overline{R} = 0.8$ 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 Fig. 2b shows the headcount resilience rates using the quadratic functional form, Fig. 2c shows the headcount rates assuming a normal distribution. Estimates of the number of 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 well-being and resilience. Similarly, the program is likely to help households transition to more remunerative technologies, which, again, improves well-being 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 prompt 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 7 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. Addition-

**Table 7**
Treatment effects on employment and income.

| | (1) Self Employment | (2) Casual Labor | Per Capita Revenue and Income | | |
|---|---|---|---|---|---|
| | | | (3) TotalRevenue | (4) Live-stock | (5) PaidIncome |
| 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 (Original) | 0.696 | 0.0476 | 523.1 | 13.48 | 0.536 |
| Time 2 impact: % change (Original) | 23.27 | −157.7 | 138.4 | 821.6 | −3147 |
| Time 1 impact = Time 2 [p-value] (Original) | 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, Eq. (6), specification. All outcomes are measured at the household level except (1) self employment and (2) casual labor, which are at individual level - women 18–65 years of age. Standard errors are clustered at the household level in column 1. Due to data limitations 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) households sold in last 3 months. Paid income is wage income from labor (salaried or casual) in the last 3 months. Total revenue, column 3, is yearly income calculated by adding yearly revenues from agriculture and livestock, paid income, micro-enterprise profits, remittance and other transfers.

ally, three and one 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 periods. The results for total revenue show that 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 8 presents conventional benefit-cost measures for project assessment and extends them to indicate the cost of achieving increases in resilience. Details of the cost-benefit calculation are presented in Appendix D. In total, the direct costs 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. In addition, 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).[14] This implies that households 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.

[14] 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.

**Table 8**
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* | $\overline{R} = 0.5$ | $\overline{R} = 0.8$ |
| i Year 1 post-intervention (USD) | 99.83 | 102.95 |
| ii Year 3 post-intervention (USD) | 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. The average cost of increasing head count resilience by one percent is the value of the transfer divided by the gains in the headcount resilient rate (see Appendix D.1).

Panel C in Table 8 focuses on the cost of improving the resilience headcount by one percent at different resilience cutoffs. Costs are calculated as total transfer value divided by the gains in resilience headcount rate (see Appendix D.1). The original transfer value of USD 2145 (USD 1853 inflated to year 3) helped increase headcount resilience by 20.8% among the treated group (Original + POG) compared to the Control group at the 0.8 resilience cutoff 18 months post-intervention. If households are distributed uniformly over asset-holdings, an investment of USD 103 into the program moves 1% of the non-resilient households into resilience after 18 months of the investment, such that they have less than a 20% probability of falling into poverty in the future.[15] Consistent with the treatment effects (Table 3), the cost of increasing headcount resilience by 1% decreases after three and half years (USD 84); a greater number of treated households become resilient as transfers become more productive and/or higher numbers of the POGs receive transfers over time. 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 effectiveness and persistence of estimated effects.

Resilience as a household outcome offers three important advantages for impact analysis. First, because it is based on the full distribution of household welfare, the development resilience measure provides a more complete picture of intervention impacts, yielding insights into household capacity to avoid falling into poverty in the foreseeable future. In particular, estimation of the conditional moment functions allows for nonlinear persistence, which can improve forecasting of households' future states. In addition, the conditional moment functions make it possible to distinguish whether estimated effects are primarily attributable to changes in the conditional mean or the conditional variance. These inferences are especially significant for households at or near the poverty threshold. 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 well-being that conventional measures like poverty headcount miss.

Second, because conventional methods use cross-sectional variation as a proxy for inter-temporal variation, they offer only limited insight into longer-term household welfare status. 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.

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 and weighs negative shocks as equally as positive shocks. 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 the first moments of outcomes.

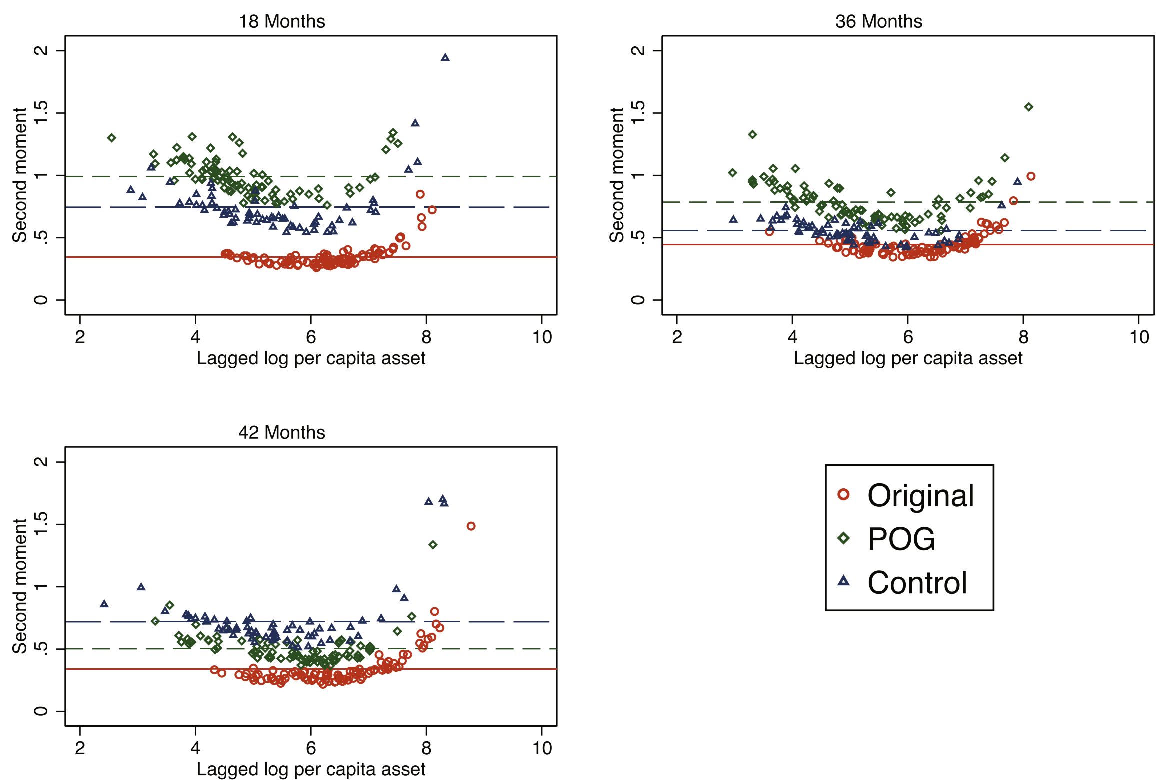
Given the science-based predictions of increasingly frequent natural disasters, unstable weather patterns, macroeconomic shocks, and other humanitarian emergencies, anti-poverty interventions will continue to focus on bolstering the capacity of poor households to mitigate risks. Our resilience estimation results suggest that the multifaceted approach focused on improving well-being 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 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 well-being using resilience 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 for future work.

## Acknowledgments

This research was made possible by a grant from Elanco Animal Health (USA) and by the cooperation of Heifer International. The work was supported by USDA National Institute for Food and Agriculture Hatch project 1014548. We thank Heifer International Zambia staff, especially James Kasongo, Joyce Phiri, and Emelda Nanyangwe, and a wonderful team of enumerators. We are grateful for comments from an anonymous referee, Chris Barrett, Jennifer Denno Cissé, Benjamin Crost, Mary Arends-Kuenning, Kathy Baylis, Rebecca Thornton, Andrew Foster, Jorge Aguero, Brian Dillon, and Elliott Collins.

[15] For this to hold households either have equal livestock rearing abilities or the abilities are orthogonal to the baseline assets. 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.

## Appendix A




Note: Horizontal lines represent group means.

**Fig. A.1** Distribution of second moment by treatment and time.

**Table A.1**
Resilience vs asset poverty - difference-in-difference results.

| | (1) Resilient($\hat{\rho}_{it} > 0.5$) | (2) AssetNon-poor |
|---|---|---|
| Time 1 Original (18 months post treatment) | 0.596*** | 0.470*** |
| | (0.082) | (0.088) |
| Time 1 POG (18 months post treatment) | 0.007 | 0.243*** |
| | (0.074) | (0.082) |
| Time 2 Original (42 months post treatment) | 0.527*** | 0.390*** |
| | (0.087) | (0.091) |
| Time 2 POG (42 months post treatment) | 0.282*** | 0.384*** |
| | (0.098) | (0.087) |
| Baseline mean | – | 0.302 |
| Time 2 impact: % change Original | – | 129.1 |
| Time 1 impact = Time 2 impact [p-value] | 0.463 | 0.277 |
| Adjusted R-squared | – | 0.216 |
| Observations | 741 | 741 |

Notes: *** (**) (*) indicates significance at the 1% (5%) (10%) level.

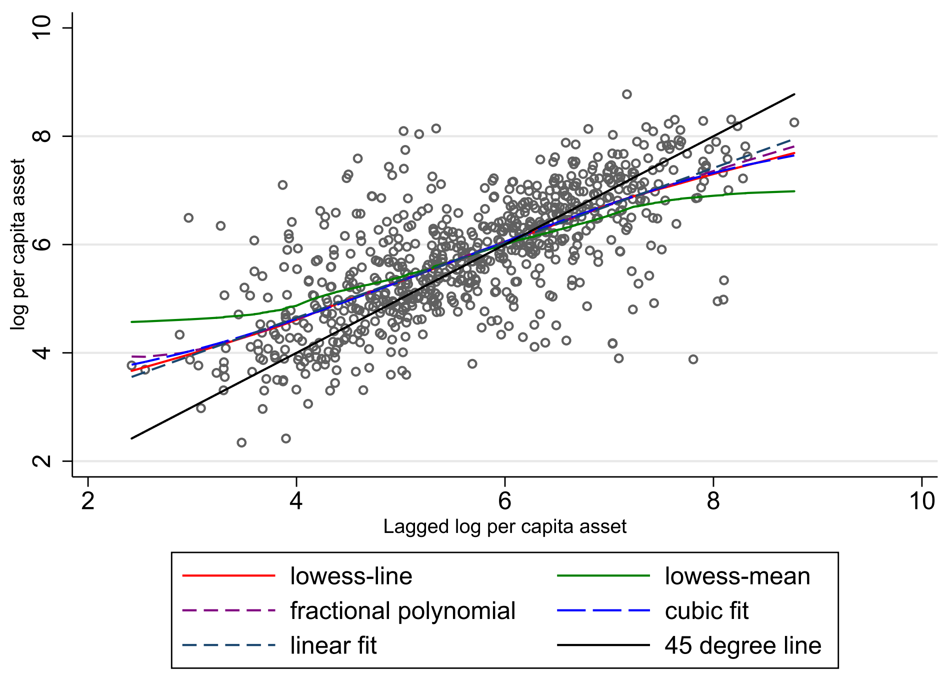
**Table A.2**
Treatment effects on poverty, food Security, and asset poverty - Robustness check using nonlinear estimation.

| | (1) BelowPoverty Line | (2) EnoughFood | (3) AssetNon-poor |
|---|---|---|---|
| Time 1 Original (12 | −0.218** | 0.181*** | 0.468*** |
| months post treatment) | (0.094) | (0.066) | (0.086) |
| Time 1 POG (12 months | −0.033 | 0.111* | 0.246*** |
| post treatment) | (0.095) | (0.064) | (0.084) |
| Time 2 Original (36 | −0.316*** | 0.213*** | 0.384*** |
| months post treatment) | (0.094) | (0.068) | (0.088) |
| Time 2 POG (36 months | −0.066 | 0.154** | 0.383*** |
| post treatment) | (0.095) | (0.066) | (0.089) |
| Observations | 741 | 741 | 741 |

Notes: *** (**) (*) indicates significance at the 1% (5%) (10%) level. Reported are average marginal effects using logistic regressions. Time 1 and time 2 refer to 12 and 36 months post-intervention except in column 3, 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 an indicator variable for subjective food security, which takes the value of 1 if the survey respondent report the household usually or always has enough food to feed all the members. Asset non-poor in column 3 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 Appendix B.2.

## Appendix B.

### B.1. *Well-being path dynamics and treatment (First Stage)*




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.

**Fig. B.1** Asset dynamics.

In order to choose the optimal functional form for the polynomial of lagged well-being we use AIC, BIC, Log likelihood criteria and the LR test. Fig. B.1 presents 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 are very similar. From above tests (not shown) and the graph, we choose cubic ($k = 3$) as our preferred functional form.

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

$$y_{it} = \alpha + \sum_{j=1}^{3} \theta_j y_{it}^{j} + \sum_{j=1}^{3} \phi_j D_{it} \times y_{i,t-1} + \lambda_t + \delta D_{it} + \beta X_{it} + \epsilon_{it} \tag{B.2}$$

We estimate Eq. (B.1) and test if the cubic lagged term ($\theta_3$) is significant, which provides the evidence of a dynamic asset growth to be S-shaped. In order to examine whether the treatment has altered the path dynamics we estimate Eq. (B.2) and perform following tests:

$$H_0 : \phi_1 = \phi_2 = \phi_3 = 0 \tag{B.3}$$

$$H_0 : \phi_2 = \phi_3 = \delta = 0 \tag{B.4}$$

$$H_0 : \delta = 0 \tag{B.5}$$

Hypothesis (B.3) tests whether the treatment has altered the rate of change of the curvature. Hypotheses (B.4) and (B.5) test if the treatment shifted the growth curve horizontally or vertically respectively.

### *B.2. 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 an asset base threshold as below:

$$\text{Log}(C_{it}) = \alpha + \gamma \text{Log}(W_{it}) + \beta X_{it} + \epsilon_{it} \tag{B.6}$$

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's consumption. We limit analysis to baseline data only. We subtract the value of asset transfer made to households at the baseline and estimate (B.6) using OLS. Using the estimated coefficients and median characteristics of the sample, we map 1.90 USD PPP ($\overline{P}$) consumption to household per capita asset level as:

$$\text{Log}(\overline{W}) = \frac{\text{Log}(\overline{P}) - \widehat{\alpha} - \widehat{\beta} X_m}{\widehat{\gamma}} \tag{B.7}$$

where $\overline{P}$ is a consumption poverty line. The hat, $(\widehat{\ })$, caret refers to estimated coefficients, $m$ subscripts represents the median value of the sample and $\overline{W}$ is the asset threshold, below which households will be considered vulnerable to poverty. Fig. B.2 presents the consumption poverty line mapping to asset threshold using baseline data. As shown in Fig. B.2 the asset poverty threshold in natural log is 5.73 ($= \text{Log}(\overline{W}) \implies \overline{W} = \exp 5.73 \approx$ 308 USD PPP).

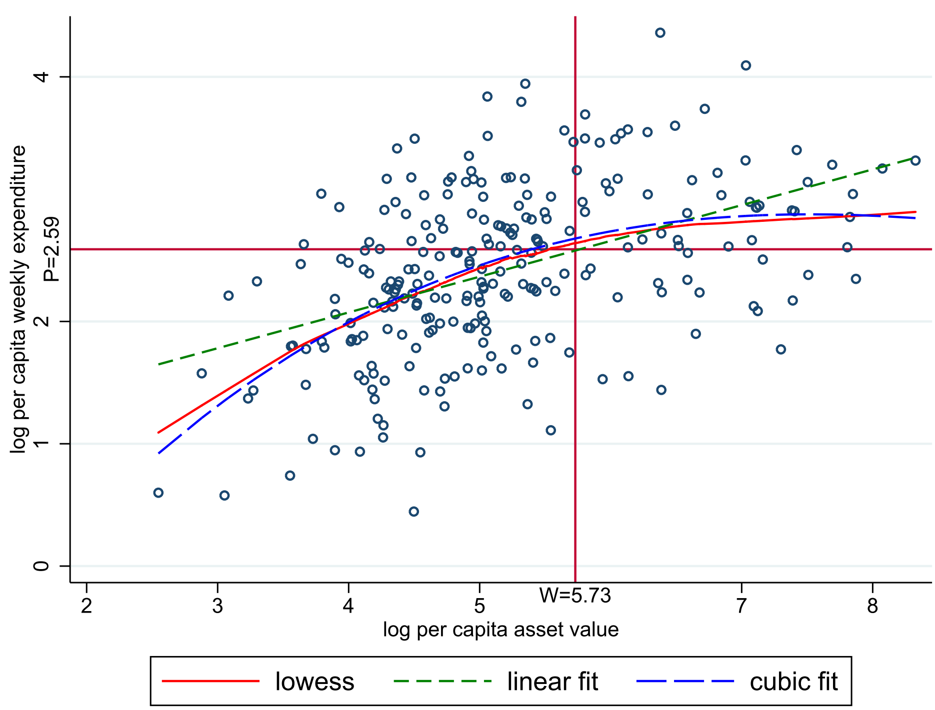



**Fig. B.2** Asset poverty line ($\overline{W}$).

## Appendix C. Test for POGs as a comparison group

We normalize the timing of transfer and perform an event-study type of analysis on the outcome of interests to check whether it could be appropriate to use POG households as a comparison group for Originals. Unfortunately, we cannot normalize the transfer amount; first, POGs received an immature animal whereas the Originals received mature pregnant animals and second, while the Originals' gift was preconditioned on passing on the first female offspring from the gift they received, the POGs do not have such requirements.

In the sample, the last of the livestock transfers to POGs were made about a year before the sixth round of data collection. Therefore, after normalizing the transfer dates, we can investigate the program effects for one-year post transfer. We limit the sample to Originals and POGs and estimate the following equation (same as the main specification in the paper, Eq. (6)).

$$y_{it} = \alpha + T_t + Original_i + \beta(T_t \times Original_i) + \eta_i + \epsilon_{it} \quad \text{(C.1)}$$

where, $y_{it}$, is an outcome of interest for household $i$ in period $t$. The period, $t$, takes the value of 0 to indicate the time of the transfer (baseline for all the Original households) and 1 to refer to one year after the transfer was made. $T_t$ is a binary variable for period 1. Estimated $\beta'$s are reported in Table C.1 (below). As expected, the treatment effects for Originals are different from POGs after one year for nearly all key outcome variables. Statistically, we do not see the differences in herd size after one year; the reason for this is likely explained by the fact that while the POGs gain immature animals (which likely mature after one year and thereafter begin increasing herd size in TLU), Originals lose one immature animal. We see the benefits of receiving the matured animals on consumption; Originals have higher consumption, less poverty and perceive themselves to be more food secure than the POGs.

Based on these results along with the experimental design discussed in the text, we do not think using POGs as the comparison group for Originals, in this particular case, will improve the identification strategy to answer the questions we explore: what are the effects of a large one-off asset transfer program on household welfare and resilience to poverty.

**Table C.1**
Treatment effects using POGs as a comparison group.

| | (1) Household herd size (TLU) | (2) Livestock value, per capita | (3) Total asset, value, per capita | (4) Below poverty line | (5) Total expenditure, per capita | (6) Enough food |
|---|---|---|---|---|---|---|
| One year post transfer × Original | 0.22 | 190.81*** | 115.33 | −0.16* | 3.01* | 0.14** |
| | (0.26) | (67.99) | (97.11) | (0.09) | (1.75) | (0.06) |
| Observations | 368 | 368 | 368 | 368 | 368 | 368 |
| Adjusted R-squared | 0.222 | 0.306 | 0.141 | 0.035 | 0.034 | 0.147 |

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.

## Appendix D. 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 $\widehat{B}$:

$$\widehat{B} = B^O \times S^O + B^P \times S^P \quad \text{(D.1)}$$

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 remaining 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 expenditures on durable goods as these 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 till additional 17 years i.e. we assume program benefits to last for 20 years. 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 cost 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:

$$C_3 = C_0 \times (1.05)^3 \quad \text{(D.2)}$$

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.

### D.1. Calculating cost of increasing resilience headcount by 1%

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

$$\widehat{R}_t = R_t^O \times S^O + R_t^P \times S^P - R_t^C \tag{D.3}$$

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. The cost of increasing resilient rate by 1% at time $t$, $\widehat{C}$ is calculated as follow:

$$\widehat{C}_t = \frac{\text{Total value of transfers at year 3}}{\widehat{R}_t} \tag{D.4}$$

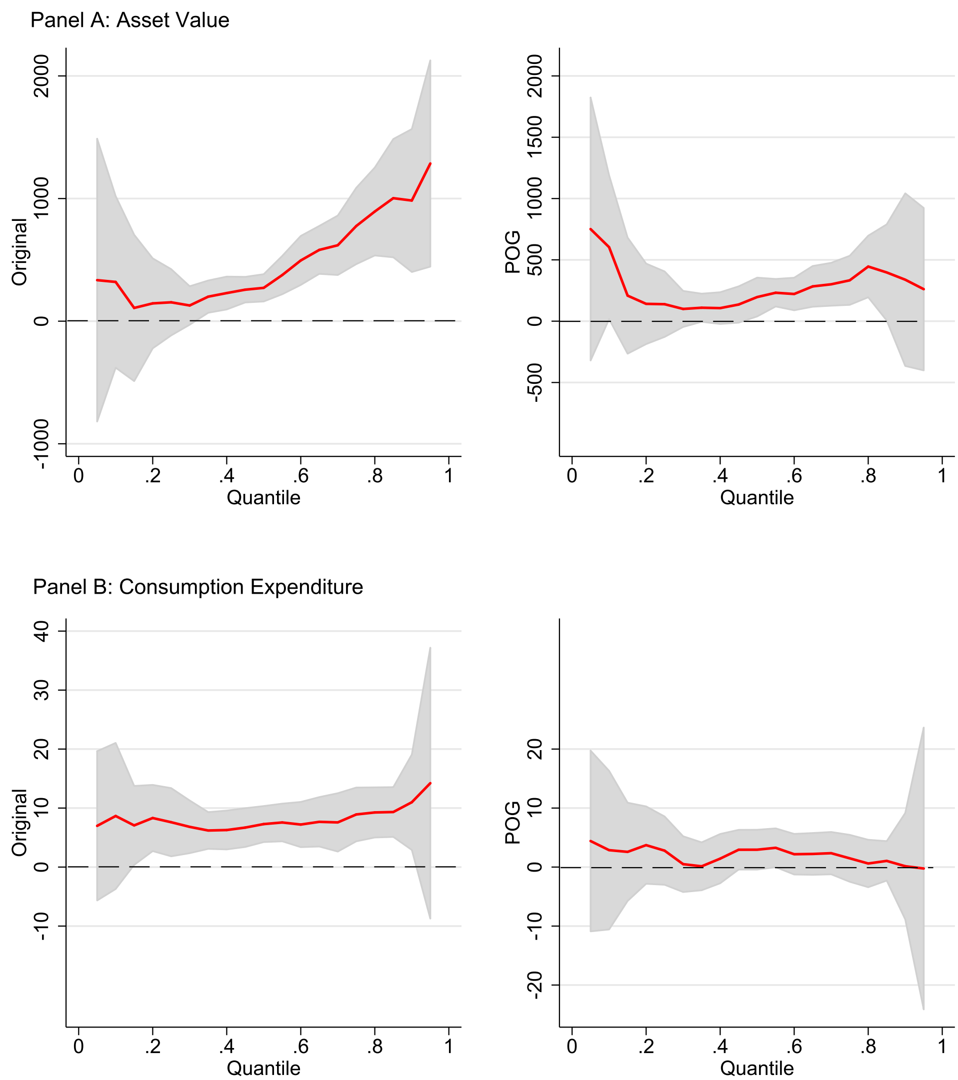
Transfer values are inflated from year 0 to year 3 using Eq. (D.2).

## Appendix E. 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.

$$Q_{\Delta y_i}(\tau) = \alpha(\tau) + \beta_1(\tau)OG_i + \beta_2(\tau)POG_i \tag{E.1}$$

where $\Delta y_i$ 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 Fig. E.1. 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.




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, assets 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).

**Fig. E.1** Three year quantile treatment effects.

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