Tangible Progress for the Very Poor: Examining the Impact of Economic Interventions in India

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Abstract

Poverty and alleviation have been widely regarded as problems in much of the developing world. Previous policies have largely failed, inspiring a comprehensive program in India, as well as several other countries in the Global South. Banerjee et al. (2018) conducted a randomized control trial to examine the effects of this thorough program. Nearly every metric examined – such as wealth and health outcomes – had a statistically significant improvement. Accordingly, it is clear that the program designed by Banerjee et al. (2018) can serve as a model for effective poverty alleviation in the developing world.

Introduction and Motivation for the Experiment

Despite rapid economic growth for several decades, India still faces persistent extreme poverty, with a significant portion of the population living in extreme poverty, designated as living on less than $1.25 per day. Poverty reduction has long been a goal of the world's most populous country, and there have been myriad attempts by the Indian government to alleviate poverty in the country. According to the World Bank (2024), in recent years, GDP per capita in India has increased substantially, but poverty remains a significant problem. Further, GDP per capita doesn't entirely recognize how well the Indian people are doing. To pursue genuine improvements in people's lives, Banerjee et al. (2018) sought to examine self-employment (e.g., rearing livestock) and well-being improvements (defined later) defined by other metrics rather than just GDP per capita. Banerjee et al. contextualizes this in a broader international context: there is emerging global consensus that an effective program could drive the extreme poverty rate ($1.25 per day) close to zero by 2030. There remains, however, an issue in finding an effective solution to do this. Past policies – such as monetary transfers – have been limited in their success, providing *some* temporary relief for very poor families in India but failing to effectively lift them permanently out of poverty. Finding a lasting solution that effectively increases outcomes is critical for India's continued development, and capitalizing on this increase in GDP per capita to improve outcomes. By providing a much more comprehensive program for poverty alleviation – including monetary transfers combined with life skills coaching, asset management training, health information, and more – Banerjee et al. (2018) believed this multifaceted approach could provide meaningful poverty reduction and *actually* improve outcomes for the very poor in India. Accordingly, Banerjee et al. (2018) sought to explore the following question: To what extent did India's poverty reduction program lead to sustained increases in household income and revenues, consumption, financial behavior, and productive asset value among the extremely poor in India?

Banerjee et al. (2018) explored the impact of a comprehensive poverty reduction program – including monetary and livestock transfers, health information, savings account provision, and more – on the aforementioned outcomes, seeking to see the impact of a poverty reduction program beyond just monetary transfers. By using a randomized control trial (RCT), Banerjee et al. (2018) is able to isolate the effect of the program and examine its effects in India. Rather than examining each component of the program, the authors seek to determine the impact of the holistic program.

Literature Review

There is a tradition of randomly controlled testing of health and financial outcomes with the implementation of programs that grant productive assets amongst the extreme poor. Typically this evidence is based on the long term effects of the implemented asset transfers among the selected groups compared to control populations that were not selected for the treatment, but share the same selection characteristics. The literature on the effectiveness of these asset transfers seems to agree in areas such as consumption, savings, and household income in that these outcomes increase with treatment among the ultra poor (Banerjee et al. 2018; Rahman et al. 2021). However, the literature on this subject faces the main challenge of understanding the relative importance of the main components that make up their asset transfer program. Since hybrid interventions have multiple components bundled together (Rahman et al. 2021), isolating each component is difficult and instead we tend to only draw conclusions from the effectiveness of the multi component plan altogether rather than its individual parts. Additionally, there is some ambiguity in the literature on the effectiveness of asset transfers vs in kind (cash) transfers in terms of overall effectiveness among the extreme poor. Especially in Banerjee et al. (2018), where we see some difficulty in distinguishing the significance of effects from training and coaching among the full intervention group. There just isn't enough experimental variation to test the effect of this component.

Description and Experiment Design

Banerjee et al. (2018) used a randomized control trial (RCT) to explore the impact of this program. By randomly distributing the program among the very poor in India, the isolated impact of the program can be determined by looking at the outcomes of those who received and followed the program relative to those families who did not receive the program. Random distribution happened within villages: the authors examined the poorest villages in India and then randomly distributed the program to half of the households in a given village. In India, the authors examined a region in West Bengal State – in the east, just to the west of Bangladesh – the area in and around the town of Murshidabad. The randomization here was done remotely by a team of researchers and local nonprofits the authors collaborated with. The authors had these partner nonprofits actually go to the households in Murshidabad to offer participation in the program. To ensure experimental integrity, the authors successfully ensured that no control household received the program, but there was one issue with the implementation of the program in India. In offering the program to half of the households in a given village, the households had to agree to participate in, and complete the program. In India, however, there was an extremely high rate of attrition, which poses a threat to validity that we will explore in depth later on in this paper. However, this means that a significant portion of the sample population either refused the program or did not participate fully through the end of the program. Approximately 48% of the households refused the program, leading the authors to explore the reasoning behind this while also raising some concerns over attrition. A plurality of the refusing households believed in one of two problems, which led them to turn the program away. First, that the local partner organization that Banerjee et al. (2018) used to actually conduct the program was a Christian group that would seek to convert them; this was, of course, not true. Second, wives believed their husbands would misuse the monetary transfer component of the program, losing status in the village. Finally, a minority of households were participating in other programs, like monetary transfers or microloans for businesses, which would make it very difficult for Banerjee et al. (2018) to effectively isolate the effects of the program. So, by randomly distributing – which we confirm quantitatively later in this paper – the program to households, the sole effect of the program could be determined. Beyond randomness, there are certain requirements for an RCT to ensure internal and external validity. We will discuss external validity later on in this paper, but the threats to internal validity are failure to randomize, failure to follow treatment, attrition, and experimental effects. The authors had some concerns over attrition due to the high proportion of households that did not complete the program, but that does not necessarily prove to be an issue. These households outright refused to participate – they didn't start and then stop or fail to adhere to protocol. Despite this high rate of attrition, the sample size is still large, allowing for an effective analysis and minimizing the risk of experimental effects.

Data

The data we analyzed comes from the research article mentioned above. The time span of this data collection was a little bit different for India than other countries examined in the study. There were 5 months between the baseline household visits and the midpoint of endline 1. Then there were 15 months between the midpoint of endline 1 and the midpoint of endline 2. This essentially means that the first follow-up to households happened 5 months after treatment (or no treatment), and the second follow-up happened 20 months after treatment (or no treatment). This study contains panel/longitudinal data: the same households in India were surveyed across three different points in time. This is different from cross-sectional data, as the households remained the same throughout the entirety of the study. While the full study contained thousands of observations, our study focused on just the portion about India. For these observations about India, some of the variables did not have any values, as they were not pertinent to the research study conducted for India. Therefore, our research study focused just on the relevant variables for the India aspect of the original study.

Key variables for the first dataset about households include expenditure variables (total monthly spending, monthly spending on food, etc.), variables for assets (total assets, productive assets, household asset index, etc.), income variables (monthly income, income from livestock, paid labor, etc.), binary food security variables (whether or not everyone received one meal, whether or not everyone received two meals, etc.), and key spending and savings variables such as total deposits, total savings balance, and total amount borrowed. The second dataset contains variables relating to physical health, mental health, political involvement, and female empowerment. Important variables for the second data set include total health index, total political involvement index, perceived health status, and perceived life status. Units of observation are consistent and mostly straightforward across the entire study. For any variable dealing with money (such as income, consumption, assets, etc.), the United States dollar was used instead of the local currency in India. These USD values were calculated using Purchasing Power Parity (PPP). For any variable dealing with time, minutes were used unless otherwise denoted. For all binary variables, the variable took on a value of 1 if the condition was true and 0 if the condition was false. Many variables were expressed as indices, meaning that data values were normalized using the sample average. For these variables, a 0 is considered average, +1 is one standard deviation above the mean, and -1 is one standard deviation below the mean.

Random Assignment Methodology

Before the treatment effects can be estimated, it is important for us to first identify whether or not the treatment was randomly assigned in the first place. In order to check for random assignment, we looked at the means and standard deviations for six key baseline characteristics among households and individuals in India. These baseline characteristics included total monthly income by household, total monthly spending per capita, individual food security index, total asset value index of households, individual health index, and perceived life status. First, we calculated summary statistics for these six baseline characteristics for the entire sample of Indian households and individuals, without considering the treatment groups. Following these summary statistics, we performed t-tests on the differences in means between households and individuals in the treatment and control groups. For each of these six t-tests, the null hypothesis was that the difference in baseline means between the treatment and control groups was not statistically significant. Of course, this means that the alternative hypothesis was that the difference in baseline means between the two groups was statistically significant. A significance level of 5% was used for these tests. If the two-sided p-value was less than 0.05, then the null hypothesis was rejected and there was an issue with random assignment of the treatment and control groups.

Results: Evidence of Random Assignment

Table 1 shows the summary statistics of the six baseline characteristics that were studied without considering the treatment status of the individual or household. The average total monthly income for a household during the baseline period was -0.43 United States dollars, although the standard deviation was extremely high at 77.39 dollars. The average total asset index for a household was 0.0386588. The average total monthly per capita expenditure was 39.36 dollars, with a standard deviation of 24.01 dollars. The average food security index of an individual was -0.0301191. The average general health index of an individual was 0.0604967. The average perceived life status was 1.250873, with a standard deviation of 1.003866. We felt as though these were very low averages, which proves the aforementioned point that a lot of work needs to be done in India.

Table 2 displays our calculations to confirm treatment distribution randomness for the Indian part of the intervention program. These households and adults, which were split up between those who did and did not receive treatment, must be randomly assigned to ensure internal validity. A key tenet to ensure randomness is that, in the absence of treatment, the two groups – treated and untreated – would have the same outcomes. This calls for the two groups to be the same, statistically, prior to the treatment. To confirm this, we looked at various criteria to examine the similarities between the treated and untreated groups that are listed in our table, including income and expenditures. All but one of our p-values, when looking at the baseline differences in means between the treatment and control groups, were greater than 0.05. This is a positive result: it shows that there is no statistically significant difference between the treated and untreated groups. This led us to fail to reject the null hypothesis and conclude that random assignment was ensured for the first five baseline characteristics variables. The only p-value that was significant comes with the general health index, showing a higher, on average, result for the treated group over the untreated group. The cause of this is likely random chance: while wealth and other economic factors are factors in health, external circumstances – genetic factors, predisposition, access to vaccines, etc. – can also play major roles in health. This attribution of the significant p-value to random chance led us to fail to reject the null hypothesis for this sixth and final variable. Also, when considering that the five other variables show a clear lack of difference between the two groups, we are confident that the groups were randomized effectively.

Regression Model Methodology

The equation below shows the difference in differences formula that we used for evaluating the effect of the treatment on the outcome variables of interest. With difference in differences, there is an identifying assumption that must be satisfied to ensure the effect of the treatment, which in this case is the intervention program. This assumption, referred to as the parallel trends assumption, states that the two groups must have been trending similarly prior to the treatment. To be more specific, the outcomes of households and individuals in the intervention program would have trended similarly to those in the control group, if the intervention program never occurred. This is tough to evaluate within the context of our problem, as the researchers only measured the baseline values of Indian households and individuals at one specific point in time. If there were multiple baseline measurements, perhaps multiple months apart, we would feel much more comfortable and confident in this parallel trends assumption.

In our study, by comparing the two groups and ensuring randomness, although we are not necessarily looking at these over time, we feel this assumption is satisfied. Because these groups are the same, essentially, we feel our sort-of difference in differences study assumption is satisfied and the effect can be labeled as causal. The five outcome variables of interest that were considered were total asset index, total monthly income, total monthly spending, individual total health index, and individual political involvement index. Two regressions were created for each of these five variables: we wanted to measure the effects of the treatment on both the endline-1 values and the endline-2 values. This allowed us to identify potential short-term and long-term effects from the intervention program. As suggested in the aforementioned research study, the baseline value of the outcome variable served as a predictor variable in our models. Because this was an RCT, no control variables were included in the regressions; further, the baseline values we included in our regression added precision for the estimated effect of the treatment on the outcome variables of interest.

$$Outcome_i = \alpha + \beta_1 Treatment_i + \beta_2 BaselineValue_i + \epsilon_i$$

For each predictor variable (particularly the treatment status) in the regression models, t-tests were performed to evaluate the effect of the variable on the outcome characteristic of interest. The null hypothesis was that the predictor variable was statistically insignificant, meaning that it did not have a causal effect on the outcome characteristic of interest. Of course, the alternative hypothesis was that the predictor variable did have a causal effect. A significance level of 5% was used for these t-tests. If the calculated p-values were less than 0.05, then the null hypothesis was rejected. We were optimistic that the treatment status for each regression would be statistically significant, which suggests that the intervention program was successful in improving outcomes in India.

For each of the ten regressions, F-tests were performed to evaluate the effect of the entire model on the outcome variable of interest. The null hypothesis was that the models were not statistically significant, meaning the treatment program and the baseline values were not predictive of the outcome variables of interest. The alternative hypothesis was that the models were statistically significant, meaning the intervention program and the baseline values were predictive of the outcomes in India. Once again, a significance level of 5% was used for these F-tests.

Results: Treatment Effects in India

Table 3 shows the effects of the treatment (intervention) on the total monthly income of an Indian household in the study, which includes income from agriculture, business, and paid labor. As seen in the table below, the treatment successfully had a positive effect on total household income in both the first endline measurement (5 months after baseline) and the second endline measurement (20 months after the baseline). For the endline-1 regression model, we found that the treatment was statistically significant with a p-value of 0.023. Five months after the treatment, a household receiving the intervention (as opposed to not receiving the treatment) received an associated increase in total monthly income by around 14.52 United States dollars. For the endline-2 regression model, we found that the treatment became even more significant, with STATA reporting a p-value of 0.000. Twenty months after the treatment, a household receiving the intervention (as opposed to not receiving the treatment) received an associated increase in total monthly income by around 23.59 United States dollars. This increase from the endline-1 regression to the endline-2 regression proved to us that the treatment had lasting positive effects on the total monthly income of a household. The null hypotheses were rejected for the treatment in both models, meaning that the intervention program had a significant effect on a household's total monthly income. Both regression models were also found to be statistically significant.

Table 4 shows the effects of the treatment (intervention) on the total monthly spending of an Indian household in the study. Similar to that of total monthly income, the treatment had a positive effect on total monthly spending in both the first and second endline measurements. For the endline-1 regression model, we found that the treatment was statistically significant with a p-value of 0.000. Five months after the treatment, a household receiving the intervention (as opposed to not receiving the treatment) increased monthly spending by around 6.79 United States dollars. For the endline-2 regression model, we found that the treatment became somewhat less significant with a p-value of 0.004. Twenty months after the treatment, a household receiving the intervention (as opposed to not receiving the treatment) increased total monthly spending by around 5.25 United States dollars. This decrease in effect from the endline-1 regression to the endline-2 regression suggested to us that total monthly spending began to return closer to baseline values. Once again, the null hypotheses were rejected for the treatment in both models, meaning that the intervention program had a significant effect on a household's total monthly expenditure. Additionally, both models were considered statistically significant.

Table 5 shows the effects of the treatment (intervention) on the total asset index of an Indian household in the study. Just as for the previous two dependent variables, the treatment had a positive effect on total asset index in both the first and second endline measurements. For both regression models, we found that the treatment was statistically significant with a p-value of 0.000. Five months after the treatment, a household receiving the intervention (as opposed to not receiving the treatment) was associated with an increase in total asset index by around .67 percentage points. Twenty months after the treatment, a household receiving the intervention (as opposed to not receiving the treatment) was associated with an increase in total asset index by around .72 percentage points. This increase in effect from the endline-1 regression to the endline-2 regression suggested to us that the treatment may have successfully improved a household’s total asset index for the long-run. The null hypotheses were rejected for the treatment in both models, meaning that the intervention program had a significant effect on a household's total asset index. Both regression models were also found to be statistically significant.

Table 6 shows the effects of the treatment (intervention) on the total health index of Indian individuals in the study. Fortunately, the treatment had a positive effect on an individual’s total health index in both the first and second endline measurements. For the endline-1 regression model, we found that the treatment was statistically significant with a p-value of 0.002. Five months after the treatment, an individual receiving the intervention (as opposed to not receiving the treatment) was associated with an increase in total health index by around .18 percentage points. We were disappointed to see that the effect of the treatment was not statistically significant in the endline-2 regression, due to a p-value as high as 0.352. Twenty months after the treatment, an individual receiving the intervention (as opposed to not receiving the treatment) was associated with an increase in total health index by around .048 percentage points. This substantial drop in effect from the endline-1 regression to the endline-2 regression suggested to us that the treatment successfully created temporary improvements in an individual's health that did not last long-term. Instead, the individual's total health index returned back to the baseline value. The null hypothesis for the treatment program was only rejected for the endline-1 regression, meaning the treatment program improved an individual's general health index in the short-term but not the long-term. Once again, both models were considered statistically significant at the 5% level of significance.

Table 7 shows the effects of the treatment (intervention) on the political involvement index of Indian individuals in the study. Once again, the treatment had a positive effect on an individual's political involvement index in both the first and second endline measurements. For the endline-1 regression model, we found that the treatment was not close to being statistically significant due to the large p-value being 0.976. Five months after the treatment, an individual receiving the intervention (as opposed to not receiving the treatment) was associated with an increase in political involvement index by around just .0015 percentage points. We were shocked to see that the effect of the treatment was extremely statistically significant in the endline-2 regression, due to a low p-value of 0.004. Twenty months after the treatment, an individual receiving the intervention (as opposed to not receiving the treatment) was associated with an increase in political involvement index by around .15 percentage points. This substantial increase in effect from the endline-1 regression to the endline-2 regression suggested to us that the treatment successfully increased political involvement in the long-term but not the short-term. The null hypothesis for the treatment program was rejected for the endline-2 regression but not the endline-1 regression. This suggested to us that the treatment program had a significant long-term effect on an individual's political involvement, but not a relevant short-term effect. Once again, both models were found to be statistically significant at the 5% level of significance.

Discussion

In terms of threats to external validity, this study focused on the very poor in India which might not translate well to groups that are considered very poor in other countries. Obviously economic situations are different everywhere, so we must be careful when drawing broader conclusions from these results. Also it is important to be wary of context dependence in that results could depend on/be influenced by local culture and norms. This is a threat to external validity because results could be skewed one way and not be representative of the treatment group on a global scale. However, the model and methodology that Banerjee et al. (2018) used is highly effective and random, allowing for application of that same model in other countries for similar studies there.

In terms of threats to internal validity, attrition can be a threat in this study as if people leave the study in different amounts in the control group compared to the treatment group then results could end up being incomparable as the groups are no longer representative. In terms of this study as we discussed earlier, there was a high rate of attrition as around 48% of households did not complete the program. However it's important to note that it was purely non-participation as households did not start the treatment and quit midway through for that proportion of the participants. Additionally, building off the issue of groups not being representative, failure to randomize is also a threat to internal validity. This is the case because when groups aren't random we may not be able to apply results to the general population among the ultra poor in India. Another threat to internal validity is when participants fail to follow treatment. This is the case because without making use of the training, temporary cash support, or any of the other aspects of the study's multifaceted treatment, it's impossible to actually see the effects of that treatment in the data. Finally, experimental effects can also be a threat to internal validity in that participants realizing that they are a part of an experiment could have caused them to act differently than they normally would, which would skew the results.

Conclusion

Despite being a country with strong GDP growth and a valuable economy, extreme poverty still persists in India to this day. In this paper we attempted to answer to what extent did India's poverty reduction program lead to sustained improvements in income, consumption, assets, health, and other social outcomes among the extremely poor.

The results support this idea that the poverty reduction program had at minimum a beneficial effect on the extreme poor in India. Some treatments had greater effects than others, but outcomes like income, consumption, and assets had statistically significant increases that support the conclusion that these programs had a beneficial effect. Specifically, total household income increased significantly at both the follow up periods, and there was a larger effect observed at the long run endline as well. This is significant as it indicates more persistent gains in income beyond the experiment. Additionally, total monthly spending increased in the short term but actually decreased in the long run, moving closer to the baseline levels after the follow up. In contrast to this however, the total asset index increased significantly at both of the endline measurements with even slightly stronger effects seen in the long run. Health outcomes were another set of outcomes that improved in the short run but then tapered off and didn't show any statistically significant effects in the long term. And finally, political outcomes did the opposite, showing no statistically significant increase in the short run, but significant increases in the long run.

In terms of internal validity, the RCT design supports a causal interpretation of our results drawn from the data. It is important to note that as we discussed before there was a high rate of initial non participation, but the model used by Banerjee et al. (2018) accounts for most of these concerns. Now in terms of external validity the findings are mostly just applicable to the extremely poor in India and it's unclear whether these results would be the same in other countries. However, the broad intervention framework means that these studies can be replicated in other settings even if the effects are a little different.

Overall the data in this paper supports the idea that poverty reduction programs can have a beneficial effect on the economic conditions of the poor. By increasing household income as well as asset ownership in the long run, the interventions provided by Banerjee et al. (2018) showed that a multi variable approach may be more effective than other short term interventions by themselves. While not all of the targeted outcomes that we tested were statistically significant in the long run, the results show just how important it is to target multiple when designing policies to reduce extreme poverty in the long run.

Works Cited

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Tables

Summary Statistics of Relevant Baseline Characteristics in India

Characteristic	**Sample Mean in India**	**Sample Standard Deviation in India**
Total monthly income, USD	-0.4303773	77.39204
Total asset index	0.0386588	1.080933
Total monthly per capita expenditure, USD	39.35705	24.01336
Food security index	-0.0301191	1.002177
General health index	0.0604967	1.079779
Perceived life status, 0-5 rating	1.250873	1.003866

Table 1: Means of relevant baseline characteristics for Indian households and individuals in the study. Treatment status was not considered for these calculations. Information generated from STATA using Lerner Desktop in Apporto.

Random Assignment Checks of Six Key Baseline Characteristics

Characteristic	Control Group Mean	Treatment Group Mean	Difference in Means (Standard Error)	P-Value of Difference (Two-sided)
Total monthly income, USD	-4.643035	3.369909	-8.012944 (4.919297)	0.1037
Total asset index	2.24 x 10^-9	0.073533	-0.075333 (0.06876)	0.2851
Total monthly per capita expenditure, USD	39.68945	39.05719	0.6322583 (1.528283)	0.6792
Food security index	1.43 x 10^-9	-0.0575322	0.0575322 (0.0641696)	0.3702
General health index	1.04 x 10^-9	0.1137595	-0.1137595 (0.0489483)	0.0202
Perceived life status, 0-5 rating	1.246937	1.254265	-0.007328 (0.0420618)	0.8617

Table 2: Means of relevant baseline characteristics for Indian households and individuals in both the treatment and control groups in India. Information generated from STATA using Lerner Desktop in Apporto.

Regression Results for Total Monthly Income (USD)

Variable	Total Endline-1 Income Effect Coefficient (Robust SE)	Total Endline-2 Income Effect Coefficient (Robust SE)
Constant	81.87546 (4.412236)	42.25428 (3.952404)
Treatment	14.51746 (6.360878)	23.58549 (6.452544)
Total Baseline Income	-0.0466309 (0.0224146)	-0.0428516 (0.0421154)
Model R-Squared	0.81%	1.52%
Model P-Value	0.019	0.0152

Table 3: Multiple linear regression results for the effects of treatment and baseline total monthly income on both the endline-1 and endline-2 values for total monthly income. Information generated from STATA using Lerner Desktop in Apporto.

Regression Results for Total Monthly Spending (USD)

Variable	Total Endline-1 Spending Effect Coefficient (Robust SE)	Total Endline-2 Spending Effect Coefficient (Robust SE)
Constant	34.19076 (3.041009)	45.88287 (3.306709)
Treatment	6.787537 (1.676809)	5.248366 (1.827782)
Total Monthly Baseline Spending	0.33799765 (0.078121)	0.2908375 (0.0822155)
Model R-Squared	12.24%	7.32%
Model P-Value	0.0000	0.0000

Table 4: Multiple linear regression results for the effects of treatment and baseline total monthly spending on both the endline-1 and endline-2 values for total monthly spending. Information generated from STATA using Lerner Desktop in Apporto.

Regression Results for Total Asset Index

Variable	Endline-1 Total Asset Index Effect Coefficient (Robust SE)	Endline-2 Total Asset Index Effect Coefficient (Robust SE)
Constant	-0.0011396 (0.0514969)	-0.0052013 (0.0467996)
Treatment	0.6700028 (0.0865307)	0.7189964 (0.0928291)
Total Baseline Asset Index	0.2420357 (0.0602922)	0.3746625 (0.0651089)
Model R-Squared	10.59%	13.28%
Model P-Value	0.0000	0.0000

Table 5: Multiple linear regression results for the effects of treatment and baseline total asset index on both the endline-1 and endline-2 values for total asset index. Information generated from STATA using Lerner Desktop in Apporto.

Regression Results for General Health Index

Variable	Endline-1 Health Index Effect Coefficient (Robust SE)	Endline-2 Health Index Effect Coefficient (Robust SE)
Constant	-0.0066377 (0.0395931)	-0.713946 (0.0366743)
Treatment	0.1836324 (0.058702)	0.0479527 (0.0515019)
Baseline Health Index	0.127059 (0.0286574)	0.1898793 (0.0407121)
Model R-Squared	2.38%	2.67%
Model P-Value	0.0000	0.0000

Table 6: Multiple linear regression results for the effects of treatment and baseline total health index on both the endline-1 and endline-2 values for total health index. Information generated from STATA using Lerner Desktop in Apporto.

Regression Results for Political Involvement Index

Variable	Endline-1 Political Involvement Index Effect Coefficient (Robust SE)	Endline-2 Political Involvement Index Effect Coefficient (Robust SE)
Constant	0.0709087 (0.0356211)	-0.0034258 (0.037986)
Treatment	0.0015195 (0.0496022)	0.1477032 (0.0518928)
Baseline Political Involvement Index	0.3132496 (0.026636)	0.1167599 (0.0258708)
Model R-Squared	1.82%	10.61%
Model P-Value	0.0000	0.0000

Table 7: Multiple linear regression results for the effects of treatment and baseline political involvement index on both the endline-1 and endline-2 values for political involvement index. Information generated from STATA using Lerner Desktop in Apporto.