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The impact of cash transfers on productive activities and household decision making. The case of LEAP program in Ghana

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Abstract

In this paper we use data data from a quasi-experimental impact evaluation of the Livelihood Empowerment Against Poverty (LEAP) cash transfer program in Ghana. The general framework for empirical analysis is based on a comparison of program beneficiaries with a group of controls selected with propensity score matching methods (PSM) from a subsample of the Ghana Socio-economic Panel Survey. The results show that poor and severely constrained beneficiary households allocated the additional funds received from the Government to reduce their loans and increase their savings. There has been neither a push on agricultural production nor a shift towards off-farm businesses or wage labour. Instead, compared to the control group, programme beneficiaries had a decrease in participation in both on-farm and off-farm activities. This lack of impacts on the productive side can be explained by several factors like i) the nature of the programme, a safety net geared to coping/protection rather than an income source for adapting/production; ii) inconsistent implementation of the programme; iii) the low level of the transfer which represents about only 7 percent of consumption among beneficiaries.

Key words: cash transfers, impact evaluation, productive impact, difference in difference, Ghana

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1. Introduction

In the past decade, cash transfers (CT) have become an important tool of social protection and poverty reduction strategies in African countries. Many of these programmes focus on those people who are ultra-poor, labour-constrained, with prevalence of adverse health conditions, elderly and/or caring for orphans and vulnerable children (OVC). As a consequence, these projects seek to reduce poverty and vulnerability by improving food consumption, nutritional, health and educational status. Indeed, investments in health and education bring about both short- and long-term economic benefits, as accumulation of human capital leads to an increase in employability and productivity. Such effects represent the fundamental motivation of some CT programmes in Latin America and the Caribbean (see Sadoulet, de Janvry and Davis (2001), Todd, Winters and Hertz (2010), Gertler, Martinez and Rubio-Codina (2012)). Impact evaluations accompany many CT programmes in sub-Saharan Africa (SSA), but pay little attention in terms of either data collection or analysis to livelihoods per se, or to the current economic and productive activities, like participation in waged labour or self-employment activities.

The Livelihood Empowerment Against Poverty (LEAP) CT is the flagship programme of Ghana's National Social Policy Strategy (NSPS), fully funded from general revenues of the Government. LEAP started in 2008, with 1,654 beneficiary households in 21 selected districts and currently it covers 100 districts nationwide with a total of 64,241 beneficiary households. LEAP aims to use CTs "to cushion the poor and encourage them to seek capacity development and other empowering objectives thus helping them leap out of poverty (Ministry of Manpower, Youth and Employment (2010))." The primary goal of the programme is twofold: i) to alleviate short-term poverty by delivering direct cash payments; ii) to push long-term human capital development, by providing health insurance and encouraging school enrolment.

LEAP households receive between G¢ 8-15 per month depending on eligible beneficiaries per household. The payment structure was tripled in 2012 but commenced only after the follow-up survey. Therefore, for the purposes of this evaluation, the transfer payment structure was G¢ 8 (1 beneficiary), G¢ 10 (2), G¢ 12 (3) and G¢ 15 (4+). Further details on the programme and the targeting procedure can be found in Park et al. (2012) and Handa and Park (2012).

Compared to other social CTs, a unique feature of LEAP is that aside from cash payments, beneficiaries are provided free health insurance through the new National Health Insurance Scheme (NHIS). In 2004 the Government of Ghana has launched the NHIS to provide universal access without out-of-pocket expense at the point of service use. Currently the NHIS covers around 66 percent of all households and is the first large-scale health national scheme in SSA (National Health Insurance Authority (2012)).

Eligibility is based on poverty and having a household member in at least one of three demographic categories: single parent with OVC, elderly poor, or person with extreme disability unable to work (PWD). The receipt of the transfer is unconditional for the over 65 and PWDs. OVCs must adhere to conditionalities which include, among others, enrolment and retention of school-age children in school; birth registration of new born babies and their attendance at postnatal clinics; full vaccination of children up to the age of five; and non-trafficking of children and their non-involvement in the 'worst forms of child labour'. However, these remain 'quasi'-conditions, as monitoring is supposed to be done by Community LEAP Implementation Committees (CLICs), consisting of traditional leaders, assembly men and some beneficiaries, raising questions about elite capture and conflicts of interest. Further, monitoring is not systematic due to both limited available resources and lack of incentives and training (Oxford Policy Management (2012)).

Although the primary goal of the programme is to reduce extreme poverty and to improve care of people in eligible households, there are reasons to believe that LEAP can have impacts also on their economic livelihoods. Most transfer beneficiaries depend on subsistence agriculture and live in rural areas where markets for financial services, labour, goods and inputs are lacking or do not function well. CTs therefore may help households in overcoming the obstacles that block their access to cash, credit or insurance (formal or informal). A large majority of beneficiaries in the evaluation sample are agricultural producers; around 60 percent of beneficiaries grow crops, and less than half have livestock. Agricultural households have low levels of inputs: on average they operate around 1.25 hectares of land, use traditional assets, mainly cutlasses and hoes, and breed a range of livestock composed in prevalence by small animals like poultry. Households diversify their income sources in various forms: around 30 percent have at least one member undertaking off-farm businesses and slightly less than 10 percent rely on earnings from waged labour. Most importantly both in-kind and cash transfers are remarkable source of income, as approximately 60 percent of households depend on these private and public flows of resources to make ends meet.

The broad hypothesis is that liquidity and security of regular and predictable cash transfers can improve livelihood choices and other productive income-generating investments, even though vulnerable households are more constrained in their decision making on how to use the additional cash. These impacts come through changes in individual and household behaviour (labour supply, investments, and risk management) and through impacts on the local economy of the communities where the transfers operate. Further the reception of this payment can influence beneficiaries' role in social networks, by increasing beneficial risk sharing arrangements and economic collaboration and by greater inclusion in decision making processes.

There is extended evidence from Latin America and increasingly SSA that cash transfers have pushed remarkable gains in access to health and education services, as measured by increases in school enrolment (particularly for girls) and use of health services (e.g. Barrientos and DeJong (2004), Davis et al. (2012)). These results are also confirmed by the preliminary evidence available for the impact evaluation of the LEAP programme discussed in Handa et al. (2012). However, there is limited empirical evidence on the productive impact of cash transfer programmes in either the Latin American or African context.

The objective of this paper is therefore to analyse the impact of the LEAP programme on household decision making regarding productive activities, including changes in the labour supply of household members. We assess how beneficiaries make decisions regarding the allocation of additional funds (consumption vs. investment vs. saving), what is the impact on farm and livestock production, agricultural investment and in off-farm productive enterprises. Further we assess heterogeneity of results for different types of beneficiaries. The overall design of the impact evaluation itself is a longitudinal propensity score matching (PSM) design. The general framework for empirical analysis is based on a comparison of programme beneficiary from three regions in Ghana (Brong-Ahafo, Central and Volta) with a group of controls, interviewed before the programme began and again two years later. We employed panel methods estimators like difference in difference (DiD) in a multivariate framework, complemented with inverse probability weighting (IPW), needed to reduce the imbalance between the treatment and the control group observed in the quasi-experimental setting.

The rest of the paper is organized as follows. Section 2 presents the analytical methods, with emphasis on empirical models and hypothesized relationships. The third section provides a discussion of the survey design and data collection methods. The main analytical results are presented and discussed in Section 4, followed by the conclusions in Section 5.

2. Analytical framework

The objective of an impact evaluation is to attribute an observed impact to the programme intervention. Specifically in this paper we seek to answer the question: "How would LEAP beneficiaries have fared without the programme?" An impact evaluation is essentially a missing data problem, as it is impossible to observe a household both participating in the programme and not participating. Without counterfactual, the best alternative is to select a group of control households from non-beneficiaries to be representative of the group of participants with one key difference: the control households did not receive the intervention. If the two groups are dissimilar in other dimensions, the outcomes of non-beneficiaries may differ systematically from what the outcomes of participants would have been without the programme, producing selection bias in the estimated impacts. This bias may derive from differences in observable characteristics between beneficiaries and non-beneficiaries (e.g. location, demographic composition, access to infrastructure, assets endowment etc.) or unobservable characteristics (e.g. natural ability, willingness to work etc.). Some observable and unobservable characteristics do not vary with time (such as natural ability), while others may vary (such as skills).

Let D_i denote a dummy variable equal to one if a household takes part in the LEAP program and equal to zero otherwise. Similarly, let Y_i denote an outcome of interest such that potential outcomes are defined as $Y_i(D_i)$ for every household. We formalize the treatment effect of the programme for household i, τ_i, as the change in the outcome caused by the CT:

$$\tau_i = Y_i(1) - Y_i(0) \quad (1)$$

Since only one outcome is observable, the counterfactual component in equation (**1** is unknown. The implications are twofold. First, the success of any impact evaluation relies crucially on identifying a valid counterfactual. And second, it is not possible to measure unit-specific treatment effects, but rather average treatment effects (ATEs) incorporating information from the counterfactual. The most direct way of ensuring a comparable control group is via an experimental design, in which eligible households are randomly allocated between control and treatment groups. This guarantees that the treatment status is uncorrelated with other (observable and unobservable) variables, and as a result the potential outcomes will be statistically independent of treatment status. Under these conditions, the ATE can be identified simply as the mean difference in outcomes between the two groups:

$$E(\tau) = ATE = E[Y(1)] – E[Y(0)] \quad (2)$$

The parameter of interest in our case is the average treatment effect on the treated (ATT), which measures the average impact of the cash transfer programme on recipients. This is defined as:

$$ATT = E[\tau | D=1] = E[(Y(1)|D=1] – E[Y(0) | D=1] \quad (3)$$

In an experimental framework the ATE equals the ATT. However, our study is based on a quasi-experimental (QE) setting, so that ATE and ATT differs. In addition, using the mean outcome of untreated individuals, $E[Y(0) | D=0]$, runs the risk of comparing apples with oranges if there is selection bias, that has to be solved by invoking some identifying assumptions. Systematic differences at baseline between treatment and control groups require econometric techniques to create a better counterfactual by removing pre-existing significant differences in key variables.

2.1 Baseline balance

In quasi-experiments (QE) statistical units under treatment tend to differ systematically from the control group, since observed data are by nature non-randomised. Therefore, it is very unlikely that covariates will be balanced in expectation. In practice, checking for balance is often done via simple t-tests on comparisons of mean baseline (pre-intervention) characteristics across groups. A more defensible test of balance is given by the Hotelling test (1931), which compares all mean differences simultaneously. This test is equivalent to the F test from a linear regression of a treatment dummy D on X, as in a linear probability model (LPM).

Balance in baseline variables is, however, a characteristic of the observed sample, not some hypothetical super-population. Therefore, as suggested by Ho et al. (2007), these kinds of tests do not provide levels below which imbalance can be ignored. Beyond using hypothesis tests for balance, Imai, King and Stuart (2008) suggest using a statistic having two key features: it should be a characteristic of the sample and not of some hypothetical population, and the sample size should not affect the value of the statistic. Among other methods, Rosenbaum and Rubin (1985) and Ho et al. (2007) proposed standardised differences, which are defined as:

$$d = \frac{|\bar{x}_{treatment} - \bar{x}_{control}|}{\sqrt{\frac{s^2_{treatment} + s^2_{control}}{2}}} \qquad (4)$$

where $s^2_{treatment}$ and $s^2_{control}$ are the sample standard deviations of a covariate in the treated and untreated subjects, respectively. The standardised difference is the absolute difference in sample means divided by an estimate of the pooled standard deviation (not standard error) of the variable. It represents the difference in means between the two groups in units of standard deviation and does not depend on the unit of measurement. Rosenbaum and Rubin (1985) suggested that a standardised difference of greater than 0.10 represents meaningful imbalance in a given covariate between treatment groups.

2.2 Difference in Difference estimator (DiD)

The simple mean comparisons in equation (2) identify treatment impacts in successful experimental designs. Nevertheless, impact estimates can be improved by applying a DiD methodology. The latter might occur, for example, if randomization by chance produces baseline differences. Similarly, when the data do not come from a randomised design the DiD estimator may be used, often in conjunction with other approaches, which is the case for this study.

When panel data are available with pre and post intervention information, then the estimator in (3) can be improved by subtracting off the difference in pre-programme outcomes between recipients of CT programme and non-recipients, as shown in equation (5)

$$\begin{aligned} ATT = E[\tau_t - \tau_{t-1} \mid D=1] &= E[(Y(1)_t - Y(0)_t) - (Y(1)_{t-1} - Y(0)_{t-1}) | D=1] \qquad (5) \\ &= E[(Y(1)_t - Y(1)_{t-1}) | D=1] - E[(Y(0)_t - Y(0)_{t-1}) | D=1] \end{aligned}$$

where $t-1$ and t represent time periods before and after the introduction of the CT programme and the binary indicator D refers to programme assignment at the baseline.

By subtracting the differences in outcomes for the treatment and control group before and after the CT has been disbursed, DiD is able to control for pre-treatment differences between the two groups, and in particular the time invariant unobservable factors that cannot be accounted for otherwise (Wooldridge (2002)). The key identifying assumption is that differences between treated and control households remain constant throughout the intervention. If prior outcomes incorporate transitory shocks that differ for treatment and comparison households, DiD estimation interprets such shocks as representing a stable difference, and estimates will contain a transitory component that does not represent the true programme effect.

The regression equivalent for the DiD estimator is represented as follows

$$Y_{it} = \beta_0 + \beta_1 D_{it} + \beta_2 R_t + \beta_3(R_t{*}\ D_{it}) + \varepsilon_{it} \tag{6}$$

where Y_{it} is the level of the outcome of interest; D_{it} is a dummy equal to 1 if household i received the treatment; R_t is a time dummy equal to 0 for the baseline and to 1 for the follow-up round; $R_t{*}D_{it}$ is the interaction between the intervention and time dummies, and ε_{it} is the error term. As for the coefficients, β_1 controls for the time-invariant differences between the treatment and control; β_2 represents the effect of going from the baseline to the follow-up period; and β_3 is the DiD estimator. Equation (6) can be also written in differences

$$\Delta Y_i = \beta_0 + \beta_1 D_i + \varepsilon_i \tag{7}$$

where $\Delta Y_i = Y_{i1} - Y_{i0}$ is the difference in outcome before and after intervention, D_i is a dummy equal to 1 if household i received the treatment and ε_i is noise. Compared to the previous version, β_0 is a constant term and β_1 is the double difference estimator, which captures the treatment effect. With two time periods, the two versions of the DiD estimator are equivalent to a fixed effects (FE) model.

When differences between groups at the baseline exist, the DiD estimator with conditioning variables has the advantage of minimizing the standard errors as long as the effects are unrelated to the treatment and are constant over time. Equation (8) presents the regression equivalent of DiD with covariates

$$Y_{it} = \beta_0 + \beta_1 D_{it} + \beta_2 R_t + \beta_3(R_t{*}\ D_{it}) + \Sigma_k \gamma_k X_{ik} + \varepsilon_{it} \tag{8}$$

where we added in $\Sigma_k X_{ik}$, a vector of baseline household characteristics to control for possible differences in the composition of the two groups.

2.3 Inverse probability weighting (IPW)

We have seen that in observational studies or QEs it may be sensible to assume that treatment assignment is unconfounded with potential outcomes conditional on a suitably extensive set of covariates. In cases in which the data analyzed are affected by both covariate unbalancing and missing data, Rosenbaum and Rubin (1983) first showed that unbiased estimates of the treatment allocation can still be independent from the outcomes of interests if conditioned on observational characteristics (unconfoundness assumption). Further they showed that condition on the vector of covariates X is equivalent to conditioning on $\dot{P}(X)$, the estimated probability of receiving the

programme intervention, or propensity score. Therefore adjusting for the propensity score removes the bias associated with differences in observed covariates in treated and control groups. Inverse Probability Weighting (IPW) works on this idea and consists of using the inverse of $\dot{P}(X)$ as a weight in the DiD estimator, in order to make treated and control observations representative of the population of interest. Weighting by the inverse of $\dot{P}(X)$ can achieve covariate balance and, in contrast to matching and stratification/blocking, uses all of the observations in the sample (Sacerdote (2004)). This estimator is essentially due to Horvitz and Thompson (1952).

With IPW, control observations are assigned weights equal to the inverse of their propensity score, i.e. $w = (\dot{P}(X)/(1-\dot{P}(X))$, and treatment observations receive a weight equal to 1. Applying these weights to control households effectively reweights the distribution of observable characteristics included in P(X) to be like that of the treatment group. Intuitively, the IPW estimator will put more emphasis on counterfactual observations having a $\dot{P}(X)$ closer to 1 while underweighting those for which $\dot{P}(X)$ is relatively small.

A regression of an outcome on treatment and X variables thus amounts to a comparison of means and produces an estimate of the ATT. One advantage of the weighting approach is that it is considered to be 'doubly robust': if either the propensity model or the outcome equation is correctly specified, the estimator will be consistent. Ensuring that a region of common support exists is necessary to avoid observations with extremely large weights, which can yield estimates with high variance and undue influence on results (Imbens and Wooldridge (2009)).

2.4 Cluster-robust standard errors

Numerous authors like Eicker (1967), Huber (1967), Moulton (1990) have noted that errors are very unlikely to be uncorrelated across observations within a cluster/group. The variables of interest in many DiD setups only vary at a group level and outcome variables are often serially correlated. To the extent that explanatory variables are also correlated across observations, conventional OLS standard errors may grossly understate the standard deviation of the estimated treatment effects, leading to serious overestimation of significance levels (see more recently Bertrand, Duflo and Sendhil (2004) and Kezdi (2004).

The cluster-robust standard error (CRSE) is an example of Eicker-Huber-White-robust treatment of errors, where it is assumed that correlation across groups equals zero as with fixed effects, but allowing for the within-group correlation to vary. CRSE estimator converges to the true standard error as the number of clusters C approaches infinity, not the number of observations N. Kezdi (2004) shows that 50 roughly equal sized clusters is often close enough to infinity for accurate inference, and further that, even in the absence of clustering, there is little to no cost of using the CRSE estimator, as long as the number of clusters is large.

In this study, households are clustered within two-hundred twenty-three communities and the average number of observations per cluster is around only 6.7. No cluster contains more than 5 percent of observations, so that the CRSE estimator should theoretically performs well.

3. Data

The evaluation strategy for LEAP is a longitudinal propensity score matching (PSM) design. Prior to program initiation in the first quarter of 2010, 699 future LEAP beneficiaries from Brong-Ahafo, Central and Volta regions were selected to participate in the evaluation study. Baseline data was collected as part of the field work of a national household survey being conducted by the Institute of

Statistical Social and Economic Research, University of Ghana (ISSER) in collaboration with the Economic Growth Center, Yale University.

Subsequently, a comparison group of 699 households from the national ISSER survey were selected by PSM, using one-to-one nearest neighbour approach, and re-interviewed after 24 months along with LEAP beneficiaries. The matched comparison group was drawn from the same three regions as the LEAP households as well as bordering regions with similar agro-ecological conditions. Supplementary 215 households from the ISSER sample were re-interviewed at follow-up, in order to generate higher statistical power for the study. These households had similar propensity scores to beneficiaries and were residing in the same communities already being visited by the enumeration teams, so could be interviewed at low additional cost. More details on the design and analysis of the matched comparison group are presented in Handa and Park (2012).

In Table 1 we provide essential information on the samples for this evaluation. Of the 1,398 target households, 1,298 were re-interviewed at follow-up, for a 7 percent attrition rate. All 215 extra control households were also re-interviewed, so that this left with a final longitudinal sample of 1,504 households (858 ISSER, 646 LEAP). However, there are questions concerning the use of all observations. While analysing the operational module available at follow-up, we came up with fifteen control households declaring to receive LEAP payments. We decided to drop these observations as they do not represent anymore a valid counterfactual. Therefore the working sample for the impact analysis used in this study is made up of the longitudinal sample of 843 ISSER control households and 646 LEAP beneficiaries.

3.1 Estimation of propensity score

As mentioned, the details of the PSM application are presented in Handa and Park (2012). When receiving the data, we did not get access to the full national ISSER sample at baseline, but just the sub-sample extracted after matching, with related propensity scores estimated by the research team at ISSER/Yale. We assessed that household characteristics between ISSER and LEAP households were still unbalanced after applying IPW with these propensity scores. Therefore we have decided to re-estimate probability of treatment assignment at baseline with just the available subsample.

We estimated selection into treatment at baseline using a simple probit model. Similar results are obtained with a logit. The set of covariates on the right hand side of the estimating equation was chosen based on the targeting protocol and includes household composition, like size and number of OVCs in the household; participation by family members to the NHIS scheme; head of household characteristics such as age, gender and education; welfare indicators such as income sources, housing index created with factorial analysis, adult equivalent food and non-food consumption; household wealth and financial position like value of durables and agricultural assets, value of savings and outstanding loans and credits; plus additional information on farming activities. Coefficients estimates are available in Table 2. Unfortunately in these regressions we cannot include regional/district fixed effects. As we show in Table 3, more than half control households live in different regions compared to LEAP recipients, so that by including regional or district effects we would completely determine selection into treatment. Ideally, we should include village level indicators, such as access to roads or distance to markets, but the lack of ISSER communities questionnaire does not allow us to retrieve such piece of information. This is a major limitation in the derivation of the propensity scores that could potentially bias the impact estimates due to bias from observable characteristics that were not controlled for. In the next draft of our work we are intended to collect geographic characteristics also from sources other than ISSER survey.

We provide evidence of reweighting in Figure 1, which shows the kernel density of the estimated propensity scores. In the upper panel, the centre of the unweighted distribution for the control group is substantially shifted to the left, with a much ticker left tail. However in the lower panel, with reweighting the distribution of the propensity score of the control group looks very similar to the distribution of the LEAP sample.

We assessed whether the weighting procedure is able to balance the distribution of the variables used in the construction of the propensity score. After some trials, we have settled on a preferred model specification for which: i) based on Hotelling test, we cannot reject the null hypothesis that the vectors of means are equal between (reweighted) control and treatment households; ii) probit covariates means are all statistically equal except one; iii) after reweighting, mean and median standardized difference collapsed from 16.4 and 15.3 percent to 3.0 and 2.4 percent respectively; iv) after reweighting, all probit covariates except one show a standardized difference less than 10 percent. In Table 4 we offer a summary of the balancing process. As we deem the reweighted sample to offer a reasonable counterfactual, results presented in this paper rely solely on the weighted regressions.

5. Results and discussion

In this section we discuss the ATT of the Ghana LEAP programme over three broad groups of outcome variables: i) consumption, ii) income-generating activities, iii) financial position. When discussing the second point, we will focus especially on farm/agricultural production. All the impact analysis and consequently the outcome measures have been undertaken at household level.

Impact on consumption

We aggregate all spending on consumption items and express in adult equivalent terms, deflating 2012 values to 2010 cedis. Figure 2 shows the density graphs for consumption by treatment group and year - the further to the right the distribution the better off are households. The graphs does not show a clear pattern, beyond a much longer right tail for both groups. It seems that LEAP households are only slightly worse off relative to the ISSER comparison sample. This does not come as a surprise for the year 2010, given that we have managed with IPW to recalibrate households in terms of some households characteristics, including expenditure. As a result of the CT intervention, one could expect in 2012 that the LEAP households were getting better off than the ISSER sample, but apparently this is not what we observe from the graph. An analogous story is observed for food consumption and non-food consumption, here unreported.

Table 5 shows the DiD impact estimates for the monthly total adult equivalent consumption and then disaggregated for food and non-food items. In this and subsequent tables of estimates we further explore heterogeneity of results by: i) female vs. male headed households; ii) household size, defined by two groups, smaller or equal than three members vs. greater or equal than four. The DiD impact estimate on total consumption is -0.307 cedis, of which 0.139 cedis is on food and -0.446 cedis on non-food. These estimates are not statistically significant and the picture appears the same also when disaggregating by gender. For smaller households we observe an insignificant impact, even though the magnitude is much higher compared to larger households.

When disaggregating food consumption, results do not change. In Table 6 we report the impact estimates for the following categories: cereals, pulses, oils and fats, dairy, meat, fruits, vegetables and starchy products. Overall, estimates are positive but insignificant, especially for smaller and male headed households. We observe statistical significant results only for households with more

than 3 members, as the monthly per adult equivalent consumption of dairy products, meat and fruits compared to the control group is lower by 0.06, 0.609 and 0.114 cedi respectively.

Impact on income-generating activities

The impact of a CT programme on the economic decision process is potentially displayed through changes in individual and household behaviour. One of the most important channels is represented by the variation in income generating strategies, facilitated by the relax of credit/liquidity constraints. These may consist of changes in labour allocation of household members, for instance because of a transition from agricultural production to off-farm business, changes in productive activities or accumulation of productive assets. In SSA, Covarrubias, Davis and Winters (2012) and Boone et al. (2013) found that the Malawi SCT programme led to increased investment in agricultural assets, and better consumption by own production. For Ethiopia, Gilligan, Hoddinott and Taffesse (2009) find that households with access to both the Productive Safety Net Programme (PSNP) as well as complementary packages of agricultural support were more likely to borrow for productive purposes, use improved agricultural technologies, and operate their off-farm enterprises.

In this paper we look at various aspects of the income strategy adopted by the household. We focus especially on agricultural activities, for both livestock and crop production, off-farm enterprises and waged labour. In Table 7 we provide the marginal effects of GLM models with probit link for the probability of i) being involved in farm activity, including livestock herding; ii) undertaking an off-farm enterprise; iii) having a household member in waged labour; iv) receiving either in kind or cash transfer, other than LEAP. Overall the impact of LEAP is negative for on-farm activity (-13.6%) and statistically significant at 1%. This results is confirmed for all household types considered and is more marked for smaller households compared to larger households. However for the other livelihood strategies, we do not observe statistically significant results, except for off-farm enterprises in smaller households, with an impact of -7.8%. There is no apparent switch to wage labour as the effect is not only statistically insignificant but also quite low in magnitude (+1.3%). After LEAP introduction, targeted households seems to receive lower amounts of transfers than control households.

In Table 8 we show impact results on agricultural production. It was not possible to aggregate quantities reported in the survey instrument in a unique metric measure, as we lack of a reliable conversion system with available units. Therefore our indicators are based on the estimated value of production. Estimates are quite unambiguous not only for overall agricultural production, but also for the most important crops, namely maize, cocoa, yam and cassava. We observe a negative impact of -186 cedis on total production, which is statistically significant and much higher for male rather than female headed households. The effect seems to be higher for cash crops like cocoa and maize, -94 and -42 cedis respectively, compared to subsistence crops like cassava and yam. The latter actually has a positive DiD coefficient which is however not statistically significant, not even for specific household types.

However, results for agricultural production must be confronted with actual input use. In Table 9 we see in fact that the differential use of inputs for LEAP beneficiaries compared to ISSER households is lower, even thought not always significantly. The estimated impact in operated land is -0.43 hectares and bigger for male headed households (both results significant at 10% level). Demand for labour in agricultural production is lower in targeted households, even though not significantly. In terms of magnitude, the biggest impact is for family labour, with less than one hundred hours. For larger households the impact is also statistically significant with a coefficient estimate of -246 hours worked. The CT programme does not seem to have been effective in pushing

investment on seeds. The estimated coefficient is in fact globally positive, 5 cedis, but it is not significant.

With respect to livestock activity, in Table 10 we look at the programme impact on the number of animals hold by the households. Total activity is in tropical livestock units (TLUs). We did the same exercise for ownership (simple dummy for having or not the indicated animal) but results were the same, so that we preferred to avoid duplications of tables. Basically, it appears there is no effect of LEAP on livestock holding, the sign being negative and statistically significant for sheep, goats and poultry. For total animals in TLU and cattle, the sign is respectively negative and positive but not significant. This behaviour is more marked in female headed and large household rather than male headed and small. These results are mirrored in Table 11, where we provide estimates on livestock expenses. On average, there is a negative impact, small in magnitude and statistically insignificant on all expenditure items. There are some differences in terms of female vs. male headed households. For the former group, we see a significant negative impact of 21 cedis, which is mainly due to differential feed and veterinary expenses.

We finally evaluate whether targeted households used the money coming from the programme more intensively in non agricultural businesses than non beneficiaries. From Table 7 we have already seen that there was no effect in terms of the percentage of households undertaking an off-farm business. However in Table 12 we observe that impact estimates are always not statistically different from zero. Further the estimated magnitude is negative, especially for the computed level of annual revenues, which have a much lower estimated DiD coefficient compared to the annual expenses.

Impact on financial position and assets

In Table 13 we explore another possible direction towards which the additional funds provided by LEAP might have been channelled. We used two types of indicators to measure the impact on the financial position of the households: i) the proportion of households with savings, loans and credits; ii) the outstanding amount of each item. The results show that the proportion of households with savings increased by 13.5 percent after LEAP introduction, while loans reduced by almost 12 percent. Both results are highly significant and stronger in magnitude for households with less than 4 members and male headed. At the same time the level of savings and the outstanding amount of the loans is negative, but not statistically significant. In terms of credits, impact estimates are insignificant too, except for small households, as we observe 7% less observations having a credit, for an amount of 12 cedis compared to the ISSER sample.

Finally we look at investment in agricultural implements. Impact estimates are generally negative and for many tools they are also significant. This is the case of the number of rakes (-0.09) and shovels (-0.087), which are 1 and 5 percent significant respectively. Further at 10 percent significance level, also axes, picks and spraying machines have negative impact. It looks like there has been distress sale of these agricultural tools.

6. Conclusions

In this paper we have analysed the economic effects of LEAP, a social CT programme run by the Government of Ghana designed to alleviate short-term poverty and foster human capital development, by providing health insurance and encouraging school enrolment. Coherently with the objectives of the programme, Handa et al. (2012) found positive impacts on children's schooling and health. Beyond such effects, we did not capture any significant economic impact. Poor and

severely constrained households allocated the additional funds received from the Government to reduce their loans and increasing their savings. There has been neither a push on agricultural production nor a shift towards off-farm businesses or wage labour. Instead, compared to the control group, programme beneficiaries had a decrease in participation in both on-farm and off-farm activities. Further, consumption increased, but at the same pace of control group.

The lack of impacts on the productive side can be explained in different ways. First, as it has been already highlighted by the qualitative report of Oxford Policy Management (2012), while LEAP is successful in targeting the very poorest, this makes it primarily a safety net geared to coping/protection rather than an income source for adapting/production. Most beneficiaries in fact tended to use their new income stream to reduce borrowing, while reducing purchases on credit and using solid cash exchange. In this way beneficiary households have shifted from being a drain on their extended family to being an active contributor with entitlements, reducing the social stigma of being borrowers. Secondly, as we can see in Figure 3, implementation of LEAP has been inconsistent. Over the two years evaluation period, households' received only 20 months' worth of payments, with a long gap in payments in 2011 followed by a triple payment in February 2012. This means that targeted households did not receive a steady flow of predictable CT to smooth consumption and plan investments. Maybe the lumpy payment in February has pushed households to pay down their loans. Further, while analysing the operational module of the follow-up survey, we observed that about 10 percent of LEAP households has not heard of LEAP and a further 10 percent had never received a payment. Imperfect take-up and implementation of an intervention is part of the daily reality, so that our ATT much more resembles an Intention-to-Treat effect, which is also what can be considered the most relevant impact estimate from the perspective of the policy maker. Finally, the LEAP payment are overall quite low. As we can see in Figure 4, the transfer level is about 7 percent of consumption among treated households, while most successful programs transfer are at least 20 percent of consumption of beneficiaries. The low level of the transfer was further eroded by a cumulative 16 percent inflation rate over the study period. These combined events may therefore well explain why we did not find any significant economic impact.

Our study suffer some limitations. While we cannot cope with the lack of randomisation, in order to properly implement quasi-experimental estimators, we need to retrieve additional information at community/district level. In fact, in the derivation of the propensity score we control only for household characteristics and not for observable differences in households' immediate surroundings or geographic characteristics, like local population density, poverty levels, soil quality, labor markets, etc. This could obviously bias the impact estimates. This piece of information is currently not available, as we received the community questionnaire for LEAP households only. A second restriction is related to the DiD approach, which is based on the assumption that in the absence of the programme the outcome variables in both treatment and control group follow the same trend. Possibly we should try to control for the differential trends over time, ideally both at regional and household level. This would help us increasing the accuracy of impact estimates. Further our results are entirely based on an IPW estimator, a method which resembles PSM. In the next draft, we will assess whether our results are robust to using nearest neighbor/caliper/kernel matching and defining the region of common support, in order to improve the comparability between the treatment and control group.

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Tables and figures

Table 1: Sample for the LEAP impact evaluation

	Year	
Groups	2010	2012
LEAP	699	646
ISSER		
matched	699	643
unmatched	215	215
Total sample	1,613	1,504

Table 2: Probit of selection into treatment at baseline, 1,506 observations

Variable	Description	Coef.	Std. Err.	
hh0_5	# hhld members under 5	-0.005	0.050	
hh6_12	# hhld members 6-12	0.060	0.040	
hh13_17	# hhld members 13-17	0.100	0.051	
hhm18_64	# male hhld members 18-64	0.334	0.065	***
hhf18_64	# female hhld members 18-64	-0.012	0.061	
hhm65	# male hhld members over 64	0.876	0.145	***
hhf65	# female hhld members over 64	0.538	0.088	***
edhigh	highest yrs of education in hh	-0.040	0.014	**
norph	# orphans living in hhld	0.123	0.038	**
femhd	female headed hh	0.001	0.001	
agehd	head of hh age	-0.002	0.004	
wdwhd	head of hh widow	0.002	0.001	*
eldrhd	head of hh is >64 old	-0.004	0.002	*
edhd	head of hh yrs of education	-0.033	0.013	*
hasnhis	% hhlds NHIS	0.203	0.073	**
index	housing index	-0.103	0.038	**
aeef	adult equiv food consumption	-0.002	0.001	*
aeenf	adult equiv non food consumption	-0.003	0.002	
farmliv	cropping and/or livestock farming, % hhlds	-0.294	0.093	**
self	non-farm self enterprise, % hhlds	0.079	0.104	
inwage	waged labor, % hhlds	-0.015	0.129	
hrscsl	hours worked in household farming, family labour	0.000	0.000	**
hrsfml	hours worked in household farming, casual labour	0.000	0.000	***
hrsprm	hours worked in household farming, permanent labour	0.000	0.000	
hrsm	hours worked by 4 most important employees in non-farm business	0.000	0.000	
cshr	cash remittances, - % hhlds	0.088	0.076	
hrv	crop production - cedis	0.000	0.000	
sell	share of sellers	-0.177	0.098	
own	crop production for ownconsumption - cedis	0.000	0.000	
lndownop	cropped land - hectares	-0.019	0.019	
TLUtotal	Tropical Livestock Unit - total	0.020	0.029	
eseed	seeds expenditure - cedis	-0.001	0.000	*
etransp	transports expenditure for sales - cedis	0.000	0.002	
svdur	value of durables - cedis	0.000	0.000	**
svagass	value of agricultural assets - cedis	-0.002	0.001	*
vsvn	savings	0.000	0.000	
vln	outstanding loans	0.000	0.000	
vlnd	outstanding credits	0.000	0.000	
_cons	constant	0.061	0.227	

Note: * p<0.1, ** p<0.05, *** p<0.01

Table 3: Households distribution by region and treatment status

Region	ISSER	LEAP	Total
Western	99	0	99
Central	112	163	275
Volta	145	81	226
Eastern	131	0	131
Ashanti	172	0	172
Brong Ahafo	125	411	536
Northern	67	0	67
Total	851	655	1,506

Table 4: Mean baseline characteristics, imbalance and reweighting

			unmatched				matched					bias
	LEAP	ISSER	diff	t-stat	p-value	bias (%)	ISSER	diff	t-stat	p-value	bias (%)	reduction
Demographics												
# hhld members under 5	0.4	0.5	-0.1	-1.7	0.085	8.7	0.4	0.0	0.0	0.982	0.1	98.7
# hhld members 6-12	0.8	0.8	0.0	-0.2	0.858	0.9	0.8	0.0	0.0	0.974	0.2	80.9
# hhld members 13-17	0.5	0.5	0.0	1.0	0.342	4.8	0.6	0.0	-0.6	0.537	3.5	27.7
# male hhld members 18-64	0.5	0.5	0.0	-0.2	0.843	1.0	0.5	0.0	0.0	0.966	0.2	77.9
# female hhld members 18-64	0.8	0.9	-0.1	-2.9	0.004	14.4	0.8	0.0	0.5	0.642	2.3	83.9
# male hhld members over 64	0.3	0.2	0.1	2.5	0.011	12.8	0.3	0.0	0.0	0.966	0.2	98.3
# female hhld members over 64	0.5	0.3	0.2	6.7	0.000	33.7	0.6	-0.1	-2.2	0.027	12.7	62.3
highest yrs of education in hh	4.9	6.2	-1.3	-6.0	0.000	30.1	5.0	-0.1	-0.5	0.622	2.5	91.8
# orphans living in hhld	0.7	0.3	0.3	5.7	0.000	28.0	0.6	0.1	0.9	0.395	4.9	82.5
Head characteristics												
female headed hh	59.2	50.1	9.2	3.7	0.000	18.5	56.6	2.6	1.1	0.292	5.3	71.6
head of hh age	61.1	56.7	4.4	4.6	0.000	23.4	62.4	-1.3	-1.4	0.160	7.0	70.0
head of hh widow	38.6	25.6	13.0	5.6	0.000	28.2	36.1	2.5	1.0	0.298	5.5	80.7
head of hh is >64 old	51.2	40.4	10.8	4.3	0.000	21.9	53.8	-2.6	-1.0	0.307	5.2	76.4
head of hh yrs of education	2.1	4.0	-1.8	-8.7	0.000	44.5	2.4	-0.3	-1.4	0.176	6.2	86.1
Other household characteristics												
% hhlds NHIS	0.6	0.6	0.1	2.2	0.028	11.1	0.6	0.0	-0.5	0.590	2.7	76.2
housing index	-0.1	0.1	-0.2	-3.3	0.001	16.8	0.0	0.0	-0.9	0.366	4.6	72.9
Consumption, monthly per adult equivalent spending, cedis												
food	38.7	44.1	-5.4	-3.2	0.001	16.0	38.4	0.3	0.2	0.861	0.8	94.8
non food	19.3	23.8	-4.6	-4.3	0.000	21.9	20.7	-1.5	-1.6	0.119	7.0	67.9
Participation in labour activities, share of households												
cropping and/or livestock farming	0.6	0.7	-0.1	-5.8	0.000	29.2	0.6	0.0	-0.9	0.389	4.5	84.5
non-farm self enterprise	0.3	0.3	0.0	-0.2	0.870	0.8	0.3	0.0	-0.6	0.570	2.9	-246.5
waged labor	0.1	0.1	0.0	-0.8	0.434	4.0	0.1	0.0	0.6	0.533	3.0	25.5
Hours worked in household farming during last major season												
family labour	205.7	251.3	-45.7	-0.8	0.398	4.1	198.5	7.1	0.1	0.899	0.6	84.4
casual labour	298.0	660.7	-362.7	-5.7	0.000	29.9	316.7	-18.7	-0.5	0.621	1.5	94.8
permanent labour	47.4	40.9	6.5	0.5	0.630	2.4	57.0	-9.6	-0.6	0.518	3.6	-48.0
Non-farm business, 4 most important employees												
monthly hours worked	63.0	67.9	-5.0	-0.6	0.518	3.3	63.4	-0.4	-0.1	0.953	0.3	91.3
Other income sources												
cash remittances, - % hhlds	0.5	0.4	0.1	3.5	0.001	17.5	0.5	0.0	-0.2	0.830	1.1	93.8
Farm activity												
crop production - cedis	233.0	542.9	-309.9	-2.7	0.007	14.5	248.8	-15.8	-0.6	0.579	0.7	94.9
share of sellers	0.3	0.5	-0.2	-7.1	0.000	35.9	0.4	0.0	-0.8	0.446	3.7	89.6
crop production for ownconsumption - cedi	97.5	203.5	-105.9	-2.3	0.023	12.1	106.5	-9.0	-0.6	0.582	1.0	91.5
cropped land - hectares	0.9	1.5	-0.6	-5.4	0.000	27.7	1.0	-0.1	-1.1	0.269	4.9	82.3
Tropical Livestock Unit - total	0.3	0.4	-0.1	-0.9	0.343	4.7	0.4	-0.1	-0.8	0.426	4.2	10.3
seeds expenditure - cedis	26.6	50.4	-23.8	-4.1	0.000	21.1	28.7	-2.1	-0.5	0.619	1.8	91.3
transports expenditure for sales - cedis	3.3	6.8	-3.5	-2.5	0.012	13.2	3.0	0.3	0.4	0.710	1.2	91.1
Durables and agricultural assets												
value of durables - cedis	289.0	590.9	-301.9	-2.7	0.007	14.3	330.3	-41.3	-1.2	0.214	2.0	86.3
value of agricultural assets - cedis	16.9	39.6	-22.6	-3.3	0.001	17.5	18.4	-1.4	-0.7	0.487	1.1	93.6
Savings and credit												
savings - cedis	28.7	63.4	-34.7	-3.9	0.000	20.4	31.0	-2.3	-0.4	0.695	1.3	93.4
outstanding loans - cedis	43.3	41.1	2.2	0.3	0.800	1.3	40.6	2.7	0.3	0.767	1.5	-22.0
outstanding credits - cedis	12.5	29.9	-17.4	-2.3	0.022	12.1	12.0	0.5	0.1	0.908	0.3	97.1
Observations	699	899										

Notes: figures in bold and underlined are respectively 1% and 5% significant.

Table 5: Impact on consumption. DiD with IPW and controls

DiD effect	all b/se	female head b/se	male head b/se	hh size<4 b/se	hh size>3 b/se
food consumption	0.139	-0.607	1.214	2.079	-2.019
	(1.38)	(2.07)	(1.70)	(2.18)	(1.54)
non food consumption	-0.446	-0.751	-0.011	0.347	-1.369
	(1.06)	(1.60)	(1.08)	(1.46)	(1.47)
total consumption	-0.307	-1.357	1.203	2.426	-3.388
	(2.27)	(3.39)	(2.64)	(3.42)	(2.68)
N	2978	1608	1370	1530	1448

Notes: * p<0.1, ** p<0.05, *** p<0.01

Table 6: Impact on food categories. DiD with IPW and controls

DiD effect	all b/se	female head b/se	male head b/se	hh size<4 b/se	hh size>3 b/se
cereals	0.119	0.261	-0.080	0.673	-0.493
	(0.38)	(0.56)	(0.48)	(0.59)	(0.42)
pulses	0.019	0.013	0.030	0.094	-0.064
	(0.08)	(0.13)	(0.13)	(0.13)	(0.09)
oils and fats	0.007	0.023	-0.015	0.081	-0.077
	(0.09)	(0.14)	(0.08)	(0.13)	(0.13)
dairy	0.010	-0.006	0.032	0.074	-0.060 *
	(0.03)	(0.04)	(0.04)	(0.05)	(0.03)
meat	0.062	-0.383	0.697	0.681	-0.609 *
	(0.36)	(0.44)	(0.56)	(0.61)	(0.32)
fruits	-0.093	-0.210	0.075	-0.076	-0.114 **
	(0.09)	(0.14)	(0.14)	(0.17)	(0.05)
vegetables	0.095	0.112	0.074	0.359	-0.203
	(0.21)	(0.33)	(0.21)	(0.36)	(0.21)
starchy	-0.052	-0.217	0.185	0.061	-0.196
	(0.32)	(0.47)	(0.40)	(0.51)	(0.38)
N	2978	1608	1370	1530	1448

Notes: * p<0.1, ** p<0.05, *** p<0.01

Table 7: Impact on income sources. GLM DiD with IPW and controls

	all	female head	male head	hh size<4	hh size>3
DiD effect	**dydx/se**	**dydx/se**	**dydx/se**	**dydx/se**	**dydx/se**
farming and livestock	-0.136 ***	-0.130 **	-0.140 ***	-0.173 ***	-0.088 **
	(0.04)	(0.05)	(0.05)	(0.06)	(0.04)
off-farm enterprise	-0.016	-0.011	-0.024	-0.078 *	0.056
	(0.04)	(0.05)	(0.06)	(0.04)	(0.06)
waged labour	0.013	0.029	-0.020	0.011	0.013
	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
transfers	-0.063	-0.070	-0.059	-0.068	-0.042
	(0.04)	(0.05)	(0.06)	(0.05)	(0.05)
N	2,978	1608	1370	1530	1448

Notes: * p<0.1, ** p<0.05, *** p<0.01

Table 8: Impact on agricultural production. DiD with IPW and controls

	all	female head	male head	hh size<4	hh size>3
DiD effect	**b/se**	**b/se**	**b/se**	**b/se**	**b/se**
total production	-186.815 **	-85.983	-329.090 ***	-138.458 **	-242.360 **
	(73.31)	(79.20)	(123.71)	(57.85)	(121.54)
maize	-42.972 **	-24.343 **	-69.298 *	-32.817 ***	-53.854 *
	(16.58)	(10.71)	(36.55)	(12.08)	(31.12)
cocoa	-94.503 **	-59.032 *	-144.724 **	-60.313 *	-131.593 **
	(37.40)	(34.10)	(70.29)	(31.30)	(64.09)
yam	32.433	11.438	62.620	0.732	63.213
	(41.15)	(53.24)	(61.85)	(25.01)	(71.85)
cassava	-28.620 **	-10.911	-53.783 **	-14.318	-44.067 *
	(12.52)	(12.15)	(23.74)	(10.34)	(22.41)
N	2978	1608	1370	1530	1448

Notes: * p<0.1, ** p<0.05, *** p<0.01

Table 9: Impact on input use. DiD with IPW and controls

	all	female head	male head	hh size<4	hh size>3
DiD effect	**b/se**	**b/se**	**b/se**	**b/se**	**b/se**
operated land	-0.433 *	-0.335	-0.574 *	-0.198	-0.679
	(0.26)	(0.38)	(0.31)	(0.15)	(0.48)
seeds	5.391	7.886	1.969	-2.043	13.157
	(6.22)	(6.04)	(11.01)	(6.08)	(10.24)
casual labour	-16.874	10.622	-56.677	46.884	-82.290
	(69.03)	(44.74)	(146.24)	(50.49)	(132.05)
family labour	-111.353	-38.422	-214.547	16.200	-246.764 *
	(75.22)	(75.18)	(137.66)	(55.23)	(136.94)
permanent labour	-6.434	0.649	-16.787	-22.926 **	12.197
	(24.41)	(16.22)	(47.00)	(10.61)	(43.98)
N	2,978	1,608	1,370	1,530	1,448

Notes: * p<0.1, ** p<0.05, *** p<0.01

Table 10: Impact on livestock holding. DiD with IPW and controls

DiD effect	all b/se	female head b/se	male head b/se	hh size<4 b/se	hh size>3 b/se
cattle	0.082	-0.056 *	0.277	0.346	-0.197
	(0.21)	(0.03)	(0.50)	(0.36)	(0.16)
sheep	-0.297 *	-0.283	-0.316	-0.054	-0.553 *
	(0.17)	(0.18)	(0.33)	(0.18)	(0.30)
goats	-0.632 **	-0.992 **	-0.123	-0.427	-0.857
	(0.32)	(0.48)	(0.39)	(0.28)	(0.55)
chicken	-1.747 *	-1.862 *	-1.587	-1.735 *	-1.745
	(0.95)	(1.03)	(1.87)	(0.95)	(1.67)
total in TLU	-0.067	-0.164 ***	0.071	0.115	-0.259 **
	(0.12)	(0.06)	(0.27)	(0.20)	(0.11)
N	2,978	1,608	1,370	1,530	1,448

Notes: * p<0.1, ** p<0.05, *** p<0.01

Table 11: Impact on livestock expenses. DiD with IPW and controls

DiD effect	all b/se	female head b/se	male head b/se	hh size<4 b/se	hh size>3 b/se
feed	-1.044	-16.484 **	20.968	0.679	-3.169
	(10.21)	(7.05)	(22.86)	(15.57)	(10.80)
veterinary	-3.004	-4.774 **	-0.465	-2.909	-3.143
	(2.53)	(1.96)	(5.21)	(2.36)	(4.46)
shelter/enclosure	0.023	0.382	-0.478	-1.717	1.890
	(1.31)	(1.17)	(2.71)	(1.57)	(2.10)
hired labour	2.213	-0.227	5.735	3.624	0.576
	(5.51)	(0.76)	(13.45)	(3.08)	(10.88)
water	-0.122	0.041	-0.354	0.133	-0.379
	(0.44)	(0.62)	(0.52)	(0.61)	(0.54)
other	-1.069 *	0.046	-2.660 **	-0.239	-1.911 *
	(0.61)	(0.43)	(1.31)	(0.51)	(1.14)
total	-3.002	-21.016 **	22.744	-0.429	-6.137
	(13.33)	(9.21)	(30.65)	(18.97)	(15.68)
N	2,978	1,608	1,370	1,530	1,448

Notes: * p<0.1, ** p<0.05, *** p<0.01

Table 12: Impact on off-farm enterprises performance. DiD with IPW and controls

DiD effect	all b/se	female head b/se	male head b/se	hh size<4 b/se	hh size>3 b/se
profit	-192.315	-204.761	-173.851	-204.244	-180.136
	(165.09)	(168.09)	(201.48)	(180.43)	(183.72)
revenues	-326.577	-481.046	-104.916	-379.482	-269.397
	(414.63)	(507.92)	(597.24)	(428.95)	(508.65)
expenses	-134.261	-276.285	68.934	-175.238	-89.262
	(264.70)	(369.34)	(448.71)	(275.02)	(358.59)
N	2,978	1,608	1,370	1,530	1,448

Notes: * p<0.1, ** p<0.05, *** p<0.01

Table 13: Impact on financial position. DiD with IPW and controls

DiD effect	all b/se	female head b/se	male head b/se	hh size<4 b/se	hh size>3 b/se
savings, %hhlds	0.135 **	0.086	0.204 ***	0.195 ***	0.070
	(0.06)	(0.06)	(0.08)	(0.07)	(0.07)
loans, % hhlds	-0.119 ***	-0.124 **	-0.113 *	-0.161 ***	-0.074
	(0.04)	(0.05)	(0.06)	(0.06)	(0.05)
credit, % hhlds	-0.035	-0.046	-0.019	-0.070 **	0.003
	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)
savings	-26.977	-30.133	-22.221	-40.230 *	-13.888
	(22.61)	(21.16)	(39.27)	(23.33)	(36.61)
loans	-21.179	-5.552	-43.331	-23.655	-18.968
	(20.27)	(19.71)	(40.71)	(25.96)	(32.33)
credit	-7.863	-16.689 *	4.560	-12.918 **	-2.586
	(5.50)	(9.05)	(8.86)	(5.59)	(9.41)
N	2,978	1,608	1,370	1,530	1,448

Notes: * p<0.1, ** p<0.05, *** p<0.01

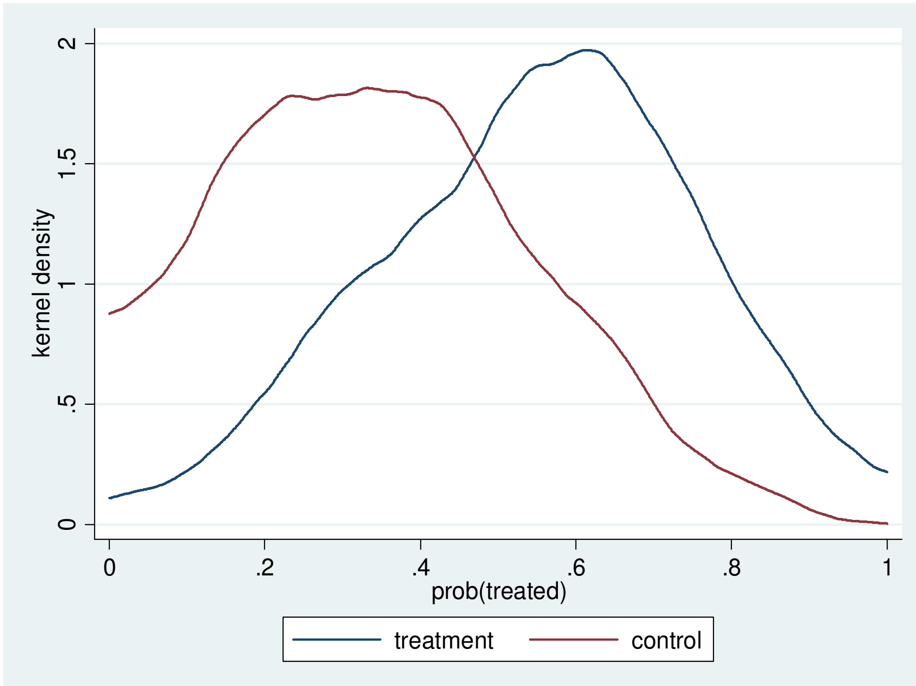
Table 14: Impact on ownership of agricultural assets. DiD with IPW and controls

	all	female head	male head	hh size<4	hh size>3
DiD effect	**b/se**	**b/se**	**b/se**	**b/se**	**b/se**
cutlass	-0.242	-0.253	-0.227	-0.229 *	-0.253
	(0.15)	(0.18)	(0.24)	(0.13)	(0.27)
hoes	-0.190	-0.368 **	0.060	-0.111	-0.262
	(0.16)	(0.14)	(0.31)	(0.17)	(0.26)
axes	-0.141 *	-0.145	-0.136	-0.150 *	-0.129
	(0.07)	(0.10)	(0.09)	(0.08)	(0.11)
shovels	-0.087 **	-0.063 *	-0.119	-0.106 ***	-0.066
	(0.04)	(0.04)	(0.08)	(0.04)	(0.07)
picks	-0.071 *	-0.009	-0.159 *	-0.101 **	-0.039
	(0.04)	(0.02)	(0.08)	(0.05)	(0.06)
spraying machine	-0.062 *	-0.047	-0.082	-0.010	-0.118 **
	(0.03)	(0.04)	(0.06)	(0.03)	(0.05)
sickles	-0.043	-0.024	-0.072	-0.009	-0.079
	(0.03)	(0.03)	(0.06)	(0.03)	(0.05)
rakes	-0.091 ***	-0.090 ***	-0.092 **	-0.086 **	-0.095 **
	(0.03)	(0.03)	(0.05)	(0.03)	(0.04)
N	2,978	1,608	1,370	1,530	1,448

Notes: * p<0.1, ** p<0.05, *** p<0.01

Figure 1: Kernel density of propensity scores for treatment and control groups

A) Unweighted



B) Weighted

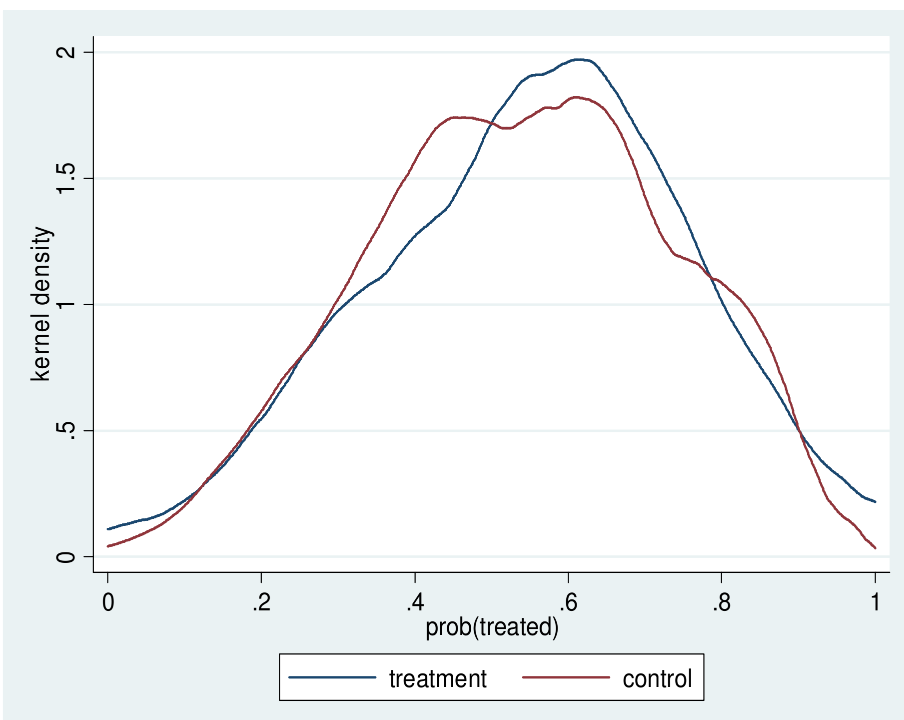
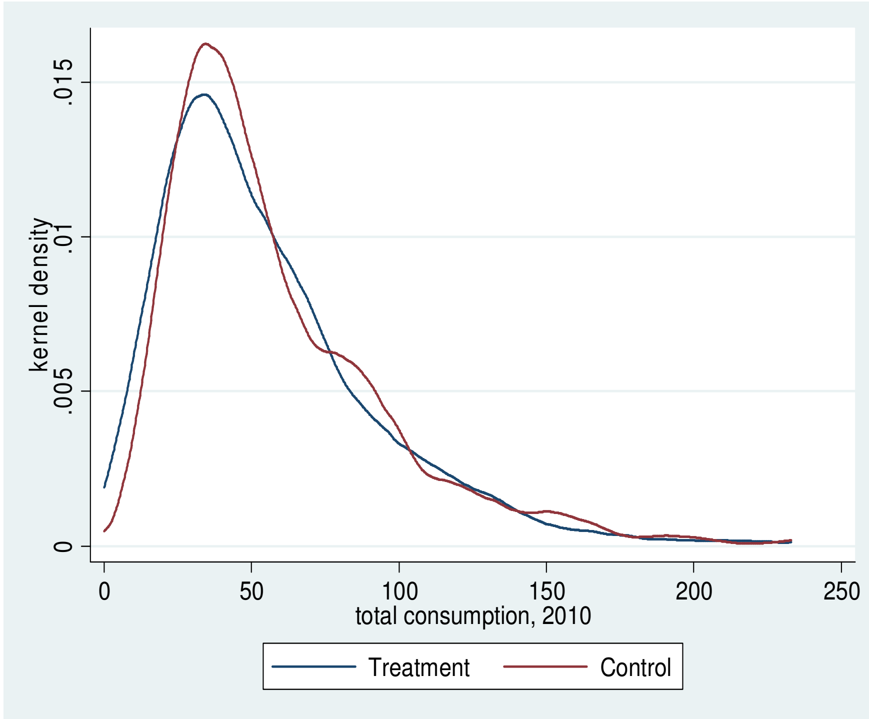


Figure 2: Distribution of per adult equivalent consumption, 2010 and 2012



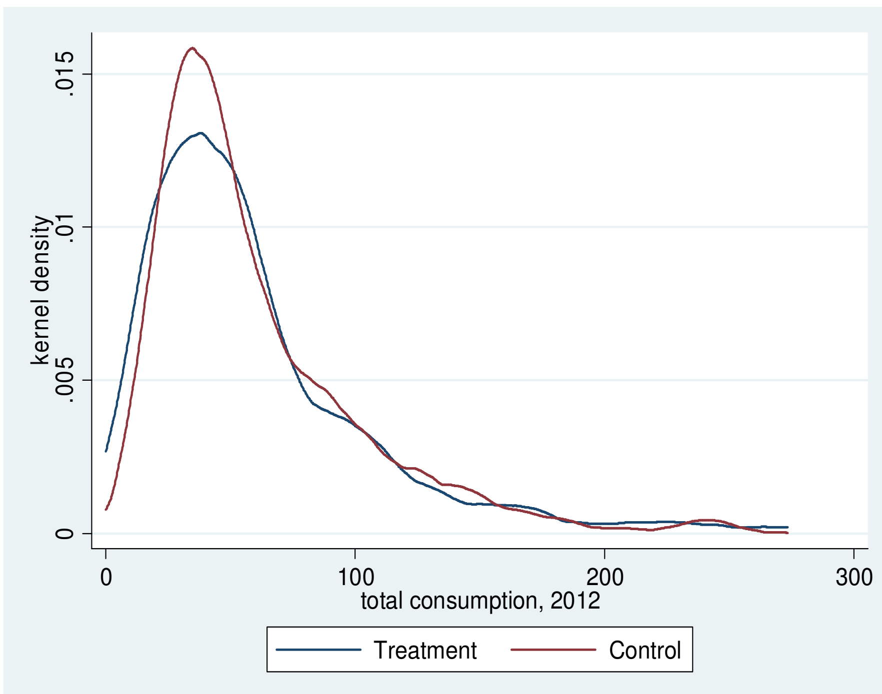
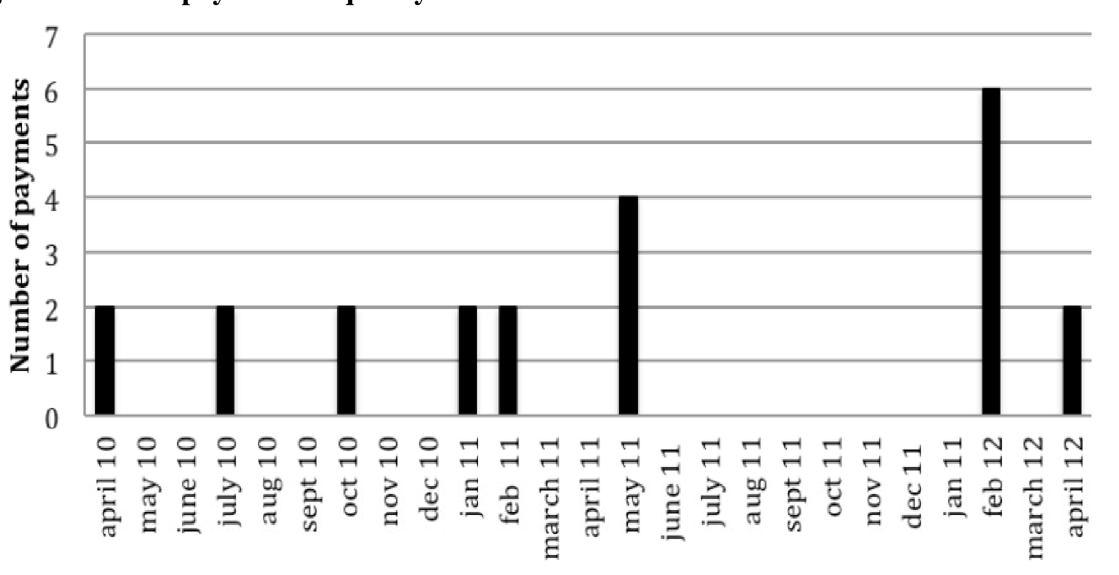
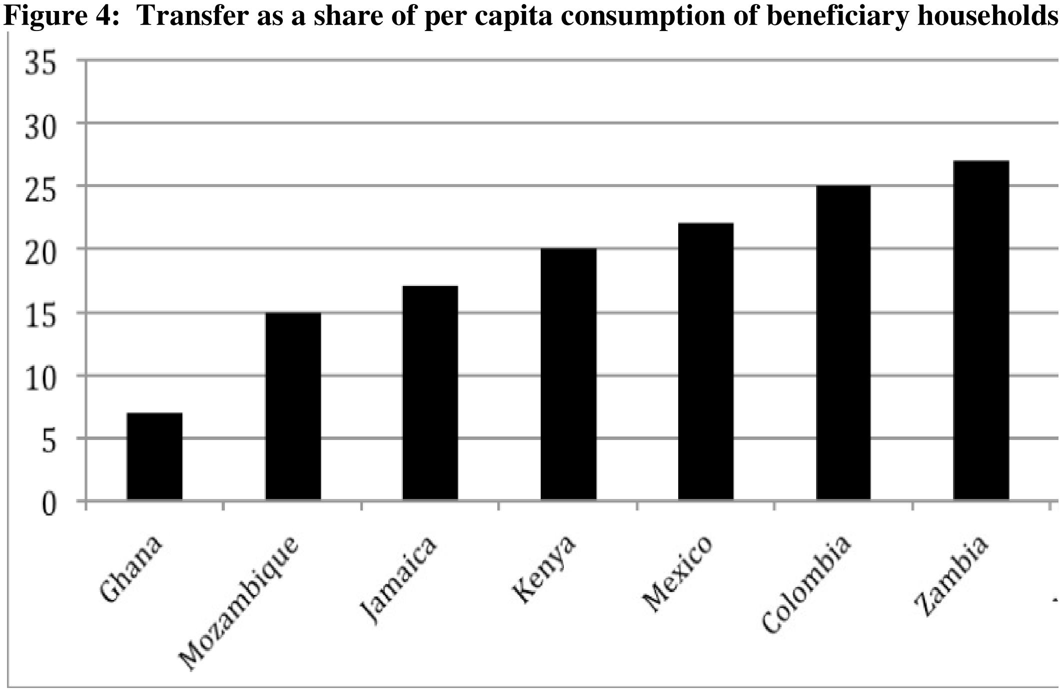


Figure 3: LEAP payment frequency



Note: figure taken from Handa et al. (2012)

Figure 4: Transfer as a share of per capita consumption of beneficiary households



Note: figure taken from Handa et al. (2012)