PTTA impact evaluation in the Northeast
Preliminary Results

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Smart subsidy programs have been advocated in number of developing countries to increase the adoption of modern inputs and increase agricultural productivity. Evidence from Sub-Saharan Africa has shown that one-time targeted subsidies can be effective at increasing adoption of fertilizer and increase agricultural productivity (Carter, Laajaj and Yang, 2015). The PTTA program in Haiti similarly provides subsidies for modern inputs, by providing vouchers for certain labor tasks, fertilizer, and pesticides. A randomized evaluation was built into the PTTA program for rice farmers in the Northeast of Haiti. In the fall of 2013, 521 households from 39 habitations were identified as eligible to receive rice vouchers. 16 of these habitations were randomly selected in an early-treatment group, and eligible farmers in these habitations received vouchers in 2014. Eligible farmers in the control habitations were to receive vouchers after the August 2015 survey. Many of the selected farmers already used fertilizer and pesticide without subsidies, and seem to do so in part by taking loans, often from traders or informal sources.

This note reports preliminary results of the short-and medium term impacts of the voucher distribution. It is based on data collected right after the 2014 agricultural seasons (during which the early treatment group received vouchers), and data collected in August 2015, capturing one-to-two seasons in which the early treatment no longer had subsidies, while the control group had not yet received the transfers. Both 2014 and 2015 were years in which many of the farmers were facing drought conditions. Building on the baseline that was conducted in fall 2013, and on the randomized assignment, we derive lessons both about the immediate impact during the year farmers were benefitting from the subsidy, and the impact one year after receiving subsidies. Almost all farmers could be re-interviewed during the two follow-up surveys; 87% of all early treatment farmers reported receiving transfers, while only 3 farmers in the control reported receiving vouchers. We hence can interpret the differences between the treatment and the control households at follow-ups as program impacts.[2]

We start by considering rice productivity. Figure 1 shows that treatment farmers **did not achieve higher yields on their rice plots** than control farmers in the year they received the vouchers (2014). The average yield for treatment farmers was less than yield in control, though this difference is not significant. **The impact on the total value of rice production is negative and significant** in 2014. Rice yields and production values for farmers in the treatment group are also significantly lower in 2015 than in control, which reflects seasons where they did not receive vouchers, and this difference is significant. The 2015 result in part reflects that not all households had harvested yet by the time of the survey. We therefore also report results for only plots that were planted early in 2015 (the 1st completed season), and find decreased yields for these plots as well. These results are robust to a variety of specifications.

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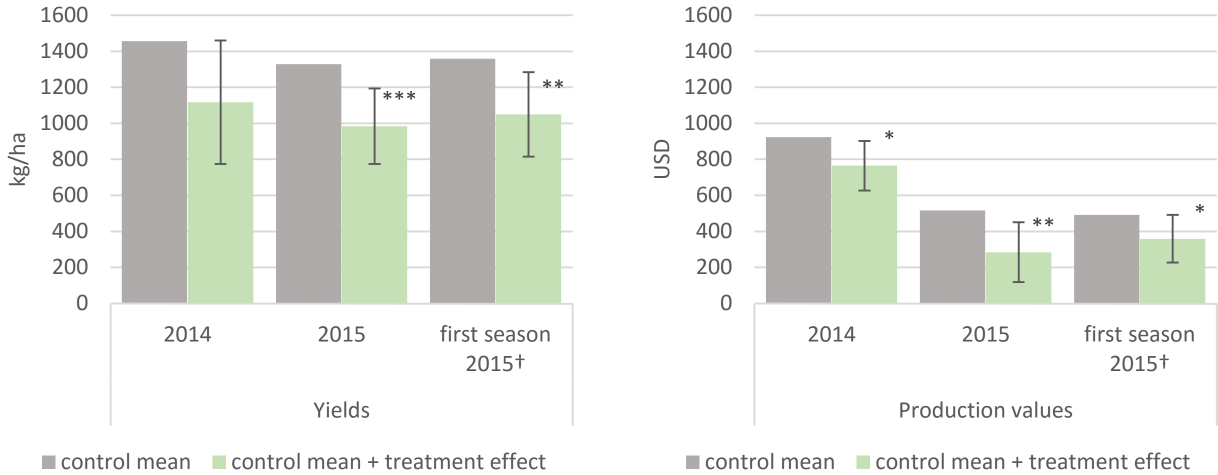
[2] Except otherwise noted, estimates present ITT results on all eligible households, including those not producing rice (as the decision to produce rice itself is endogenous to treatment assignment). All graphs are based on the results of regressions with controls for stratification, baseline outcomes (except where noted), as well as plots' water access, as measured by its location in one of the lagoons in the region. These variables correct for some of the imbalances at baseline.

In the charts, the first column of each cluster (in gray) is the mean of the outcome variable in the control group. The second column is the estimated treatment effect added to the control mean. The error bars represent the 90 percent confidence interval of the treatment effect. A control mean that falls outside of the error bars hence means that the treatment effect is greater than zero, at the 90 percent significance level. Confidence of treatment effects is also represented with stars. One, two, and three stars mean the treatment effect is statistically different from zero with p-values of .10, 0.05, and .01 respectively.

Figure 1: Rice Yields and Rice Production Values



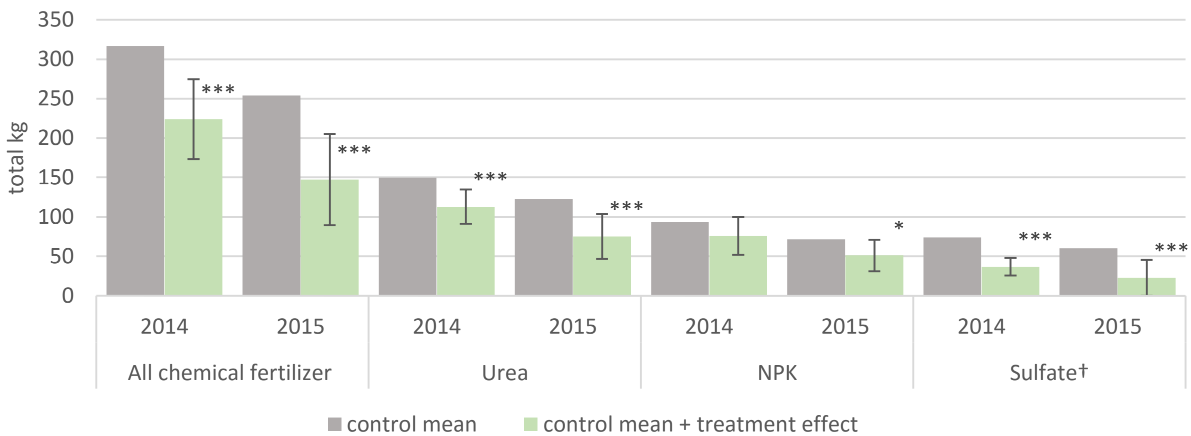
See footnote 2 for graph interpretation. 2014 and 2015 yield outcomes shown here can be interpreted as household's average yield per season. They are total rice harvested per year over total area used for rice, where if the same plot is used in two seasons, its area is included twice in the denominator. Where households practice "retonn", or multiple harvests from the same seeds, the plot area is also included twice in the denominator. Yields are only defined for rice growers. First season 2015 only includes households (310) that had a completed season of rice (harvested or lost, not including entirely lost seedbeds) by the time of the August 2015 survey. Rice production values are defined for all farmers, except for the first season of 2015.

†First season 2015 does not control for baseline outcomes.

What can explain this unexpected decrease in productivity? The reasons are undoubtedly diverse, but considering the impacts on input use can provide part of the explanation. Figure 2 shows that the program led to a **significant decrease in the amount of fertilizer** used in the year the household received the voucher, and the lower fertilizer use persists in the following year. The decline is large (about 1/3) and driven by a reduction in urea and sulfate. We do not see any significant changes in pesticide use. The fertilizer result at first may seem counterintuitive, but may be related to the fact that the value of the fertilizer voucher corresponded to much less than the recommended amount, and also vouchers were not provided for sulfate.[3] In 2014, farmers in the treatment were indeed significantly more likely to use exactly the amount provided by the subsidy. Farmers hence do not use the voucher as complement of other sources of financing, but rather as substitute. This suggests they were not necessarily liquidity constrained prior to the intervention, even if loans imply liquidity with a substantial cost.

[3] Recommended kg of fertilizer per demi-hectare is 200 kg (400 kg/ha), but amount of the full voucher is 4500 which corresponded to 3 bags, or only 135 kgs per demi-hectare (270 kg/ha). This corresponds approximately to the calculated fertilizer use of the control farmers (260 kg/ha).

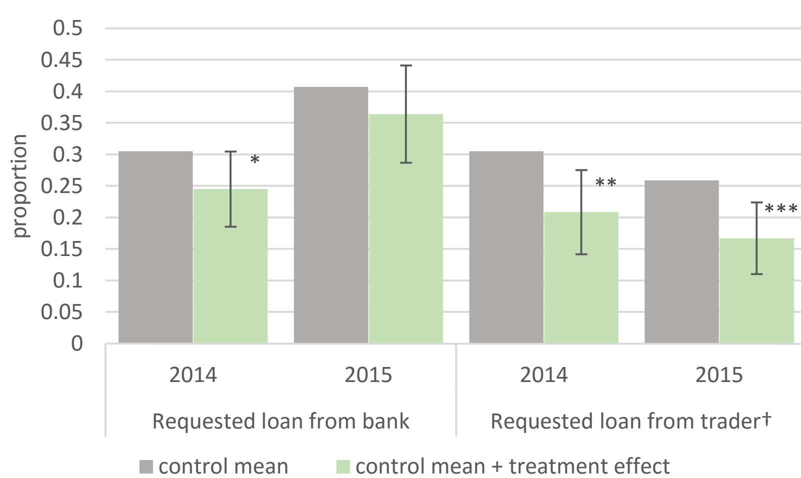
Figure 2: Total Fertilizer Use



See footnote 2 for graph interpretation. 2015 values include fertilizer used for rice planted from December 2014 through August 2015. Quantities are unconditional on growing rice.
†Does not control for sulfate quantities at baseline.

Indeed, treatment farmers **are much less likely to have taken loans**, especially from traders (madame Saras), and specifically report less loans for inputs in the year they received the vouchers. The vouchers possibly allowed indebted farmers to pay off their loans and not engage in new lending, hence avoiding the large *de facto* interest rates such loans might imply. Interestingly, in 2015 farmers were again less likely to take loans from traders. We don't have direct evidence on the underlying reasons, but one explanation is that farmers chose to stay away from new loans (and investments in fertilizer), possibly because the particular risky climatic environment in both years.

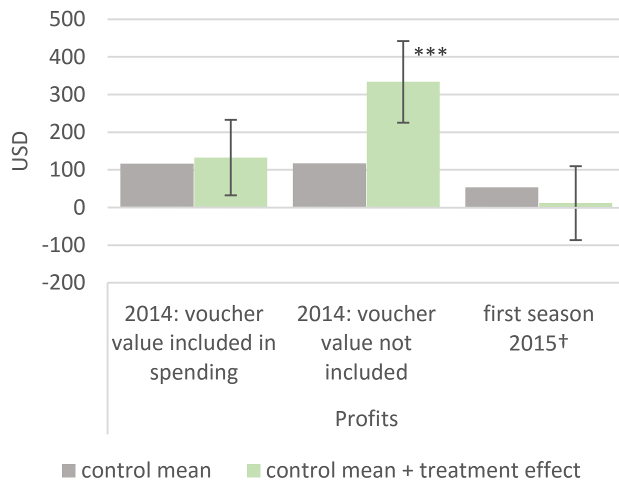
Figure 3: Loans



See footnote 2 for graph interpretation. Answers to the question "Have you requested a loan in the past 12 months?" and "Have you already repaid the loan?"
†Does not control for loans from traders (Madame Saras) at baseline.

Importantly, household **agricultural profits (for rice cultivation) do not show the same negative impact** as found for yields or production values. When considering the value of the vouchers as spending, profits are unchanged in 2014. When the vouchers used are not counted as spending, there is a positive impact on nominal profits in 2014 as inputs were provided for free, though this positive impact in profit is smaller than the value of the vouchers.

Figure 4: Rice Profits

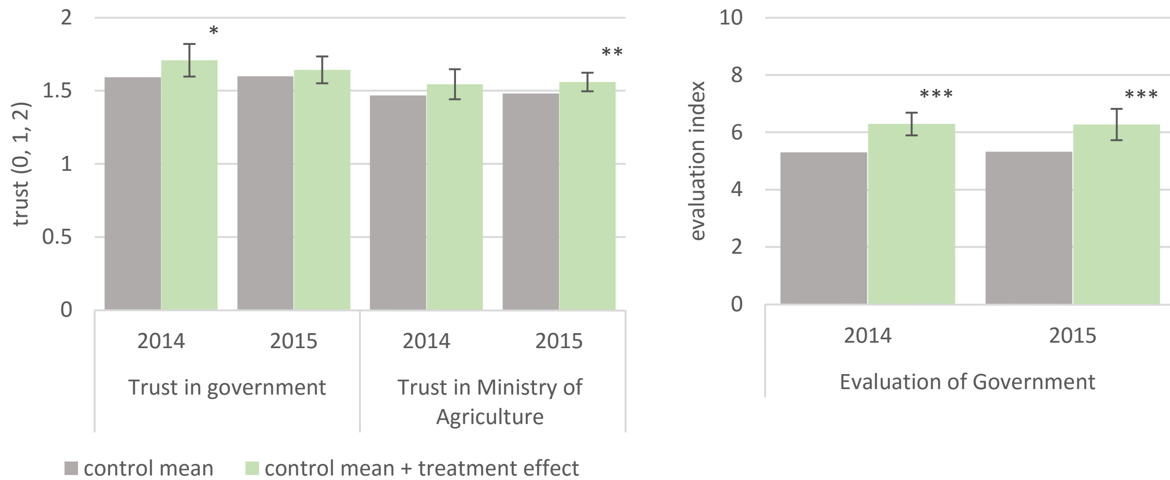


See footnote 2 for graph interpretation. 2014 profits include all costs incurred during the survey period and is defined for all farmers. First season 2015 only includes households (310) that had a completed season of rice (harvested or lost, not including entirely lost seedbeds) by the time of the August 2015 survey.

†2014 with voucher value not included and 1st completed season in 2014 do not control for baseline outcomes.

The weather context in both years is important to understand these results. First, because of the adverse drought conditions in the beginning of 2014, the program decided to delay most of the voucher distribution. Possibly as a result, the treatment farmers on average planted about 20 days later than the control farmers, implying that weather shocks may have affected their crops differently. Treatment farmers are indeed more likely to report crop losses due to drought. Overall, drought conditions were bad for many farmers, and under those conditions, lower input use might well have been perceived by treatment farmers to have been a good strategy. This could explain why they persist in taking less loans and using less inputs the year after the voucher distribution. In addition, in 2015 treatment farmers seem to have shifted to plots with less reliable water access. This is consistent with lowered fertilizer use, as water and fertilizer are complimentary inputs. Indeed 2015, was another year with unreliable rainfall, resulting in low profits for both treatment and control farmers, but no significant differences between them. While we do not observe any clear impacts on other welfare indicators, there are notably **positive impacts on farmers' confidence in and opinion of government**, which is sustained in 2015.

Figure 5: Opinion of Government



See footnote 2 for graph interpretation. Trust levels as responses to the question "What level of trust/confidence do you have in the government/ministry of agriculture?" Government evaluation index constructed based on the answers to 7 questions concerning the role of government.
Does not control for baseline outcomes.

Overall, these results, while still preliminary, suggest important lessons for PTTA and related programs. In contrast with smart subsidy programs in Sub-Saharan Africa where subsidies allow farmers to learn and adopt new technologies, the PTTA subsidies in the Northeast were for inputs that were already widely used. The subsidies instead may have allowed farmers to shift to a new lower-intensive equilibrium, paying off their loans and taking less new ones, while using less fertilizer. Given the high risk related to rain-fed agriculture, this may well be an optimal strategy. A possible implication is that annual rain-fed crops in Haiti might not be the ideal focus area for a smart subsidy program, in particular if the objective is to increase yields. This likely holds especially for crops for which farmers are already using key inputs (as was the case for rice), as the vouchers may just serve to substitute for other forms of financing. This would suggest then that the benefits of any new smart subsidy program might be higher if its targeted to crops that are less weather dependent, and for which lumpy one-time investments might be important to reach substantial productivity increases in the long-run.

References

Carter, Michael R., Rachid Laajaj, and Dean Yang. *Subsidies and the persistence of technology adoption: Field experimental evidence from Mozambique*. No. w20465. National Bureau of Economic Research, 2014.