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## Weather information for smallholders: Evidence from a pilot field experiment in Benin

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Rosaine N. Yegbemey  
Gunther Bensch  
Colin Vance

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# Imprint

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Rosaine N. Yegbemey, Gunther Bensch, and Colin Vance<sup>1</sup>

# Weather Information for Smallholders: Evidence from a Pilot Field Experiment in Benin

## Abstract

*Weather conditions are an important determinant of agricultural factor input, particularly labor allocation. The availability of weather forecasts can therefore lead to efficiency gains in the form of cost decreases and productivity increases. We test the practical feasibility, the uptake, and the effect of providing basic weather forecasts in the rainy season on the labor productivity of smallholder farmers. For this purpose, we conducted a Randomized Controlled Trial as a pilot with monthly data collections involving 331 farmers across six villages in north Benin. We find that most farmers subscribe to the intervention and report satisfaction with the service. The impact estimates indicate positive and economically significant intention-to-treat and local average treatment effects on labor productivity for maize and cotton cultivation. These findings suggest that weather-related information and mobile phone outreach help smallholder farmers to better adapt to changing weather.*

*JEL-Code: D13, O12, Q12*

*Keywords: Pilot field experiment; climate and weather information; labor productivity; smallholder farming; information technology; impact evaluation*

*December 2021*

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## 1. Introduction

Smallholder farmers in poor countries are increasingly challenged to adapt to rapidly changing economic and environmental conditions. General economic development (Letta et al., 2018) and crop diversification (Bozzola and Smale, 2020) are ways to build up farmers' adaptation capacity. In addition, agricultural advice provided through mobile technologies has the potential to enhance resilience by improving smallholder farmers' production decisions (Fabregas et al., 2019). Climate information services, in general, and weather forecasts, in particular, can provide timely information on weather variability, which is an important constraint in rain-fed agricultural production systems. However, smallholder farmers in rural regions of developing countries often lack access to weather forecasts, in part due to the lack of access to Smartphone applications. In Benin, the site of the present study, only a quarter of the population are mobile internet subscribers, with more than half the population living in areas without a mobile broadband network (GSM Association, 2019).

This infrastructure and appliance deficit makes it necessary to find simple, inexpensive solutions to provide farmers with weather information. Short message services (SMS) are a promising candidate given the widespread use of basic feature phones (GSM Association, 2019; Pew Research Center, 2019). Nevertheless, there is scant empirical evidence that supports the benefits of such services. In two flagship studies, Fafchamps and Minten (2012) and Camacho and Conover (2019) rigorously explored the impacts of providing smallholder farmers in India and Colombia with basic weather-related information, combined with information on agricultural output prices. Neither study finds a significant effect of the combined treatment on weather-related crop losses, and the results on cultivation practices are mixed, though Camacho and Conover (2019) observe reduced labor cost.

The present article contributes to this small body of evidence with a study of the impacts of weather forecasts in the West African context, which has relatively low productivity coupled with high dependency on rainfed agriculture (Mechiche-Alami and Abdi, 2020; World Bank, 2020). Distinguished from the above referenced studies, we abstract from the impacts of price information by employing a treatment that specifically isolates the impact of weather forecasts. This focus is facilitated by the fact that the farmers in our sample villages all sell to the same central market, for which price information is widely disseminated. We assess the practical feasibility, the uptake, and the impact of providing basic forecasts of precipitation via SMS throughout the agricultural season. Our main outcome indicator is labor productivity, which we further explore by decomposing into farmers' factor input and yield.

Following Yegbemey et al., 2020, we argue that weather is an even more important driver of farmers' production decisions in times of climate variability and climate change. The underlying hypothesis of our study is that weather forecasts provide information that makes weather a more predictable production factor for farmers, who can therefore take more informed decisions to optimize their labor allocation. The main crop for which we conduct this analysis is maize, a crop whose flexibility makes it especially sensitive to information on weather conditions. We also estimate the effect of the intervention on cotton, the main commercial crop in the study area. Our approach employs a clustered Randomized Controlled Trial (RCT) design conducted as a pilot field experiment among 331 farmers from six villages with monthly survey data collections between April and December 2018. Recognizing the small-scale pilot character of the experiment, we use a robust estimation technique to account for possible inferential biases from the study's small number of clusters.

Our work thereby contributes to the overlapping strands of the literature on the use of Information and Communication Technology (ICT) and technology-driven climate change adaptation interventions in agriculture. As described by Oladele (2015) and Aker et al. (2016), ICTs may ameliorate the consequences of missing or thin markets, and reduce the extent to which information asymmetries can be exploited by the relatively informed at the expense of the relatively uninformed. This, in turn, may impact farmers' livelihoods in different ways, such as improving efficiency in resource allocation, reducing transaction costs, and technical improvements that result in an outward shift of the production function. More specifically, Carr and Onzere (2018), McKune et al. (2018) and Naab et al. (2019) posit that climate information services can influence major farming decisions such as what, when and how much to plant.

While some studies have shown that farmers are willing to pay for climate information services (Amegnaglo et al., 2017; Ouédraogo et al., 2018; Yegbemey et al., 2014), there is generally a dearth of conclusive evidence on the actual value of climate information services and the role of framework conditions (see Tall et al., 2018; Vaughan et al., 2019). Moreover, climate information per se may have a muted effect in the absence of complementary measures. Feleke (2015), for example, concludes in her study on smallholder farmers in the central rift valley of Ethiopia that their adaptation capacity in using weather information are constrained by several problems, including language issues, difficulty in understanding forecast terminology, absence of a center for coordination that downscales weather information to the local level, and inconsistency in the time of information provision. Not least, the effectiveness of the climate information depends on its quality. As Rosenzweig and Udry (2014) show, forecasts of monsoon rainfall significantly influence planting-stage decisions of Indian



farmers, which leads to improvements in labor allocations on average but exacerbate wage volatility because the forecasts are imperfect.

Our results suggest an economically and statistically significant impact of the intervention on labor productivity for maize and cotton cultivation, albeit one that is subject to wide confidence intervals, a likely consequence of the modest number of clusters in our sample design. Our main specifications estimate Intention-To-Treat (ITT) effects, but we also undertake robustness checks that estimate the Local Average Treatment Effect (LATE) for those farmers that self-report using the weather-related SMS information. We conclude that SMS-delivered precipitation forecasts can contribute to optimizing labor allocation, but should ideally be coupled with measures to ensure that the information is as locally specific as possible and conveyed in a way that can be readily understood by farmers.

The remainder of this paper is organized in three sections. Section 2 provides a description of the study zone and the methodology, followed by a presentation and discussion of the results in Section 3, and a conclusion in Section 4.

## **2. Material and methods**

### **2.1. Study area**

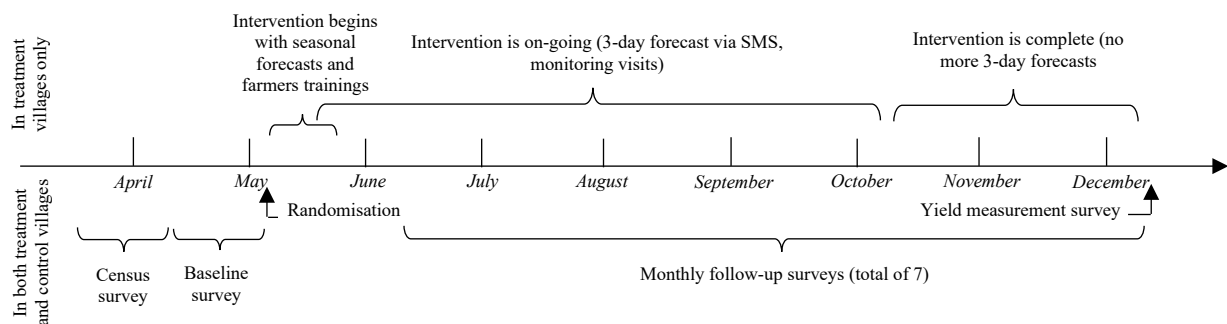
The site for our pilot experiment is one of the country's major agricultural regions, the municipality of Bembèrèkè in northern Benin. This selection was made after consultations with the national agricultural extension office. Most farmers in the region practice small-scale slash-and-burn cultivation with limited external inputs and no use of weather forecasts. Maize is the main staple crop in the region while cotton is the main cash crop. Nearly all of the farmers in our sample plant maize, while about 86% additionally plant cotton. Among farmers producing both maize and cotton, we expect that cotton production would benefit from the weather information to a lesser extent than maize given that cotton is supported by government outreach programs that provide advice on production timing and techniques, in addition to seeds, fertilizers and pesticides on credit.

Our pilot field experiment covers six maize-growing villages separated from one another by a minimum of a five-kilometer buffer (see Figure A1 in the Annex). We randomly selected three of the villages as treatment sites, leaving the remaining three as control sites. A village is thus the experimental- as well as the sampling cluster unit. A power calculation

yielded a total sample size of about 300 respondents, i.e. about 50 per village.<sup>1</sup> We adopted three criteria for households to belong to our target population and thus be eligible for the experiment: first, farmers should plan to produce maize during the rainy season of 2018/2019. Second, farmers should own a mobile phone, including a valid and functional line number, and, third, farmers should have the ability to operate their mobile phone (i.e. read SMS) or have a permanent household member who can do so. The eligibility criteria turned out to exclude only very few farmers. A full list of eligible smallholder farming households compiled in a census survey in April 2018 served as the sampling frame to randomly select 50 to 60 households per village. All but eight selected households were willing to participate in the study,<sup>2</sup> leaving a total sample size of 323 farmers.

Data related to the intervention, the farmers' socio-economic characteristics, and the labor allocation to maize and cotton were collected using tablets over multiple site visits. We also collected data on farm capital, land holdings, access to credit, and access to agricultural extension services. Additionally, qualitative investigations were conducted at baseline and throughout the intervention period.

**Figure 1:** Illustration of the intervention implementation and survey timeline



## 2.2. Overview of the intervention

The intervention consisted in providing forecasts of precipitation through mobile phone SMS among the target population of smallholder farmers. Farmers in the treatment group received a seasonal forecast at the beginning of the intervention in May and daily precipitation forecasts every three days via SMS at no cost to them. Focus group discussions (FGDs) were organized

<sup>1</sup> The power calculation was done in *Optimal Design Plus* and suggested that a sample of 300 respondents in 6 villages (50 farmers per village) was required to detect an effect size of at least 0.8 standard deviations with 80% of power, 5% level of significance and an Intra-Cluster Correlation of 0.05.

<sup>2</sup> Five of these households belonged to the control, three to the treatment group. Reasons for attrition include migration out of the villages, refusal to participate because of being randomly assigned to the control group or unavailability to participate in the monthly surveys.

in each treatment village to share information on seasonal weather forecasts such as the on-set date, duration, and total precipitation expected for the rainy season. During the FGDs, farmers were also trained to interpret daily rainfall forecasts. Their expectations were managed by explaining the experimental nature of the study and the probabilistic nature of weather forecasts, making clear that forecasts are not 100% accurate and that neither the research team nor the implementing agency could provide hard recommendations on precise dates to carry out different production activities.

The treatment was carried out during the agricultural campaign 2018-2019, with the SMS component starting on the 29<sup>th</sup> of May 2018 (after the baseline) through the 31<sup>st</sup> of October 2018 (see Figure 1). Forecasts were village-specific. An agreement was made with the Benin meteorological office, Meteo-Benin, to get their support in accessing accurate weather forecast information. Forecasts from three different models – the European Centre for Medium-Range Weather Forecasts (ECMWF) model (with horizontal resolution of 9 km), the Global Forecast System (GFS) model (22 km) and the National Environmental Modeling System (NEMS) model (4 to 12 km) – were averaged and transmitted to the farmers.

The intervention was implemented by a local Non-Governmental Organization, *Bureau de Recherche et Développement en Agriculture* (BReDA), which organized the FGDs, trained farmers and sent via SMS the weather forecasts compiled by the research team. To facilitate the smooth functioning of SMS signals, a platform was set-up that generated reports of each SMS campaign, which helped to keep track that farmers in the treated villages were regularly receiving signals. BReDA also involved two field officers who were based in the treatment villages and tasked to provide routine on-the-ground technical support (e.g. helping farmers to free-up phone memory). BReDA also offered a call service to farmers for fielding questions.

### **2.3. Outcome variables**

The study was primarily designed to assess the effects on the agricultural production of the key staple food in the study region, maize, whose cultivation is sensitive to weather conditions. In addition, the study covers the region's main cash crop, cotton, which is the highest priority cash crop in Benin's agricultural policy. The main outcome of interest is labor productivity in the production of the two crops, each expressed as harvested output in kilograms (kg) per labor expenditure in US dollars (USD), denoted kg/ USD. To better understand the underlying mechanisms that drive observed changes in labor productivity, we model two additional outcomes, the yield and labor costs per hectare. The yield is given by kg per hectare of land (ha), denoted kg/ ha, while labor cost is given by labor expenditure per hectare, denoted

USD/ ha. Recognizing that productivity equals  $\text{kg/ ha} \cdot \text{ha/ USD}$  – or  $\text{kg/ ha} \cdot 1/\text{USD/ ha}$  –, it is seen that both increases in the yield and decreases in labor costs per hectare increase labor productivity.

These outcomes are based on three pieces of household information: the size of cultivated land, the harvested product, and monthly labor costs, each for maize and cotton separately. Land size is measured using GPS trackers. The harvested product in kilograms is measured by means of the yield squares method, which consists in placing a square randomly at the plot to determine through a crop cut method an average yield at harvest (GSARS, 2017). This measurement is taken in December, toward the end of harvesting period.

For most farmers, labor costs are primarily incurred from in-kind labor that comprises adults and children of both genders who reside in the home, but can also include friends, neighboring farmers and self-help groups. About 85% of the farm households additionally hire salaried labor at some point of the agricultural season. We infer the value of in-kind labor by multiplying the labor days by the average unit price of hired labor in the area. This price is typically differentiated by gender and age. It amounts to about 2.5 USD/ day for adult males and 75 and 50% of this amount for female adults and children, respectively (i.e. 1.9 and 1.25 USD/ day). While there is little guidance in the existing literature as to whether the 1:1 inference from market to shadow wages is appropriate, Barrett et al.'s (2007) analysis from neighboring Côte d'Ivoire suggests that the valuation of household labor comes close to observed market wages once accounting for allocative inefficiency due to uncertainty or transactions costs.

We elicited both paid and in-kind labor separately for six different agricultural activities: field preparation, sowing/ planting, weeding, application of fertilizers, application of herbicides/ insecticides, and harvesting. Our main models use the sum of the paid and in-kind labor components over the observation period from June to December to calculate our outcome measures, but we also undertake a robustness check where we restrict our analysis to paid labor to determine the impact on actual monetary spending. This restriction avoids the ambiguities of inferring shadow wages and recognizes that the intervention may have heterogeneous effects on paid and unpaid labor. It is conceivable, for example, that demand for paid labor may react first before household labor is adjusted.

## 2.4. Analytical framework

Our point of departure is an Ordinary Least Squares (OLS) regression to estimate the impact of the weather-forecast treatment on the above-defined outcome variables. This framework is expressed in the following econometric specification in the spirit of an Analysis of Covariance (ANCOVA) estimation:

$$Y_i = \alpha + \beta T_i + \gamma Y_{i,m=0} + \delta Z_{i,m=0} + \varepsilon_i \quad [Eq. 1]$$

where  $Y_i$  is the outcome of interest of the  $i^{th}$  farmer at endline and the subscript  $m$  refers to the month of the intervention. The explanatory variables include treatment status  $T$ , the outcome at baseline,  $Y_{i,m=0}$ , and  $Z$ , a vector of covariates from baseline, including dummies indicating the district (Arrondissement) within which the village is situated. Baseline covariates also include the farmer's age, gender, education, and experience in agriculture, as well as household size, total land holding, access to credit, contact with extension services, and asset ownership and access (radio, TV, and internet). Two additional controls that are of relevance to maize cultivation are dummies indicating improved seed use and the practice of intercropping. The estimated parameter  $\beta$  reflects the Intention-to-Treat (ITT) effect of the precipitation-forecast information treatment. Note that productivity measures can only be determined for farmers who actually cultivate maize or cotton and thus incur labor costs, which is the denominator of the productivity measures; these farmers therefore effectively represent those intended to be treated in our estimations (and not all treatment group members as in a classical ITT).

One concern with the estimator arises from the small number of clusters, which might lead to downward-biased standard errors and inflated type I error rates. A number of methods can be used to address the problem of small cluster sample RCTs with continuous outcomes. Based on simulations with varying numbers of clusters, Leyrat et al. (2018) recommend the use of Generalized Estimating Equations (GEEs) for samples of four to eight clusters. This method, which is applied here, generates the same coefficients as OLS but with a small-sample correction of the standard errors with bootstrapping.

As upwards of 30% of farmers in the treatment group reported not using the SMS in a given month, we also estimate the Local Average Treatment Effect (LATE) to reveal how treatment affects the outcome for compliers, defined here as farmers who self-report using the weather-related SMS information. We define the SMS use as a binary variable that equals one if a farmer self-reports that s/he used the weather-related information in June, July and August. This definition is consistent with the critical sub-period of the treatment period when farmers need to carry-out important farming activities such as the planting and the first application of

fertilizers or pesticides. Recognizing the likely endogeneity of self-reported SMS use, we instrument it with treatment status and estimate the model using two-stage least squares (2SLS). As documented in the regression tables presented below, the high F-statistics from the first stage regressions of the 2SLS models— all well above 10 – assuages concern that treatment status is a weak instrument.

Our main specifications thus employ OLS, GEE with bootstrapped error terms, and 2SLS. We use aggregated data from June to December. This includes the treatment period (spanning June through the end of September) and the following three months which cover most of the harvesting season except for some residual harvesting activities in January and February. As a robustness check, we estimate the models of labor costs by making use of our monthly data. Here, the left-hand side of equation [1] is represented by  $Y_{i,m>0}$ , and the right-hand side additionally features month dummies and the related coefficient vector,  $\vartheta M_{m>0}$ .

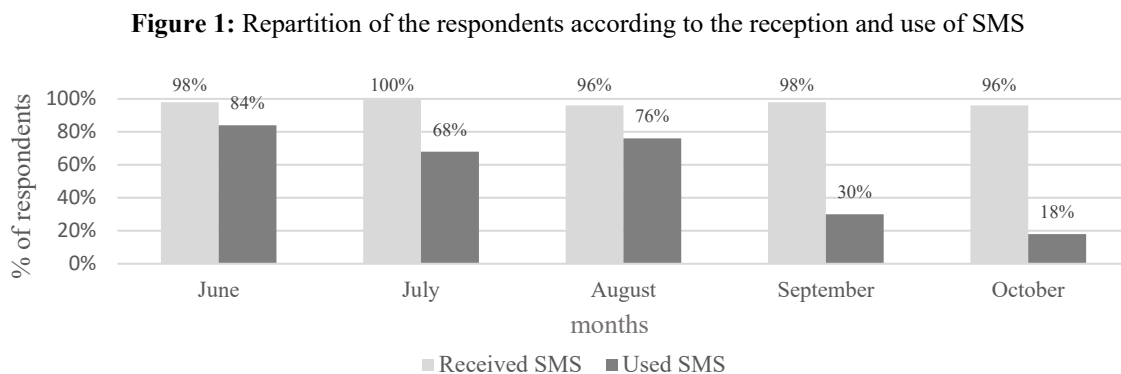
### 3. Results

We begin with a descriptive analysis of SMS usage that includes usage rates, purposes, perceptions of accuracy, and satisfaction. This is followed by a presentation of balance tests. We then undertake a monthly trend analysis that tracks labor costs (USD/ ha) over the seven-month survey period for the treated and control group. We complete the analysis with econometric results that quantify the impact of the intervention on our outcome variables.

#### 3.1. Feasibility and acceptability of the intervention

##### 3.1.1. SMS Reception and usage rates

Figure 1 shows the rates of SMS reception and usage by smallholder farmers in the treatment group.



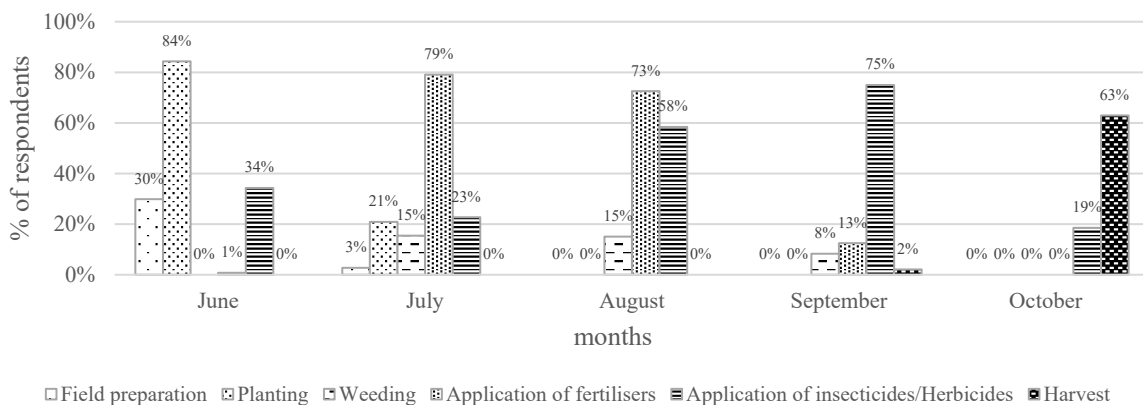
Most of the farmers reported that they received the SMS during the treatment period. According to the self-reports, the lowest delivery rates (96%) are observed in August and October. These

figures are consistent with the report generated through the SMS platform and suggest that the information reached the intended targets. There is, however, a gap between reception of SMS weather-related information and its usage. While the majority of farmers (68 to 84%) reported to have made use of it in June to August, the rate drops drastically to 30 and 18% in September and October, respectively. The low usage rate in these months can be explained by the fact that rain is not a crucial input in production at this time of the season.

### 3.1.2. Types of usage of weather-related information

Farmers use weather-related information to make decisions for different activities. Figure 2 shows the extent to which farmers used the information for the main agricultural activities such as planting and weeding. The figure suggests that the weather-related information is useful for different production activities and that the relevance changes over the months. In June, the information is mostly used for planting decisions, while in July, it is mostly used for the application of fertilizers. In August, in addition to the application of fertilizers, the information is also used for application of insecticides and herbicides. In September, the application of pesticides is the main activity that benefited from weather-related information.

**Figure 2:** Repartition of the respondents according to the types of usage of weather forecasts



### 3.1.3. Accuracy and importance of weather information

The analysis of the dichotomous rainfall predictions showed that out of 211 days of actual rains, the forecasts rightly predicted 180 days (85% of correct predictions). With respect to rainfall intensity, we find a correlation coefficient of 0.2499 ( $p < .01$ ) between forecasted and actual rainfall in millimeters. Notwithstanding this seemingly weak correlation, farmers perceived the accuracy of the weather-information shared with them as relatively high. Except for the month of October, which falls outside the rainy season, more than 60% of the respondents find the weather information to be very accurate or accurate and at most

10% perceive the accuracy to be low or worse. Correspondingly, over 96% of farmers consider the weather information at least important and 55% as very important.

### 3.2. Balance tests

Table 1 shows main household characteristics to check the balance between the control and treatment group. We use two tests for this purpose, a standardized  $t$ -test and a Wilcoxon rank sum test (WRS). The latter is a non-parametric alternative to the  $t$ -test that may be preferred for asymmetric small-sample distributions (Bridge and Sawilowsky, 1999).

The data suggest that both groups are well-balanced on the covariates and the self-reported baseline outcome variables from the previous agricultural season (2017/18). One exception is that farmers in the control villages have, on average, slightly larger household sizes ( $p$ -values of 0.03 and 0.05 for the two tests) and higher cotton yields ( $p$ -values of 0.09 and 0.13 for the two tests). This occurrence of statistically significant differences is in line with what would be expected by chance given the 21 tests presented in the table. We seek to attenuate this imbalance by controlling for the respective variables in accordance with equation [1] in Section 2.4.

**Table 1:** Balance tests on baseline characteristics at cluster level

Variables	Full sample <i>mean</i>	Control (C) <i>mean</i>	Treatment (T) <i>mean</i>	T – C	
				<i>p-value</i> ( <i>t-test</i> )	<i>significance</i> <i>level</i> ( <i>WRS test</i> <sup>#</sup> )
<i>Socioeconomic characteristics</i>					
Age (years)	41.90 (2.07)	42.78 (2.69)	41.01 (1.05)	0.35	0.28
Gender (1=Male)	0.96	0.96	0.96	0.80	0.28
Education (1=Yes)	0.36	0.34	0.37	0.75	0.83
Experience in agriculture (years)	17.20 (2.14)	18.16 (2.70)	16.24 (1.18)	0.32	0.28
Household size	13.82 (1.42)	14.92 (1.01)	12.73 (0.65)	0.03	0.05
Total land holding (ha)	20.95 (7.49)	22.34 (10.36)	19.55 (5.21)	0.70	0.51
Access to credit (1=Yes)	0.53	0.50	0.55	0.81	0.83
Extension contact (1=Yes)	0.86	0.90	0.83	0.19	0.51
Improved seed use (1=Yes)	0.56	0.51	0.61	0.23	0.51
Practicing intercropping (1=Yes)	0.09	0.10	0.08	0.83	0.66
Radio ownership (1=Yes)	0.88	0.93	0.83	0.50	0.83
TV ownership (1=Yes)	0.40	0.42	0.38	0.82	0.83
Access to internet (1=Yes)	0.03	0.03	0.04	0.80	0.82



Variables	Full sample mean	Control (C) mean	Treatment (T) mean	<i>p</i> -value ( <i>t</i> -test)	T – C significance level ( <i>WRS</i> test <sup>#</sup> )
<i>Maize-related characteristics (self-reported ‡)</i>					
Land acreage (ha)	6.54 (2.12)	6.28 (1.92)	6.79 (2.71)	0.80	0.83
Yield (kg/ha)	2049.83 (330.52)	1993.77 (316.83)	2105.88 (404.10)	0.72	0.51
Labor productivity (kg/USD)	20.23 (12.35)	18.92 (9.81)	21.53 (16.72)	0.83	0.83
Labor costs (USD/ha)	152.52 (64.50)	153.23 (69.22)	151.82 (74.87)	0.98	0.83
<i>Cotton-related characteristics (self-reported ‡)</i>					
Land acreage (ha)	3.78 (1.38)	4.45 (1.80)	3.12 (0.45)	0.28	0.28
Yield (kg/ha)	1336.87 (84.46)	1394.21 (81.11)	1279.53 (37.27)	0.09	0.05
Labor productivity (kg/USD)	7.47 (3.83)	7.24 (3.96)	7.71 (4.57)	0.90	0.83
Labor costs (USD/ha)	274.46 (129.96)	286.36 (140.22)	262.57 (148.79)	0.85	0.51

Values in brackets are standard deviations for continuous variables. <sup>#</sup>*WRS* refers to the Wilcoxon rank sum test. <sup>‡</sup>Different from our measured values during the treatment period, the maize- and cotton-related baseline values are based on recall data for the 2017-18 agricultural season.

\*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.10$ .

Table 2 presents the cultivation decisions reached at the beginning of the agricultural season (2018/19) just prior to the treatment allocation. The table shows that – in line with our eligibility criteria – basically all farmers cultivate maize, while about 86% of sampled farmers cultivate cotton. Since we cannot determine productivity measures for non-cultivating households, we restrict our sample to farmers who actually cultivate maize or cotton, respectively.<sup>3</sup> We see that 91% of control farmers cultivate cotton compared with 82% of treated farmers, a difference that is just out of the range of statistical significance. Among cotton cultivators, the control group has, based on the *WRS* test, significantly larger cotton fields. We also note that labor productivity positively correlates with field sizes (not shown in the table), which is in line with expectations regarding economies of scale. These differences should be borne in mind in the later analysis. Specifically, the positive correlation between

<sup>3</sup> Redoing the balancing tests conducted in Table 1 for these restricted samples of farmers actually cultivating maize ( $N=316$ ) or cotton ( $N=278$ ) makes clear that these analytical samples are similarly well balanced.

field size and productivity, coupled with the negative correlation between field size and the treatment, could impart downward bias on the estimated treatment effect on productivity – particularly for cotton.

**Table 2:** Cultivation decisions in agricultural season of treatment

Variables	Full sample mean	Control (C) mean	Treatment (T) mean	T – C	
				<i>p</i> -value ( <i>t</i> -test)	significance level ( <i>WRS</i> test <sup>#</sup> )
Any maize cultivated (1=Yes)	0.98	0.98	0.98	0.75	0.80
Maize cultivation land acreage, among maize-cultivating farmers (ha, GPS measured)	4.97 (1.30)	5.52 (1.47)	4.42 (1.06)	0.36	0.13
Any cotton cultivated (1=Yes)	0.86	0.91	0.82	0.11	-
Cotton cultivation land acreage, among cotton-cultivating farmers (ha, GPS measured)	3.92 (1.47)	4.82 (1.69)	3.02 (0.31)	0.14	0.05

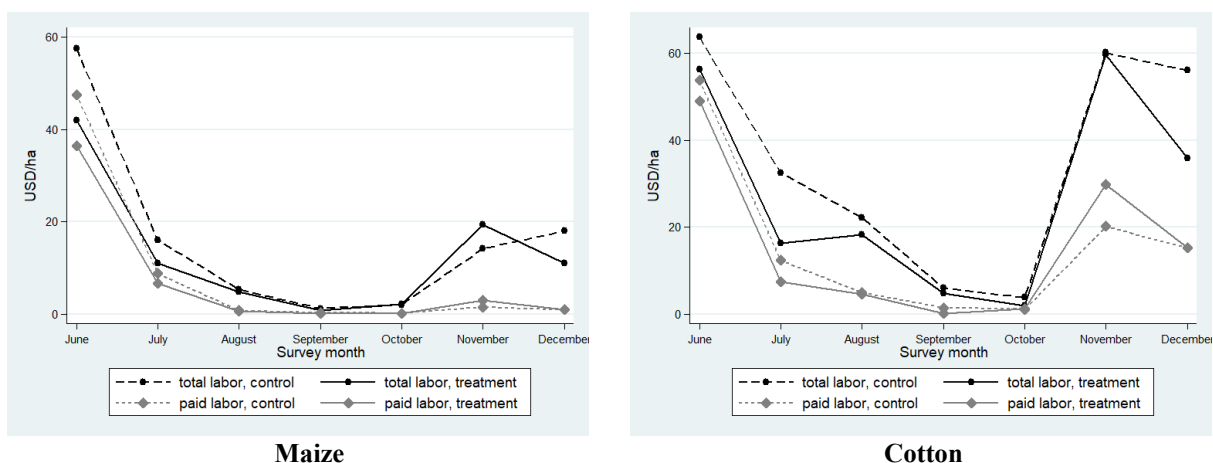
Values in brackets are standard deviations for continuous variables. <sup>#</sup> *WRS* refers to the Wilcoxon rank sum test (see also Table 1). \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.10$

### 3.3. Impact assessment of the intervention

#### 3.3.1. Monthly impact on labor costs

Figure 3 shows trends in monthly labor expenditures per hectare (USD/ ha) for the treatment and control group through December.

**Figure 3:** Trends of labor costs per hectare



Compared with their counterparts in the control group, maize producers in the treatment group spend less on labor per hectare between June and September. The largest differences, which are statistically significant, are observed between June and July, and range between \$ 5 and \$ 16 per hectare. Virtually no difference is seen in September, an unsurprising result given that labor expenditures at this time are close to zero. After the treatment period, around the middle of the harvest in November, the figures tentatively suggest a short reversal, with farmers in the control group spending less. This pattern, which is again reversed in December, may simply reflect a slightly different timing of harvesting across treatment groups. Since the months from October until December do not span the entire harvest period, which sometimes extends into January and February and for which we do not have information on labor costs, data from these months should in any case be interpreted cautiously. These results on aggregate trends are confirmed by trend analyses of labor allocation between treatment and control groups for individual production activities (see Table A1 in the Annex).

The trends of labor costs in the production of cotton are similar to that observed in the case of maize. From June to December, cotton producers in the treatment group spend slightly less on labor per hectare. The largest gaps, observed in July and December, amount to about \$ 16 and \$ 20 per hectare, respectively, and are statistically significant. Again, we confirm the similarity of the disaggregate trends by production activities (Table **A1** in the Annex).

The trend analyses in the annex presents further details on individual production activities, where farmers in the treatment groups are seen to require lower labor input for activities such as weeding, application of fertilizers, application of herbicides or insecticides. For activities such as field preparation, sowing or planting and harvest, farmers in both the treatment and the control groups record more or less the same level of labor costs. This may be explained by the fact that cotton seeds are distributed to farmers by the national agricultural extension office, which provides clear recommendations on when and how much to sow.

### ***3.3.2. Econometric evidence: labor productivity, labor costs, and yield***

Table **3** presents the estimated impact of the intervention on labor productivity and its components for maize and cotton. Our discussion proceeds row-wise, first covering the estimates of the ITT followed by the LATE. The full set of estimates including the control variables are presented in the Annex (Table A3 to Table A6).

Starting with maize production, the point estimate of the ITT indicates that the treatment increases total labor productivity by about 77kg/ USD. Relative to the control group mean of 117, this suggests an increase in labor productivity of about 66%. Although large, the estimate

is subject to a high degree of uncertainty. The 95% confidence interval of the OLS estimate ranges between 27 and 128 while that of the GEE model crosses zero. The estimated treatment effect of paid labor is somewhat smaller at 65 kg/ USD and is statistically insignificant in both the OLS and GEE models.

With respect to the components of labor productivity in maize cultivation, the provision of precipitation forecasts reduces the costs per hectare of both total- and paid labor. The estimated reduction in total costs of labor per hectare is nearly 26 USD, a 23% decrease relative to the control group mean, while the estimate on paid labor is somewhat lower at 13 USD, corresponding to a 22% decrease. All of the estimates are statistically significant at the 5% level except for that of paid labor from the GEE model. The positive estimate of yield is small in magnitude and statistically indistinguishable from zero.

Consistent with the intuition of a stronger treatment effect among compliers, all of the LATE estimates in the second row are considerably higher in magnitude than the corresponding ITT estimates, and, with the exception of paid labor productivity and yield, are statistically significant at the 5% level. Although it is not possible to definitively say whether the LATE estimates differ statistically from the ITT estimate given the overlap of the 95% confidence intervals, the magnitude of the point estimates suggest that compliers benefit substantially from the weather forecasts. With respect to total labor costs, savings of up to 52 USD/ ha are reached. Considering the average land size cultivated with maize among treatment farmers (see Table 2 above), this amounts to about 230 USD between June and December.

Turning to cotton production, the estimated ITT effects generally indicate a beneficial, if somewhat smaller, impact of the precipitation forecast. The ITT estimate of productivity, for example, indicates a 38% increase relative to the control group mean. Moreover, the estimates are subject to higher statistical imprecision and, in the case of paid labor, an unexpected negative sign. This anomaly, also seen in the 2SLS models, is driven by the months of November and December, as is revealed if these two months are omitted from the analysis (not presented). Bearing in mind the imbalance observed in cotton cultivation and cotton field sizes across the treatment and control groups, this may partly reflect economies of scale in paid labor during the harvesting season. Productivity estimates with paid labor in the denominator are also more prone to outliers for farmers with low expenses for hired labor.<sup>4</sup>

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<sup>4</sup> *In fact, the coefficients go down by about half if one winsorizes the top 2% outliers for the paid labor estimates for both ITT and LATE.*

The most notable result, which contrasts with the case of maize, is the positive and statistically significant effect of the precipitation forecast on cotton yield across the three models. The ITT effect suggests an increase of 461 kg/ ha, roughly 10% higher the control group mean. The LATE is nearly double the magnitude.

The appendix presents robustness checks with labor costs as measured on a monthly basis, which also corroborates the results from Table 3 (Table A2 in the Annex).

**Table 3:** Estimates of the impact on labor productivity

		Labor productivity in kg per USD		Labor cost in USD per ha		Yield in kg per ha
		Total labor	Paid labor	Total labor	Paid labor	-
<i>Maize</i>						
ITT	$\beta$	77.45	64.09	-26.07	-12.87	749.6
	s.e. (OLS)	(25.55) <sup>[0.03]</sup>	(33.51) <sup>[0.11]</sup>	(6.72) <sup>[0.01]</sup>	(3.97) <sup>[0.02]</sup>	(1131.61) <sup>[0.54]</sup>
	s.e. (GEE)	(44.92) <sup>[0.08]</sup>	(57.49) <sup>[0.26]</sup>	(11.52) <sup>[0.02]</sup>	(8.46) <sup>[0.13]</sup>	(2287.24) <sup>[0.74]</sup>
LATE	$\beta$	159.75	109.42	-52.03	-25.70	1560.81
	s.e.	(34.35) <sup>[0.00]</sup>	(82.76) <sup>[0.19]</sup>	(11.51) <sup>[0.00]</sup>	(8.35) <sup>[0.00]</sup>	(2480.74) <sup>[0.53]</sup>
	1 <sup>st</sup> -stage $F$	119.98	131.22	129.68	130.36	123.01
Control group mean		116.65	269.65	113.55	59.41	10570.75
No. of observations		295	224	305	305	298
<i>Cotton</i>						
ITT	$\beta$	10.55	-37.58	-41.90	0.64	461.18
	s.e. (OLS)	(4.01) <sup>[0.05]</sup>	(15.89) <sup>[0.06]</sup>	(18.18) <sup>[0.07]</sup>	(10.76) <sup>[0.95]</sup>	(119.37) <sup>[0.01]</sup>
	s.e. (GEE)	(7.09) <sup>[0.14]</sup>	(33.16) <sup>[0.26]</sup>	(32.73) <sup>[0.20]</sup>	(23.98) <sup>[0.98]</sup>	(181.26) <sup>[0.01]</sup>
LATE	$\beta$	20.50	-67.94	-81.36	1.23	920.87
	s.e.	(6.31) <sup>[0.00]</sup>	(28.92) <sup>[0.02]</sup>	(27.43) <sup>[0.00]</sup>	(16.35) <sup>[0.94]</sup>	(398.25) <sup>[0.02]</sup>
	1 <sup>st</sup> -stage $F$	121.13	123.38	128.19	122.03	117.77
Control group mean		27.85	100.08	246.77	109.01	4840.58
No. of observations		256	237	259	259	261

*Standard errors (s.e.) in parentheses clustered at village level for ITT results and heteroskedastic-consistent for LATE results, p-values in squared brackets.  $\beta$  refers to the coefficient estimate derived from the Equation [1] presented in Section 2.4. 1<sup>st</sup> stage  $F$ -Stat refers to the Kleibergen-Paap rank Wald statistic for the first stage of the two-stage IV regression underlying the LATE.*

#### 4. Conclusion

We conducted a pilot study in six villages of northern Benin to analyze the effect of providing basic precipitation forecasts in the rainy season, focusing on labor productivity, labor costs, and yield. We conclude that this type of informational intervention holds promise for improving the livelihoods of farmers. The results suggest that it is practically feasible to set up a system to compile simple weather forecasts and share them with farmers via mobile phone

SMS. Most farmers were willing to receive the weather information and reported satisfaction with its accuracy. Most importantly, the intervention had positive effects on our three outcome indicators.

Specifically, we find that farmers in the treatment group register higher labor productivity and lower labor costs per hectare in maize production, with statistically significant estimates even when controlling for the small number of clusters. Relative to the control group, the effect sizes, measured as intention-to-treat, are substantial: productivity increases by about 66% while labor costs decrease by about 23%. No statistically significant effects are found for the maize yield.

Cotton, a commercial crop for which weather information may play a lesser role given its more standardized cultivation, also benefits from the intervention, though with generally smaller effect sizes and lower statistical precision. An exception is yield: Contrasting with maize, the estimated effects are highly statistically significant, with an ITT effect that is 10% higher than the control group mean.

Beyond the specific crop types studied, one explanation for the positive effects of precipitation forecasts on the outcomes identified in this study is that they were facilitated by a uniform language, extensive training sessions with farmers to understand terminology and the use of the technology, centralized coordination, downscaling of the information to the local level, and timely provision of delivery and monitoring support from field officers. The absence of any one of these factors could undermine the effectiveness of the intervention. Disseminating weather information via simple text messages thus helped to improve on the three *Cs* – connectivity, content, and capacity – considered necessary to take advantage of the opportunities provided by ICTs (Nakasone and Torero, 2016): Marginalized population groups were reliably *connected* via the text messages; the *content* of the information provided was relevant to their needs; and their *capacity* to act on the information they received was fostered by framework conditions surrounding the intervention.

The results provide a proof-of-concept for using weather-related information transmitted by mobile phones as a means to build smallholder farmers' resilience to climate variability. We find beneficial effects of the intervention for both a subsistence crop, maize, and a commercial crop, cotton. Given the pilot nature of the study and the scarcity of supporting evidence from other sources, more well-powered research is required, especially on the impact on yield and farm profit, to build a solid evidence base to inform agricultural policies.

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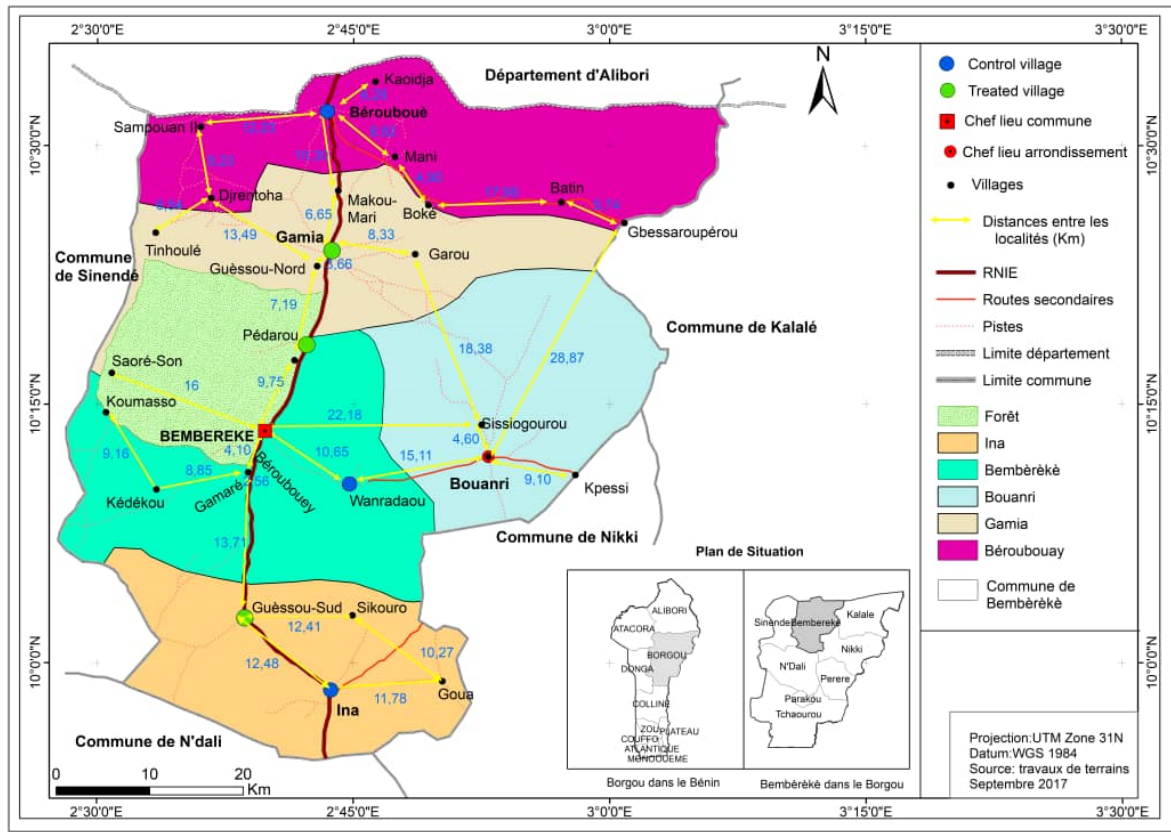
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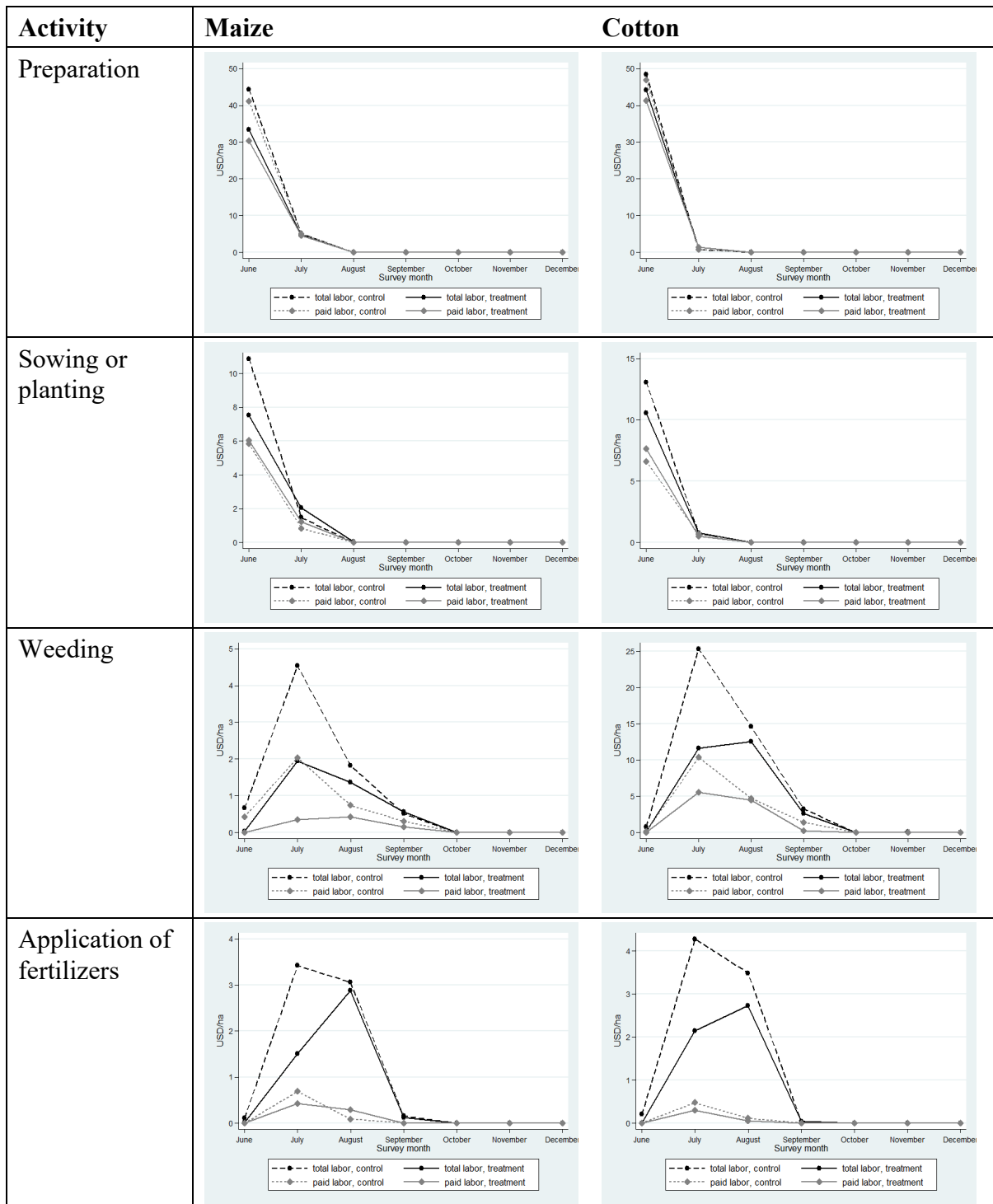
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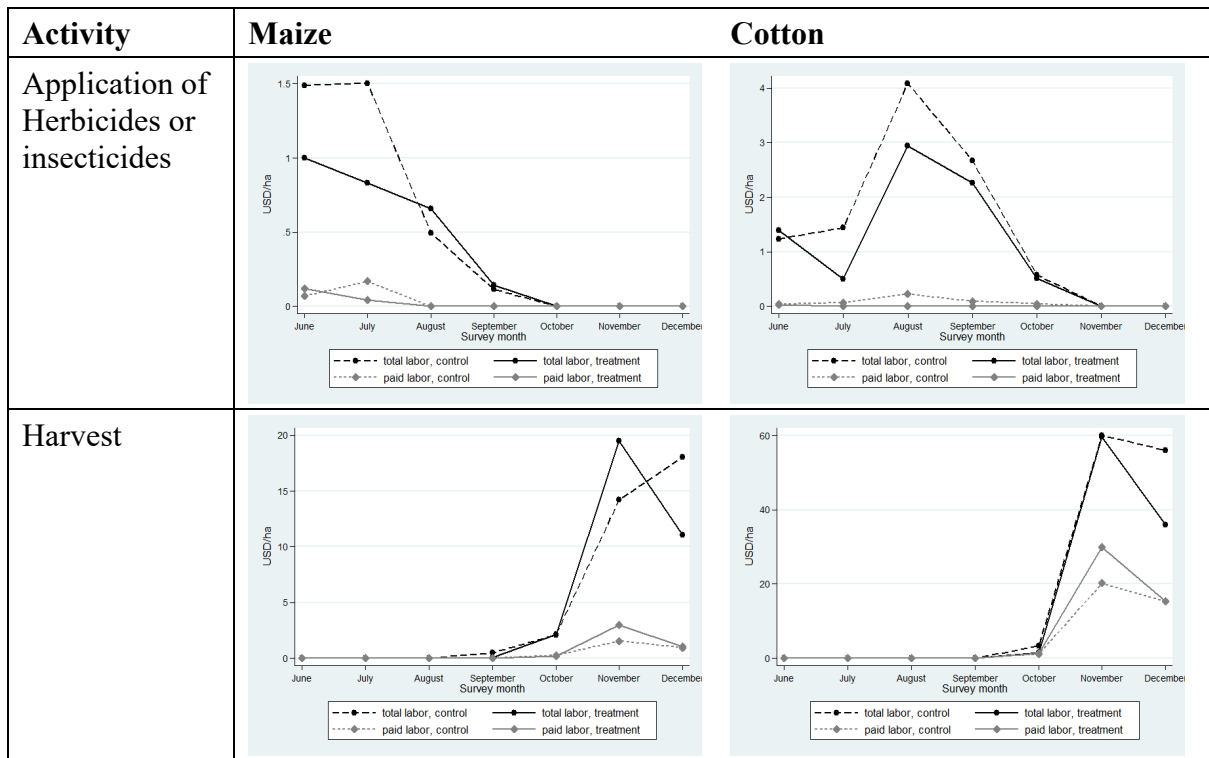
# Annex

Figure A1: Map of survey sites in Bembèrèkè municipality



**Table A1: Production activities-wise trends of labor costs per hectare**





**Table A2:** Estimates of the impact on monthly labor costs per hectare

		Total labor	Paid labor
<i>Maize</i>			
ITT	$\beta$	-3.32	-1.48
	s.e. (OLS)	(1.12) <sup>[0.03]</sup>	(0.49) <sup>[0.03]</sup>
	s.e. (GEE)	(1.93) <sup>[0.09]</sup>	(1.07) <sup>[0.16]</sup>
LATE	$\beta$	-6.71	-3.00
	s.e.	(1.82) <sup>[0.00]</sup>	(1.35) <sup>[0.03]</sup>
	1 <sup>st</sup> -stage $F$	967.86	978.29
Control group mean		16.25	8.47
Number of observations		2135	2135
<i>Cotton</i>			
ITT	$\beta$	-6.09	0.1
	s.e. (OLS)	(2.48) <sup>[0.06]</sup>	(1.44) <sup>[0.95]</sup>
	s.e. (GEE)	(4.73) <sup>[0.20]</sup>	(3.13) <sup>[0.97]</sup>
LATE	$\beta$	-12.08	0.21
	s.e.	(3.57) <sup>[0.00]</sup>	(2.56) <sup>[0.94]</sup>
	1 <sup>st</sup> -stage $F$	913.17	876.47
Control group mean		35.37	15.64
Number of observations		1820	1820

*In the regression results, standard errors (s.e.) in parentheses are clustered at village level for ITT results and heteroskedastic-consistent for LATE results, p-values in squared brackets.  $\beta$  refers to the coefficient estimate derived from the monthly variant of Equation [1] as described in Section 2.4. 1<sup>st</sup> stage F-Stat refers to the Kleibergen-Paap rank Wald statistic for the first stage of the two-stage IV regression underlying the LATE. The treatment period refers to the months June to September.*

**Table A3:** ITT results for maize with full set of OLS estimates

	Labor productivity		Labor cost		Yield	Monthly labor costs	
	in kg per USD		in USD per ha			in USD per ha	
	Total labor	Paid labor	Total labor	Paid labor		Total labor	Paid labor
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment	77.45** (25.55)	64.09 (33.51)	-26.07** (6.72)	-12.87** (3.97)	749.60 (1131.61)	-3.32** (1.12)	-1.48** (0.49)
Arrondissement=2	-28.42 (31.54)	-91.56* (37.27)	-10.17 (8.66)	17.99*** (2.77)	-1182.52 (1347.00)	-1.27 (1.41)	2.64*** (0.22)
Arrondissement= 3	-92.67** (32.95)	-181.94*** (35.29)	61.08*** (10.60)	27.30*** (4.55)	-54.75 (1649.86)	9.19*** (1.81)	4.22*** (0.51)
Baseline outcome	0.69 (0.73)	0.08 (0.41)	-0.01 (0.01)	0.27** (0.08)	0.16 (0.37)	-0.00 (0.00)	0.04** (0.01)
Missing outcome	-76.56** (26.67)	-150.41** (45.48)	28.85** (9.16)	26.58*** (2.93)	-	-	-
Baseline age of respondent	-0.18 (1.18)	-5.36 (4.90)	0.13 (0.70)	0.64 (0.37)	61.09 (43.10)	0.05 (0.09)	0.11* (0.05)
Gender of respondent (1=Male)	50.67** (16.71)	-197.72 (274.25)	-12.25 (9.49)	-6.65 (10.74)	2758.68 (2473.25)	-1.54 (1.83)	-0.64 (1.42)
Baseline education of respondent	14.24 (17.55)	25.40 (52.17)	4.35 (4.25)	-0.26 (3.21)	2142.84 (1565.05)	0.63 (0.57)	-0.03 (0.48)
Baseline experience in agriculture of respondent	0.63 (1.02)	6.94 (5.49)	-0.14 (0.57)	-0.69** (0.27)	-63.03 (61.20)	-0.05 (0.07)	-0.12** (0.03)
Baseline household size	-0.04 (0.66)	2.89 (2.31)	-0.21 (0.24)	-0.29 (0.28)	2.74 (58.73)	-0.01 (0.05)	-0.03 (0.04)
Total baseline land holding, in ha	0.62 (0.56)	1.29 (2.59)	-0.21 (0.22)	0.12 (0.19)	-9.48 (28.56)	-0.03 (0.03)	0.02 (0.03)
Access to credit at baseline	2.91 (17.90)	4.61 (38.83)	-3.73 (4.80)	-0.63 (6.01)	1606.33 (1143.50)	-0.33 (0.67)	0.03 (0.81)

	Labor productivity in kg per USD		Labor cost in USD per ha		Yield in kg per ha (5)	Monthly labor costs in USD per ha	
	Total labor	Paid labor	Total labor	Paid labor		Total labor	Paid labor
	(1)	(2)	(3)	(4)		(6)	(7)
Contact with extension services at baseline	-9.64 (31.27)	34.96 (17.87)	-6.84 (7.47)	4.95 (4.08)	-159.26 (666.36)	-0.65 (0.90)	0.95 (0.48)
Use of seed variety at baseline	-38.57* (17.67)	-43.84 (30.50)	10.60** (3.11)	9.58** (3.46)	-1389.40 (1701.82)	1.20 (0.71)	1.10* (0.48)
Practicing intercropping at baseline	13.61 (31.24)	-28.51 (120.10)	-4.23 (5.98)	0.51 (4.97)	-1030.76 (1908.84)	-0.89 (0.83)	-0.15 (0.65)
Radio ownership at baseline	-11.65 (15.66)	2.78 (129.41)	-6.95 (9.58)	4.92 (9.44)	-361.15 (1084.04)	-0.07 (1.28)	1.31 (1.27)
TV ownership at baseline	26.18* (10.55)	-25.81 (58.11)	2.06 (5.94)	8.86 (6.55)	2118.11 (1527.13)	-0.25 (0.68)	0.87 (0.79)
Access to internet at baseline	-29.69 (27.06)	-38.74 (82.34)	-1.54 (11.41)	-0.22 (12.55)	-3435.13 (2259.59)	0.06 (1.49)	0.19 (1.73)
Month = July						-36.36*** (7.29)	-34.48*** (6.39)
Month = August						-44.87*** (8.08)	-41.39*** (6.22)
Month = September						-48.95*** (8.72)	-41.97*** (6.56)
Month = October						-48.07*** (8.73)	-41.99*** (6.53)
Month = November						-33.13** (10.10)	-39.85*** (7.03)
Month = December						-35.54*** (4.20)	-41.31*** (6.49)
Control group mean Y	116.65	269.65	113.55	59.41	10570.75	16.25	8.47
Adj. R-Square	0.18	0.02	0.34	0.21	-0.02	0.40	0.48
Number of Observations	295	224	305	305	298	2135	2135

**Table A4:** LATE results for maize with full set of 2SLS estimates

	Labor productivity in kg per USD		Labor cost in USD per ha		Yield in kg per ha	Monthly labor costs in USD per ha	
	Total labor	Paid labor	Total labor	Paid labor		Total labor	Paid labor
	(1)	(2)	(3)	(4)		(6)	(7)
Treatment	159.75*** (34.35)	109.42 (82.76)	-52.03*** (11.51)	-25.70*** (8.35)	1560.81 (2480.74)	-6.71*** (1.82)	-3.00** (1.35)
Arrondissement=2	-28.61 (28.38)	-101.61 (66.14)	-7.58 (8.29)	20.04*** (6.24)	-1264.89 (1194.45)	-0.95 (1.31)	2.87*** (1.04)
Arrondissement= 3	-118.91*** (23.62)	-203.68*** (63.18)	69.76*** (7.84)	31.27*** (5.33)	-315.02 (2236.02)	10.30*** (1.17)	4.67*** (0.84)
Baseline outcome	0.38 (0.51)	0.05 (0.38)	-0.02 (0.02)	0.29*** (0.08)	0.15 (0.28)	-0.00 (0.00)	-34.48*** (2.19)
Missing outcome	-52.71** (26.50)	-133.18*** (46.38)	23.21* (13.96)	24.03*** (8.70)	0.00 (.)	0.00 (.)	-41.37*** (1.91)
Baseline age of respondent	-0.49 (1.43)	-5.52 (4.72)	0.22 (0.52)	0.70 (0.46)	57.13 (52.19)	0.07 (0.08)	-41.96*** (1.90)
Gender of respondent (1=Male)	46.05 (40.89)	-200.37 (281.41)	-14.00 (17.34)	-7.55 (13.57)	2684.47 (1973.19)	-1.53 (2.77)	0.04*** (0.01)
Baseline education of respondent	-1.00 (19.98)	20.14 (50.09)	8.36 (6.21)	1.71 (4.70)	2002.20 (1826.90)	1.15 (0.98)	0.00 (.)
Baseline experience in agriculture of respondent	0.90 (1.46)	7.04 (4.74)	-0.19 (0.52)	-0.72 (0.46)	-58.71 (59.08)	-0.06 (0.08)	0.12* (0.06)
Baseline household size	-0.27 (0.85)	2.83 (2.66)	-0.13 (0.35)	-0.25 (0.28)	-0.30 (46.60)	-0.00 (0.06)	-0.65 (2.23)
Total baseline land holding, in ha	0.59 (0.43)	1.32 (2.15)	-0.21 (0.19)	0.12 (0.17)	-9.82 (30.12)	-0.03 (0.03)	0.20 (0.74)
Access to credit at baseline	6.54 (16.95)	12.62 (46.02)	-4.30 (6.09)	-1.07 (4.62)	1623.94 (1228.25)	-0.38 (0.94)	-0.12* (0.06)



	Labor productivity in kg per USD		Labor cost in USD per ha		Yield in kg per ha	Monthly labor costs in USD per ha	
	Total labor	Paid labor	Total labor	Paid labor		Total labor	Paid labor
	(1)	(2)	(3)	(4)		(6)	(7)
Contact with extension services at baseline	-7.63 (26.46)	41.51 (37.38)	-7.51 (8.18)	4.60 (5.01)	-113.77 (684.49)	-0.75 (1.33)	-0.03 (0.04)
Use of seed variety at baseline	-39.10** (18.59)	-45.53 (57.90)	11.20** (5.58)	9.92** (4.25)	-1405.70 (1443.65)	1.30 (0.88)	0.02 (0.03)
Practicing intercropping at baseline	16.15 (23.68)	-39.79 (72.72)	-5.27 (9.44)	0.24 (5.61)	-1006.10 (1426.21)	-1.03 (1.40)	-0.01 (0.74)
Radio ownership at baseline	-11.07 (29.89)	8.60 (92.33)	-6.12 (9.52)	5.76 (7.49)	-370.72 (1253.78)	0.01 (1.50)	0.90 (0.90)
TV ownership at baseline	30.47 (18.90)	-25.89 (52.07)	0.71 (6.59)	8.18* (4.77)	2137.49 (1817.70)	-0.36 (1.03)	1.15* (0.68)
Access to internet at baseline	-25.92 (48.26)	-41.60 (68.61)	-3.12 (14.51)	-1.19 (13.27)	-3382.61 (2454.26)	-0.15 (2.57)	-0.19 (0.97)
Month = July						-36.35*** (2.31)	1.40 (1.21)
Month = August						-44.84*** (2.03)	0.82 (0.78)
Month = September						-48.93*** (1.99)	0.07 (2.23)
Month = October						-48.05*** (2.00)	-41.98*** (1.90)
Month = November						-33.12*** (2.20)	-39.84*** (1.93)
Month = December						-35.53*** (2.38)	-41.30*** (1.91)
Control group mean Y	116.65	269.65	113.55	59.41	10570.75	16.25	8.47
1 <sup>st</sup> -stage <i>F</i>	119.98	131.22	129.68	130.36	123.01	967.86	978.29
Number of Observations	295	224	305	305	298	2135	2135

**Table A5:** ITT results for cotton with full set of OLS estimates

	Labor productivity		Labor cost		Yield	Monthly labor costs	
	in kg per USD		in USD per ha		in kg per ha	in USD per ha	
	Total labor	Paid labor	Total labor	Paid labor		Total labor	Paid labor
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment	10.55**	-37.58*	-41.90*	0.64	461.18**	-6.09*	0.10
	(4.01)	(15.89)	(18.18)	(10.76)	(119.37)	(2.48)	(1.44)
Arrondissement=2	14.69**	-81.48*	-44.37*	45.62*	199.99	-6.31*	6.13*
	(4.87)	(33.38)	(19.47)	(19.41)	(114.11)	(2.87)	(2.63)
Arrondissement= 3	-14.71*	-61.32*	158.18***	54.36**	81.79	22.62***	7.39**
	(5.77)	(28.47)	(17.11)	(13.95)	(114.56)	(2.39)	(1.90)
Baseline outcome	0.07	0.75**	0.04	0.22*	0.23*	-35.46***	-41.70***
	(0.06)	(0.19)	(0.06)	(0.11)	(0.11)	(5.51)	(6.47)
Missing outcome	4.17	-15.46	-26.60	-9.69	0.00	-40.17***	-47.33***
	(3.99)	(16.69)	(34.69)	(9.27)	(.)	(6.42)	(6.76)
Baseline age of respondent	0.17	-1.96	0.26	0.32	8.32	-55.26***	-51.03***
	(0.29)	(1.62)	(1.07)	(0.78)	(9.28)	(8.40)	(7.74)
Gender of respondent (1=Male)	16.75*	52.30	-37.95	-35.18	977.24	0.01	0.03*
	(7.21)	(35.63)	(24.47)	(19.75)	(665.90)	(0.01)	(0.02)
Baseline education of respondent	-2.19	14.97	11.13	9.28	345.00*	0.00	0.00
	(3.48)	(14.32)	(9.37)	(6.61)	(161.14)	(.)	(.)
Baseline experience in agriculture of respondent	-0.12	1.34	0.10	-0.68	-15.73	0.00	0.06
	(0.19)	(1.43)	(1.77)	(1.24)	(10.67)	(0.17)	(0.12)
Baseline household size	-0.12	-1.27	2.67**	1.46	20.00*	-6.13	-2.53
	(0.10)	(1.09)	(0.93)	(1.27)	(9.91)	(3.09)	(1.64)
Total baseline land holding, in ha	0.05	0.23	0.31	0.45	9.30	1.49	1.38
	(0.07)	(0.29)	(0.85)	(0.57)	(6.98)	(1.34)	(0.97)
Access to credit at baseline	-2.80	-36.35	-10.49	6.93	-217.84	0.05	-0.10
	(3.33)	(28.45)	(22.53)	(17.34)	(263.27)	(0.26)	(0.19)

	Labor productivity in kg per USD		Labor cost in USD per ha		Yield in kg per ha	Monthly labor costs in USD per ha	
	Total labor	Paid labor	Total labor	Paid labor		Total labor	Paid labor
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Contact with extension services at baseline	-1.49 (2.35)	17.28 (33.47)	-2.61 (22.33)	6.22 (4.18)	-348.39 (210.51)	0.36* (0.14)	0.19 (0.17)
Radio ownership at baseline	-14.62 (8.25)	-43.13** (12.83)	11.44 (16.20)	27.22 (15.05)	-501.62 (249.27)	0.05 (0.12)	0.06 (0.08)
TV ownership at baseline	0.31 (1.29)	-9.78 (8.30)	-2.97 (20.11)	6.70 (14.72)	-129.20 (119.67)	-1.80 (2.72)	0.69 (2.26)
Access to internet at baseline	2.67 (2.83)	-23.08 (40.83)	-67.79 (41.87)	-19.00 (21.09)	-154.62 (447.08)	-0.28 (3.49)	0.98 (0.66)
Month = July						1.48 (1.70)	3.97 (2.07)
Month = August						-0.02 (2.49)	1.23 (2.03)
Month = September						-9.74 (5.81)	-2.95 (3.03)
Month = October						-57.97*** (9.53)	-50.83*** (8.05)
Month = November						0.22 (5.88)	-27.20 (15.31)
Month = December						-13.34 (8.89)	-36.60*** (3.44)
Control group mean Y	27.85	100.08	246.77	109.01	4840.58	35.37	15.64
Adj. R-Square	0.28	0.09	0.37	0.12	0.05	0.30	0.25
Number of Observations	256	237	259	259	261	1820	1820

**Table A6:** LATE results for cotton with full set of 2SLS estimates

	Labor productivity		Labor cost		Yield	Monthly labor costs	
	in kg per USD		in USD per ha		in kg per ha	in USD per ha	
	Total labor	Paid labor	Total labor	Paid labor		Total labor	Paid labor
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment	20.50*** (6.31)	-67.94** (28.92)	-81.36*** (27.43)	1.23 (16.35)	920.87** (398.25)	-12.08*** (3.57)	0.21 (2.56)
Arrondissement=2	14.03*** (4.15)	-78.60** (32.70)	-48.67** (22.68)	45.58*** (12.29)	158.97 (334.33)	-6.86** (2.82)	6.12*** (1.69)
Arrondissement= 3	-17.50*** (2.98)	-52.43** (26.43)	164.87*** (21.63)	54.20*** (12.69)	-45.97 (253.38)	23.66*** (2.76)	7.36*** (1.81)
Baseline outcome	0.05 (0.09)	0.76 (0.49)	0.01 (0.04)	0.22*** (0.07)	0.23** (0.10)	-35.41*** (3.60)	-41.70*** (3.10)
Missing outcome	7.64* (4.28)	-25.92 (17.93)	-40.27 (25.52)	-9.49 (12.58)	0.00 (.)	-40.08*** (3.42)	-47.33*** (3.02)
Baseline age of respondent	0.14 (0.26)	-2.00 (1.41)	0.41 (1.13)	0.32 (0.70)	5.93 (15.06)	-55.19*** (3.31)	-51.03*** (2.97)
Gender of respondent (1=Male)	16.29** (7.69)	56.77* (29.16)	-35.10 (28.98)	-35.22 (23.14)	904.83* (523.21)	0.00 (0.00)	0.03*** (0.01)
Baseline education of respondent	-4.06 (3.05)	19.53 (29.52)	17.84 (17.64)	9.17 (12.23)	257.91 (212.17)	0.00 (.)	0.00 (.)
Baseline experience in agriculture of respondent	-0.13 (0.23)	1.50 (1.04)	0.19 (1.39)	-0.68 (0.78)	-14.49 (14.63)	0.04 (0.14)	0.06 (0.10)
Baseline household size	-0.13 (0.17)	-1.23 (0.98)	2.69* (1.55)	1.46 (1.35)	19.10 (12.96)	-5.07 (4.09)	-2.55 (2.73)
Total baseline land holding, in ha	0.03 (0.06)	0.27 (0.30)	0.32 (0.78)	0.45 (0.45)	8.49 (5.17)	2.48 (2.21)	1.36 (1.64)
Access to credit at baseline	-2.95 (3.00)	-36.45 (22.29)	-10.28 (17.82)	6.92 (10.88)	-222.70 (198.59)	0.05 (0.17)	-0.10 (0.11)

	Labor productivity in kg per USD		Labor cost in USD per ha		Yield in kg per ha	Monthly labor costs in USD per ha	
	Total labor	Paid labor	Total labor	Paid labor		Total labor	Paid labor
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Contact with extension services at baseline	-1.34 (3.38)	17.93 (20.83)	-3.19 (31.63)	6.23 (14.41)	-326.25 (332.19)	0.37** (0.16)	0.19 (0.13)
Radio ownership at baseline	-14.26 (8.94)	-45.92* (25.69)	8.36 (23.24)	27.23 (17.05)	-484.04 (423.72)	0.05 (0.09)	0.06 (0.07)
TV ownership at baseline	0.72 (2.77)	-11.06 (13.09)	-5.06 (18.67)	6.72 (10.24)	-111.80 (259.11)	-1.80 (2.15)	0.69 (1.55)
Access to internet at baseline	1.86 (6.62)	-20.54 (29.97)	-67.32** (33.02)	-19.02 (19.95)	-180.09 (551.93)	-0.51 (3.74)	0.98 (2.17)
Month = July						0.95 (3.09)	3.97* (2.24)
Month = August						-0.31 (2.38)	1.24 (1.61)
Month = September						-9.66** (4.11)	-2.95 (3.24)
Month = October						-57.89*** (3.33)	-50.83*** (2.96)
Month = November						0.29 (4.71)	-27.20*** (3.69)
Month = December						-13.31*** (5.00)	-36.60*** (3.99)
Control group mean Y	27.85	100.08	246.77	109.01	4840.58	35.37	15.64
1 <sup>st</sup> -stage <i>F</i>	121.13	123.38	128.19	122.03	117.77	913.17	876.47
Number of Observations	256	237	259	259	261	1820	1820