Harnessing ICT to Increase Agricultural Production: Evidence From Kenya[*]

Lorenzo Casaburi
Stanford University
casaburi@stanford.edu

Michael Kremer
Harvard University
mkremer@fas.harvard.edu

Sendhil Mullainathan
Harvard University
mullain@fas.harvard.edu

Ravindra Ramrattan**
Innovations for Poverty Action

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Abstract

Sending SMS messages with agricultural advice to smallholder farmers increased yields by 11.5% relative to a control group with no messages. These effects are concentrated among farmers who had no agronomy training and had little interaction with sugar cane company staff at baseline. Enabling farmers to report input provision delays to the company reduces the proportion of delays in fertilizer delivery by 21.6%. There is evidence that reporting a complaint has positive geographic spillovers, since it induces the company to deliver inputs to several neighboring plots.

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1. Introduction

Mobile phone technology has achieved high penetration very rapidly in much of the developing world (Aker and Mbiti (2010), Nakasone, Torero, and Minten (2013)). While there is some encouraging evidence on its impact on market integration (Jensen (2007), Aker (2011)), education (Aker, Ksoll, and Lybbert (2012), and access to finance (Karlan et al. (2010), Jack and Suri (2013)), there is little evidence on output effects.

Agricultural yields in Sub-Saharan Africa have been mostly stagnant and there has been limited adoption of new technologies (Udry (2010), Jack (2011)). There is widespread consensus that efforts to deliver agricultural information via traditional extension have been disappointing (Anderson and Feder (2007)), in part due to the difficulty in monitoring agriculture extension workers, the expense of the activity (BenYishay and Mobarak (2013)), and the high farmer-extension ratio. Mobile phones could potentially offer the opportunity to deliver personalized agricultural information to farmers at low cost and in a way that is tailored to their context and timed to coincide with the relevant part of the agricultural season. It could also help them coordinate with buyers and secure inputs from suppliers more efficiently. While there is some evidence on impact on coordination with buyers, there is little evidence on production impact or on the ability to coordinate with suppliers of productivity-enhancing agricultural technological inputs.[1] Earlier work on General Purpose Technologies suggests that the impact of ICT may depend on additional complementary technologies and organizational changes (Helpman (1998), Jovanovich and Rosseau (2005)).

We document that at least in one context, ICT can have a substantial impact on production. We collaborate with one of the largest agri-business companies in East Africa. The partner company runs a sugarcane contract farming scheme, which currently includes more than 100,000 plots, mostly below one hectare. In the contract farming arrangement, the company provides inputs on credit that are recouped at harvest through

1 See, however Cole and Fernando (2012).

payment deductions.

The paper evaluates two interventions that leveraged on the growing penetration of mobile phones in the region to improve agricultural productivity, either by improving farmer decision making or by improving input delivery from the company. In the first intervention, farmers receive a set of text messages that inform them about agricultural tasks to be performed right around the time they need to complete such tasks on the plot. In the second, farmers access a hotline service, which also includes routine calls from company operators, where they can file reports about delays or other issues concerning company input delivery and payments.

For the evaluation, we rely primarily on rich plot-level administrative data collected by the company to measure their impact. The main outcomes of the analysis are plot yields and fertilizer deliveries. In addition, the evaluation uses several other variables recorded in the company database to define strata bin, check balance, and improve precision of the estimates. The interventions are evaluated through randomized controlled trials. Randomization occurred at the level of the field, defined as a set of plots (typically, three to ten) that the company treats homogeneously in terms of planting cycle, input delivery, and harvesting in order to achieve economies of scale in these activities.

We find that access to the SMS project raises yields by around 3.3 tons per hectare, or 8% of the control group average. With a sign-up rate for the text message program of 65% in the treatment group, this implies a treatment-on-treated effect of about 11.5%. These effects are concentrated among farmers who at baseline had no agronomy training and had little interaction with company field staff. This provides suggestive evidence that, at least in our setting, face-to-face and electronic communication are substitutes.

Access to the farmer hotline reduces the likelihood that a plot does not receive fertilizer by 3.8 percentage points, 36.5% of the control average, and reduces the likelihood of a delay in fertilizer delivery (relative to the optimal time window prescribed by the agronomy department, by 8.5 percentage points, 21.6% of the control group average. In addition, we find evidence of significant positive spillovers. About half of the farmers in the study sample are not eligible for the intervention because they have not registered their phone number with the company or because they do not have access to one. We find that the improvement in company performance in delivering fertilizer to non-eligible farmers in treatment fields (relative to non-eligible farmers in control fields) is similar to the one for eligible farmers (relative to eligible farmers in control fields). This is consistent with the fact that the company input delivery is highly clustered at the field level.

In the final part of the paper, we discuss the potential advantages that large contract farming companies have as a source of information provision for small farmers. We estimate that the increase in yields generated an increase of about $43 in company profits and of about $54 in farmer earnings, while the per-farmer cost of the program is about $0.3 per farmer. We then present results from another trial that used farmer response rates to a mobile-based survey to shed light on some of the barriers to information flow in agricultural value chains.

The findings from the paper are in line with those by Cole and Fernando (2012), who show that, in response to a mobile phone based agricultural extension program in India, *Avaaj Otalo*, farmers increased the adoption of more effective and less hazardous pesticides. Another line of work shows mixed evidence for the role of mobile phones in improving price information the (Jensen (2007), Aker (2011), Aker and Fafchamps (2013), Mitra, Mookherjee, Torero, and Visaria (2013)). Relative to this previous literature, we shift the focus toward agricultural yields. We also use administrative data, as opposed to self-reported outcomes. The risks of social desirability bias and Hawtorne effects in survey responses (Zwane et al. (2011)) seem particularly relevant for information provision interventions, as these generally make recommendations on what the target respondents should be doing. From this standpoint, access to an objective measure of productivity is a major advantage of our study. Finally, the results are also related to the empirical literature that looks at the relation between ICT and firm performance (Baker and Hubbard (2000), Bloom at al. (2011), Paravisini and Schoar (2012)).

The remainder of the paper is organized as it follows. Section 2 provides background on the experimental setting. Section 3 and 4 describes the farmer SMS and the hotline interventions, respectively. Section 5 discusses the relative advantages of large organizations, such as contract farming schemes, in leveraging the use of ICT to increase agricultural output. Section 6 concludes.

2. Background

The research described in this paper was conducted in partnership with one of the largest agri-business companies in East Africa. The company runs a large sugarcane contract farming scheme, involving mostly smallholders with plot sizes less than one hectare.[2] Following the establishment of five outgrower schemes between 1968 and 1981, sugarcane has become the most common cash crop in the region of study.

Sugar cane crushing and boiling are capital intensive processes and are subject to significant economies of scale, with a large fixed cost component. The factory we study serves more than 100,000 farmers scattered over a 530 square kilometer area.

Marginal costs (other than sugar cane input and transport costs) for the factory are low, because its capital stock and crushing capacity are fixed, and raw material inflow is almost always less than the plant capacity. The factory runs 24 hours a day and factory labor needs vary little with throughout. The plant is actually a net energy seller, because it burns by-product from crushed cane.

Transport costs for sugar cane are very high. The nature of the processing also limits the development of spot markets and the degree of potential competition from other buyers

2 Additional details on the study setting are provided in Casaburi, Kremer, Mullainathan (2014).

located farther away. These transport costs, combined with economies of scale in processing, thus give the factory substantial market power as a cane buyer. The sugarcane price is de facto regulated through the Kenya Sugar Board. The gap between the input price of sugar cane and the price of processed sugar means that the farmer and the factory are both de facto residual claimants on gains in yield per acre.

Each harvest cycle lasts from 18 to 22 months. The company and the farmer sign a contract that typically spans for one replant cycle, made up of one planting and several ratoon harvests.[3] Planting and harvesting occur in a staggered fashion throughout most of the year, in order to provide a constant supply of cane to the processing mill. Sugar production processing requires high coordination across harvesting, transporting, and processing. Processing needs to occur shortly after harvesting as sugar content starts declining after the cane is cut.

Farmers are paid based on the tonnage of cane provided at harvest time. Input charges plus interest are deducted from the payment. The cane prices are based on the current sugar price, via a formula that includes the conversion rate between cane and final sugar output and taxes on sugar production. As a result of the pricing formula, the company estimated revenue per ton of cane purchased from the farmers is \$30. Since the plant is almost never at capacity, the marginal processing costs are quite low, with an estimated upper bound of \$5 per ton of cane purchased. As a result, the company profit per additional tons of cane is \$25. On the other hand, farmers make around \$30 per extra ton of cane, computed as the difference between the cane price and the harvesting and transport charges per ton of cane.

Each plot is typically matched to one parcel as defined by the Kenyan land registry. In addition, accounts are aggregated into *fields*, sets of plots that are usually treated homogeneously for land preparation, input provision, and harvesting, in order to exploit

3 Ratooning leaves the root and lower parts of the plant uncut at the time of harvesting. Yields typically fall across ratoons. A contract typically spans two or three ratoons.

economies of scale in these activities. Typically, on farmer is contracted on each plot, though there is a small fraction of ``joint plots", cultivated by two or more farmers. While the majority of the farmers live in the same area where the plot is located, we estimate that 15-20% of the contracting farmers in the scheme are ``telephone farmers", who reside away from the plot (typically in larger towns) and, for the most part, hire labor to complete the cane farming tasks.

The factory is concerned about farmers exerting low level of effort and engaging in input diversion (e.g., use of fertilizer on crops other than sugarcane or re-selling). Some farmers complain about poor performance of company staff and contractors and about the delays in input provision and payments. Moral hazard concerns in the company hierarchy are also likely to be relevant. For instance, managers need to monitor field staff in order to ensure that the scheduling of input delivery occurs timely. The ability of the company to deliver information to the farmers was traditionally limited by the low ratio between field staff members and farmers, in the order of 1 to 1,000.[4] In addition, the distance between farmers' residences and the company premises implies farmers would need to bear high transport costs in order to report concerns at the company premises. As a result, most farmers report few interactions with company staff. The two interventions described in the next sections used mobile phones to increase the flow of information between the company and the farmers.

3. The Farmer SMS Intervention

The SMS experiment was designed in close collaboration with the agronomy department of the partner company. The intervention team compiled a list of messages to be sent to farmers subscribing for the service. The content of these messages was primarily based on the age of the cane and on the harvest cycle (i.e., plant vs. ratoon). The messages warned the farmer about the need to complete a task on the plot. For instance, with

4 In Kenya, the extension agent to farmer ratio is 1:1,500. Figures are even lower in other countries in SSA (for instance, BenYishai and Mobarak (2013) on Malawi).

regards to weeding: ``Hello Mr./Ms. {farmer name}. It is 12 weeks since you planted, your plot may have weeds by now from the last time you weeded your plot; Please remember to weed this week. This message is from Mumias Sugar Outgrowers Helpline". Similar messages concerned other tasks such as trashlining (i.e. sorting of the leaf trash from the previous harvest), intercropping, and parasite controls. Other messages were prompted by the timing of delivery of company provided inputs, such as fertilizer: "Hello Mr./Ms. {farmer name}, fertilizer (UREA) will be delivered in your field/bloc shortly/soon. Please prepare to receive and apply in time because timely fertilizer application is essential for good cane growth. This message is from Mumias Sugar Outgrowers Helpline".

The experiment targeted 2,327 plots in 354 fields that were about to enter a new harvest cycle according to the company records. The randomization was conducted at the field level in six waves (roughly one per month), stratifying on harvest cycle type (plant vs. ratoon), two geographic zones in which the contract farming catchment area was divided, and average yield groups.[5] Table 1 shows that the randomization achieved balance across a range of baseline variables.

Company staff managed the recruitment for the treatment fields. They held at least one meeting in each field, inviting all the farmers listed for selection. The take-up rate for the SMS project was 65.7%. The majority of the non-compliance is due to farmers not attending the recruitment meetings, as opposed to farmers explicitly turning down the offer (the acceptance rate conditional on showing up to the meeting was 87%). Table 2 shows that take-up was substantially lower for telephone farmers.

About 19.5% of the plots ended up not entering the cane cycle targeted by the experiment. This was primarily due to the fact that the company did not complete land preparation or that farmers opted to use the plot for other crops. In Table 3, we verify that access to the SMS project did not affect the likelihood that a given plot entered the

5 Baseline yield data are available for 81.5% of the plots targeted by the study.

targeted cane cycle. Column 1 shows that the ITT coefficient on the SMS group is not significant at conventional levels. This is unchanged when including the vector of controls (column 2). In column 3 we show that the entry rate into was not differentially correlated with baseline yields, plots size, and cane cycle across treatment and control. We notice however the entry rate varied by treatment group for one of the zones of the catchment scheme. In order to assess this concern, we show later in the paper that our main results are robust both in a specification where we include zone dummies as controls. In addition, in another specification we treat the missing yields as zeros.

In Table 4, we study the impact of having access to the SMSs on plot yields. All the regressions include stratification dummies. Standard errors are clustered at the field level, the unit of randomization. Plots in the treatment group achieve yields that are 3.33 tons per hectare larger than the control group, or 8% the control group mean. The treatment on treated for compliers is equal to 11.5% of the control group mean yields. In column (2) we add to the regression model a vector of plot-level controls, which include zone, cane cycle, baseline yields, and plot size. The first three are just finer versions of the strata variables. Plot size have high explanatory power given the presence of decreasing returns in this setting (Casaburi, Kremer, and Mullainathan (2014)). Adding these controls increases estimate precision while not changing the coefficient of interest significantly. The results are unchanged in column (3), where we further add a dummy for telephone farmers and a dummy for leased plot.

Table 5 presents several robustness checks. In column (1), we redefine our outcome variable to equal zero if a plot never entered the harvest cycle targeted by the experiment. We find that the coefficient displays little changes relative to the main specification. In columns (2) and (3) we winsorize our outcome variable at the 99^{th} and 95^{th} percentile, respectively, in order to show that outliers in the yield distribution do not drive the results. The estimated coefficients are similar to the one of the main specification and both significant at 95%. In column (4), we use the natural logarithm of yields. The point estimate suggests in the logarithmic regression, 0.07, is consistent with the percent increase estimated in the level regression. In column (5), we drop from the sample plots that are below 0.2 acres, reducing the sample size by 7.3%. The coefficient on the cell phone group remains similar, confirming that very small plots do not drive the results. Finally, we also run our regressions dropping one at a time each of the six randomization waves and each of the five zones in which the catchment area is split. We verify that the ITT estimates are quite stable across these specifications, thus confirming that our results are not driven by any specific sub-sample (results available on request).

In order to shed light on the economic mechanisms that could drive the results, we use farmer survey data collected around the beginning of the cycle, before the randomization occurred. We have a baseline survey with the above information for 1,719 farmers from 1,676 plots, 72% of the study sample. Farmers for which we lack baseline data were absent both in the initial meeting and in subsequent revisit and tracking attempts. Therefore, the sample for which baseline survey data are available is a non-representative sample of the study sample. For instance, 57% of the farmers for which we are missing survey data are ``telephone farmers" while these make only 18% of the overall sample. Importantly, the proportion of farmers surveyed is 69% for the treatment group and 75% for the control, a difference significant at 5%.[6]

In this survey, we asked whether the farmer had attended agronomy training in the previous 12 months. If one of the effects of the SMSs is to increase information about the range, timing, and frequency of agronomic tasks, then we would expect their impact to be lower for farmers that had received such training. We also gathered information on whether the farmer interacted with a company field assistant around the beginning of the cycle (i.e., in the month preceding the survey).

In Table 6, column (1) and (2), we run our ITT yield regression on the sub-sample of plots for which we have survey data. The point estimates of the intention-to-treat effect

6 Later in the paper, we verify that the impact of the treatment on yields is very similar when restricting the sample to plots that completed the baseline survey.

are slightly higher than the ones in the main sample (3.59 vs. 3.32 in the baseline specification and 3.87 vs. 3.33 with control), though within one-third of a standard error. This difference primarily arises from the fact that the survey subsample includes a lower proportion of telephone-farmers, who are less likely to take-up the option to receive the SMS (as we reported in Table 2). Consistent with this observation, the treatment-on-treated effect is comparable across the two samples (4.8 in the full sample and 4.7 in the survey subsample).

In columns (3) and (6), we interact the treatment variable with the field assistant contact and training dummies, respectively. Consistent with the hypothesized channels, the coefficient on the interaction terms are negative and significant at 1% and 5%, respectively. In Columns (4) and (7) we add the vector of plot controls. The point estimates are still significant at 5%, though the coefficient on the interaction with company staff dummy shrinks. The results are similar when we further add a full vector of interactions among the plot controls and the treatment dummy (columns 5 and 8).

The interpretation of these heterogeneity results must take into account that the interaction variables could be correlated with other unobserved plot characteristics. With this caveat in mind, we argue that these interaction terms are consistent with the fact that SMSs operate through an information channel. We also note that the result on the interaction with the sugarcane company staff may also arise from a monitoring effect if the farmers perceive that the company is observing their harvest cycle when they receive the text messages. However, the company did not specifically conduct plot inspections following the sending of the text messages.

4. The Farmer Hotline Intervention

The second intervention aimed to improve communication flowing from the farmers to the company. Farmers have information that is valuable for the company. In particular, we focus on input delivery performance. Lower level managers and external contractors manage most of the delivery activities, often following interactions with lower level managers of the company. The monitoring of such activities is costly. For instance, while the company collects data on input deliveries, compiling and analyzing such data is a time-consuming task. In addition, higher-level manager time is often required to address problems in delivery timing and inputs (consistent with the theoretical literature pioneered by Garicano (2000)).

Anecdotal evidence from field visits suggests that delays and low performance in input delivery are an important source of concern for the farmers. Field assistants face substantial time constraints and often delay in visiting the fields. As a result they also delay assigning them to fertilizer delivery. In some instances, a plots even fails to Urea fertilizer at all during the harvest cycle. In certain cases, farmers find it worth to travel all the way to the company main offices to resolve their issues. This picture finds support in the company administrative data. Figure 1 presents the distribution of delivery dates for Urea fertilizer in the year before the study. According to the agronomy department guidelines, this type of fertilizer should be delivered between the fourth the sixth month of the cane. However, the figure shows that, in the year preceding the intervention, about 30% of the fields experience a delay relative to this optimal time window. In the year before the intervention, plots that receive the Urea fertilizer in the optimal time window have yields higher by 1.76 tons/ha relative to the plots that experience delays (significant at 5%), an increase of 3.5% of the average yield. With the obvious caveat that this evidence is not causal, this estimate suggests that the delays are costly both for the farmers and the company.

Input delivery is highly clustered by field, consistent with the description of the input delivery process provided in Section 2: contractor trucks typically deliver fertilizer to most plots in a given field in the same day. This generates an important scope for positive geographic externalities: a query reported by one farmer in a given field will likely affect the relevant input delivery outcomes for other farmers in the same field. We discuss this channel in more detail below.

A low ratio of field assistants to farmers and high transport costs between the fields and the company offices limit opportunities for the farmers to report problems with the company and contractors' performance. It could be the case that the delays observed in the data are optimal from the company perspective. For instance, the company may choose to deliver all the fertilizer to a given area in one day to save on transport costs, even if this implied a delay for some of the plots. If the observed performance in input delivery were optimal given these other concerns, we would expect no response to the hotline. On the other hand, improving farmer ability to communicate with the company could change the company decision if it enables company managers to note the delays caused by lower level staff in the company hierarchy or by the contractors. Therefore, whether farmer increased ability to report problems affects the input delivery performance is an empirical question.

The second intervention described in this paper– the farmer hotline – tries to address this question. The project enabled farmers to report delays or other problems concerning input delivery and other tasks (e.g. payments). The hotline service included two main components. First, farmers had the opportunity to make calls to a dedicated number during office hours. Second, farmers received periodic calls (approximately every two months) from the hotline operators in which they were explicitly asked to report any query they may have about the company services. Recorded queries were then channeled to the relevant company department. For instance, queries about fertilizer deliveries were channeled both to the Zonal Manager, in charge of the section of the contract farming scheme where the plot is located, and to the Fertilizer Delivery team, which supervises the contractors in charge of the deliveries of inputs.

The hotline pilot evaluated in this paper covered a total of 8,414 plots in 1,016 fields. For logistical purposes, the recruitment targeted fields that had just entered the new cane cycle, as opposed to fields that were about to harvest. As a consequence, we focus our analysis on Urea fertilizer, typically delivered a few months into the cycle. We cannot study seedcane and DAP fertilizer deliveries, since most of the plots in our sample had already received these inputs by the time they entered the hotline treatment.

During the recruitment for the intervention, which was conducted before the randomization, farmers of 3,768 plots out of the 8,414 included in the study, recorded their cell phone number and qualified as eligible for the service in the case in which their field was randomized into the treatment group. The randomization of fields across treatment groups occurred in three waves. In the first two, roughly half of the fields were each allocated to a hotline and to a control group. For these waves, farmers had to pay the cost of the call when contacting the operator. In wave 3, a free hotline was added as third treatment. In the analysis presented in this paper, we bundle the two hotline treatments.[7] Field-level randomization was stratified on wave indicator, plant vs. ratoon cycle, a zone indicator, and a variable capturing the field-level average response rate to a phone survey done before the intervention. Table 7 confirms that the randomization achieved substantial balance across several plot-level variables measured in the company administrative data. However, baseline yields are slightly higher for non-eligible plots in treatment fields relative to non-eligible plots in control fields (this difference is significant at 10%).

Based on company records, about 13% of the eligible farmers in treatment fields reported a complaint through the hotline. In turn, this implied that 70% of the treatment fields had an entry logged in the system. About 38% of the reported issues concerned fertilizer deliveries, followed by queries on payments and harvesting. About 91% of the complaints were marked as resolved by the hotline operators.

The analysis focuses on two main outcomes, obtained from the company administrative data: the likelihood that a plot does not receive the Urea fertilizer during the cycle and the likelihood that it does not receive Urea within the recommended time window (i.e.

7 We do not have sufficient power to distinguish outcomes of the free and for-payment hotline.

between the fourth and the six month of the cane cycle). Table 8 presents the results of the evaluation for the eligible plots (i.e., the plots whose farmers recorded their phone numbers). Column (1) shows that the likelihood that a plot does not receive fertilizer decreases by 3.8 percentage points among eligible plots in the treatment fields (compared to eligible plots in control fields), significant at 5%. This is equivalent to 36.5% of the control group mean. The coefficient is stable when we add the plot-level controls (Column 2). Column (3) focuses on the likelihood that the Urea fertilizer is not received within the optimal time window identified by the agronomy department. The treatment group average falls by 8.5 percentage points for eligible plots in treatment fields, 21.6.% of the mean for eligible plots in control fields. Again, the coefficient is stable when adding plot-level controls.

Table 9 reports a similar analysis for neighbors of the targeted plots (i.e., comparing non-eligible plots in treatment fields vs. non-eligible plots in control fields). Columns (1) and (2) show that there is no significant impact on the likelihood that a plot does not receive fertilizer. However, in columns (3) and (4), we observe that non-eligible plots in treatment fields experience a reduction of 7.5 percentage points in the fertilizer delivery delays(19.8% of the average for non-eligible plots in control fields), significant at 5%. The coefficient is robust when adding plot-level controls.

Conversations with the staff in charge of the project suggest that access to the hotline enabled farmers to bypass multiple layers in the company hierarchy, represented in Figure 2. Specifically, through their complaints, farmers were able to communicate much faster with the high level managers of the outgrower service department and with the coordinators of fertilizer deliveries, instead of relying on (sporadic) interactions with lower level field assistants and with representatives of the input delivery contracting firms. This in turn generated positive geographic spillovers for those non-eligible farmers. These farmers, while not included in the hotline intervention, benefited from the company response in input delivery, since this typically targeted most plots in a given field[8]

There are two other types of externalities that could arise from the experiment. First, the reduction in delays in the treatment fields may induce an increase in the delays in other fields, either in the control group or outside of the study sample. Second, the hotline could help the company managers to identify and address problems with specific field assistants or contractors, thus generating further positive spillover for non-treatment fields. The ideal design to test such a mechanism would be to vary intensity across "regions" (Baird et al. (2013)). However, such a design is not feasible in our setting. The contractors that deliver fertilizer cover large areas (in some instances, the whole catchment scheme). In addition, the coverage area changes over time and overlap across contractors. Instead, we exploit the time series dimension of our delivery data to delve into these issues.

[THIS AND THE NEXT PARAGRAPH ARE PRELIMINARY RESULTS] The Urea delivery data contain information on deliveries from January 2011 to December 2013. We compute the number of treatment plots and of non-treatment plots (control and outside of the study) that end the optimal delivery time window in each of these 36 months. We then identify two key variables: the proportion of non-treatment plots that receive fertilizer within the optimal time window and the number of treatment plots, as determined by the timing of the randomization waves and by the variation in the age at which treatment fields entered the intervention (typically, between the first and the third month of the harvest cycle).

In Table 10 we present the results of the analysis of these variables on the sample of 36 months available in the data. Column 1 presents the results of a bivariate regression where the dependent variable is the percentage of plots that do not receive fertilizer within the optimal time window and the independent variable is the number of treatment

8 Fabregas, Kremer, Robinson, and Schilbach (2014) provides another example of the public good nature of information acquisition and provision.

plots. The coefficient of interest is small and non-significant. Adding calendar month fixed effects leaves the results unchanged (column 2). Column 3 adds trends by month (starting from January 2011). In this specification, the coefficient on the number of treatment plots become larger (in absolute value) and it is now significant at 5%: an extra treatment plot reduces the fraction of non-treatment plots in the contract farming scheme that experience a delay inreceiving Urea fertilizer by 0.1 percentage points. These results are unchanged when we add year fixed effects (column 4). These findings must be interpreted cautiously because they are based on a small sample size (36 months) and because they identify the coefficient of interest from non-random variation in the number of treatment fields across months. With this important caveat in mind, we argue that this analysis mitigates the concerns that the results arise primarily from a transfer of resources from other plots to the treatment plots. If anything, there is evidence that the hotline may have induced a positive factory-level spillover by inducing managers to focus a larger portion of their time on inefficiencies in fertilizer delivery. This is consistent with anecdotal evidence from discussion with company managers that the hotline put more pressure on the company field staff.

5. Contract Farming and Information Provision

Our findings suggest that ICT-driven services can substantially affect productivity in the supply chain. The two interventions described so far induced a remarkable increase in the oucomeswe study. For instance, the LATE estimate of the impact of the SMS program on plot yields is comparable to 20-30% of the increase in yields expected from the introduction of high-yielding sugarcane varieties in other Sub-Saharan African countries (Chambi and Isa (2010), SASRI (2013)) and to 30% of the estimated increase in yields from soybean intercropping, a commonly recommended practice to alleviate sugarcane nitrogen requirement (Shoko, Zhou, and Pieterse (2009)).

Our partner, a large contract farming scheme, was particularly well positioned to design and pilot such interventions. First, as discussed above, the company has an incentive to research and invest in ICT solutions because, as the price paid to the farmer is below the marginal revenue product, it profits from the additional plot productivity. Given the low-cost of the text messages ($0.02 per text message, for a total of around $0.3 per plot), the intervention was not only extremely cost-effective from but it raised profits for the company as well as farmer revenues. Given the average plot size (0.52 ha.), the SMS intervention increased production in the average plot by 1.73 tons. Using the figures provided in Section 2, we estimate that this increased company profits by $43 and the farmer revenues (net of additional harvesting and transporting costs) by $54.

Second, there are significant economies of scale in information production (agronomy trials, data collection, management, and analysis). A large company is better positioned to bear some of the potentially large fixed costs involved in these activities.

Third, farmers are more likely to perceive the company as credible information.[9] We investigate the importance of credibility concerns a survey response experiment. In a pilot program, we ran several polls via SMS. These asked questions about farmer preferences (e.g. ``would you be interested in receiving chemical herbicides on credit from the company"), farmer information about company practices (e.g. "where are the company weigh-bridges?"), and farmer characteristics (e.g. "do you have a saving account"?). The response rates to these polls are quite low. In a basic treatment where farmers receive the SMS from a dedicated short-code and pay for answering, the overall response rate is 7%. We introduce several variations of this basic treatment in order to shed light on the importance of credibility of the source. In one treatment, we deliver a company brochure about the survey to a subset of farmers. In another subsample, we increase the uncertainty about the source by sending SMS from a regular 10-digit number as opposed to the dedicated short-code. These long codes are more likely to be associated with less reliable and respectable sources. Finally, we waive the SMS cost to another subsample of farmers.

9 On the other hand, Duflo, Kremer, and Robinson (2008) show that information on fertilizer dosage provided by a government affiliated research center leads negative returns.

Table 11 presents the results of the survey response trials. The comparison across the different treatments is presented in column (1). We find that providing farmers with a brochure increases response rates by 3.6 percentage points, or 51% of the basic group. mean. This amounts to 64% of the increase we observe when waiving the SMS price to the farmer (5.6 percentage point). We argue that the brochure reduces uncertainty about the source. However, it could also affect response rates by inducing farmers to pay more attention to the messages (a "de-cluttering" effect). In addition, we find that sending SMSs from a long-code lowers response rates by 2.1 percentage points (relative to the standard short-code). Finally, for a subset of survey polls, we vary the nature of the question sent to different farmers. Specifically, in these polls, a subset of questions is labeled as confidential, as farmers were asked about their account, input charges and payment terms. In column (2) of Table 10, we show that the impact of the long-code on response rates is significantly more negative when the SMS surveys request the farmer to include confidential information in their response. We interpret the results from these trials as consistent with the hypothesis that credibility of the source is an important determinant of the volume of information flows across agents in the value chain. We argue that, relative to other agents such as the government or commercial information providers, a large processor has more immediate gains from delivering accurate information and that the farmers will take into account this incentive when responding to the information provided.

6. Conclusion

The results of the paper suggest that ICT can increase agricultural productivity, at least in the context of this study. Sending text messages with agricultural advice to smallholder farmers increased yields by 11.5% relative to the control group. These effects are concentrated among farmers who had no agronomy training and had little interaction with sugar cane company staff at baseline. The intervention generated large returns in terms both of farmer earnings and company profits.

Enabling farmers to report input provision delays to the company reduces the proportion of delays in fertilizer delivery by 21.6%. Finally, we provide evidence of positive geographic spillovers, since the hotline induces the company to deliver inputs to several neighboring plots. We hope future research will shed light on the replicability of these results in other settings.

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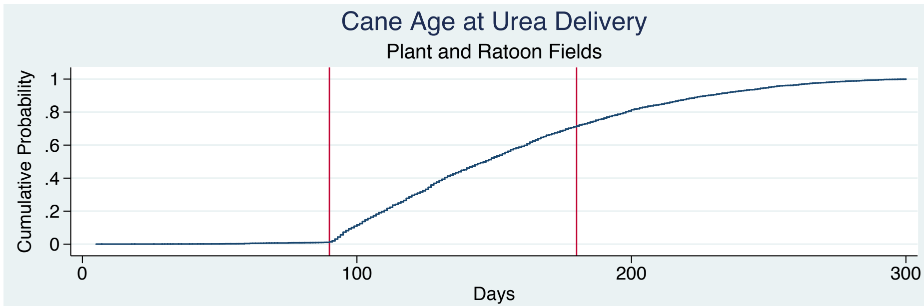
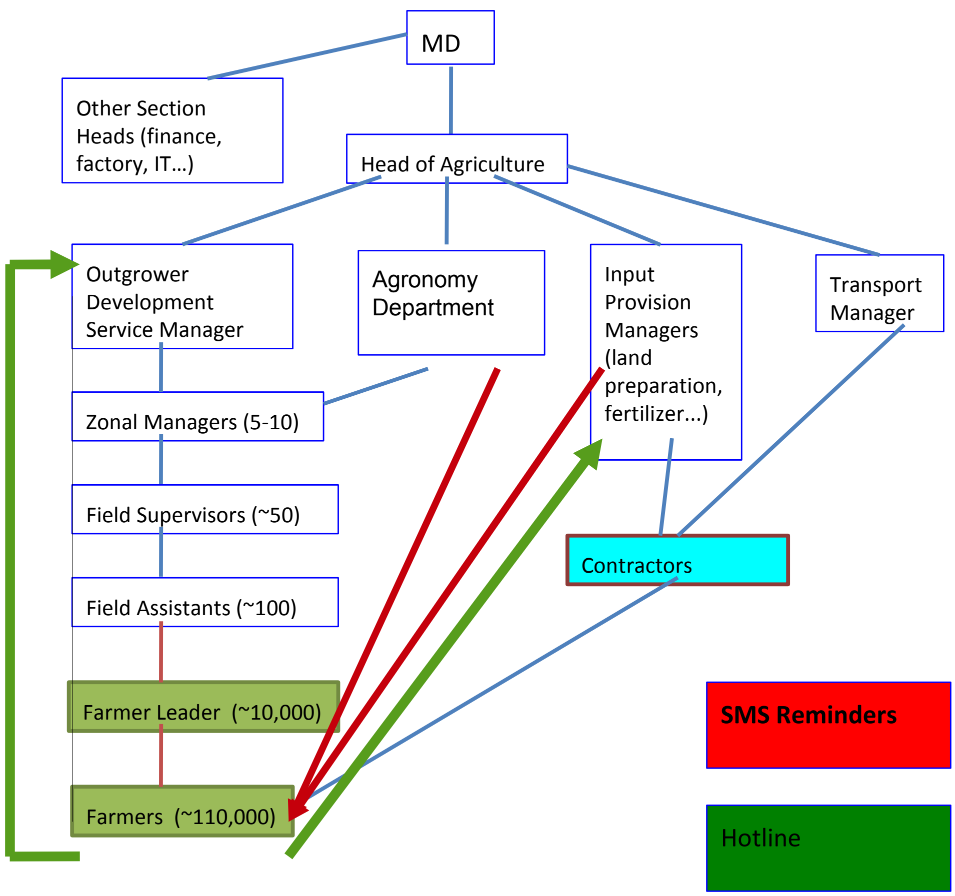
Figure 1: Distribution of Cane Age at Urea Delivery



Notes: The figure plots the distribution of the age of cane (in days) at the time of Urea Fertilizer delivery. The two vertical red lines represent the optimal time window identified by the agronomy department (90-180 days).

Figure 2: Company Organizational Chart, SMS and Hotline



Notes: The chart describes the organization of the company and the multiple layers of interaction among company staff, contractors and farmers. The red and green arrows identify the lines of communication enabled by the SMS and by the hotline intervention, respectively.

Table 1: Randomization Balance: SMS Intervention

	Control	SMS	p-value	N
Plant Cycle	0.45	0.43	0.49	2327
	(0.50)	(0.49)		
Ratoon 1 Cycle	0.15	0.11	0.53	2327
	(0.36)	(0.31)		
Ratoon 2 Cycle	0.40	0.46	0.44	2327
	(0.49)	(0.50)		
Plot Size (ha.)	0.53	0.53	0.88	2327
	(0.39)	(0.45)		
Zone 1	0.24	0.32	0.22	2327
	(0.43)	(0.46)		
Zone 2	0.16	0.18	0.45	2327
	(0.37)	(0.39)		
Zone 3	0.21	0.18	0.68	2327
	(0.41)	(0.38)		
Zone 4	0.16	0.16	0.69	2327
	(0.36)	(0.37)		
Zone 5	0.23	0.16	0.23	2327
	(0.42)	(0.37)		
Leased Plot	0.03	0.02	0.33	2327
	(0.16)	(0.14)		
Telephone Farmer	0.18	0.18	0.81	2327
	(0.38)	(0.38)		
Baseline Yields	49.15	50.25	0.66	1898
	(27.36)	(26.37)		
Spoke to Company Staff in Last Month	0.31	0.30	0.67	1627
	(0.46)	(0.46)		
Agronomy Training in Last 12 Months	0.15	0.16	0.98	1643
	(0.36)	(0.36)		

Notes: All the regressions include field-level stratification dummies. Standard errors are clustered at the field-level. * $p<0.1$, **$p<0.05$, ***$p<0.01$.

Table 2: SMS: Take-up

	(1)	(2)
Take-up cell Treatment Group	0.657***	
	[0.014]	
Ratoon 1 Cycle		0.043
		[0.051]
Ratoon 2 Cycle		-0.025
		[0.034]
Plot Size (ha.)		-0.027
		[0.031]
Zone 1		-0.087**
		[0.042]
Zone 2		-0.081*
		[0.047]
Zone 3		-0.080*
		[0.047]
Zone 4		-0.093*
		[0.048]
Leased Plot		-0.108
		[0.101]
Telephone Farmer		-0.243***
		[0.036]
Baseline Yields		0.000
		[0.001]
Observations	1172	1172

Notes: Column 1 is the take-up rate in the cell-phone group. Column 2 reports take-up determinants among the cell-phone group. Column 2 also includes a binary variable equal to one if baseline yields are missing. * p<0.1, **p<0.05, ***p<0.01.

Table 3: SMS: Entry into the Project Cane Cycle

	(1)	(2)	(3)
SMS	0.024	0.017	-0.074
	[0.029]	[0.027]	[0.097]
Ratoon 1 Cycle		0.247	0.239
		[0.175]	[0.180]
Ratoon 1 Cycle*SMS			0.007
			[0.059]
Ratoon 2 Cycle		0.025	0.007
		[0.171]	[0.178]
Ratoon 2 Cycle*SMS			0.039
			[0.062]
Plot Size (ha.)		0.089***	0.104***
		[0.021]	[0.036]
Plot Size (ha.)*SMS			-0.028
			[0.041]
Zone 1		0.156***	0.051
		[0.052]	[0.069]
Zone 1*SMS			0.211**
			[0.097]
Zone 2		-0.112	-0.112
		[0.088]	[0.091]
Zone 2*SMS			0.048
			[0.088]
Zone 3		-0.028	-0.069
		[0.086]	[0.090]
Zone 3*SMS			0.119
			[0.083]
Zone 4		-0.066	-0.074
		[0.066]	[0.080]
Zone 4*SMS			0.045
			[0.107]
Leased Plot		-0.037	-0.055
		[0.046]	[0.062]
Leased Plot*SMS			0.029
			[0.090]
Telephone Farmer		0.004	0.020
		[0.023]	[0.033]
Telephone Farmer*SMS			-0.030
			[0.045]
Baseline Yields		0.004***	0.004***
		[0.000]	[0.001]
Baseline Yields*SMS			0.000
			[0.001]
Mean Y Control	0.795	0.795	0.795
Observations	2327	2327	2327

Notes: All the regressions include field-level stratification dummies (wave, plant cycle, macro-zone, baseline average productivity). Standard errors are clustered at the field level. *p<0.1, **p<0.05, ***p<0.01.

Table 4: SMS: Yield Regressions

	Yields		
	(1)	(2)	(3)
SMS	3.326*	3.339**	3.331**
	[1.719]	[1.536]	[1.532]
Plot Controls	N	Y	Y
Extra Controls	N	N	Y
Mean Y Control	41.625	41.625	41.625
Observations	1849	1849	1849

Notes: The table reports intention-to-treat estimates. *Yields* are measured in tons/hectare. The sample includes the 1,849 plots that entered the project cycle (out of the 2,327 included in the randomization). *Plot Controls* include plot size zone fixed effects, cane cycles fixed effects, baseline yields and a dummy for whether baseline yields are available. *Extra Controls* include a telephone farmer dummy and a leased plot dummy. All the regressions include field-level stratification dummies (wave, plant cycle, macro-zone, baseline average productivity). Standard errors are clustered at the field-level. * p<0.1, **p<0.05, ***p<0.01.

Table 5: SMS: Yield Regressions Robustness

	With zeros	Winsor Top 99	Winsor Top 95	Log	Drop Plots <.2ha
	(1)	(2)	(3)	(4)	(5)
SMS	3.297*	3.106**	2.749**	0.071*	3.047**
	[1.766]	[1.451]	[1.320]	[0.040]	[1.550]
Average Y Control	33.084	41.379	40.642		40.583
Observations	2327	1849	1849	1849	1714

Notes: In the column *With zeros*, yields equal zero for plots for which we do not observe yields. All the regressions include the following controls: plot size, zone fixed effect, cane cycle, baseline yields, telephone farmer dummy, leased plot dummy, and a dummy for whether baseline yields are available. Standard errors are clustered at the field-level. * p<0.1, **p<0.05, ***p<0.01.

Table 6: SMS: Heterogeneity by Baseline Survey Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SMS	3.589*	3.867**	5.999***	5.381***		4.299**	4.588**	
	[1.909]	[1.749]	[2.128]	[1.943]		[2.073]	[1.865]	
SMS*Spoke to Company Staff			-8.402***	-5.579**	-6.057**			
			[2.929]	[2.583]	[2.623]			
Spoke to Company Staff			4.950**	4.722**	4.831***			
			[2.106]	[1.871]	[1.858]			
SMS*Agronomy Training						-6.075*	-7.528**	-7.556**
						[3.374]	[3.048]	[3.014]
Agronomy Training						2.107	2.848	2.773
						[2.373]	[2.275]	[2.258]
Controls	N	Y	N	Y	Y	N	Y	Y
Controls Interactions	N	N	N	N	Y	N	N	Y
Mean Y Control	41.871	41.871	42.124	42.124	42.124	41.885	41.885	41.885
p-value main coeff+interaction			0.396	0.938		0.558	0.303	
Observations	1391	1391	1343	1343	1343	1342	1342	1342

Notes: The dependent variable is plot yields. The variable *Spoke to Company Staff* is equal to one if the respondent spoke to a member of the company staff in the previous month. The variable *Agronomy Training* is one if the respondent attended an agronomy training in the previous 12 months. The columns with *Controls* include a vector of plot level controls (plot size, telephone farmer dummy, leased plot dummy, zone fixed effect, cane cycle, baseline yields and a dummy for whether baseline yields are available). The columns with *Controls Interactions* include the above controls and their interaction with the treatment status. These controls include continuous variables such as plot size and yields. Therefore, for these columns, we do not report the baseline coefficient on *SMS* since this would capture the ITT effect of the experiment when all these covariates are equal to zero. All the regressions include field-level stratification dummies (wave, plant cycle, macro-zone, baseline average productivity). Standard errors are clustered at the field-level. * p<0.1, **p<0.05, ***p<0.01.

Table 7: Summary Statistics

	Eigible Plots				Non-Eigible Plots			
	Control	Hotline	p-value	N	Control	Hotline	p-value	N
Plot Size (ha.)	0.44	0.43	0.45	3768	0.44	0.44	0.81	4313
	(0.32)	(0.29)			(0.31)	(0.31)		
Zone 1	0.12	0.11	0.15	3768	0.09	0.08	0.14	4313
	(0.32)	(0.32)			(0.28)	(0.27)		
Zone 2	0.28	0.24	0.91	3768	0.30	0.25	0.28	4313
	(0.45)	(0.42)			(0.46)	(0.44)		
Zone 3	0.26	0.27	0.32	3768	0.27	0.27	0.35	4313
	(0.44)	(0.44)			(0.45)	(0.45)		
Zone 4	0.18	0.19	0.92	3768	0.15	0.19	0.35	4313
	(0.38)	(0.39)			(0.36)	(0.40)		
Zone 5	0.17	0.19	0.05*	3768	0.18	0.20	0.28	4313
	(0.37)	(0.39)			(0.39)	(0.40)		
Ratoon 1	0.25	0.27	0.42	3768	0.26	0.29	0.19	4313
	(0.43)	(0.45)			(0.44)	(0.45)		
Ratoon 2	0.24	0.30	0.33	3768	0.25	0.33	0.30	4313
	(0.43)	(0.46)			(0.43)	(0.47)		
Ratoon 3	0.10	0.09	0.78	3768	0.09	0.07	0.66	4313
	(0.30)	(0.28)			(0.28)	(0.26)		
Yield	57.10	59.66	0.22	2693	53.40	58.10	0.10	3024
	(31.79)	(35.12)			(30.25)	(34.18)		
UREA Not Delivered	0.29	0.27	0.75	2693	0.29	0.28	0.86	3024
	(0.46)	(0.45)			(0.45)	(0.45)		
UREA Not Delivered in Time	0.53	0.50	0.47	2693	0.49	0.50	0.71	3024
	(0.50)	(0.50)			(0.50)	(0.50)		

Notes: P-values are from regressions that include field level stratification dummies. Standard errors clustered at the field level. *p<0.1, **p<0.05, ***p<0.01.

Table 8: Hotline Intervention: Eligible Plots

	Urea Not Delivered		Urea Not Delivered in Time	
	(1)	(2)	(3)	(4)
Hotline	-0.038**	-0.040***	-0.085***	-0.085***
	[0.015]	[0.015]	[0.028]	[0.028]
Mean Y Control	0.104	0.104	0.393	0.393
Controls	N	Y	N	Y
Observations	3768	3768	3768	3768

Notes: All the regressions include field level stratification dummies. Controls include the baseline value of the outcome variable, plot size, zonal dummies, cycle dummies, an indicator for whether the plot had a harvest before the intervention, and baseline yields (=-1 if not available). Standard errors clustered at the field level. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table 9: Hotline Intervention: Non-Eligible Plots

	Urea Not Delivered		Urea Not Delivered in Time	
	(1)	(2)	(3)	(4)
Hotline	-0.010	-0.015	-0.075**	-0.075**
	[0.016]	[0.016]	[0.032]	[0.032]
Mean Y Control	0.097	0.097	0.378	0.378
Controls	N	Y	N	Y
Observations	4313	4313	4313	4313

Notes: All the regressions include field level stratification dummies. Controls include the baseline value of the outcome variable, plot size, zonal dummies, cycle dummies, an indicator for whether the plot had a harvest before the intervention, and baseline yields (=-1 if not available). Standard errors clustered at the field level. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table 10: Hotline Intervention: Impact on Non-Treatment Plots

	(1)	(2)	(3)	(4)
N. treatment plots	0.001	-0.011	-0.092**	-0.098**
	[0.040]	[0.035]	[0.035]	[0.035]
Mean Y Control	39.247	39.247	39.247	39.247
Calendar Month FE	N	Y	Y	Y
Time (year-month) Trend	N	N	Y	Y
Year FE	N	N	N	Y
Observations	36	36	36	36

Notes: The unit of observation is the month (January 2011 to December 2013). The dependent variable is the percentage of non-treatment plots that experience a delay in Urea delivery relative to the optimal window out of the total number of non-treatment plots that finish the optimal time window in that month. The regressor is the number of treatment plots that finish the optimal delivery time window (i.e. they complete the sixth month in the cycle) in each month. * p<0.1, **p<0.05, ***p<0.01.

Table 11: Farmer-Polls: Response Rates

	(1)	(2)
Brochure	0.036***	0.037**
	[0.006]	[0.015]
Brochure*Confidential		-0.005
		[0.021]
Long Code	-0.021***	-0.035***
	[0.006]	[0.012]
Long Code*Confidential		-0.050***
		[0.018]
Free SMS	0.056***	0.070***
	[0.007]	[0.015]
Free SMS*Confidential		-0.008
		[0.021]
Confidential		0.058***
		[0.013]
Mean Y Control	0.070	0.094
Observations	57615	7139

Notes: The dependent variable is a dummy equal to one if the farmer respond to the specific poll. The variable *Brochure* equals one if the respondent receives a brochure about the polls at the beginning of the intervention. The variable *Long Code* equals one if polls are sent from a standard 10-digit number, as opposed to the dedicated short-code. The variable *Free SMS* equals one if answering the poll is free for the farmer. All the regressions include field level stratification dummies. Standard errors clustered at the field level. * p<0.1, **p<0.05, ***p<0.01.