Is There an App for That?
The Impact of Community Knowledge Workers in Uganda

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The International Food Policy Research Institute (IFPRI), established in 1975, provides evidence-based policy solutions to sustainably end hunger and malnutrition and reduce poverty. The Institute conducts research, communicates results, optimizes partnerships, and builds capacity to ensure sustainable food production, promote healthy food systems, improve markets and trade, transform agriculture, build resilience, and strengthen institutions and governance. Gender is considered in all of the Institute’s work. IFPRI collaborates with partners around the world, including development implementers, public institutions, the private sector, and farmers’ organizations, to ensure that local, national, regional, and global food policies are based on evidence. IFPRI is a member of the CGIAR Consortium.

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ABSTRACT

Rapidly increasing mobile phone coverage, cheaper technology, and an open platform that allows for the development of applications that extend the use of mobile devices provide new ways to reach farmers in isolated places. We investigate the impact of an intervention that uses information and communication technology devices to provide real-time agricultural information and extension services in Uganda. Using a difference-in-differences setup, we find that the introduction of this technology through a network of community knowledge workers induce farmers to adapt their crop portfolio, moving away from low-risk, low-value crops toward more commercially oriented commodities. We also find that, for the case of maize, the intervention causes farmers to sell less on the market, but at significantly higher prices. Further, our analysis suggests important spillover effects. We do not find an effect on maize productivity.

Keywords: agricultural extension, impact evaluation, Uganda, smartphones
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1. INTRODUCTION

In 2010, the Grameen Foundation, a global nonprofit organization, initiated an innovative project to deliver extension and marketing information to smallholder farmers in rural villages in Uganda. Grameen equipped locally recruited villagers (referred to as community knowledge workers [CKWs]) with Android smartphones, preloaded with an in-house-developed mobile application called CKW Search. CKWs can use this app to search for up-to-date and location-specific information related to farming and commodity marketing. In this way, the Grameen Foundation aims to build a scalable network of resident rural information providers who use smartphones to help close critical information gaps faced by smallholder farmers in the area of extension and marketing information.

The use of information and communication technology (ICT) for development has attracted considerable attention in development policy and research circles (Aker and Mbiti 2010). Expectations are high for various reasons. ICT and cell-phone-based technology, is growing extremely fast in developing countries due to the relatively low cost of mobile phone usage in these countries. Cell phone technology does not involve the fixed costs that are characteristic of landline communications, leading to often fierce competition by operators. As for the benefits of cell phones, large costs of providing agricultural extension and information to farmers in remote places give mobile communications a comparative edge in developing countries. Mobile phone operators are also rapidly developing new products and services (such as mobile money transfer services). Portable devices such as cell phones or smartphones are also well adapted to situations where power supply is erratic. Increasingly, both private and public initiatives are starting to use this infrastructure to provide extension services and disseminate information to those who can benefit from it (Aker 2011).

While there is growing consensus that ICT changes the general equilibrium conditions through the reduction of transaction costs (Aker 2010; Jensen 2007), it seems to be much more difficult to pin down direct gains for smallholders. Recently, four studies have tried to assess the impact of projects that aim to increase the price information advantage at the household level through ICT (Fafchamps and Minten 2012; Camacho and Conover 2011; Cole and Hunt 2010; Mitra et al. 2012). Farmers who possess price information should be in a much better bargaining position. However, none of these studies find a significant increase in the price received by farmers who participated in the project compared to those that did not participate. This is surprising, given the vast amount of anecdotal evidence. In addition, farmers themselves often point to the lack of information as a key constraint to increased market participation.

There are various reasons why the above studies may fail to find an impact. It may be that, in spite of the anecdotal evidence and the self-proclaimed information deficiencies, agents are simply sufficiently informed even without ICT interventions (Ebiyau, Arach, and Serunjogi 2005). Alternatively, it may be that farmers receive potentially useful price information through ICT interventions, but this information does not change their bargaining power vis-à-vis traders or middlemen. In other words, the threat of selling at a higher price in a distant market instead of at a lower price at the farmgate to the trader may not be very credible if the farmer does not have accurate additional information, such as the availability and price of transportation services. The intervention we study in this paper is different in that it takes a more holistic approach to information provision. Finally, it may be that the experimental design used to evaluate the above interventions was inappropriate due to the nonrival nature of information. In this study, we will therefore also reflect on spillover effects.

This paper looks at the causal impact of the CKW intervention on the crop mix grown by farmers, on maize productivity, on the share of maize marketed, and on the price received for maize. We collected data on the above outcome variables one and a half years after the intervention for a sample of farmers who were exposed to the CKW intervention. We collected data on the same outcome variables in a sample

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1This is especially the case in countries that have policies in place that allow for different players in the market, such as Uganda (MTN, Orange, Warid, UT Mobile, Airtel). In Ethiopia, where telecommunications is currently a monopoly controlled by the state-owned Ethio Telecom company, cell phone penetration is relatively low.
of farmers who were not included in the project but were living in villages that share the same characteristics as the villages that did receive CKWs. However, since we cannot exclude that selection of CKW villages may have been based on pretreatment values of the outcome variables, we will also use data on these two groups that were gathered before the intervention. The change over time of the four outcome variables for the farmers that had access to a CKW will be contrasted to the change over time for a sample of farmers that were not affected by the intervention.

We find that the CKW initiative led to a change in the crops that farmers report growing. In particular, the intervention induces farmers to cultivate fewer food-security crops, such as cassava and sweet potatoes. While these crops are associated with lower risks of being adversely affected by drought or disease, they also have a lower value both in nutritional content and as a potential source of income. We see that the intervention motivates farmers to substitute these food-security crops for more commercially oriented commodities. We also find that, for the case of maize, the intervention induces farmers to sell less of their maize as a share of total quantity produced. Most strikingly, our estimates suggest that the presence of a CKW is associated with an average increase in the price at which farmers sell maize of about 12 percent. Further, our analysis suggests important spillover effects. We do not find an effect on maize productivity.

The remainder of the paper is organized as follows. Section 2 sketches the CKW model and details how it differs from similar interventions. In Section 3, we present the research method, followed by a description of the sources of data in Section 4. We present the results of the analysis in Section 5. Lastly, in Section 6 we provide a summary and conclusion.
2. THE CKW INITIATIVE

The CKW initiative was designed to improve the lives of smallholder farmers by improving access to information delivered by a resident community member. The idea is inspired by the successful community health workers initiative, in which community members are assigned to provide basic health and medical care to their communities (Haines 2007). In facilitated sessions, villagers are asked to choose an individual from their community, whom they deem suitable to take up the role of a CKW. This person is then screened by Grameen, provided with an Android smartphone, and trained on how to use it. The smartphone is preloaded with three mobile applications: CKW Search, CKW Survey, and CKW Pulse. The CKW Search app allows CKWs to look up information requested by farmers about farming and crop marketing. These questions address topics ranging from local weather information to market prices to crop and livestock management.

The applications are designed and developed in Uganda at Grameen’s App lab. The CKW Search application provides information that can broadly be classified into four categories. First, current prices for various crops in different locations can be requested. This information is provided by FIT Uganda, a business development consulting company that collects prices on 46 commodities in 20 markets across Uganda. Second, three-day weather forecasts, along with seasonal forecasts, provided by the Uganda’s department of meteorology, can be retrieved. Third, there is an extensive knowledge base on farmer best practices. This information was collected from expert organizations such as the National Agricultural Research Organization (NARO), the National Agricultural Advisory Services (NAADS), and the International Institute of Tropical Agriculture (IITA). Finally, Uganda National Agro Inputs Dealers’ Association (UNADA) provides information on farm input suppliers across the country that includes their locations down to sub-counties and contact information. There is also an extensive directory of traders, brokers, and transporters that can be accessed using the app.

The project originally started off using the HTC Dream, the first smartphone to be marketed running the Android operating system. This device cost about US$400 at its release in 2009. Since then, numerous other manufacturers have developed smartphones powered by Android for different market segments. Today, the CKW project uses Chinese manufacturer Huawei’s IDEOS handset. This is an entry-level smartphone designed in partnership with Google with Africa in mind. The device was priced at US $80 during its introduction. The success of the IDEOS led other manufacturers to enter the market, with both established firms such as Samsung and newcomers such as ZTE and TECNO offering low-cost mobile devices. This development is expected to reduce the operation costs of the CKW project further in the future. The handsets are optionally provided together with ReadySets. These devices, developed by Fenix International, a Silicon Valley based renewable energy company, use solar power to charge the handsets. CKWs who receive ReadySets are encouraged to engage in cost recovery by offering mobile phone charging services to other community members.

The CKW model differs from other interventions that use ICT as a mode of information transmission in several ways. First, it aims to provide farmers with a comprehensive information package, increasing the chances that farmers will act upon it. For instance, while some initiatives may deliver price data to farmers, it may not be possible for farmers to use this information to their benefit because they lack access to transport. This lack of access to transport not only means farmers cannot cash in on their

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2 The apps can be downloaded from Google Play for free on Android 2.3 (Gingerbread) devices. CKW Survey is used for simple data collection by CKWs in the field. CKW Pulse is an app that allows CKWs to communicate with the headquarters. In this study, we will only be concerned with the CKW Search app.

3 www.grameenfoundation.applab.org/.

4 Android is a mobile operating system for mobile devices such as smartphones and tablet computers developed by Google. It is based upon the Linux kernel and open source software.

5 When we think of other similar interventions, we may be disproportionately referring to SMS-based price-dissemination services, such as the one evaluated by Falchamps and Minten (2012). This is because they are the most widely used mode of information delivery in Uganda, and probably in the rest of the developing world as well.
knowledge of prices in consumer markets because of their inability to transport the commodities directly, but any threat to do so when used against a middleman to negotiate a better price will appear incredible. The CKW app therefore also has a directory of traders in different regions.

Another characteristic feature is the fact that the information is delivered through a CKW, a person who has been living in the community for many years and has been assigned this role by the community through democratic consultation. Clearly, having extension available within remote areas is one advantage compared to a system in which an extension worker is allocated to serve a village. Not only will this result in lower costs and better access to agricultural information and extension services, but a resident CKW knows the local context and is better able to contextualize the information obtained through the phone. CKWs are assumed to employ a more holistic approach to agricultural extension, factoring in things such as the farmer’s ability to deal with risk. Again, the idea is to increase the chances that farmers will act upon the information and knowledge obtained.

A more technical difference is the fact that smartphones use mobile package data (GPRS, EDGE, UMTS), which means that information is sent and received instantly. This is not necessarily the case for SMS-based models, where messages may be held by the operator if networks are busy. Clients of SMS price information services complain that they need the information at the time of the request and that by the time the network operator releases the reply message, the information is of little use to the farmer. Smartphones also enable the information to be illustrated with pictures, which is useful for identifying plant or animal diseases, for example.
3. RESEARCH METHODS: DIFFERENCE-IN-DIFFERENCES AND FIXED EFFECTS

The impact of a development intervention such as Grameen Foundation’s CKW project (in a generic impact-assessment analysis in development studies often referred to as treatment; see Ravallion [2009]) can be calculated as the difference in the average outcome between a treatment group that received the intervention and a control group that was not exposed to the intervention. But, when using observational data, simply comparing outcomes between treated and untreated groups is unlikely to uncover the true treatment effect. If the treatment was not explicitly randomized, chances are that individuals with particular characteristics have a higher probability of ending up in one of the two groups. For example, it may be that Grameen Foundation tries to optimize the expected benefits of the CKW project by searching for locations that are particularly isolated from the rest of the world. In this case, the treated group is likely to be disadvantaged as defined by the outcome variable to begin with. The fact that a particular project will attract particular groups is what is known as selection bias.6 In this study, we will use the difference-in-differences method to account for the possibility of selection bias.7

The difference-in-differences method controls for selection bias by comparing the change in the outcome variable over time in the control group to the change in the outcome variable over time in the treatment group. Therefore, the method needs observations on the outcome variable before the intervention (usually collected in what is called a baseline survey) and after the intervention (usually collected in what is called an end-line survey) for both a treated group and a control group. If the treatment group has fared differently over time than the control group, this is interpreted as impact.

Central to the difference-in-differences approach is the parallel trend assumption. This assumption states that the counterfactual would follow the same trend over time as the control group. While we cannot test this assumption directly since one does not observe a counterfactual, we can increase the credibility of difference-in-differences in two ways. First, we try to choose a control group that is sufficiently similar to the treatment group by sampling control villages from areas reasonably close to the treatment villages to ensure that they are the same in terms of market access, climate, geology, and so on. We also statistically test whether the treatment and control population differ in a range of characteristics. Second, we add more time periods to our difference-in-differences (Angrist and Pischke 2008). In particular, instead of just using one pretreatment baseline, we add a second one. If we find that the difference in outcome for the control group between the first pretreatment and the second pretreatment baseline is not significantly different from the difference in outcome for the treatment group between the first pre-treatment and the second pretreatment baseline, we may feel more comfortable with the assumption of a parallel trend.8

Above, we defined the intervention as the mere presence of a CKW. In this case, having access to a CKW is somehow exogenous to the individual farmer and the selection bias is likely to work mostly at a more aggregate level. However, if we define the intervention as the act of seeking information from a CKW, the selection bias may be situated at the individual level. In other words, it may be that certain individuals are more likely to contact the CKW because of individual specific characteristics (for example a particular farmer likes to stay current on market price, because his deceased father taught him the importance of this information when bargaining). To control for this, we can estimate a fixed effects

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6Unless admission to the treatments was randomized. Randomization eliminates selection bias. However, in development projects, randomization may be constrained by the mission of the implementing organization to serve certain subgroups of the population, which is often defined on the basis of a continuous variable (for example “the poorest of the poor”). Randomizing a treatment among “the poor” clearly conflicts with “serving the poorest first”.

7A difference-in-differences approach is only one of several methods that try to account for the selection problem. Other quasi-experimental methods include regression discontinuity designs and propensity score matching estimators.

8Introducing more time periods in a difference-in-difference analysis, however, may lead to another problem. Bertrand, Duflot, and Mullainathan (2004) show that serially correlated outcomes in difference-in-difference studies that use many years of data leads to inconsistent standard errors, resulting in over-rejection of the null hypothesis of no effect. While this may be a substantial issue in the studies analyzed by Bertrand, Duflot, and Mullainathan (2004), which have on average 16.5 periods, we feel our three periods provide a good compromise between more time periods to defend the parallel trend assumption and less time periods to avoid serial correlation.
regression with individual-level fixed effects. However, instead of simply looking at the treatment effect in this fixed effects regression, we will investigate the number of farmer contacts with the CKW to obtain an estimate of the treatment intensity effect. It will also be informative to compare the results of a specification that controls for individual specific effects to one that controls for effects at the treatment level, as this will allow us to say something about treatment spillover effects.
4. STUDY AREAS AND DATA SOURCES USED

A difference-in-differences approach needs, at a minimum, baseline data and end-line data on both the treatment group and the control group. We collected end-line data using a survey of randomly selected treated farmers and randomly selected farmers in control populations. We concentrate on five districts in two regions in Uganda.

In the Eastern region, CKWs were trained and introduced in Kapchorwa district in 2010. Kapchorwa is on the slopes of Mount Elgon, bordering Kenya, but also covers the extensive Kapchorwa plains. The area is poorly accessible, especially during rains, when bridges in the mountains frequently wash away and the plains become flooded. As a control area, we selected Sironko, a neighboring district that shares the same geology as Kapchorwa. The primary activity is semi-subsistence agriculture with a focus on food crops such as beans, groundnuts, sorghum, millet, cassava, potatoes, and sweet potatoes. Coffee and cotton are the main cash crops.

In the Northern region, the project started in October 2010 in Gulu district and in December 2010 in neighboring Oyam district. We sampled from Lira district to assemble a control group. The north of Uganda is generally dryer and less densely populated than the rest of Uganda. Soil productivity is also lower. We collected end-line data using a survey of randomly selected treated farmers and randomly selected farmers in control populations. The interviews in treatment and control areas were done simultaneously. The survey in the Eastern region was done in August 2012 and the survey in the North was one October 2012. We interviewed a total of 606 households, about half of them registered as users of a CKW and the other half residing in areas that did not have access to a CKW.

Unfortunately, baseline data was not available for the sample of households that were not subjected to the treatment. However, we have access to data for households in the same area from the Uganda National Household Survey (UNHS) of 2005/2006. The UNHS is a household survey that is representative at the district level collected by the Uganda Bureau of Statistics with support from the World Bank. The 2005/2006 edition is particularly interesting because it included an extensive module on agriculture. The use of secondary data is assumed to be superior to other methods of baseline reconstruction, such as recall (Bamberger et al. 2004). We restricted ourselves to households from the above-mentioned treatment and control districts. These data will allow us to estimate difference-in-differences effects using repeated cross-sections.

An alternative baseline will be constructed on the basis of more recent data. Before the intervention in 2009/2010, Grameen Foundation conducted baseline surveys. However, these baseline surveys have only been administered to the treated population. We therefore need to reconstruct a baseline in 2009/2010 in the control areas. Our starting point for this reconstruction is again the UNHS 2005/2006 data. More specifically, we try to update the data from households in the control districts to what they are likely to be four years later. This is done by constructing average growth rates between 2005/2006 and 2009/2010 in the control districts for the outcome variables, using other secondary data sources. For instance, we use FIT price series data on maize from markets in control districts to calculate average maize price inflation. These average growth rates are then applied to the individual 2005/2006 data to reconstruct the 2009/2010 baseline.

Table 4.1 summarizes the resulting structure of the dataset, showing the sample sizes by region, treatment regime, and time of the survey. The earliest baseline, drawn from the UNHS 2005/2006, basically takes all households that are located in the control and treatment districts. The UNHS 2005/2006 uses a two-stage sampling design. At the first stage, enumeration areas were drawn with probability proportional to size, and at the second stage, households, which are the ultimate sampling units, were drawn using simple random sampling. Doing so leaves us with a sample of 518 households, of which about 64 percent are located in districts that would be treated in 2010. The alternative baseline is

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9 For the other outcome variables (maize marketing shares and maize productivity), we used the Uganda Census of Agriculture 2008/2009 to calculate average changes.
constructed around the random sample of treated households that was taken by Grameen prior to the intervention. This sample contains 1,989 households. As mentioned in the previous paragraph, since there were no data for a control group collected in 2009/2010, we recycled the 188 households from the control group in the UNHS 2005/2006. Finally, for the end-line data, we revisited a random sample of 1,989 treated households in 2011/2012. In the control areas, we used a two-stage cluster sampling approach, in which we first randomly selected villages from a list of all villages in the district and then randomly selected households from a list of households obtained from the village leaders.

Table 4.1 Sample design

<table>
<thead>
<tr>
<th>Year</th>
<th>Gulu/Oyam (T)</th>
<th>Lira (C)</th>
<th>Kapchorwa (T)</th>
<th>Sironko (C)</th>
<th>T</th>
<th>C</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>2005/2006</td>
<td>294</td>
<td>136</td>
<td>36</td>
<td>52</td>
<td>330</td>
<td>188</td>
<td>518</td>
</tr>
<tr>
<td>2009/2010</td>
<td>1,147</td>
<td>136</td>
<td>842</td>
<td>52</td>
<td>1,989</td>
<td>188</td>
<td>2,177</td>
</tr>
<tr>
<td>2011/2012</td>
<td>133</td>
<td>142</td>
<td>173</td>
<td>158</td>
<td>306</td>
<td>300</td>
<td>606</td>
</tr>
<tr>
<td>Total</td>
<td>1,574</td>
<td>414</td>
<td>1,051</td>
<td>262</td>
<td>3,025</td>
<td>676</td>
<td>3,301</td>
</tr>
</tbody>
</table>


Note: T = Treatment; C = Control.

One of the attractive features of a difference-in-differences study is that it does not necessitate panel data (Meyer 1995). Since one assumes the potential omitted variable bias works at the treatment level (the treated group versus the nontreated group) one can simply compare the aggregates (for example, the means or medians of the two groups). This can be done with repeated cross-sections, as long as the before and after control groups are comparable. The decision to use a repeated cross-section in the control group obviously reduces tracking costs. In addition, it eliminates the problem of panel attrition. However, it prevents us from controlling for individual specific time-invariant (potentially unobservable) effects. In the treatment group, we will also look at treatment intensity, so the treatment becomes heterogeneous at the individual level. Here we need to include individual-level fixed effects to eliminate confounding factors at this level.

Table 4.2 lists some key household characteristics of the farm households that were included in our UNHS baseline survey. For most of the characteristics, there is no significant difference between farm households that would be treated and those that would serve as control groups. The only difference is that relatively more households in the control group seem to live in urban areas. This also explains why the average size of landholdings is smaller in the control sample. Some of these characteristics would also be used in the difference-in-differences regressions with additional controls.

Table 4.2 Means of key variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Control</th>
<th>Treatment</th>
<th>Test statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Household size</td>
<td>6.13</td>
<td>6.49</td>
<td>-1.36</td>
<td>0.174</td>
</tr>
<tr>
<td>Rural</td>
<td>76.53%</td>
<td>83.63%</td>
<td>3.63</td>
<td>0.057</td>
</tr>
<tr>
<td>Male headed</td>
<td>77.04%</td>
<td>71.64%</td>
<td>1.60</td>
<td>0.205</td>
</tr>
<tr>
<td>Age head</td>
<td>42.12%</td>
<td>43.17%</td>
<td>-0.80</td>
<td>0.421</td>
</tr>
<tr>
<td>Head no formal education</td>
<td>41.81%</td>
<td>41.33%</td>
<td>-0.09</td>
<td>0.985</td>
</tr>
<tr>
<td>Number of rooms in house</td>
<td>4.24</td>
<td>3.99</td>
<td>-0.13</td>
<td>0.198</td>
</tr>
<tr>
<td>Land size</td>
<td>2.92</td>
<td>4.08</td>
<td>-3.04</td>
<td>0.002</td>
</tr>
</tbody>
</table>

Source: Author’s survey (2011/12).
Note: *A t-test was used to test equality of continuous variables; a χ²-test was used in case of proportions.
5. RESULTS

We will now investigate the causal effects of the intervention. We will start by estimating difference-in-differences models. These models will then be augmented with other control variables to check the robustness of our findings. Finally, we will look at individual treatment effects, treatment intensity, and spillover effects.

Difference-in-Differences

We start by identifying the effect of the CKW intervention on the mix of products that farmers typically grow. After that, we look at maize productivity. Much of the information CKWs disseminate attempts to connect subsistence farmers to markets. Therefore, we will also investigate whether CKWs alter the market orientation of farmers for the case of maize. Finally, we want to examine whether better access to price information significantly improves the bargaining power of the farmer when selling maize, through a higher producer price.

Impact on Crop Portfolio

We first investigate whether the introduction of a CKW in the community leads to changes in the crops that farmers grow. For instance, does the information and extension provided by CKWs lead to more households cultivating maize? In order to answer this question for a range of important agricultural commodities, we estimate the change in the percentage of households that report growing a particular crop over time for the households that did receive access to a CKW. This difference is then contrasted to the change in percentage over time for the sample of farmers who did not receive information and extension from CKWs. These differences-in-differences effects for a range of crops are displayed as the bar charts in Figure 5.1, with the whiskers indicating the standard errors of the estimates.\footnote{The difference-in-differences effects are estimated using the 2005/2006 UNHS baseline data. The agricultural module of this survey lists all crops that are cultivated on the different plots farm households have access to.}

The results suggest that access to information and extension through CKWs leads to a significant increase in the percentage of farmers growing coffee, beans, maize, and sorghum. The importance of millet, cassava, sweet potatoes, and groundnuts seems to have declined as a result of the CKW intervention. No statistically significant change in the share of farmers growing matooke and Irish potatoes is observed. The observed pattern suggests a tendency to move away from low-risk low-return crops to more risky but more commercially oriented crops.

It may seem that the increase in the importance of sorghum in farmers’ crop portfolios runs against the general trend of farmers moving away from low-risk, low-return crops to more commercially oriented crops. However, more and more, sorghum is becoming valued as a key ingredient in the commercial production of beer. For instance, in 2003, Uganda’s Nile Breweries, which is owned by SABMiller, the world’s second-largest brewer, introduced Eagle, a beer that is brewed from sorghum. The weak Ugandan shilling and high excise duties, as well as a new brewing method that avoids the long and costly malting process, give locally-sourced sorghum a clear advantage over imported barley. The resulting lager is two-thirds cheaper and closer to the traditional beer Ugandans are accustomed to, reportedly making it a huge success. This development may have increased the commercial value of a traditional food-security crop in Uganda in recent years (Ebiyau, Arach, and Serunjogi 2005).
Figure 5.1 Change in proportion of farmers reporting growing crop attributed to community knowledge workers

![Box plot showing change in proportion of farmers reporting growing crop attributed to community knowledge workers.](image)


**Changes in Maize Productivity**

Second, we examine whether CKWs have improved maize productivity. To do so, we compare amounts harvested in kilograms (kg) per area of cultivation in acres (prodacre) before and after the intervention, both for a sample of treated farmers and a sample of farmers who make up the control group. As a reference, FAOSTAT’s latest available information reports that maize productivity averaged about 643 (kg) per acre for the whole of Uganda in 2010. The results for our analysis are presented in Table 5.1.

The first model in the table uses only end-line data and is presented as a reference. It estimates the difference between treated and untreated farmers in maize productivity, but also controls for location (east or north). We find that farmers in control villages in the north have an average yield of 381 kg per acre (indicated as the constant in our regression). In the east, average productivity is significantly higher, as was expected due to the better agroecological conditions on the slopes of Mount Elgon (east). Here, farmers harvest on average 766.73 kg of maize per acre, more than the national average reported by FAOSTAT in 2010. More important, however, is that we also find a significant and positive additional treatment effect (treat): living in a treated area increases maize productivity by 116 kg per acre, irrespective of where one lives. That is, a farmer in the north that has access to a CKW will harvest on average 497 kg per acre (constant+treat). One living in the east and having access to a CKW will on average produce 882.7 kg of maize per acre (constant+treat+east).
Table 5.1 The effect of community knowledge workers on maize productivity

<table>
<thead>
<tr>
<th>Dummy variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treat</td>
<td>116.039** (45.447)</td>
<td>86.002* (50.500)</td>
<td>144.867*** (51.832)</td>
<td>174.793*** (56.866)</td>
</tr>
<tr>
<td>Mid</td>
<td></td>
<td></td>
<td>169.505** (66.447)</td>
<td></td>
</tr>
<tr>
<td>Post</td>
<td>5.111 (59.172)</td>
<td>219.726*** (52.252)</td>
<td>180.884*** (56.930)</td>
<td></td>
</tr>
<tr>
<td>East</td>
<td>385.710*** (50.741)</td>
<td>497.201*** (22.622)</td>
<td>355.947*** (35.466)</td>
<td>477.575*** (20.635)</td>
</tr>
<tr>
<td>Treat:mid</td>
<td></td>
<td></td>
<td>–87.820 (74.888)</td>
<td></td>
</tr>
<tr>
<td>Treat:post</td>
<td>29.878 (68.415)</td>
<td>–28.786 (65.532)</td>
<td>–58.886 (72.173)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>381.020*** (48.746)</td>
<td>295.451*** (49.640)</td>
<td>182.773*** (44.721)</td>
<td>133.842*** (47.713)</td>
</tr>
</tbody>
</table>

| Observations   | 389     | 1,711   | 668     | 1,990   |
| R²             | 0.143   | 0.232   | 0.265   | 0.248   |
| Adjusted R²    | 0.138   | 0.230   | 0.261   | 0.246   |
| Residual standard error | 448.172 | 455.162 | 395.329 | 438.248 |
| F-statistic    | 32.183*** | 128.694*** | 59.889*** | 109.270*** |


Note: * p < 0.10; ** p < 0.05; *** p < 0.01.

The second model (2) in Table 5.1 presents a basic pre-post treatment-control difference-in-differences model. It regresses the outcome variable (prodacre) on a constant, a treatment dummy (treat), an end-line dummy (post), and an interaction term of the treatment and the end-line dummies (treat:post). We also control for region in all specifications (east). The second model differs from the third model only in the choice of the baseline data source. While the second model uses the 2009/2010 World Food Programme (WFP) data as the baseline, the third model uses the UNHS 2005/2006 baseline. The results, regardless of which baseline data are used, suggest that the difference in productivity found in model 1 is not caused by the CKW intervention. The treated population has, on average, a higher productivity than the control population, irrespective of the timing of the measurement (treat). Depending on what baseline has been used, productivity in the treated group is 86 kg or 145 kg per acre higher to begin with than productivity in the control group. The interaction of the treatment dummy with the end-line dummy (treat:post), which measures the actual treatment effect, does not significantly differ from zero. We do, however, find a significant and positive trend in maize yields if we look at

---

11 As mentioned above, WFP did only collect baseline data in the treated population. Therefore, we will use data from the UNHS 2005/2006 to reconstruct the baseline for the control group. We updated the productivity figures to 2009/2010 by multiplying UNHS 2005/2006 productivity by a factor that represented average productivity change. The factor we used is 1.52. It was calculated on the basis of maize production and area under cultivation data taken from the UNHS 2005/2006 and the Uganda Census of Agriculture 2008/2009.
differences over a 2005/2006 to 2011/2012 period (post). But this increase is general and hence cannot be attributed to the CKW intervention. The fact that we do not find this trend when we use 2009/10 as a baseline (model 2), together with the observation that the constant in model 2 is substantially higher than in model 3 means that this general productivity increase happened in the period between the 2005/2006 baseline and the 2009/2010 baseline.

The fourth model combines the two different baseline datasets into a difference-in-differences model with multiple pre-intervention time periods. The dummy variable mid takes the value of one if the observation comes from the 2009/2010 baseline and zero otherwise. The dummy variable post takes the value of one if the observation comes from the 2011/2012 end-line data and zero otherwise. A credible treatment effect would manifest itself through a post-treatment interaction (treat:post) that is significantly different from zero together with a mid-treatment interaction (treat:mid) that is not significantly different from zero. However, we find no significant treatment effect for maize productivity (treat:post). Irrespective of the time period, treated farmers always have higher average maize productivity than farmers in the control group (treat). Also, while average productivity was significantly higher in both 2009/2010 (mid) and in the end-line data (post) compared to the 2005/2006 baseline, these increases are not significantly different between the control and treatment samples.

There may be different reasons why, contrary to our expectations, we fail to find a significant effect on maize productivity. First, measuring productivity is difficult. It requires the farmer to estimate the area that is planted with maize and the amounts harvested. Both of these quantities may be subject to substantial measurement error. In addition, it will take some time before the impact of extension information is reflected in productivity measures. For example, it may take several years of manure application before topsoil regains sufficient nutrients and micro-organisms to lead to significantly higher yields. At the moment, however, without additional research, this remains mere speculation.

Changes in Share of Maize Sold

While the previous section looked at changes in maize productivity, we now examine if the increased extension and marketing information brought by the CKWs has changed farmer participation in the market as suppliers of maize. Maize is a special crop in that it is both a staple food crop and highly marketable. As a staple food crop, it is usually preferred to other staples because of its nutritional properties and taste. However, in the face of adverse shocks, households may be obliged to sell (part of) their maize. Thus, high amounts of maize sold as a share of total maize harvested may indicate distress sales. In such cases, households tend to concentrate on the short run, and do not prioritize the nutritional outcomes of their offspring or even the availability of planting materials in the future.

Table 5.2 shows the results for the share of the total harvest that is sold (sellshare). As in the previous section, the first model compares the post-intervention situation of individuals who have access to a CKW to those who do not (treat), controlling for region (east). We see that, on average, farmers sell about 38 percent of the maize they harvest (constant). There seems to be no significant difference between farmers in the north and farmers in the east (east). In addition, there also seems to be no impact of the CKWs, as the difference between treated and control populations is not significantly different from zero (treat).
Table 5.2 The effect of community knowledge workers on share of maize harvest sold

<table>
<thead>
<tr>
<th>Dummy variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treat</td>
<td>-4.322</td>
<td>4.684</td>
<td>10.509**</td>
<td>12.054***</td>
</tr>
<tr>
<td></td>
<td>(3.032)</td>
<td>(3.636)</td>
<td>(5.159)</td>
<td>(4.215)</td>
</tr>
<tr>
<td>Mid</td>
<td></td>
<td></td>
<td>0.00000</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(5.103)</td>
<td></td>
</tr>
<tr>
<td>Post</td>
<td></td>
<td>20.834***</td>
<td>13.874***</td>
<td>20.523***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(4.008)</td>
<td>(5.121)</td>
<td>(4.052)</td>
</tr>
<tr>
<td>East</td>
<td>1.619</td>
<td>-12.075***</td>
<td>0.561</td>
<td>-11.510***</td>
</tr>
<tr>
<td></td>
<td>(3.237)</td>
<td>(1.091)</td>
<td>(2.707)</td>
<td>(1.070)</td>
</tr>
<tr>
<td>Treat:mid</td>
<td></td>
<td>-7.552</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(5.585)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4.345)</td>
<td>(5.941)</td>
<td>(4.852)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>38.029***</td>
<td>26.742***</td>
<td>24.893***</td>
<td>26.660***</td>
</tr>
<tr>
<td></td>
<td>(3.155)</td>
<td>(3.571)</td>
<td>(4.427)</td>
<td>(3.612)</td>
</tr>
</tbody>
</table>

Observations 372 1,827 526 1,981
R² 0.006 0.097 0.017 0.092
Adjusted R² 0.001 0.095 0.009 0.089
Residual standard error 29.165 22.841 28.234 23.107
F-statistic 1.171 48.969*** 2.199* 33.265***

Note: * p < 0.10; ** p < 0.05; *** p < 0.01.

Models 2 and 3 provide estimates for standard difference-in-differences regressions. As before, model 2 uses the 2009/2010 data as the baseline and model 3 the UNHS 2005/2006. We now find a positive common trend (post). Between the surveys before the intervention and the survey after the intervention, the share of maize sold increased by 13 to 20 percentage points, depending on which baseline is chosen. More importantly, we find a significant and negative treatment effect (treat:post). The presence of a CKW reduces the share of the harvest of maize that is sold in a significant way. There is some indication that the treated population sold a larger share than the control population before the intervention (treat), and that this difference is offset by the intervention.

The final model 4 again looks at all available data in one nested model. We find that there is a significant increase in the share of maize sold over time, but this effect is entirely attributed to the period between 2009/2010 and 2011/2012 (post). In addition, there seems to be evidence of a selection effect, as treated farmers have a significantly higher share of sales (treat). Most importantly, we find again that the CKW intervention reduces the share of the maize harvest sold on the market (treat:post). As anticipated, the interaction between the indicator for the baseline of 2009/2010 (treat:mid) and treatment status is not significant, indicating that the parallel trend assumption holds before 2009/2010.

As mentioned in footnote 11, also here we have no baseline data for the control group and we therefore extrapolate the baseline from the 2005/2006 UNHS data. The inflation factor, again calculated using UNHS 2005/2006 and Uganda Census of Agriculture 2008/2009 data, is now 1.34.
**Price Received for Maize Sold**

Farmers were asked the highest price they had received for maize sold over the last agricultural year (*price*). The results of four regression models similar to the ones for maize productivity and shares sold are reported in Table 5.3. The first model (1) again looks only at end-line data. We find that, at the time of the end-line survey in 2011/2012, the average price was about USh100 higher in the Mount Elgon area than in the north (*east*). Thus, farmers in the control population received on average USh513 per kilogram of maize sold in the north (*constant*), and USh613 in the east (*constant+east*). We also find a significantly positive effect of the treatment status (*treat*). Treated farmers received on average about USh91 per kilogram of maize.

### Table 5.3 The effect of community knowledge workers on the price received for maize

<table>
<thead>
<tr>
<th>Dummy variable</th>
<th>Price</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>Treat</td>
<td>91.83***</td>
</tr>
<tr>
<td>Mid</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Post</td>
<td>188.757***</td>
</tr>
<tr>
<td></td>
<td>(18.290)</td>
</tr>
<tr>
<td>East</td>
<td>100.538***</td>
</tr>
<tr>
<td></td>
<td>(26.879)</td>
</tr>
<tr>
<td>Treat:mid</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Treat:post</td>
<td>85.510***</td>
</tr>
<tr>
<td></td>
<td>(23.383)</td>
</tr>
<tr>
<td>Constant</td>
<td>513.112***</td>
</tr>
<tr>
<td>Observations</td>
<td>346</td>
</tr>
<tr>
<td>R^2</td>
<td>0.067</td>
</tr>
<tr>
<td>Adjusted R^2</td>
<td>0.061</td>
</tr>
<tr>
<td>Residual Std. Error</td>
<td>230.471</td>
</tr>
<tr>
<td>F-statistic</td>
<td>12.240***</td>
</tr>
</tbody>
</table>


Note: *p < 0.10; **p < 0.05; ***p < 0.01.

Again, models 2 and 3 present difference-in-differences models to account for possible selection bias in model 1. Model 2, uses the more recent 2009/2010 baseline data, estimates baseline price levels at about USh427 per kilogram of maize (*constant*).\(^{13}\) Unsurprisingly, we find that, for all farmers irrespective of treatment status and location, prices rose significantly between the baseline survey of 2009/2010 and the end-line survey of 2011/2012 (*post*). This general maize price inflation of about USh189 represents a 44

\(^{13}\) As mentioned in footnote 11, also here we have no baseline data for the control group and we therefore extrapolate the baseline from the 2005/2006 UNHS data. The inflation factor, calculated from time series of maize prices obtained from FOODNET and FIT Uganda, is now 2.03.
percent increase. However, on top of this 44 percent increase, farmers who had access to a CKW received an additional premium of about USh85 \((treat:post)\), such that the price at which they sold was on average about USh700. When not interacted, the treatment status is not significantly different from zero \((treat)\), meaning that the allocation of the treatment appears to have been independent of the initial prices farmers received for their maize. Model 3 uses the relatively older baseline constructed from the 2005/2006 UNHS. This fact is reflected in a much lower baseline price level \((constant)\) and a much higher absolute general price increase between the baseline and the end-line surveys \((post)\). The conclusions of a significant treatment effect \((treat:post)\) and no selection bias \((treat)\) remain the same as in model 2. The CKW premium is slightly lower, at about USh68 per kilogram.

Model 4 presents the results for the pooled sample, with all three surveys included. The average price of maize in 2005/2006 is estimated to be about USh218 in the north \((constant)\) and about USh184 in the east \((constant+east)\). These prices had increased by about USh208 by 2009/2010 due to general maize price inflation \((mid)\). By 2011/2012, they had increased by about USh395 \((post)\). There is no significant difference between the treatment and the control group before the intervention \((treat)\). In addition, the fact that the interaction between the treatment indicator and the time indicator for the 2009/2010 survey \((treat:mid)\) is insignificant lends support to the hypothesis of a parallel trend. We find a significant positive treatment effects as the interaction between the treatment indicator and the end-line dummy shows \((treat:post)\).

The robust positive effect on the price farmers receive for their maize is surprising, given that other studies such as Fafchamps and Minten (2012) do not find significant effects on prices. However, from a theoretical point of view, it is evident that price information should improve the bargaining power of the farmer. The fact that the CKW intervention leads to a more optimistic conclusion than the other studies may mean that other aspects of the intervention, as described above, are crucial in making price information productive for farmers. For instance, price information is useless if there are no alternatives to the trader the farmer is bargaining with. More research would be needed to find out exactly what types information (and in which combinations) is needed to increase bargaining power most.

**Regression Adjusted Models**

The models presented in the previous sections found no impact from the CKW project on maize productivity, a negative impact on share sold, and a positive impact on the price at which farmers sold this maize. However, apart from a dummy indicating survey site (north or east) these models did not allow for other sources of variation in the dependent variables. Therefore, in this section, we control for other variables that may reduce the residual variance. Adding additional controls also investigates the robustness of the treatment effect identified in the previous section to the inclusion of additional household characteristics, such as household size, education of the household head, and so on. We add these controls to our preferred specification, which is the difference-in-differences model that uses the UNHS 2005/2006 as a baseline (that is model 3 in the previous sections). We add controls for the size of the household \((hhsize)\), the age of the household head \((agehead)\), a dummy indicating if the household is headed by a female \((femhead)\), a dummy indicating that the education level of the household head is lower than primary \((prim)\), a dummy that is one if each household member has at least one pair of shoes \((hasshoes)\), and a dummy that is one if each household member has at least two sets of clothes \((hasclothes)\). For some of the models, we also add total area planted with maize in acres \((land)\) and the share of maize harvest sold \((sellshare)\).

The results of regression adjusted difference-in-differences regression are presented in Table 5.4. For instance, model 1 in this table expands model 3 in Table 5.1. Maize productivity, measured as kilogram harvested per acre \((prodacre)\), seems to be negatively correlated to the age of the household head \((agehead)\). According to expectations, we find that farmers who have less education have significantly lower productivity \((prim)\). The questions on clothes \((hasclothes)\) and shoes \((hasshoes)\) can be regarded as indicators of well-being, hence it is expected that they are positively related to productivity. We find
indeed that coefficients on both dummies are positive, but for shoes it is not significant. What is most important is that after inclusion of additional controls our earlier conclusions remain valid: Maize productivity, for which conditions are more conducive in the east (east), has increased over time (post). Productivity is higher in the treatment group (treat), but since this was also the case before the intervention, this higher productivity cannot be attributed to the intervention. There is no effect of the CKW intervention on maize productivity (treat:post).

Table 5.4 Difference-in-differences regressions with additional controls

<table>
<thead>
<tr>
<th>Dummy variable</th>
<th>Sellshare</th>
<th>Price</th>
<th>Sellshare</th>
<th>Price</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>Treat</td>
<td>141.284***</td>
<td>11.492**</td>
<td>16.582</td>
<td>11.926**</td>
</tr>
<tr>
<td></td>
<td>(51.881)</td>
<td>(5.171)</td>
<td>(16.717)</td>
<td>(5.319)</td>
</tr>
<tr>
<td>Post</td>
<td>183.807***</td>
<td>12.178**</td>
<td>344.579***</td>
<td>12.291**</td>
</tr>
<tr>
<td></td>
<td>(53.738)</td>
<td>(5.242)</td>
<td>(20.450)</td>
<td>(5.375)</td>
</tr>
<tr>
<td>East</td>
<td>346.243***</td>
<td>0.626</td>
<td>39.560***</td>
<td>0.916</td>
</tr>
<tr>
<td></td>
<td>(36.770)</td>
<td>(2.830)</td>
<td>(14.446)</td>
<td>(2.877)</td>
</tr>
<tr>
<td>Hhsize</td>
<td>6.697</td>
<td>0.100</td>
<td>5.404**</td>
<td>0.058</td>
</tr>
<tr>
<td></td>
<td>(5.720)</td>
<td>(0.454)</td>
<td>(2.124)</td>
<td>(0.459)</td>
</tr>
<tr>
<td>Agehead</td>
<td>−2.147*</td>
<td>−0.150</td>
<td>0.166</td>
<td>−0.147</td>
</tr>
<tr>
<td></td>
<td>(1.130)</td>
<td>(0.094)</td>
<td>(0.433)</td>
<td>(0.095)</td>
</tr>
<tr>
<td></td>
<td>(42.873)</td>
<td>(3.564)</td>
<td>(15.566)</td>
<td>(3.614)</td>
</tr>
<tr>
<td>Prim</td>
<td>−64.176*</td>
<td>−1.395</td>
<td>−33.056**</td>
<td>−1.496</td>
</tr>
<tr>
<td>Hasshoes</td>
<td>59.680</td>
<td>3.124</td>
<td>25.884*</td>
<td>3.015</td>
</tr>
<tr>
<td></td>
<td>(38.119)</td>
<td>(3.118)</td>
<td>(14.717)</td>
<td>(3.142)</td>
</tr>
<tr>
<td>Hasclothes</td>
<td>159.457***</td>
<td>5.383</td>
<td>−9.783</td>
<td>5.176</td>
</tr>
<tr>
<td></td>
<td>(52.657)</td>
<td>(4.156)</td>
<td>(18.215)</td>
<td>(4.236)</td>
</tr>
<tr>
<td>Land</td>
<td>0.068</td>
<td>−0.242</td>
<td>−0.329</td>
<td>(0.093)</td>
</tr>
<tr>
<td>Sellshare</td>
<td>0.759**</td>
<td>(0.338)</td>
<td>0.797**</td>
<td>(0.338)</td>
</tr>
<tr>
<td>Treat:post</td>
<td>−47.650</td>
<td>−19.079***</td>
<td>68.272***</td>
<td>−19.520***</td>
</tr>
<tr>
<td>Constant</td>
<td>136.365</td>
<td>29.398***</td>
<td>181.917***</td>
<td>29.332***</td>
</tr>
<tr>
<td></td>
<td>(86.980)</td>
<td>(7.173)</td>
<td>(30.544)</td>
<td>(7.238)</td>
</tr>
</tbody>
</table>


Note: *p < 0.10; **p < 0.05; ***p < 0.01.

Model 2 in Table 5.4 adds controls to model 3 in table 5.2 which takes share of maize sold (sellshare) as the dependent variable. Only one of the added controls seems to be significant. Female-headed households sell a significantly lower share of their maize on the market (femhead). All other estimates remain similar to the ones found in Table 5.2. In fact, the negative treatment effect (treat:post) seems to become even more important after controlling for household characteristics. Model 3 corresponds to model 3 in Table 5.3. While it is unclear why household size (hhsizc) is positively related to the price at which households are able to sell their maize, the effect of the education level of the household head (prim) is as expected: heads who have no or only primary education sell their maize at lower prices.
Households that report having at least one pair of shoes for each household member (hasshoes) report higher prices. Most importantly, controlling for these characteristics does not change our conclusion that the CKW intervention increases the price at which farmers are able to sell their maize (treat:post).

The remaining three models add two variables to the regressions for share sold (sellshare) and price at which maize is sold (price). We find no effect on share sold or price from the area of land that is used for growing maize, and the treatment effects remain virtually the same. In the last column, we add the share of the maize harvest sold as an explanatory variable for the price received. We find that farmers who are more engaged in business also receive higher prices. Again, the treatment effect is robust to the inclusion of this variable.

All in all, the results in Table 5.4 show that the impact (or the lack thereof) of the CKW intervention we identify is unlikely to be due to specification issues. After controlling for commonly used household characteristics, treatment effects remain as they were in simpler specifications.

### Treatment Intensity and Spillover Effects

Table 5.5 investigates whether there are additional effects associated with repeated direct, personal interactions with a CKW, which exceed those found above. In particular, we added the number of interactions each farmer had with a CKW (freq) and estimated a fixed effects model. The estimates are not significantly different from zero for any of the outcome variables, signifying that what matters is that one lives in an area served by a CKW, not how often one interacts. This suggests substantial spillover effects. There are different ways in which these effects can come about. Information may be perceived as nonrival and public, and information looked up on the smartphone during a CKW farmer interaction may be shared within the communities very quickly. It may also be that farmers who interact with a CKW are seen as model farmers and their practices are copied by other farmers.

**Table 5.5 Treatment intensity**

<table>
<thead>
<tr>
<th>Dummy variable</th>
<th>Prodacre (1)</th>
<th>Sellshare (2)</th>
<th>Price (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Freq</td>
<td>−6.463</td>
<td>−0.505</td>
<td>1.025</td>
</tr>
<tr>
<td></td>
<td>(7.227)</td>
<td>(0.369)</td>
<td>(3.408)</td>
</tr>
<tr>
<td>Post</td>
<td>−56.621</td>
<td>−17.167***</td>
<td>285.078***</td>
</tr>
<tr>
<td></td>
<td>(52.414)</td>
<td>(2.861)</td>
<td>(30.298)</td>
</tr>
</tbody>
</table>

Observations: 338 431 369
R²: 0.027 0.233 0.463
Adjusted R²: 0.009 0.096 0.163
F-statistic: 1.642 27.024*** 55.977***


Note: *p < 0.10; **p < 0.05; ***p < 0.01.

The fact that we find effects if we control for selection bias at the treatment level but not at the individual level may also provide an explanation as to why we find an effect of the intervention while other studies that evaluate similar interventions do not. The other studies treat the information as private and randomize at the individual level. If, in reality, this price information is shared with the neighbors, there will be spillover of the treatment to the control group. This will result in a smaller difference in the outcome variables between the two groups. This suggests that a better experimental design to look at the impact of ICT on outcomes of semi-subsistence farmers would take the village as the experimental unit, rather than the individual or the household.
6. CONCLUSION

In 2010, the Grameen Foundation rolled out an innovative project to deliver extension and marketing information to smallholder farmers in rural villages in some districts in the eastern and northern regions of Uganda. They equipped locally recruited individuals with Android smartphones. These devices were running a mobile application called CKW Search that can be used to search up-to-date and location-specific information related to farming and product marketing. While ICT and mobile phones in particular have been used for disseminating information in several other development projects, this model explicitly aims to increase the chances that farmers will act upon this extension and marketing information.

This paper assesses the impact of this project, employing a difference-in-differences design. In particular, we investigate whether the productivity of maize increases due to the presence of a CKW. We also look at maize commercialization and estimate the causal effect of the CKW intervention on the share of total maize harvested that has been sold in the market. Finally, we also determine the causal effect of the intervention on the highest price farmers receive during the agricultural season.

We find that the availability of a CKW in the village increases the percentage of farmers who grow high-value crops such as coffee and maize. At the other end of the spectrum, we find that CKW presence reduces the percentage of farmers who report growing food-security crops, such as groundnuts, cassava, and sweet potatoes. The latter crops typically have a lower risk of losses in the face of drought or pests and/or have lower value. It seems that access to information on agriculture and commodity marketing through a CKW induces farmers to adjust their crop portfolio, moving from low-risk, low-return to higher-return crops, but with larger variance. The CKW project may thus be useful in mitigating a particular type of poverty trap, whereby poor farmers choose low-risk, low return crops because they cannot afford risk, which in turn keeps them poor (Dercon 1996).

We also investigate the impact of the CKW intervention on maize, a crop that is valued as both a food crop and a cash crop in East Africa. The first maize-related output variable is maize productivity, as measured by kilogram harvested per acre. We do not find evidence that the presence of a CKW alters maize productivity. Second, we look at the share of the maize harvest that is marketed by the farmers. Here we find that the intervention reduces the share of maize marketed by about 15 to 20 percent. Finally, we look at the effect on the price farmers receive for the maize they sell. We find that farmers who have access to a CKW receive prices that are on average about 12 to 16 percent higher. Fixed effects models exploring effects from the number of interactions between a CKW and a farmer suggest no additional effects, which may indicate substantial sharing of the extension and marketing information obtained from the CKW.

This study finds that the CKW intervention is effective in changing crop portfolios, maize market participation, and returns from maize sales. The failure to find an effect on maize productivity may be related to the longer period that is needed for benefits to be realized. A follow-up study would be needed to test this hypothesis. The reason we find significant effects while other studies that focus on similar interventions do not may be related to the holistic approach taken by the CKW project. For instance, a CKW can not only help in identifying a disease that affects maize, but also propose a solution as well as direct the farmer to shops that sell the required pesticides. A second reason may be related to study design. The public nature of extension and price information may make an impact evaluation through a randomized experiment at the individual level inappropriate.
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