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Information Technology and Farm Households in Niger

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Abstract: This technical report seeks to understand the impact of improved access to information technology on farmers' agricultural production and marketing practices in sub-Saharan Africa, with a specific focus on Niger. Related research suggests in that access to mobile telephony can reduce communication and search costs, thereby increasing rural households' access to price and labor market information. Reducing information asymmetries should, in theory, allow households to better respond to shocks. We find that increased access to a mobile phone via an adult education program increases the diversity of crops planted, particularly marginal cash crops grown by women. This also increases the likelihood that these cash crops are grown, but does not increase the farm-gate price received.

Keywords: Agricultural prices; ICT; mobile phones; program evaluation; Niger

JEL Classification: O1, O3, O4

I. Introduction

Information technology has transformed markets in developing countries faster than ever imagined. This is particularly dramatic in the rural areas of sub-Saharan Africa, where mobile phone infrastructure often represents the first modern infrastructure of any kind. It is estimated that over 60 percent of the population in sub-Saharan Africa has access to mobile phone service, with over 400 million subscribers (ITU 2009). This technology has greatly reduced communication and search costs for rural households, especially compared with traditional methods of searching for information (Aker and Mbiti 2010).

High search costs are more than a theoretical concern, as they can have important welfare implications for rural households in sub-Saharan Africa. High search costs make it difficult for farmers to engage in optimal arbitrage; without information on the spatial distribution of prices, farmers might sell their commodities at lower than average prices in nearby markets. While policymakers have attempted to address these information constraints by providing price information via market information services (MIS), there is little evidence of their impact on farmers' behavior and welfare, perhaps because they do not provide timely information on applicable markets. As a result, mobile phone technology offers an important opportunity to overcome information constraints.

A key challenge in measuring the impact of mobile phone coverage or ownership on rural households' search costs, access to information and welfare is causal attribution. Simple correlations between mobile phone ownership and higher farm-gate prices or incomes does not imply a causal relationship. Rather, it is possible that more active and motivated farmers own mobile phones and therefore have better outcomes. This technical report therefore exploits a randomized experiment in Niger, which provided access to group mobile phones and taught farmers how to use them (Project ABC). By exploiting the exogenous variation in mobile phone access across farmers, we are able to causally identify the impact of mobile phone usage on agricultural outcomes.[2]

Results suggest that access to information technology has short-term impacts on farm households' agricultural production and marketing practices. Farm households in ABC villages planted more crop varieties, as compared with their non-mobile phone counterparts. In particular, households are more likely to grow okra, a marginal cash crop grown by women. These effects were relatively stronger in a region with better access to agricultural markets. Households also sold more of these cash crops than their non-mobile phone counterparts, but this did not receive a higher sales price. These results appear to be due to a change in farmers' search behavior: farmers in mobile phone villages sold in more markets and were more likely to search for price information, although these results are not statistically significant at conventional levels.

Prior evidence on the effect of information technology on agricultural outcomes is limited and contradictory. Goyal (2010) finds that the rollout of internet kiosks providing price information and quality-testing in India resulted in higher soybean prices for farmers. Similarly, Jensen (2007) finds that the introduction of mobile phone coverage increased fishermen's sales prices and

[2]A detailed discussion of the ABC program, and its impact upon adult learning outcomes, is provided in Aker, Ksoll and Lybbert (forthcoming).

reduced their losses. By contrast, Aker and Fafchamps (2011) find that the rollout of mobile phone coverage did not affect farm-gate prices in Niger, and Fafchamps and Minten (2011) find a mobile phone-based price information system had no effect on the farmers' sales prices.

Theoretically, there is little reason to believe that the introduction of mobile phones would lead to an increase in farm-gate prices in *all* countries for *all* crops. If markets function well, then price differences across markets might be lower than transport costs and improved access to information would have no impact. However, if markets are poorly integrated or controlled by a few large traders, then access to information could allow farmers to bargain for higher prices and could create incentives to produce more diverse crops. Yet this partially depends on the assumption that there are no credit market failures, and that markets are competitive.

The remainder of the paper is organized as follows. Section II summarizes the theoretical background on search costs and welfare. Section III provides background information on agricultural production and marketing in Niger as well as the randomized project. Section IV describes some key features of the data, whereas Section V outlines the estimation strategy. Section VI presents the results and Section VII concludes.

II. Theoretical Framework

Economic theory relies upon the assumption that all market agents have access to the necessary price information to engage in optimal arbitrage (Jensen 2007, Aker 2010). Yet information is rarely costless or symmetric, particularly in developing countries with high search costs. As a result, price differences between two markets might exceed transport costs, even for homogenous products.[3] This can lead to the inefficient allocation of goods, and overall lower producer and consumer welfare (Stigler 1961, Reinganum 1971, Pratt, Wise and Zeckhauser 1979, Stahl 1989, Brown and Goolsbee 2002, Baye, Morgan and Scholten 2007). While improved access to information could potentially reduce price dispersion and lead to net welfare gains, the distribution of these gains among farmers, traders and consumers is ambiguous (Jensen 2007, Aker and Fafchamps 2011, Andrianarison 2011).[4]

In markets where traders link farmers to markets, farm-gate prices can be thought of as the outcome of a bargaining process between farmers and sellers (Svensson and Yanagizawa 2009). This is especially relevant in the presence of high search costs, as is the case when farmers must physically travel to markets to learn about prices. In these cases, rather than spend time and money in searching for price information, farmers might decide to sell their crops at a price that is lower than average market prices.

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[3] Other reasons for special misallocation could be political. For example, Dreze and Sen cite political interference as a reason for spatial misallocation of commodities, which prevents prices directing resources to areas of scarcity (Dreze, J. and A. Sen (1995). *The Political Economy of Hunger*, Oxford: Clarendon Press.)

[4] Andrianarison (2011) has developed one of the few formal models of inter-market arbitrage in a developing country, and the impact of mobile phone technology on spatial arbitrage opportunities. The model predicts that while the introduction of mobile phone technology improves overall welfare, farmers might lose. Standard trade models also suggest that that farmers in areas with traditionally higher prices will receive lower prices on average, as farmers from further markets sell their products in the high price markets.

The introduction of mobile phone technology could potentially affect farmers' agricultural outcomes and welfare in a number of ways. First, mobile phones could potentially reduce farmers' search costs, thereby allowing them to obtain price information in a greater number of markets and sell in the market with the highest price net transport costs. Second, in the absence of selling in a different market, improved access to information could potentially improve farmers' bargaining position vis-à-vis traders, thereby allowing them to negotiate a higher sales price. Third, mobile telephony could potentially allow farmers to conclude a sale via the mobile phone, thereby reducing uncertainty associated with selling in a distant market. Fourth, if information technology increases the prices that farmers receive, and agricultural production is price elastic, then this would increase the production of such commodities in the future.

The potential impacts of information technology on agricultural outcomes depend upon a variety of assumptions. In general, farmers are more likely to benefit when search costs are indeed the reason for large differences in prices between the farm-gate and the market or between different markets. Furthermore, the impacts are likely when there are not other market failures affect farm-gate prices, such as credit constraints or uncompetitive markets. This is evident in the recent by growing literature on the impact of information technology on farmers' welfare: While Jensen (2007) and Goyal (2010) find that information technology improved farmers' and fishermen welfare in India (leading to higher farm-gate prices), Aker and Fafchamps (2011) found no effect on farm-gate price levels in Niger. In the context of specific projects that provided price information via mobile phones, neither Fafchamps and Minten (2011) or Camacho and Conover (2011) found that the mobile phone-based price information had a statistically significant impact upon farm-gate prices. While all of these papers focus on different types of information technology, different contexts and different commodities, these divergent results suggests that the impact of information technology on agricultural outcomes is context-specific.

III. Context of the intervention

3.1. Agriculture in Niger

Niger is landlocked country located in the Sahelian region of West Africa, and one of the poorest countries in the world. With a unimodal rainfall distribution and an average of 500 mm of rainfall per year, the country is heavily dependent upon rainfed agriculture, and is subject to frequent droughts. Primary staple food crops are millet and sorghum, and cash crops are cowpea, peanut and sesame. These commodities are traded via a national system of agricultural markets, each of which is held on a weekly basis. On average, farmers live 10 km from the nearest market, and travel to such markets on foot and via donkey carts on unpaved roads (Aker 2008).

The role of women in agricultural production and marketing is crucial towards understanding the potential impacts of information technology. While women and men jointly produce staple food and cash crops on common land, women often produce marginal cash crops – such as okra, voandzou and sesame – on marginal lands. The role of women in agricultural marketing partially depends upon the geographic location and ethnicity: Women of the Zarma ethnic group are more likely to travel to markets than their Hausa counterparts. Women in Zinder are generally less likely to visit markets (25 percent).

3.2. Mobile Phone Intervention

The results in this paper are based upon data from a randomized intervention in Niger. Between 2009 and 2011, Catholic Relief Services, an international non-governmental organization, implemented an adult education program across 113 villages in two regions of Niger (Dosso and Zinder). In an effort to improve the relevancy and effectiveness of the adult education program, simple mobile phones were incorporated into the adult education curriculum, known as Project ABC. Participants in ABC villages received a shared mobile phone, and learned how to operate the mobile phone during courses (Aker, Ksoll and Lybbert, forthcoming). In an effort to measure the impact of the ABC program on adult outcomes, villages were randomly assigned to the standard adult education program or the ABC program.

IV. Data

4.1. Data Description

The data used in this report are derived from household surveys conducted with 1,038 farm households across 96 villages in January 2009 and January 2010. Survey respondents were chosen at random from among all literacy participants in the village, with half of the respondents among female literacy participants. The survey collected information on household socio-demographic characteristics, agricultural production and marketing, assets and mobile phone usage and ownership, search activities and costs, knowledge about prices and interactions with traders.

4.2. Summary Statistics

Table 1 suggests that ABC and non-ABC households were largely similar before the program. Average household size was eight, and over 60 percent of households had experienced a drought in the past year. Households cultivated an average of five different crops, primarily millet, sorghum and cowpea. Thirty-percent of households owned a mobile phone prior to the program, and over 50 percent of households had used a phone since the previous harvest.

V. Estimation Strategy

5.1. Estimation Strategy

We estimate the impact of the ABC program on farm households' agricultural production and marketing behaviour using a difference-in-differences approach, comparing outcomes of the treatment (ABC) and control (non-ABC) before and after the program:

(1) $$y_{iv} = \beta_0 + \beta_1 mobile_v + \beta_2 post_t + \beta_3 mobile_v * post_t + \mathbf{X'}_{iv}\gamma + \vartheta_R + \varepsilon_{iv}$$

In this specification, y_{iv} is defined as the outcome of interest for farm household *i* in village *v*. This includes the types of crops the farm household decided to cultivate, the quantity of each commodity produced, the likelihood of selling a particular commodity, the quantity sold and the price received for the commodity during the most recent transaction. $Mobile_v$ is a binary variable, equal to 1 if the farm household lived in an ABC village, 0 otherwise, whereas *post* is a binary variable equal to one after the first year of the program. X_{iv} is a vector of time-invariant household variables, whereas ϑ_R are sub-regional fixed effects. The primary coefficient of interest is β_3, which captures the effect of mobile phones on the outcomes of interest. As villages were randomly assigned to the ABC program, assuming that the randomization "worked", we can interpret this coefficient as the causal impact of the program. Nevertheless, it is important to note that this represents the impact of learning how to use a mobile phone during an adult education program, as compared to participating in a simple adult education program.[5]

VI. Results

6.1. Impact on Agricultural Production

Table 2 presents the results from a regression of equation (1) on farmers' crop choices, as measured by the number of crops cultivated during the previous agricultural season. Overall, farmers in the ABC villages cultivated between .33 and .42 more crops as compared to their non-ABC counterparts, with a statistically significant difference between the two. This represents an eight-percent increase as compared to the baseline number of crops cultivated.

Table 3A disaggregates these effects separately by the different geographic regions in the study (Dosso and Zinder). While both regions are in the same agro-climatic zone of Niger, Dosso is relatively closer to the capital city (Niamey), has a higher density of agricultural markets and is in closer geographic proximity to Nigeria. In addition, while households in both regions are predominantly from the Hausa ethnic group, households in the Dosso region also include the Zarma ethnic group.

The analysis by geographic region reveals that the impact of the program is primarily in the Dosso region. Households in ABC villages planted an average of .48 more types of crops as compared with their non-ABC counterparts, with a statistically significant difference between the two. While the number of crops cultivated in ABC villages was also higher in Zinder, there is not a statistically significant difference between the two. Nevertheless, it is important to note that there is not a statistically significant difference between the Dosso and Zinder regions.

Table 3B disaggregates these effects by gender. The analysis reveals that the impact of the program occurred primarily among those households where women participated in the ABC program: ABC households with female literacy participants produced .48-.6 1 more types of crops, with a statistically significant effect. While ABC households with male literacy participants also cultivated more types of crops, there was not a statistically significant effect.

Table 4A provides some evidence on the ways in which the ABC program affected crop choices. Overall, the mobile phone program did not increase the likelihood of farm households cultivating staple food and cash crops, such as millet, sorghum, cowpea or sesame. Rather, the program increased the likelihood that farm households cultivated marginal cash crops. Farm households in the ABC villages were 15 percentage points more likely to cultivate okra than their non-ABC counterparts, with a statistically significant difference. This crop is primarily grown by women, as is consistent with the results in Table 4B.

[5] As a robustness check, this report also conducts a simple difference specification, comparing the results of farmers in ABC and non-ABC villages after the program.

6.2. Impact on Agricultural Marketing

While the ABC program affected farm households' crop choices, a key question is whether this affected farm households' marketing behaviour. Tables 5A and 5B present the regression results using a variety of agricultural marketing outcomes. Consistent with the results in Table 4, the ABC program did not appear to affect farm households' likelihood of selling staple food and cash crops, such as millet, sorghum, cowpea, peanuts and sesame (Table 5A). Nevertheless, it did increase the likelihood that a household sold okra: Households in ABC villages were 7 percentage points more likely to sell *okra* than their non-ABC counterparts, with a statistically significant difference between the two. Households in ABC villages also sold more okra than their non-ABC counterparts, selling, on average, 26 percent more okra (Table 5B). This is equivalent to an additional 14 kg of okra sold by ABC households since the last marketing season. Considering that the average farm-gate price of *okra* ranges from US$ 0.64-$1.50 per kg in these regions of Niger, this would have translated into an additional USD$10-21 in household income per year generated by okra sales, even if ABC households did not receive higher farm-gate prices.

6.3. Mechanisms

There are several potential reasons for the improvements in agricultural production and sales in the ABC villages. This include reduced search costs related to price and weather information, thereby allowing households to make more informed planting and cropping decisions; or, similarly, using this price information to receive higher farm-gate prices.

Table 6 shows the impact of the program on a variety of outcomes related to agricultural marketing behaviour. Overall, it does not appear as if farm households changed the composition of their sales markets (Columns 1 and 2), nor did they receive a higher sales price for their commodities (Columns 3 and 4). While farmers in ABC villages were more likely to follow market information, both in general and via the mobile phone, these differences are not statistically significant at conventional levels (Columns 5 and 6). The lack of results might due to the limited number of observations for some of the regression results, thereby reducing the precision of our estimates. This could also suggest that other market failures, such as credit constraints or non-competitive markets, are preventing farmers from receiving higher farm-gate prices for these commodities.

VII. Conclusion

The results in this report clearly suggest that farmers with access to mobile phones in Niger increased the diversity of their crop choices, primarily by increasing their production of a marginal cash crop. These effects are larger in one region (Dosso) and among households with female program participants. The increase in the quantity of okra sold could have increased farm households' agricultural revenues by an additional USD $21. Nevertheless, this was not due to a change in the composition of sales markets or farm-gate prices. This suggests that, while access to information via mobile telephony reduced information asymmetries in Niger, this did not translate into higher farm-gate prices. This could be due to credit constraints, thereby forcing farmers to sell immediately after the harvest, or limited bargaining power vis-a-vis traders. Thus, the impact of information technology is highly dependent upon the local context.

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Table 1: Baseline Household Descriptive Statistics

	ABC Mean	Non-ABC Mean	Difference ABC-non-ABC
Panel A: Socio-Demographic Characteristics			
Age of respondent (in years)	37.15	37.89	-0.41
Number of household members	8.32	8.43	0.01
Number of asset categories owned	4.98	4.99	-0.03
Household owns mobile phone (1=Yes, 0=No)	0.30	0.30	0.00
Respondent has access to mobile phone	0.80	0.76	0.04
Used mobile to talk about trade in Niger	0.05	0.06	0.00
Panel B: Agro-Pastoral Production			
Household experienced drought in past year	0.61	0.64	-0.06
Farming is respondent's primary occupation	0.86	0.88	-0.02
Respondent member of a farmers' association	0.41	0.36	0.05
Household received training in agricultural marketing	0.04	0.03	0.01
Number of agricultural crops cultivated in past season	5.50	5.62	-0.03
Livestock is a source of household income	3.18	3.12	0.05
Number of livestock categories owned by household	0.91	0.90	0.00
Household has sold livestock since previous harvest	0.58	0.54	0.06

Notes: Column 1 presents the mean for ABC villages, Column 2 presents the mean for non-ABC villages. Column 3 reports the coefficient from a regression of the dependent variable on an indicator variable for ABC and sub-region fixed effects to account for randomization. Thus, Column (3) is not exactly equal to the difference between Columns 1 and 2. Results are robust to omitting the sub-region fixed effects. Huber-White standard errors clustered at the village level presented in parentheses. ***, **, * denote statistical significance at the 1, 5, 10 percent levels, respectively.

Table 2: Average Program Effects on Number of Crops Grown

	(1)	(2)	(3)
Mobile * Post	0.33**	0.43**	0.42**
	(0.14)	(0.21)	(0.18)
Mobile		0.01	
		(0.16)	
Post		0.95***	0.95***
		(0.16)	(0.12)
Female	0.21***	0.12*	0.11
	(0.07)	(0.06)	(0.07)
Sub-region fixed effects	Yes	Yes	No
Village fixed effects	No	No	Yes
Number of observations	989	2,022	2,022
R^2	0.16	0.17	0.23

Notes*:* Column 1 presents results from a simple difference regression which includes data only for January 2010. Columns 2 and 3 present results from difference in difference regressions. Sub-regional fixed effects control for the level of randomization. ***, **, * denote statistical significance at the 1, 5 and 10 percent levels, respectively. Robust standard errors clustered at the village level.

Table 3A: Number of crops grown by region

	Dosso			Zinder		
	(1)	(2)	(3)	(4)	(5)	(6)
Mobile * Post		0.49**	0.48**	0.21	0.31	0.31
		(0.19)	(0.19)	(0.24)	(0.31)	(0.31)
Mobile	0.48***	0.06			-0.00	
	(0.14)	(0.21)			(0.19)	
Post		0.54***	0.54***		1.38***	1.38***
		(0.11)	(0.12)		(0.25)	(0.25)
Literacy * Post		0.17**	0.18**	0.18	0.04	0.03
	0.00	(0.08)	(0.08)	(0.12)	(0.10)	(0.10)
Literacy	(0.15)	0.21		0.16	0.86***	
	(0.15)	(0.16)		(0.22)	(0.20)	
Female	0.22**	0.17**	0.18**	0.20	0.03	0.02
	(0.09)	(0.08)	(0.08)	(0.12)	(0.10)	(0.10)
Sub-region fixed effects	Yes	Yes	No	Yes	Yes	No
Village fixed effects	No	No	Yes	No	No	Yes
Number of observations	515	1,045	1,045	474	977	977
R^2	0.08	0.10	0.15	0.23	0.25	0.30

Notes: Columns 1-3 report results for Dosso. Columns 4-6 report results for Zinder. Columns 1 and 4 presents results from a simple difference regression which includes data only for January 2010. Columns 2, 3, 5 and 6 present results from difference in difference regressions. Sub-regional fixed effects control for the level of randomization. ***, **, * denote statistical significance at the 1, 5 and 10 percent levels, respectively. Robust standard errors clustered at the village level.

Table 3B: Number of crops grown by gender

	Females			Males		
	(1)	(2)	(3)	(4)	(5)	(6)
Mobile * Post		0.61**	0.59**		0.23	0.22
		(0.24)	(0.26)		(0.27)	(0.29)
Mobile	0.47***	0.06		0.18	0.06	
	(0.15)	(0.21)		(0.20)	(0.21)	
Post	-0.13	0.54***	0.54***	0.01	0.96***	0.96***
	(0.14)	(0.11)	(0.12)	(0.18)	(0.18)	(0.19)
Sub-region fixed effects	Yes	Yes	No	Yes	Yes	No
Village fixed effects	No	No	Yes	No	No	Yes
Number of observations	497	1,013	1,013	492	1,009	1,009
R^2	0.15	0.17	0.26	0.19	0.18	0.27

Notes: .Column 1 presents results from a simple difference regression which includes data only for January 2010. Columns 2 and 3 present results from difference in difference regressions. Sub-regional fixed effects control for the level of randomization. ***, **, * denote statistical significance at the 1, 5 and 10 percent levels, respectively. Robust standard errors clustered at the village level.

Table 4A: Impact of ABC Program on Likelihood of Growing Specific Crops

	Millet	Sorghum	Cowpea	Oseille	Peanut	Okra	Voandzou
Mobile * Post	0.00	0.05	0.03	0.08	0.04	0.15***	0.01
	(0.00)	(0.03)	(0.02)	(0.06)	(0.07)	(0.05)	(0.06)
Mobile	-0.00	-0.01	-0.01	-0.00	-0.02	-0.08*	0.04
	(0.00)	(0.04)	(0.02)	(0.04)	(0.05)	(0.04)	(0.04)
Post	-0.00	0.10***	0.03**	0.16***	0.20***	0.12***	0.17***
	(0.00)	(0.02)	(0.01)	(0.03)	(0.04)	(0.04)	(0.05)
Female	-0.01*	-0.05***	-0.01	0.03	0.04**	0.02	0.04**
	(0.00)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Only 2010	No	No	No	No	No	No	No
Sub-region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Village fixed effects	No	No	No	No	No	No	No
Number of observations	2,022	2,022	2,022	2,022	2,022	2,022	2,022
R^2	0.02	0.09	0.05	0.08	0.26	0.17	0.24

Notes: The table present results from difference in difference regressions. Sub-regional fixed effects control for the level of randomization. ***, **, * denote statistical significance at the 1, 5 and 10 percent levels, respectively. Robust standard errors clustered at the village level.

Table 4B: Impact of ABC Program on Likelihood of Growing Specific Crop for Females

	Millet	Sorghum	Cowpea	Oseille	Peanut	Okra	Voandzou
Mobile * Post	0.00	0.08	0.04	0.11	0.02	0.24***	0.03
	(0.00)	(0.06)	(0.03)	(0.07)	(0.07)	(0.06)	(0.07)
Mobile	-0.00	-0.03	-0.01	-0.01	0.00	-0.11*	-0.00
	(0.00)	(0.05)	(0.03)	(0.06)	(0.06)	(0.06)	(0.06)
Post	-0.00	0.13***	0.04**	0.15***	0.22***	0.05	0.17***
	(0.00)	(0.04)	(0.02)	(0.05)	(0.05)	(0.04)	(0.05)
Female Respondent	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sub-region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Village fixed effects	No	No	No	No	No	No	No
Number of observations	1,013	1,013	1,013	1,013	1,013	1,013	1,013
R^2	0.03	0.10	0.05	0.09	0.29	0.18	0.31

Notes: The table present results from difference in difference regressions. Sub-regional fixed effects control for the level of randomization. ***, **, * denote statistical significance at the 1, 5 and 10 percent levels, respectively. Robust standard errors clustered at the village level.

Table 5A: Impact of the ABC Program on the Likelihood of Selling Commodities

	Millet	Sorghum	Cowpea	Oseille	Peanut	Okra	Voandzou
Mobile * Post	0.04	0.01	0.00	-0.04	0.03	0.07*	0.01
	(0.07)	(0.04)	(0.09)	(0.05)	(0.04)	(0.04)	(0.04)
Mobile	0.06	0.03	-0.02	0.03	-0.05	-0.06	-0.05
	(0.05)	(0.03)	(0.06)	(0.03)	(0.04)	(0.04)	(0.03)
Post	0.01	-0.00	-0.35***	-0.00	-0.03	-0.07**	-0.01
	(0.04)	(0.02)	(0.07)	(0.03)	(0.03)	(0.03)	(0.03)
Female	-0.02	-0.02	-0.09***	-0.00	-0.01	0.00	0.06***
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)
Sub-region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Village fixed effects	No	No	No	No	No	No	No
Number of observations	2,017	2,045	2,045	2,045	2,045	2,045	2,045
R^2	0.10	0.09	0.17	0.09	0.31	0.19	0.26

Notes: The table present results from difference in difference regressions. Sub-regional fixed effects control for the level of randomization. ***, **, * denote statistical significance at the 1, 5 and 10 percent levels, respectively. Robust standard errors clustered at the village level.

Table 5B: Impact of the ABC Program on the Quantity Sold

Dependent variable: ln(Quantity sold)	Millet	Sorghum	Cowpea	Oseille	Peanut	Okra	Voandzou
Mobile * Post	0.12	0.01	-0.05	-0.15	0.17	0.26*	0.03
	(0.33)	(0.12)	(0.41)	(0.20)	(0.19)	(0.13)	(0.22)
Mobile	0.37	0.12	-0.06	0.14	-0.27	-0.24*	-0.23
	(0.23)	(0.11)	(0.30)	(0.14)	(0.23)	(0.12)	(0.18)
Post	-0.16	-0.03	-1.71***	-0.07	-0.13	-0.32***	-0.16
	(0.17)	(0.08)	(0.31)	(0.13)	(0.12)	(0.11)	(0.14)
Female	-0.31***	-0.09*	-0.53***	-0.05	-0.08	-0.01	0.20**
	(0.10)	(0.05)	(0.08)	(0.07)	(0.09)	(0.03)	(0.08)
Sub-region * Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	2,045	2,045	2,045	2,045	2,045	2,045	2,045
R^2	0.08	0.09	0.21	0.11	0.37	0.21	0.26

Notes: The table present results from difference in difference regressions. Sub-regional fixed effects control for the level of randomization. ***, **, * denote statistical significance at the 1, 5 and 10 percent levels, respectively. Robust standard errors clustered at the village level.

Table 6: Impact of the ABC Program on Marketing Behavior

Dependent variable:	Number of sales markets	Number of sales market for cash crops	Price received for okra	Price received for voandzou	Followed price information	Received price information via mobile phone
Mobile * Post	0.21	0.20	-16.41	160.44	0.01	0.03
	(0.19)	(0.23)	(13.05)	(162.46)	(0.05)	(0.02)
Mobile	-0.11	-0.10	-3.24	-336.27	-0.04	
	(0.14)	(0.17)	(37.63)	(204.21)	(0.04)	
Post	-0.80***	-0.92***	12.38	-156.15	0.06**	-0.02
	(0.14)	(0.16)	(9.57)	(161.16)	(0.03)	(0.01)
Female	-0.29***	-0.23***	-5.66	180.03	-0.22***	-0.03**
	(0.06)	(0.07)	(19.16)	(111.88)	(0.02)	(0.01)
Sub-region * Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	1,667	1,266	297	460	1,937	635
R^2	0.11	0.14	0.00	0.02	0.11	0.04

Notes: The table present results from difference in difference regressions. Sub-regional fixed effects control for the level of randomization. ***, **, * denote statistical significance at the 1, 5 and 10 percent levels, respectively. Robust standard errors clustered at the village level.