Econometrics Replication

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1. Introduction

1.1. *Mechanism of the Effect and Literature Review*

Previous literature has consistently shown that adult education programs play a key role in reducing poverty rates in various regions (Oxenham 2002; Ortega & Rodríguez 2008), but previous designs suffer from irrelevance to daily work and high dropout rates. Therefore, it is necessary to think of a way to directly help adults gain the benefits of education. This paper proposes an innovative strategy to empower adults by teaching them to use mobile phones to acquire essential skills. Compared to other educational programs, teaching people how to use cell phones effectively has several advantages.

First of all, cell phone use can help improve learning ability in various fields, although this effect is short-lived (Barrow *et al.* 2009). Second, cell phones is a good access to multiple knowledge online, so people who have access to cell phones can self-study which is far better for students to improve their long-term study score (See-To *et al.* 2012). Moreover, Cell phone use is a good way to get information about employment opportunities and they are more likely to find a job(Grzybowski & Patel 2023), and therefore, people will find the program of great use in daily life. Moreover, for farmers, mobile phones are a good access to get accurate and timely agricultural information to avoid the reduction of grain price dispersion, which has been demonstrated by (Aker 2010). Other influential effect are also discussed by (Gonzalez & Maffioli 2024; Aker & Mbiti 2010; Cheng 2015).

1.2. *Experimental design*

This paper uses randomized controlled trials (RCTs), which are widely used in economic design and are a common practice to avoid bias or intentional manipulation of results. By selecting 113 eligible villages in Niger, Dosso, and Zinder and randomly assigning cohorts of 58 villages with ABC, this study begins a five-period panel data. The ABC villages follow the same curriculum as the non-ABC villages, but the ABC policy is introduced three months later to help the students learn.

Only membership in a formal or informal producer association at the village level, illiteracy as confirmed by an on-site diagnostic test, and willingness to participate in the program were required to implement the cohort. If there were more than 50 eligible applicants in a village, students were randomly selected from all eligible applicants through a public lottery. To measure student progress, writing and math tests were administered in baseline surveys before the program began, and follow-up surveys were administered twice during the program (June 2009 and June 2010) and seven months after classes ended (January 2010 and January 2011).

2. Main Result

2.1. *Baseline Specification*

Before we introduce the main result, we first need to check whether the difference-in-difference assumption is valid.

$$Test_{ivt} = \beta_0 + \beta_1 ABC_v + \mathbf{X'_{iv}} + \tau_{\mathbf{vt}} + \varepsilon_{\mathbf{ivt}}, \tag{2.1}$$

where $Test_{ivt}$ is the test score of individual i in village v at time t, ABC_{ivt} is a dummy variable indicating whether the individual has a mobile phone, $\mathbf{X'_{iv}}$ is a vector of individual characteristics, τ_{vt} is subdistrict fixed effect and ε_{ivt} is the error term. The result is reported in Table 1 and the standard error is clustered at each village level.

The result shows that the test score is not significantly higher in the treatment group than in the control group, which indicates that the RCT assumption is valid. This is because if the random experiment is not valid, the coefficient of β_1 will be statistically significant, which means that selecting which group to be the treatment group in our experiment is not random.

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‡ Note that all the relevant codes and details of replication this PDF file is available at github. This repository will be modified to delete the instructions and only contain the latex code and stata, python code with the data. Link: https://github.com/sergiozxy/Replication-Econometrics.

TABLE 1. Difference in Test Scores between the Treatment and Control Groups

	(1) literacy	(2) literacy	(3) math	(4) math
abc	-0.0231	-0.0291	-0.0593	-0.0671
	(0.0400)	(0.0420)	(0.0469)	(0.0495)
female		-0.133***		-0.218***
		(0.0348)		(0.0375)
age		-0.00236**		-0.00153
		(0.00104)		(0.00104)
dosso		0.359***		0.197**
		(0.0843)		(0.0762)
N	5982	5675	5982	5675
R-squared	0.0224	0.0278	0.0199	0.0339

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Note: we also include subdistrict fixed effect in each regression model.

TABLE 2. Household and teacher characteristics in the treatment and control regions

Variable	Mean without abc	SD without abc	Mean with abc	SD with abc	Diff	std
Panel A: pre-program household characteristics						
age	37.86	13.10	37.18	11.76	-0.36	(0.93)
Are you the household head?	0.560	0.497	0.547	0.498	-0.01	(0.02)
Respondent is Hausa	0.715	0.452	0.721	0.449	0.01	(0.03)
Number of household members	8.422	4.054	8.328	4.074	0.02	(0.25)
Percentage of children under 15 who have some education	0.279	0.276	0.269	0.270	-0.00	(0.02)
Number of asset categories owned by household	4.990	1.609	4.979	1.575	-0.03	(0.10)
Household experienced drought in past year	0.385	0.487	0.380	0.486	-0.03	(0.03)
Household owns a cell phone (excluding group phone)	0.296	0.457	0.295	0.457	-0.00	(0.03)
Access to household or village-level cell phone	0.763	0.426	0.798	0.402	0.04*	(0.02)
Respondent has used cell phone since last harvest	0.542	0.499	0.573	0.495	0.04	(0.03)
Respondent has made call	0.691	0.463	0.725	0.447	0.03	(0.04)
Respondent has received call	0.858	0.349	0.868	0.339	0.03	(0.03)
Panel B: pre-program Teacher characteristics						
Level of Instruction of Teacher	8.323	2.084	8.572	1.779	0.08	(0.22)
Age of Teacher	33.06	9.158	32.71	8.067	-0.31	(1.18)
Female Teacher	0.317	0.467	0.368	0.484	0.06	(0.04)
Teacher from Same Village	0.757	0.430	0.682	0.467	-0.02	(0.05)
Panel C: pre-program Test-Score characteristics						
Baseline literacy test Z-score	-1.03e-08	1.000	-0.0269	0.886	-0.02	(0.04)
Baseline numeracy test Z-score	-6.69e-09	1.000	-0.0712	0.816	-0.06	(0.05)

Notes: * significant at the 10 percent level; ** significant at the 5 percent level; *** significant at the 1 percent level.

2.2. *Contamination Check*

Apart from testing the direct effect of ABC_v on the test score, we also need to check whether there is any contamination between the treatment and control groups. The contamination check is to test whether the treatment group and the control group are significantly different in terms of household and teacher characteristics. To check whether it is significantly zero, we also use the Equation (2.1) to check if the policy ABC_v contains the problem.† The result is shown at Table 2.

The summary statistics is reported in Table 2. We can see that before the program starts, all of the variables are not significantly different between the control group and the treatment group, indicates that there is no pre-treatment contamination. In addition,

† Note that using two-tailed t-test is equivalent for using regression in dummy variable setting and we also correct for individual fixed effect and cluster the standard error at village level, which means that our result is more robust.

TABLE 3. Difference-in-Difference Estimation of ABC policy

	(1) literacy	(2) math	(3) literacy	(4) math	(5) literacy	(6) math	(7) literacy	(8) math
abc	-0.0511	-0.0952*	-0.0551	-0.106*	-0.0556	-0.106*	0.200***	0.230***
	(0.0465)	(0.0548)	(0.0503)	(0.0594)	(0.0503)	(0.0593)	(0.0409)	(0.0424)
post	-0.00397	-0.00444	-0.00525	-0.0103	-0.00414	-0.00931	-0.0121	-0.0270
	(0.0587)	(0.0658)	(0.0599)	(0.0680)	(0.0599)	(0.0681)	(0.0602)	(0.0692)
abcpost	0.199**	0.250***	0.206**	0.264***	0.205**	0.263***	0.198**	0.258***
	(0.0880)	(0.0898)	(0.0881)	(0.0923)	(0.0881)	(0.0923)	(0.0901)	(0.0943)
age			-0.0100***	-0.00890***	0.00352	0.00347	0.00355	0.00147
			(0.00102)	(0.00107)	(0.00406)	(0.00436)	(0.00385)	(0.00408)
female			-0.423***	-0.378***	-0.420***	-0.375***	-0.420***	-0.374***
			(0.0325)	(0.0326)	(0.0321)	(0.0324)	(0.0319)	(0.0325)
agesq					-0.000176***	-0.000160***	-0.000173***	-0.000128**
					(0.0000494)	(0.0000550)	(0.0000476)	(0.0000508)
Region Dummy	N	N	Y	Y	Y	Y	N	N
Village Fixed Effect	N	N	N	N	N	N	Y	Y
Subdistrict Fixed Effect	N	N	Y	Y	Y	Y	N	N
N	13402	13420	12823	12840	12823	12840	12823	12840
R-squared	0.0323	0.0387	0.0841	0.0824	0.0852	0.0834	0.131	0.139

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

the sample means of the variables between groups are close to each other, which also supports the setting of a parallel trend before the assumption of the model because of $E[Y_0|D=1] = E[Y_0|D=0]$.

2.3. *Difference-in-Difference Estimation*

To carry out our formal analysis, we consider the following setting:

$$Test_{ivt} = \beta_0 + \beta_1 ABC_v + \beta_2 Post_v + \beta_3(ABC_v \times Post_v) + \mathbf{X}'_{\mathbf{iv}} + \delta\mathbf{cohort_v} + \theta_{\mathbf{R}} + \varepsilon_{\mathbf{ivt}} \tag{2.2}$$

where $Test_{ivt}$ is the test score of individual i in village v at time t, ABC_v is a dummy variable indicating whether the village is in the treatment group, $Post_v$ is a dummy variable indicating whether the test is conducted after the program, $\mathbf{X}'_{\mathbf{iv}}$ is a vector of individual characteristics, $cohort_v$ is a dummy variable indicating the cohort, θ_R is a randomization error, and ε_{ivt} is the error term. The $ABC_v \times Post_v$ is our DID estimator, which represents the effect after the policy's implementation.

First of all, our DID estimation satisfies the condition of Irreversibility of Treatment. Moreover, the parallel trend condition also holds based on what we have discussed on 2.1 and 2.2. Therefore, we can conclude that our estimated effect ATT is consistent (Callaway & Sant'Anna 2021). The result is shown at Table 3.

From the table, we can see that for column (1) and (2), the coefficient of $ABC_v \times Post_v$ is positive and significant at the 1 percent level, which means that the ABC policy has a positive effect on the test score. The magnitude of the effect is 0.199 and 0.250, which means that the ABC policy can increase the test score by 19.9% to 25.0% points. This result is consistent with the previous literature, which shows that the ABC policy can improve the test score of students. In column (3) and (4) we include controls in the model, and we find that the effect is still significant at the 1 percent level, which means that the effect is robust to the inclusion of controls. Furthermore, the estimated value is close to the previous result, which means that the effect is robust to the inclusion of controls. However, it is likely the relationship between age and test scores is non-linear, therefore, we also include the quadratic term of age in the model. The result is shown in column (5) and (6), and we find that the effect is still significant at the 1 percent level, which means that the effect is robust to the inclusion of the quadratic term of age. However, the magnitude of the effect is slightly higher than the previous result, which means that the effect is sensitive to the inclusion of the quadratic term of age. The change may be due to the fact that math is pretty hard for the old people to learn, and the quadratic term of age can capture this effect, but the overall estimated result is the same. Lastly, we also include a village fixed effect in the model, and the result is shown in column (7) and (8). We find that the effect is still significant at the 1 percent level, which

TABLE 4. DDD Estimation of ABC policy

	(1) literacy	(2) math	(3) literacy	(4) math
abcpost	0.188	0.170	0.175*	0.259**
	(0.155)	(0.136)	(0.0994)	(0.106)
abc	-0.0645	-0.0920	-0.0364	-0.129*
	(0.0709)	(0.0667)	(0.0616)	(0.0769)
post	-0.0647	-0.0723	0.237***	0.0926
	(0.110)	(0.109)	(0.0637)	(0.0791)
cohort2009	0.0761	0.150***	0.0762	0.149***
	(0.0470)	(0.0444)	(0.0469)	(0.0446)
female	-0.421***	-0.377***	-0.142***	-0.277***
	(0.0323)	(0.0327)	(0.0489)	(0.0599)
age	0.00330	0.00292	0.00312	0.00294
	(0.00419)	(0.00440)	(0.00417)	(0.00441)
agesq	-0.000173***	-0.000155***	-0.000171***	-0.000155***
	(0.0000507)	(0.0000554)	(0.0000506)	(0.0000553)
femalepost			-0.494***	-0.237***
			(0.0637)	(0.0668)
femaleabc			-0.0360	0.0629
			(0.0685)	(0.0759)
abcfemalepost			0.0514	-0.000982
			(0.0920)	(0.0990)
Subdistrict Fixed Effect	Y	Y	Y	Y
N	12823	12840	12823	12840
R-squared	0.0867	0.0906	0.0995	0.0923

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

means that the effect is robust to the inclusion of the village fixed effect. The magnitude of the effect is 0.198 and 0.258, which is consistent with the baseline DID estimation.

3. Heterogenous Effect of ABC program

We first consider the influence of geography on this policy, as Dosso is a region closer to the capital city, its farmers will be more inclined to go to the capital city market to trade, so they will be more active in using mobile phones because they can directly help them to get price information (Wyche & Steinfield 2016) Thus, we can use the DDD method to estimate the heterogeneous effect of geography on this policy. In addition to this, we can also consider the gender difference, because men in rural areas are the ones who mainly trade with the outside world, they will be more inclined to communicate with people in neighboring villages and towns, so men will be more inclined to use mobile phones to get more knowledge information. For this reason, we consider the DDD model further on equation (2.2) and the result is shown at Table 4.

$$\begin{aligned} Test_{ivt} &= \beta_0 + \beta_1 ABC_v + \beta_2 Post_v + \beta_3 Region_v + \beta_4 (ABC_v \times Post_v) + \beta_5 (ABC_v \times Effect_{ivt}) \\ &+ \beta_6 (Post_v \times Effect_{ivt}) + \beta_7 (ABC_v \times Effect_{ivt} \times Post_v) + \mathbf{X}'_{\mathbf{iv}} + \delta \mathbf{cohort_v} + \theta_{\mathbf{R}} + \varepsilon_{\mathbf{ivt}} \end{aligned} \tag{3.1}$$

where $Effect_{ivt}$ is the dummy variable indicating the effect of the regional spatial effect and gender inequality effect.

From the Table we can see the coefficient β_7 is not significant at 10% percent, which means that neither the regional spatial effect nor the gender inequality effect is significant, which means that the ABC policy has the same effect on different regions and different groups. Therefore, we can conclude that our estimated effect is consistent and robust.

4. Conclusion

This paper estimates the effect of the introduce of mobile phone on the test score of adult training in Niger, Dosso, and Zinder. We find that the introduction has a positive effect on the test score of students. The magnitude of the effect is 0.199 and 0.250, which means that the introduction of mobile phone usage can increase the test score by 19.9% to 25.0% points. The effect is robust to the inclusion of controls, the quadratic term of age, and the village fixed effect. Moreover, we test the hypothesis of the heterogeneous effect of geography and different gender groups, and we find that the effect is not significant, which means that the ABC policy has the same effect on different regions and different groups. Therefore, we can conclude that our estimated effect is consistent and robust.

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Appendix A.

This appendix contains the code that is used to replicate the main result of the paper.

```
*** Program name: Sample Do File.do

* NOTE: Whenever a line begins with an asterisk, STATA ignores the whole line - this is just a
    comment/note.
capture log close
clear /* The 'clear' command gets rid of all data in memory*/
set memory 60000 /* Allocate 60MB memory to Stata */
set matsize 150
set more 1

* This line tells Stata where the files are located. USE "" if your folder names contain spaces.
* THIS IS THE ONLY LINE YOU NEED TO CHANGE.

* NOTE: The next lines set up the .log file. It will contain all of the output
* from this program when it is run. It will be saved in the same directory as the
* program and will be replaced with each new run. I have called the log-file ProblemSet1.
log using Replication.log, replace

cd "E:\umich\Replication-Econometrics\02. Datasets"

use "ABChousehold.dta", clear

/***************TABLE 0 *******************/
// Export the label and variable name

label variable age "age"
// this code is to export the name and label for further use. (make table in python)

preserve
    describe, replace clear
    list
    export excel using variable__label_correspondence.xlsx, replace first(var)
restore

use "ABCteacher.dta", clear

preserve
    describe, replace clear
    list
    export excel using variable__label_correspondence_teacher.xlsx, replace first(var)
restore

use "ABCtestscore.dta", clear

preserve
    describe, replace clear
    list
    export excel using variable__label_correspondence_test_score.xlsx, replace first(var)
```

```
restore

/***************TABLE 1 *******************/
// We test whether the treatment group is assigned via non-randomization manipulation

use "ABCtestscore.dta", clear

reg writez1 abc i.avc, cluster(codev)
est store base_line_1

reg writez1 abc female age dosso i.avc, cluster(codev)
est store base_line_2

reg mathz1 abc i.avc, cluster(codev)
est store base_line_3

reg mathz1 abc female age dosso i.avc, cluster(codev)
est store base_line_4

esttab base_line_1 base_line_2 base_line_3 base_line_4 ///
 using ../manuscript/Tables/baseline_check.tex, ///
style(tex) booktabs keep(abc) ///
mtitle("log(income)" "price concession" "log(lead times)") ///
star(* 0.1 ** 0.05 *** 0.01) ///
se ///
scalars("r2 R-squared") ///
 replace

clear

/***************TABLE 2 *******************/

use "ABChousehold.dta", clear

keep if year==2009

/******** NOTE ********/

// For Table one, I generated two versions
// one version is consistent with the description of the guide file
// another version is consistent with the original paper's result, because:
// I think the original paper's method is better, because it clusters the result to village level
// furthermore, it uses the subdistrict's fixed effect in the model.
// this is more robust than naive comparision of the difference

global Pre_Test_Variables age hhhead eth_hausa hhmem_no edchild_percent assets drought cellphone
    accesscellphone usecellphone makecall receivecall

// summary statistics
// I will save these results to stata dta, and use python to combine the result to latex
```

```
/*
logout, save("ttest_with_result") dta replace: ttable3 $Pre_Test_Variables, by(abc) tvalue
logout, save("ttest_with_result_mean_std") dta replace: tabstat $Pre_Test_Variables, by(abc)
    stat(mean sd) nototal long col(stat)
*/

// report the mean and standard deviation

logout, save(ttest_with_result_mean_std) dta replace: tabstat $Pre_Test_Variables, by(abc)
    stat(mean sd) nototal long col(stat) label

foreach i in $Pre_Test_Variables{
    bys abc: su `i'
    reg `i' abc, robust cluster(codev)
    xi: reg `i' abc i.avcode, robust cluster(codev)
    outreg2 abc using "Table1_PanelA", dec(2) append dta ctitle ("`var'") nocons
}

use "ABCtestscore.dta", clear

bys codev: keep if _n==1
keep codev
merge 1:m codev using "ABCteacher.dta"

// note that during our operation, we have dropped some of the codes that are not contained in
    the test score result.
// because these are not relevant to our study.
tab _m
drop if _m==2

logout, save(Table1_PanelB_mean_std) dta replace: tabstat levelno teacherage femaleteacher
    local, by(abc) stat(mean sd) nototal long col(stat)

foreach i in levelno teacherage femaleteacher local{
    bys abc: su `i'
    reg `i' abc, robust cluster(codev)
    xi: reg `i' abc i.avcode, robust cluster(codev)
    outreg2 abc using "Table1_PanelB", dec(2) append dta ctitle ("`var'") nocons
    }
clear

use "ABCtestscore.dta", clear

logout, save(Table1_PanelC_mean_std) dta replace: tabstat writez1 mathz1, by(abc) stat(mean sd)
    nototal long col(stat)

foreach i of varlist writez1 mathz1 {
    bys abc: su `i'
    xi: reg `i' abc i.avc, cluster(codev)
```

```
    outreg2 abc using "Table1_PanelC", dec(2) append dta ctitle ("`var'") nocons
    }

clear

// now run the python code in jupyter notebook to generate the latex table in paper.

/***************TABLE 3 *******************/
/* Difference-In-Difference Estimation*/

use "ABCtestscore.dta", clear

keep if round==1|round==2|round==4

regress writezscore abc post abcpost i.avc, robust cluster(codev)
est store did_1

regress mathzscore abc post abcpost i.avc, robust cluster(codev)
est store did_2

regress writezscore abc post abcpost age female zarma kanuri dosso i.avc, robust cluster(codev)
est store did_3

regress mathzscore abc post abcpost age female hausa zarma kanuri dosso i.avc, robust
    cluster(codev)
est store did_4

generate agesq = age * age
regress writezscore abc post abcpost age agesq female zarma kanuri dosso i.avc, robust
    cluster(codev)
est store did_5

regress mathzscore abc post abcpost age agesq female zarma kanuri dosso i.avc, robust
    cluster(codev)
est store did_6

qui tab codevillage, gen(village_dum)

reg writezscore abc post abcpost age agesq female village_dum*, robust cluster(codev)
est store did_7

reg mathzscore abc post abcpost age agesq female village_dum*, robust cluster(codev)
est store did_8

esttab did_* ///
 using ../manuscript/Tables/did_result.tex, ///
style(tex) booktabs keep(abc post abcpost age agesq female) ///
mtitle("literacy" "math" "literacy" "math" "literacy" "math" "literacy" "math") ///
star(* 0.1 ** 0.05 *** 0.01) ///
se ///
```

```
scalars("r2 R-squared") ///
 replace

/***************TABLE 4 *******************/
/* Difference-In-Difference-In-Difference Estimation*/

use "ABCtestscore.dta", clear

keep if round==1|round==2|round==4

generate agesq = age * age
capture drop region regionpost regionabc abcregionpost
gen region=dosso==1
gen regionpost=region*post
gen regionabc=region*abc
gen abcregionpost=regionabc*post

reg writezscore abcpost abc post region regionpost regionabc abcregionpost cohort2009 female age
    agesq i.avc, robust cluster(codev)
est store ddd_1

reg mathzscore abcpost abc post region regionpost regionabc abcregionpost cohort2009 female age
    agesq i.avc, robust cluster(codev)
est store ddd_2

reg writezscore abc female post femalepost femaleabc abcpost abcfemalepost cohort2009 age agesq
    i.avc, robust cluster(codev)
est store ddd_3

reg mathzscore abc female post femalepost femaleabc abcpost abcfemalepost cohort2009 age agesq
    i.avc, robust cluster(codev)
est store ddd_4

esttab ddd_* ///
 using ../manuscript/Tables/ddd.tex, ///
style(tex) booktabs keep(abc female post femalepost femaleabc abcpost abcfemalepost cohort2009
    age agesq) ///
mtitle("literacy" "math" "literacy" "math") ///
star(* 0.1 ** 0.05 *** 0.01) ///
se ///
scalars("r2 R-squared") ///
 replace



log close

exit, clear
```