adoption: A Stata routine for consistent estimation of population technology adoption parameters

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Stata Conference, July 26-27, 2012 San Diego, California

Outline of presentation

- Background
- Population adoption parameters and functions:
 - A structural view
- ATE estimation of structural population adoption parameters
- Implementation of the Command
- Example
- Conclusion

The problem addressed

- Estimation of population *adoption* parameters for a new technology not universally <u>known</u> in the population:
 - > Mean population adoption rates
 - Population adoption gap
 - > Determinants of adoption
- Separation of adoption and diffusion concepts/factors
 - >Adoption= incidence or extent of use of a technology
 - Diffusion= extent of awareness or knowledge of the existence of a technology in the population

The Literature

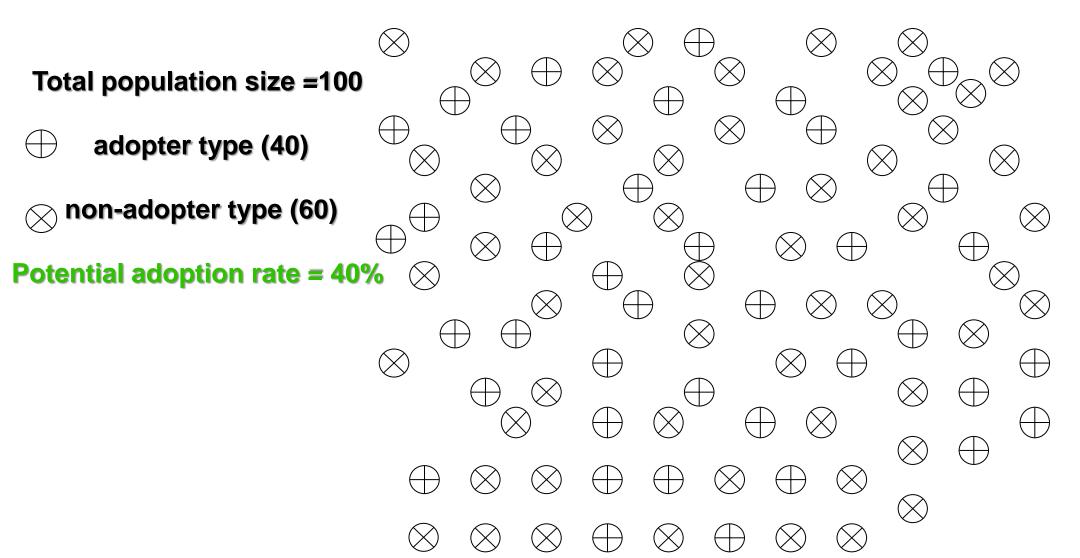
- Empirical models of adoption include source of information, contact with extension, or education as explanatory variables to account for the role of information (Feder, Just and Zilberman (1985))
- But separation of adoption and diffusion parameters remains an issue
 - Besley and Case (1993): difficulty in interpreting the coefficients of adoption models under incomplete diffusion of the technology
 - Saha et al (1994) and Dimara. and Skuras (2003): Daberkow and McBride (2003) separate models for information acquisition and adoption but discussion and estimation in terms of a classic sample selection problem

Contribution

- Stata routine that implement the estimation procedure described in Diagne and Demont. 2007. "Taking a New look at Empirical Models of Adoption: Average Treatment Effect estimation of Adoption rate and its Determinants". Agricultural Economics, Vol 37:3. pp. 201-210.
- Show that sample adoption rates and classical adoption models do not inform about population potential adoption when the awareness of the technology in the population is not universal
- Estimate parameters that allow to assess the intrinsic merit of a new technology in terms of its potential demand independently of diffusion issues

Population adoption parameters and functions: A structural view

Partitioning of a population by a technology: Structural population adoption parameters



The structural population adoption function

$$R^{K} \times R^{L} \mapsto \{ \oplus \otimes \}$$
$$(x, u) \to f(x, u)$$

adopter type
non-adopter type

x = observed covariates u = unobserved covariates

Population after partial exposure to the technology

Total population size =100

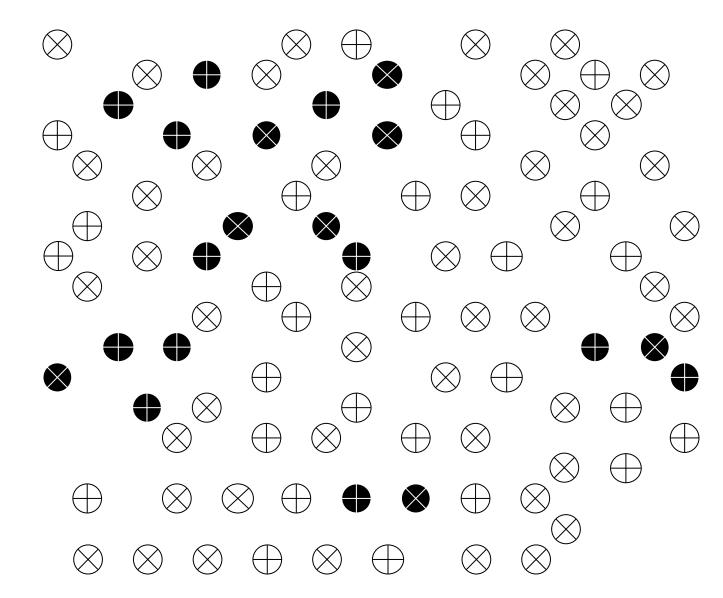
adopter type (40)
non-adopter type (60)
exposed (20)

Population exposure rate = 20%

Population adoption rate = 40%

Population exposure and adoption rate =12%

Adoption rate among the exposed: = 60%



Structural adoption and exposure functions

Adoption function

Exposure function

$$f: R^{K} \times R^{L} \mapsto \{ \bigoplus \otimes \} \text{ not observed} \qquad e: R^{M} \times R^{N} \mapsto \{ \bigcirc \bullet \} \text{ observed}$$
$$(x, u) \to f(x, u) \qquad (z, v) \to e(z, v)$$

Joint exposure and adoption function

$$\{ \bigoplus \bigotimes \}$$
 not observed
 $h: R^M imes R^K imes R^L imes R^N \mapsto \{ \bigoplus \bigotimes \bigcirc \}$ observed

$$(z, x, u, v) \longrightarrow h(z, x, u, v) = e(z, v) \times f(x, u)$$

adopter type non-adopter type

exposed
non-exposed

x, z = observed covariates u, v = unobserved covariates

Structural and classical adoption functions

The structural joint exposure and adoption function: exposure observed

$$\begin{array}{cccc} \{ \bigoplus \otimes \} & \text{not observed} \\ h : R^M \times R^K \times R^L \times R^N & \longmapsto & \{ \bigoplus \bigotimes \bigcirc \} & \text{observed} \\ (z, x, u, v) & \longrightarrow & h (z, x, u, v) = e(z, v) \times f(x, u) \end{array}$$

The classical "adoption" function: exposure not observed

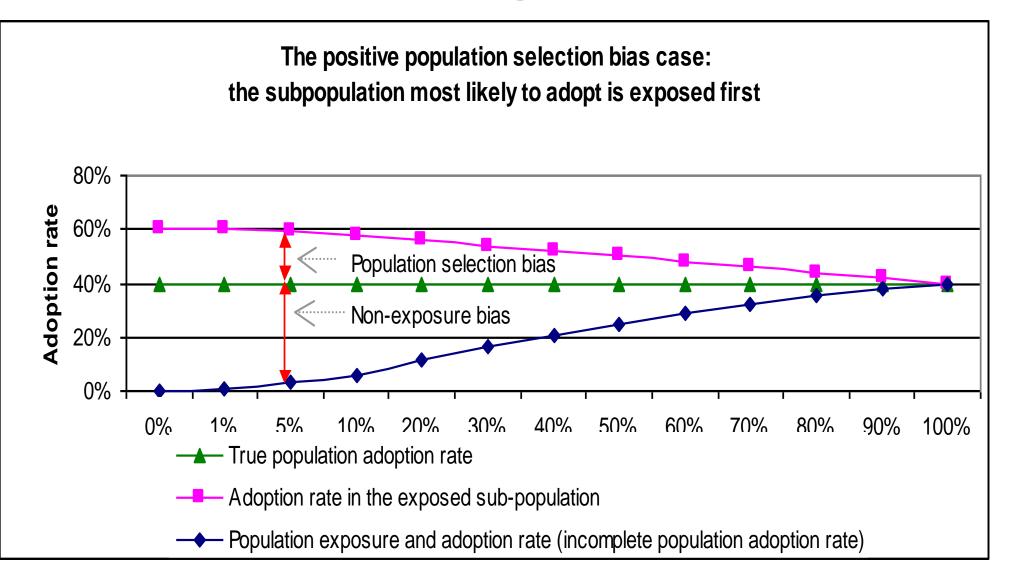
$$g: R^{M} \times R^{K} \times R^{L+N} \mapsto \{ \bigoplus \bigcirc \} \text{ observed}$$

$$(z, x, \varepsilon) \longrightarrow g(z, x, \varepsilon)$$

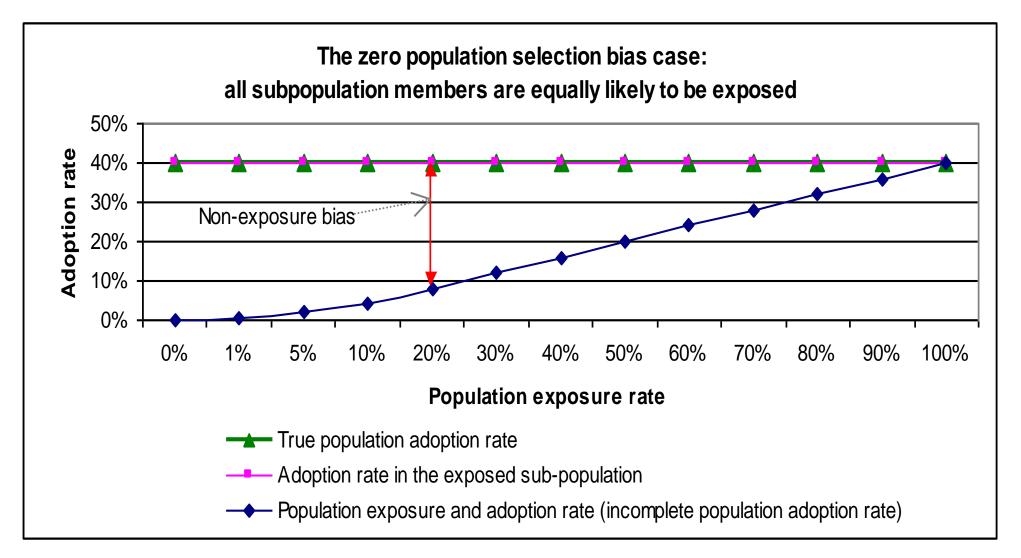
$$(z, x, \varepsilon) \longrightarrow g(z, x, \varepsilon)$$

$$(x, z) \mapsto g(z, x, \varepsilon)$$

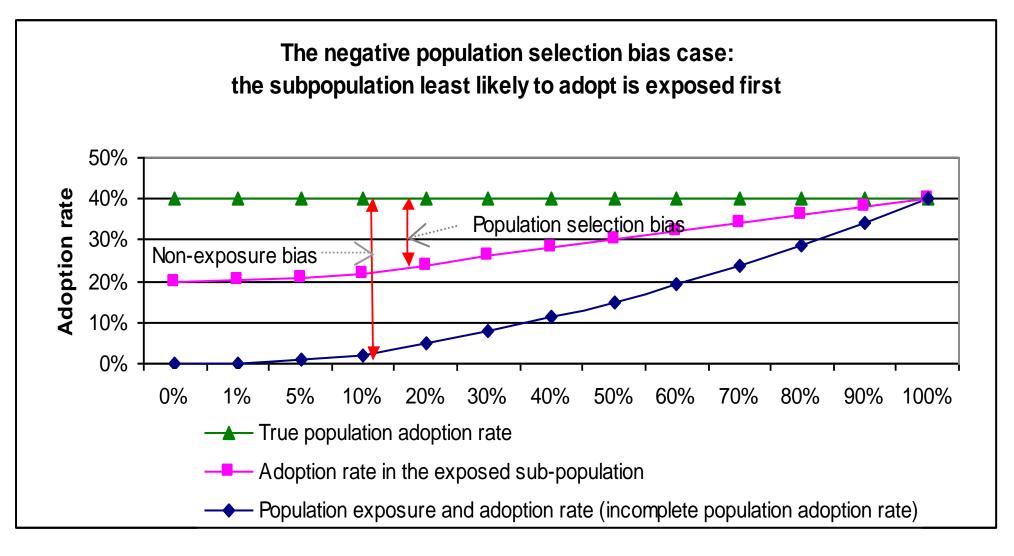
Population adoption rates and biases as function of exposure rate



Population adoption rates and biases as function of exposure rate



Population adoption rates and biases as function of exposure rate



Random Sampling from the partially exposed population

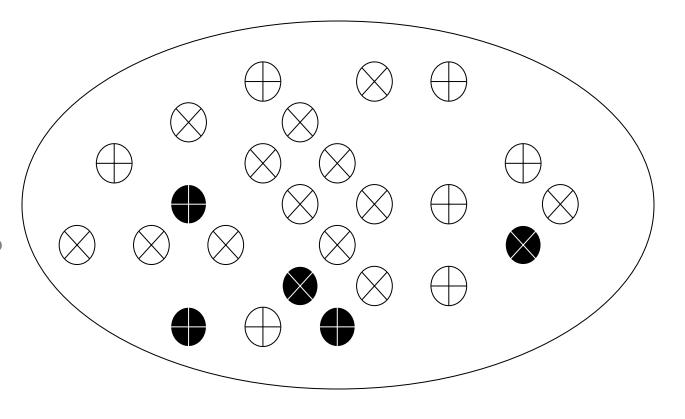
Sample size =25

 \oplus adopter type (10) \otimes non-adopter type (15) \bullet exposed (5)

Sample exposure rate = 20%

Sample adoption rate =12%

Sample adoption rate among the exposed: = 60%



The Adoption Estimation Problems

 How can the structural population adoption parameter be estimated?

i.e. how to estimate the 40% in the example

How can the structural adoption function be estimated?

i.e. how to estimate the function

$$f: R^{K} \times R^{L} \mapsto \{ \oplus \otimes \}$$
$$(x, u) \to f(x, u)$$

Adoption outcomes as results of treatment/policy intervention

- Treatment/Policy intervention = >exposure to the technology
- The two counterfactual states:
 being exposed to the technology
 not being exposed to the technology
- The two counterfactual outcomes:
 - > adoption outcome under exposure
 - > adoption outcome under non-exposure

The Average Treatment Effect (ATE) Estimation framework

• ATE: average treatment effect

measures the effect of a "treatment" on a person randomly selected in the population

- ATT: average treatment effect on the treated measures the average effect of a "treatment" on the treated subpopulation
- ATU: *average treatment effect* on the untreated measures the average effect of a "treatment" on the untreated subpopulation

ATE estimation of structural population adoption parameters

- *W* = exposure status (observed)
 - W=1 exposure
 - W=0 non-exposure
- Y_1 = Potential adoption outcome when exposed
- Y_0 = Potential adoption outcome when not exposed
- $Y = w Y_1 + (1-w) Y_0 = observed adoption outcome$

- Y_{1i} Y_{0i} = treatment effect for farmer *i*
- $E(Y_1 Y_0) = \text{Average treatment effect (ATE)}$
- $E(Y_1 Y_0 | w=1) =$ Average treatment effect in the treated subpopulation (ATT)
- E(Y₁ Y₀ | w=0) = Average treatment effect in the non-treated subpopulation (ATU)

Potential adoption outcome $Y_0 = 0$ for all W

- ATE= $E(Y_1)$ = adoption rate
- $ATT=E(Y_1 | w=1)$ = adoption rate among exposed
- $ATU=E(Y_1 | w=0)$ = adoption rate among non-exposed

$Y = wY_1 = observed adoption outcome$

E(Y) = E(w Y₁) = joint exposure and adoption rate (JEA)
 = P(w=1)×E(Y₁ | w=1)

Other population adoption parameters

- Adoption gap (NEB) = JEA ATE
- Population selection bias (PSB)= ATT-ATE

We observe Y_1 only for w=1

- Cannot estimate ATE=E(Y₁) by sample average (missing Y₁ values for w=0)
- Can estimate ATT=E(Y₁ | w=1) consistently by sample average among exposed

The ATE Estimation framework: Identification

How can ATE and ATU be identified and estimated if we don't observe Y₁ for w=0?

Answer: The Conditional Independence (CI) and common support assumptions (e.g.Rosenbaum and Rubin, 1983):

- w is independent of Y₁ and Y₀ conditional of X
- $\bullet 0 < Prob(W = 1|X) < 1$

The ATE Estimation framework: Identification

$$ATE = E(y_1) = E\left(\frac{y}{p(x)}\right)$$
(1)

(2)

Where p(x)=P(w=1|x) is the conditional probability of exposure (the propensity score)

Two alternative methods of estimation of ATE:

- Method 1: semiparametric (based on Eq 1):
 - Step 1: Estimate p(x) by a nonparametric method or by probit or logit
 - Step 2: Use the predicted propensity score values p(x) to compute the sample analogue of formula in Eq 1

Two alternative methods of estimation of ATE:

Method 2: Parametric (based on Eq 2):

Step 1: Estimate a parametric model of E(y | x) using a random sample <u>restricted to the exposed sub-</u> <u>population</u>

Step 2: form the predicted values E(y|x) for the f<u>ull</u> sample (exposed and non exposed) and takes average across all observations

Implementation of the adoption command

Structure of the adoption command

Adoption is essentially a wrapper of Stata estimation commands with some additional standard errors computation

1-Parse user inputs

1-Identification, 2-Parameters, 3-Estimation methods,

4-Parametric functional form

2- Estimate propensity score (the exposure function) by probit or logit and store in e(b) and e(V)

3- Call estimation routine that estimate the parametric structural adoption function using Stata estimation commands.

- Adjust covariance matrix in case of Two steps estimation (following MacFadden and Newey, 1994).
- Save results in e(b) and e(V)

4- Call routine that estimate the ATE adoption parameters (ATE, ATT, and ATU) with their standard errors

The general syntax of the command is as follows:

adoption depvar [expvar] [if] [in] [weight] [using filename] [, options]

depvar is the observed dichotomous adoption variable

expvar exposure variable

Options

zexposure ([probit|Logit =]zvar) zvar is the varlist of independent variables of exposure variable (expvar)

ate([sp| stata|model=]xavar) option for the choice of the ATE estimation method: semi-parmertric (sp) or parametric method. **xavar** is varlist of independent variables for the parametric method.

opexp(stata option) options of the Stata probit or logit command to be used in the exposure model (noconstant : suppress constant term of the regression model , Robust : synonym for vce(robust), etc.)

Options

opatepara(stata option) options of the Stata internal parametric model (regress, nls, etc..) to be used in the parametric ATE estimation methods.

atestata (stata command syntax) Option for using an existing Stata estimation command as it would be used in the stata command window

classic(varlist=xeavar|xavar) Estimation of classic adoption model with joint exposure and adoption independent variables (**xeavar**) or adoption variable (**xavar**)

Options

SE/Robust

vce(vcetype) vcetype may be robust, bootstrap, or jackknife robust synonym for vce(robust)

cluster(varname) adjust standard errors for intragroup correlation Reporting

level(#) set confidence level; default is level(95)

adoption postestimation

- Post estimation commands specific to the stata estimation commands used internally by adoption (e.g. probit, reg, nls, etc..): estimates restore model name
- 2. Prediction of adoption rates for subpopulations (ATE, ATT and ATU): adoption [if *exp*]
- Marginal effects of exposure, adoption and joint exposure and adoption at observed values and mean of observed values. mfxadoption [if *exp*], options

- Observed sample adoption rate
 - . adoption aner00

ATE ESTIMATION OF THE POPULATION ADOPTION PARAMETERS...

.... ESTIMATION BY SAMPLE AVERAGE AS IF EXPOSURE WERE UNIVERSAL

SUMMARY of MODELS AND PARAMETERS ESTIMATED

name	command	depvar	npar	title
adoption	adoption	aner00	1	Observed sample adoption incidence rate

Observed sample adoption incidence rate

Number of obs: N = 1509Number of adopters: Na = 53

_	aner00	parameter	Robust Std. Err.	z	P> z	[95% Conf.	Interval]
_	Na/N	.0351226	.0047405	7.41	0.000	.0258313	.0444139

- Semi-parametric Method

ATE ESTIMATION OF THE POPULATION ADOPTION PARAMETERS...

... ESTIMATION BY THE SEMIPARAMETRIC WEIGHTING METHOD....

SUMMARY of MODELS AND PARAMETERS ESTIMATED

name	command	depvar	npar	title
adoption	adoption	aner00	9	ATE semiparmetric estimation of population adoption incidence rates
<u>exposure</u>	probit	kner	21	probit regression of the probability of exposure (propensity score)

ATE semiparmetric estimation of population adoption incidence rates

·						e = 124
aner00	parameter	Robust Std. Err.	z	P> z	[95% Conf.	Interval]
ate	.2244926	.0639927	3.51	0.000	.0990692	.3499159
ate1	.3709677	.0504818	7.35	0.000	.2720252	.4699103
ate0	.2085182	.0684713	3.05	0.002	.0743169	.3427194
jea	.036479	.0049641	7.35	0.000	.0267495	.0462085
ğap	1880136	.0617382	-3.05	0.002	3090182	067009
psb	.1464752	.0592475	2.47	0.013	.0303523	.2625981
erved						
Ne/N	.0983347	.0083886	11.72	0.000	.0818933	.1147761
Na/N	.036479	.0052816	6.91	0.000	.0261272	.0468308
Na/Ne	.3709677	.0537106	6.91	0.000	.2656969	.4762386

- parametric Method

... ESTIMATION OF POPULATION ADOPTION PARAMETERS ...

SUMMARY of MODELS AND PARAMETERS ESTIMATED

name	command	depvar	npar	title
adoption	adoption	aner00	9	ATE parametric (Probit) estimation of population adoption incidence rates
<u>exposure</u>	probit	kner	21	probit regression of the probability of exposure (propensity score)
<u>parametric</u> <u>classic</u>	probit probit	aner00 aner00	14 23	ATE Probit regression (restricted to the exposed subsample) Classic Probit regression (joint exposure and adoption)

ATE parametric (Probit) estimation of population adoption incidence rates

Number		obs:		=	1261
Number	of	avnosad	No	_	124

Number of exposed: Ne = 124 Number of adopters: Na = 46

aner00	parameter	Robust Std. Err.	z	P> z	[95% Conf.	Interval]
ATE						
ate	.3072747	.0480065	6.40	0.000	.2131837	.4013656
ate1	.3723981	.0371878	10.01	0.000	.2995115	.4452848
ate0	.3001724	.051408	5.84	0.000	.1994144	.4009303
jea	.0366196	.0036568	10.01	0.000	.0294524	.0437869
gap	270655	.0463529	-5.84	0.000	3615049	1798051
psb	.0651235	.044326	1.47	0.142	0217539	.1520009
Observed						
Ne/N	.0983347	.0083886	11.72	0.000	.0818933	.1147761
Na/N	.036479	.0052816	6.91	0.000	.0261272	.0468308
Na/Ne	.3709677	.0537106	6.91	0.000	.2656969	.4762386

- Parametric Method

Coefficients estimates of estimated parametric models

exposure	parametric	classic
.91835685***	1.904404**	.86175005***
20362235		.24240977
21234504		-2.1049415***
1.5686352***		1.8813963***
		1.1459965***
.03981253***		01527343
12715179*		33521354***
.06774571		.0412896
.09937416	.90556827*	.39801704
.89257809***	.48174778	.06795873
.15726343	13022016	.28978154*
.00620782		02552549
.24058739		42360128*
.00274973	01323842	02637045***
.28015257*	.45288544	.14766215
.03895033*		02459032
		04732435
		60412819
		-1.4912903***
.91145078		-3.9803813***
	.97605853	.77421446
		.2999906
	.0516281	.02931401
-6.1913474***		
1261	124	1261
.3656829		
296.41958	47.35847	535.93065
20	14	23
-257.08614	-64.963349	-140.71391
556.17228	157.9267	327.42781
	.91835685*** -20362235 -21234504 1.5686352*** .50895438*** .03981253*** -12715179* .06774571 .09937416 .89257809*** .15726343 .00620782 .24058739 .00274973 .28015257* .03895033* .29474026 -99144975*** 1.1956274 .91145078 -6.1913474*** 1261 .3656829 296.41958 20 -257.08614	.91835685*** -20362235 -21234504 1.5686352*** .50895438*** .03981253*** -12715179* .06774571 .09937416 .90556827* .89257809*** .48174778 .15726343 13022016 .00620782 .24058739 .00274973 .01323842 .28015257* .45288544 .03895033* 04720465 .29474026 01661318 99144975*** 1.1178406** 1.1178406** 1.1178406** 1.1178406** 1.1178406* 1.1178406* 1.1178406* 1.1178406* 1.1178406* 1.1178406* 1.1178406* 1.1956274 .29286214** .97605853 .19508971 .0516281 -6.1913474*** 1261 124 .3656829 296.41958 47.35847 20 14 -257.08614 -64.963349

legend: * p<0.05; ** p<0.01; *** p<0.001

- Parametric Method

Marginal effects of exposure, adoption and joint exposure and adoption at mean of observed values

Variable	dfx_exposure	dfx_adoption	dfx_atejea	dfx_classic
vpvs	.03993268*	.58767655***	.02865662*	.0025498
canaderv	00604327		00131611	.00043029
ccidtgvv	00598074		00130249	00421657
coldorgv	.12669467**		.02759164**	.02587919
nknerv	.01549178*		.00337381	.00187732
nktrav	.00121183*		.00026391	00002502
nknauv	0038703		00084288	00054913
nkwau∨	.00206207		.00044908	.00006764
pvstpast	.00332064	.3231725*	.00539729	.00117151
plateau	.0199939*	.12959869	.00542493	.00010616
1x5totar	.00478685	03833309	.00059596	.00047471
hhsize96	.00018896		.00004115	00004181
origvil	.00628965		.00136976	00111246
age	.0000837	00389701	00002717	0000432
actsec	.00901048	.13589854	.00385133	.00025211
anscol	.00118559	0138957	.00009633	00004028
woman	.01020286	00487944	.00214453	00007551
bete	01717925*	.39152842**	00241683	00059967
senoufo	.05852211	31706811*	.00277032	00314528
forest	.0310087	75016573***	00192179	10040788***
ccidtgiv		.35192686	.00409943	.00428456
coldorg		.06124992	.00071347	.00079161
hhsize		.01519784	.00017703	.00004802
N	1261	1261	1261	1261

legend: * p<0.05; ** p<0.01; *** p<0.001

Conclusions

 Adoption surveys need to collect information on individual awareness of the technologies

- When diffusion is incomplete, sample adoption rates and the classical adoption model are about joint adoption and exposure
- When diffusion is incomplete, ATE estimation provides reliable information on population potential adoption rates, gaps and determinants

Ways Forward

- Extend adoption to account for when the new technology is not universally available to the population.
- Use margins to estimate ATE, ATT and ATU instead of using predict and computing standard errors manually.

 Implement other ATE estimation methods (matching, Doubly robust, MTE, etc..)

Wishes to Stata

 Make Stata estimation commands, suest and margins aware of two-step estimation when done manually (e.g. declaration through an option)

→ Automatic adjustment of standard errors (e.g. McFadden and Newey 1994)

 Make accessing estimated coefficients sub vectors of e(b) possible and usable in operations and commands like margin:

i.e. extend _b[varname] to allow for _b[varlist]

– More non-parametric regression commands

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THANK YOU !