The Impact of CCT’s on Vulnerability Ex-ante: Evidence from Progresa

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THE PROBLEM:

Despite successes in poverty reduction, still however, 10 % people in the world live under $1.90 a day (World Bank, 2016), and many millions live in the nearness of this poverty line

Luckily a mass of social protection programs are protecting many people, but we don’t know enough of their impact on vulnerability

How well did one of the most influential flagship social protection programs, the Progresa, do in reducing vulnerability to poverty?

Outline

1. Vulnerability Measures
2. Literature
3. Institutional background & identification strategy
4. Results
5. Conclusion

STUDYING VULNERABILITY EXTENDS OUR UNDERSTANDING OF POVERTY

- Vulnerability (ex-ante definition) cannot be observed ex-post, as some people were vulnerable, but did not end up poor
- The concept of vulnerability incorporates the sense of insecurity that results from being exposed to risks and feeling defenseless against them (Fuente et al. 2015)
- Vulnerability reinforces poor people's sense of ill-being, exacerbates their material poverty and weakens their bargaining position (World Development Report, 2001)
- The threat of poverty is costly on people's health (Weissman et al. 2015) and can protract poverty when people choose to refuse profitable opportunities to avoid risk (Dercon, 2006)

IN ADDITION TO VULNERABILITY AS EXPECTED POVERTY (VEP) THERE ARE:

1. Vulnerability as exposure to Risk (VER)

a) Inability to smooth consumption (ex-post), B) Extended poverty line approach, C) Exposure to downside risk

2. Vulnerability as low expected utility (VEU)

a) Expected utility approach b) Threat of poverty approach c) Reference-dependent utility approach

3. Vulnerability by mean risk

a) Mean deviation approach b) Downside mean deviation approach

Follows list of Gallardo (2017)

Some advantages of the VEP-model

1. Can be estimated from cross-sectional data
    i. Model assumes time-stationarity: $\tilde{y}_{j,t+1}$ behaves as $\tilde{y}_{j,t}$
2. Gives a probability statement regarding poverty in the future
3. Allows analysing the effect of each predictor on predicted conditional variance
4. The FGLS has an impact on the estimates, (especially if there is eg. heteroscedasticity or serial correlation)
5. Does not require subjective information regarding perceptions about future (expected risks and subjective probabilities) and it does not require assuming particular functional form for the welfarist approach as in VEU-model

LITERATURE

- No paper on VEP-vulnerability on Progresa or any other similar CCT
- There is literature on effects of various interventions on VEP-vulnerability (microfinance, public works, public food subsidy programmes, and social security systems for aged people (for example Jha et al. 2009; Bronfman and Floro, 2014))
- One paper studied VER-vulnerability using Progresa (Skoufias, 2007)
- Magnitude of vulnerability can be found on national level using nationally representative datasets (de la Fuente et al. 2014)
- Progresa's program impacts have been studied on many other outcomes (eg. health, education, nutrition)

VEP-MODEL IN A NUTSHELL

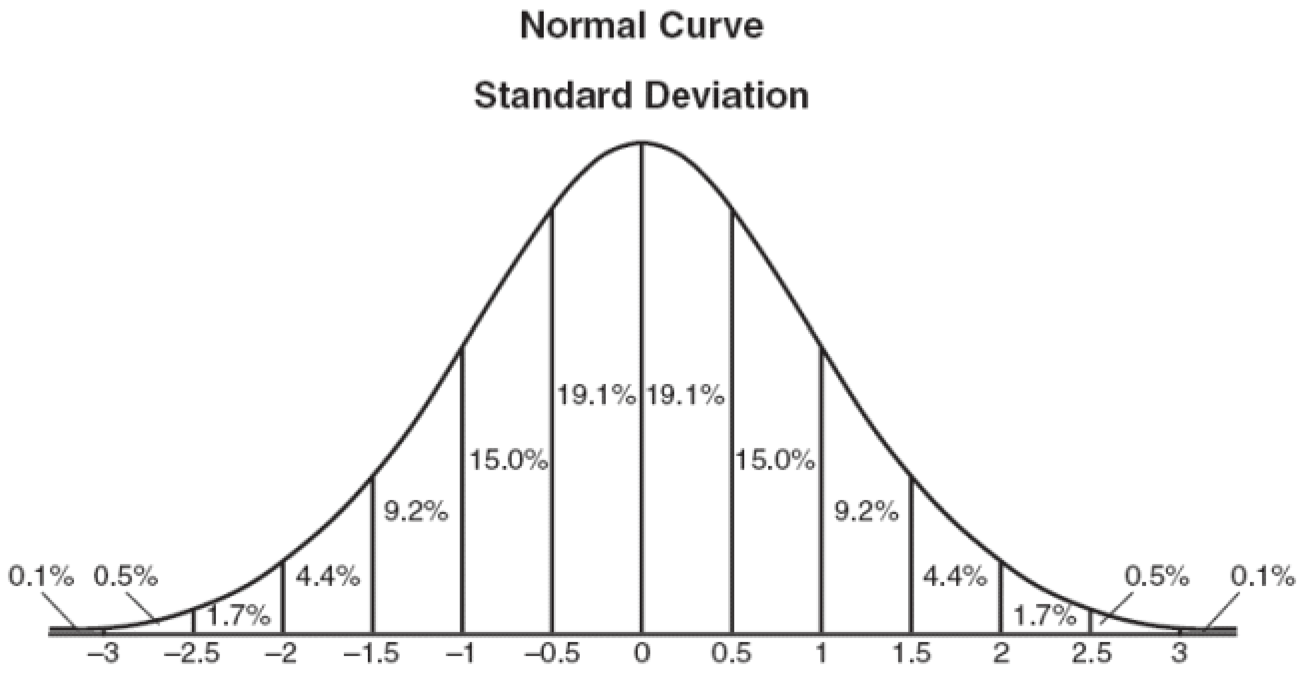
1. Predicting consumption (income) model that assumes a certain generation process using variables of coping capacity and risk exposure $\ln c_{ij,t+1} = \alpha + \ X_{ijt}\beta + \phi\tau_{ij} + \varepsilon_{ijt}$
2. Running an FGLS-prodecure
   i. To find the impact of each predictor on predicted variance
   ii. Using these predictions as individual weights in the FGLS- 3rd stage

→

THE ESSENCE OF THE MODEL

$$V_{ijt} = \Phi\left(\frac{\ln z - \ln c_{ij,t+1}}{\sigma_{t+1}}\right)^{\gamma}$$

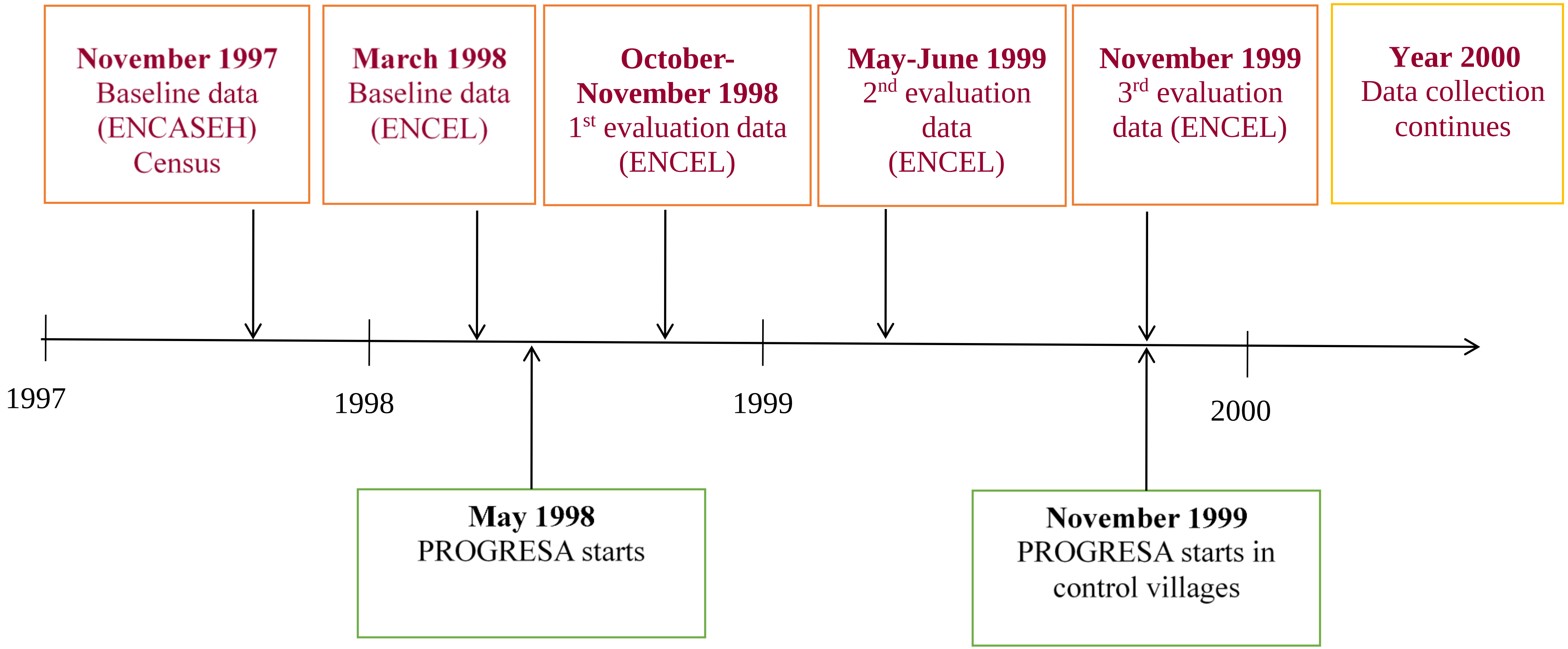
So a certain expected deviation from the poverty line will be considered large or small in accordance to the distribution characteristics of what follows a small or in a high probability



PROGRESA IS A FLAGSHIP SOCIAL DEVELOPMENT PROGRAM

- Progresa was among the first conditional cash transfer programs in the world aiming to end poverty and hunger, improve health and human capital
- Currently has benefitted 6 million people in Mexico and similar programs have been replicated in 52 countries
- Cash transfers, conditional on health care and schooling give an increase of 20 % over monthly income + food supplements for selected groups
- The evaluation data, consisting of 24,000 households, is gathered following the ideals of RCT's (with some caveats)

Timeline of the Progresa and its evaluation



Identification strategy

Intention to treat effect on the treated (ITT)

- Previous literature unanimous that 97 % of the initially eligible were treated
- Eligibility determined also for control group →later added to the program

Average treatment effect of living in treatment locality (ATE)

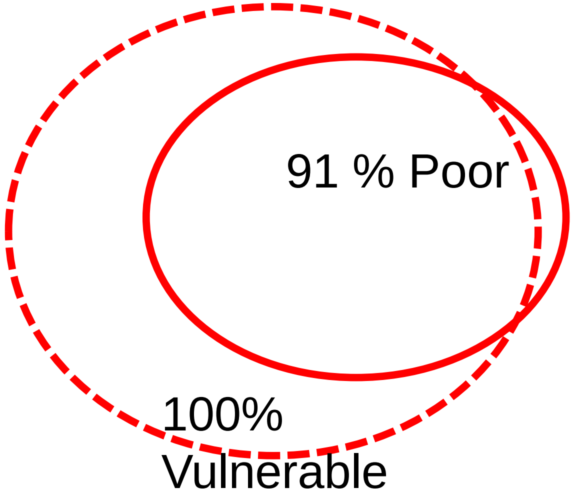
- Due to the spillovers

+ Heterogenous effects on disadvantaged groups

ALMOST ALL ARE EXTREMELY POOR

Poverty headcount 1998	Mexican population ENIGH 1998	Population in Progresa ENCEL 1998
Under national poverty line (USD 2.2/day) %	14	99
Under national food poverty line (USD 1.1/day) %	2	91
Under intl. ultra-poverty line (USD 0.5/day) %	<1	50

- Often there are more vulnerable than poor
- If all are vulnerable, finding any effects among control and treatment group become difficult
- SOLUTION: using ultra-poverty line and studying expected future consumption and income

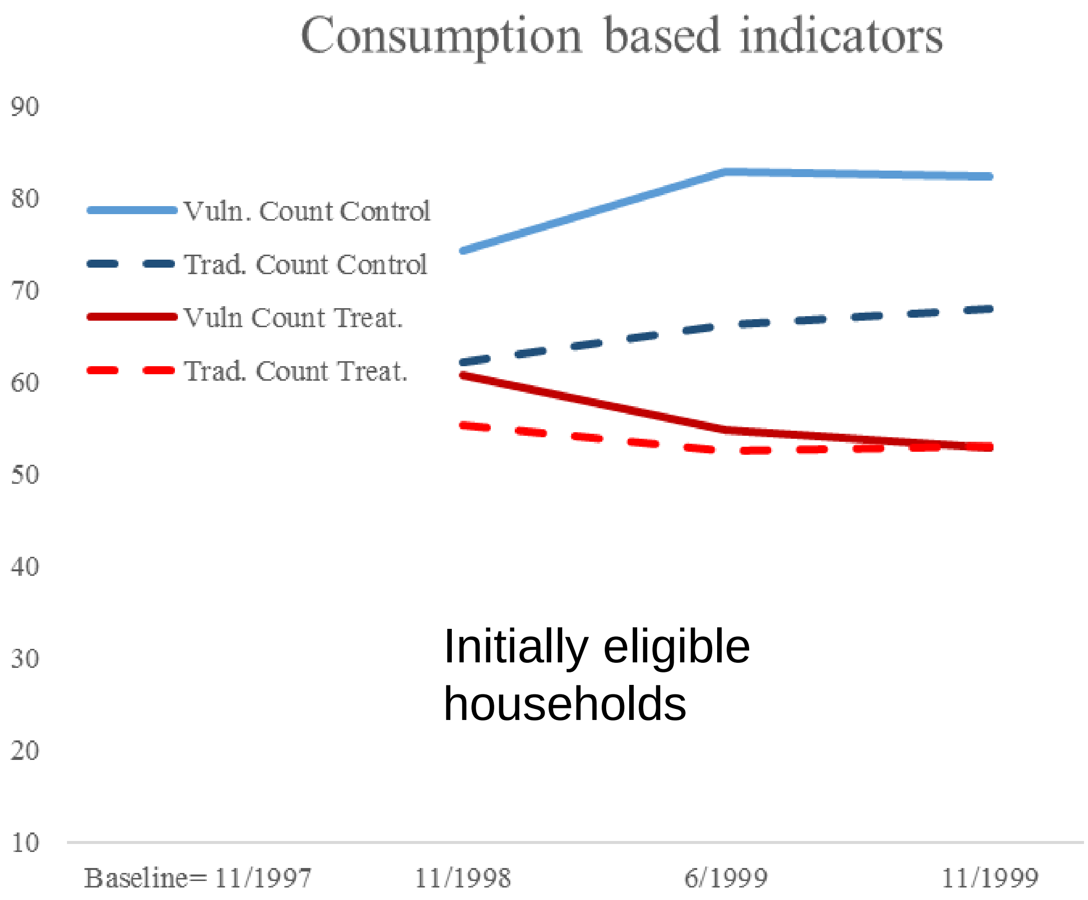


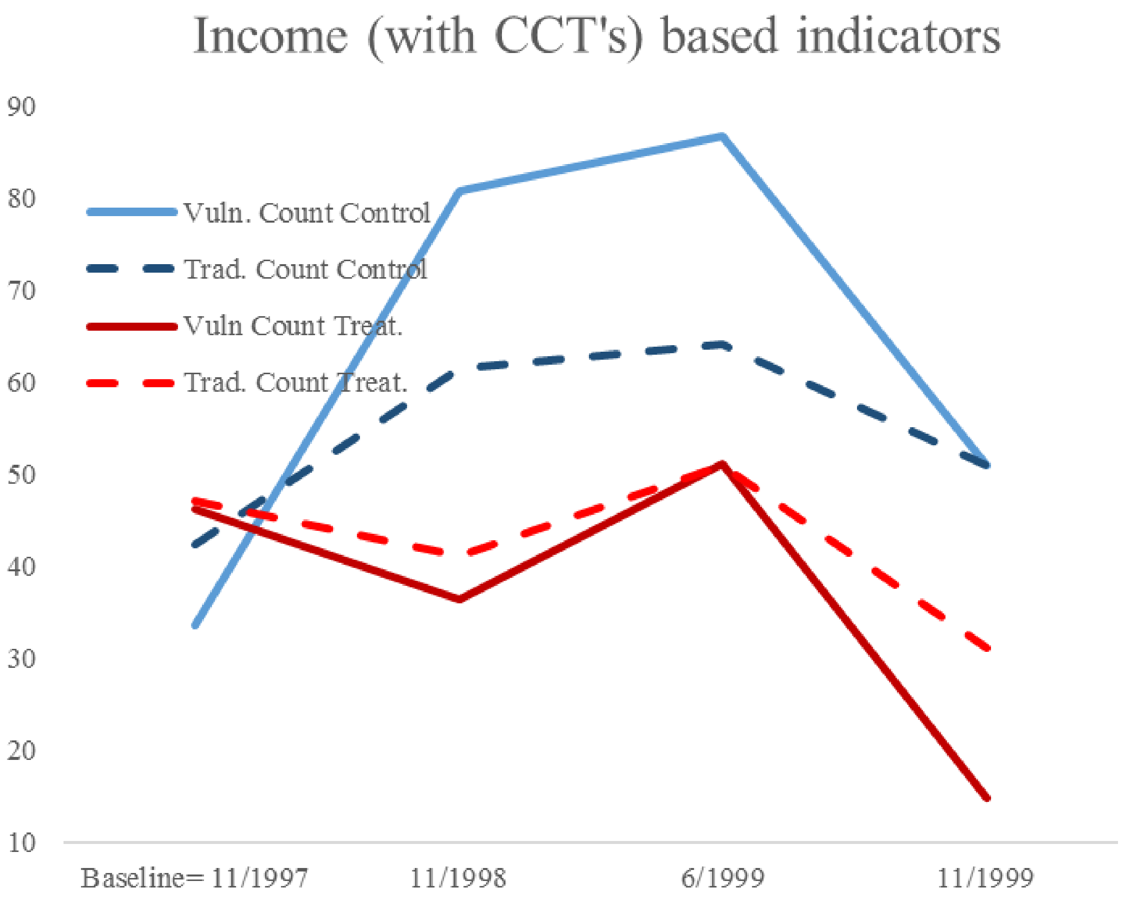
ULTRA-POVERTY LINE: TRADITIONAL POVERTY HEADCOUNTS (CONS & INC.)

Round	Traditional Headcount of Ultra-Poor (Consumption)		Balance test	Traditional Headcount of Ultra-Poor (incl. CCT's)		Balance test
	Control (1)	Treatment (2)		Control (5)	Treatment (6)	
Sample of initially eligible households						
11/1997	*n.a.*	*n.a.*		42	47	0.00
No. Obs.	-	-		3643	4165	
11/1998	62	55	0.00	61	41	0.00
No. Obs.	3481	5720		3267	3804	
6/1999	66	52	0.00	64	51	0.00
No. Obs.	2709	4224		2855	3355	
11/1999	68	53	0.00	51	31	0.00
No. Obs.	3013	4835		2911	3577	

It appears that Progresa seems to have had an impact on traditional headcount ultra-poverty

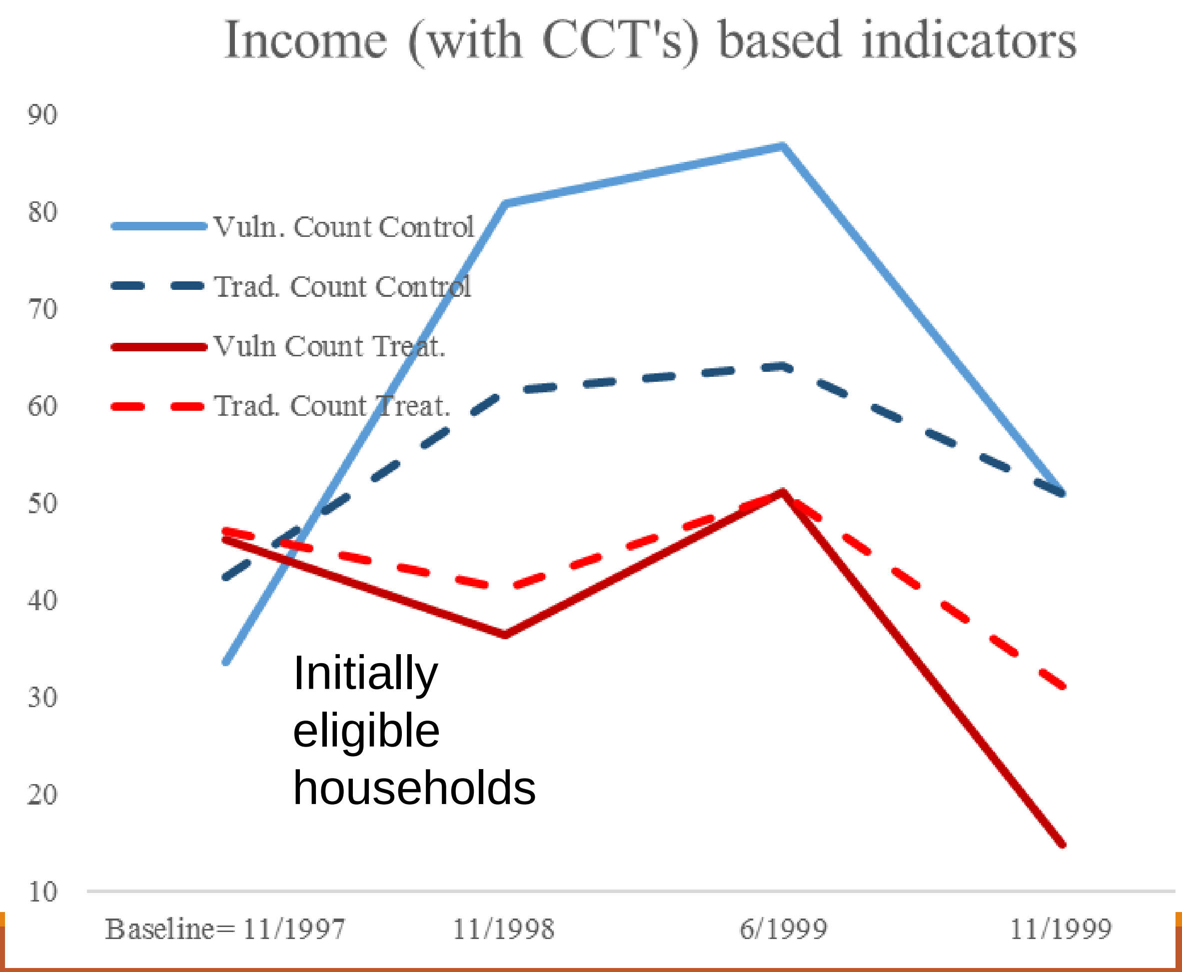
CONTRASTING TRADITIONAL HEADCOUNT POVERTY AND VULNERABILITY HEADCOUNT



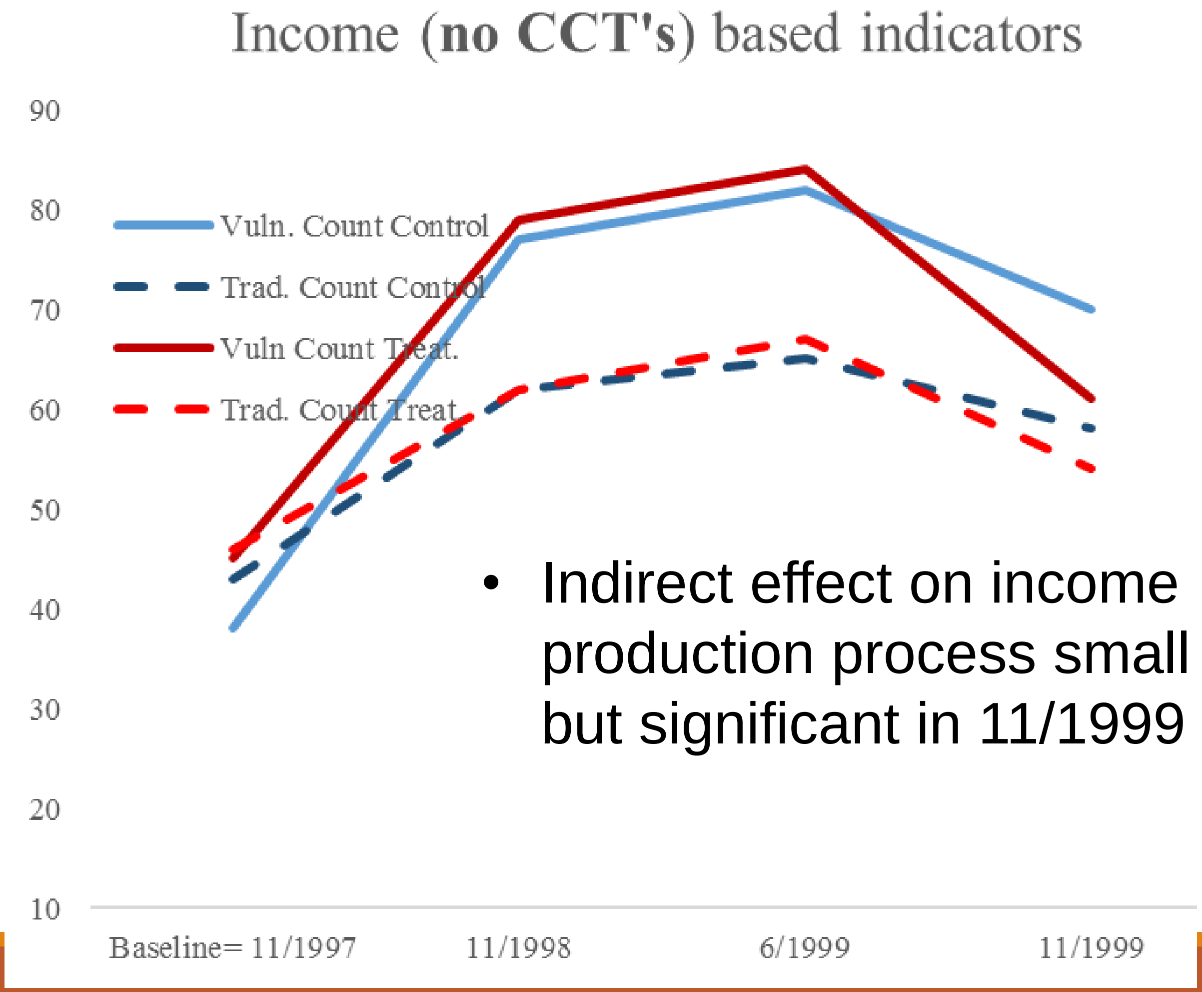


Vulnerability Count=Count of pop. with a VEP-probability of impoverishment under ultra-poverty line >50%

CONTRASTING DIRECT AND INDIRECT PROGRAM EFFECTS ON TRAD. AND VULN. HEADCOUNTS

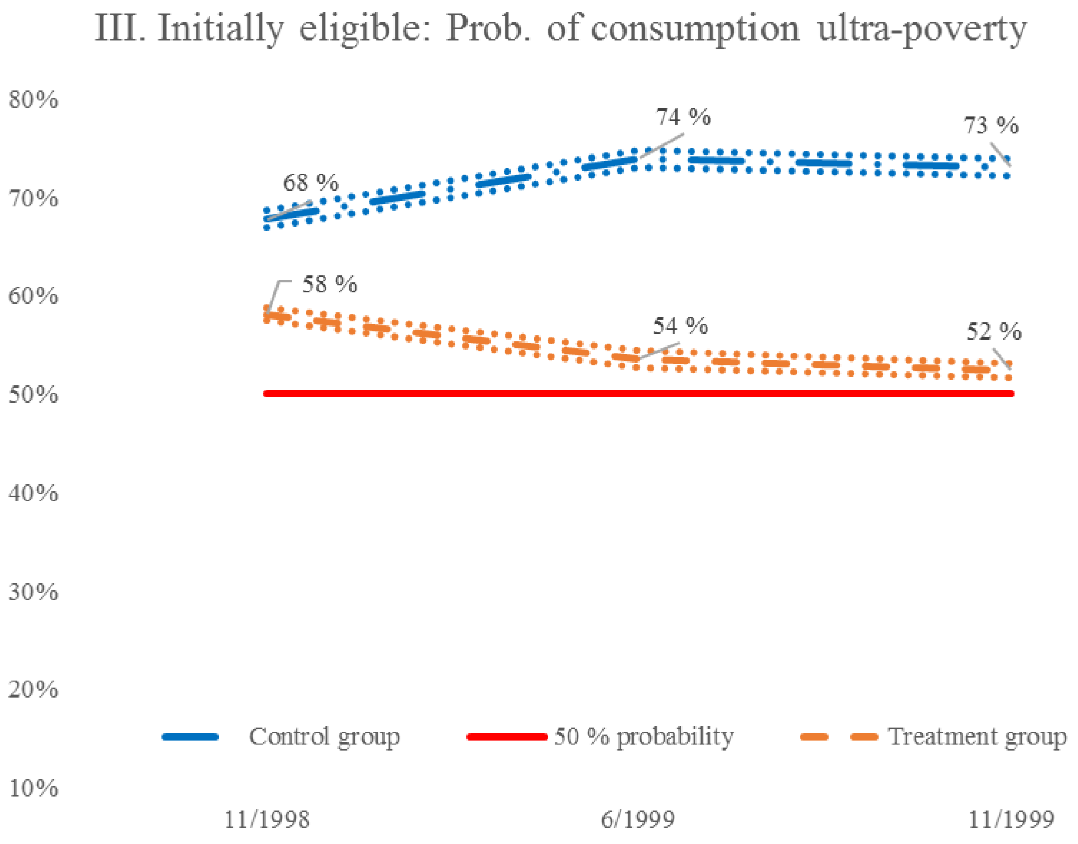


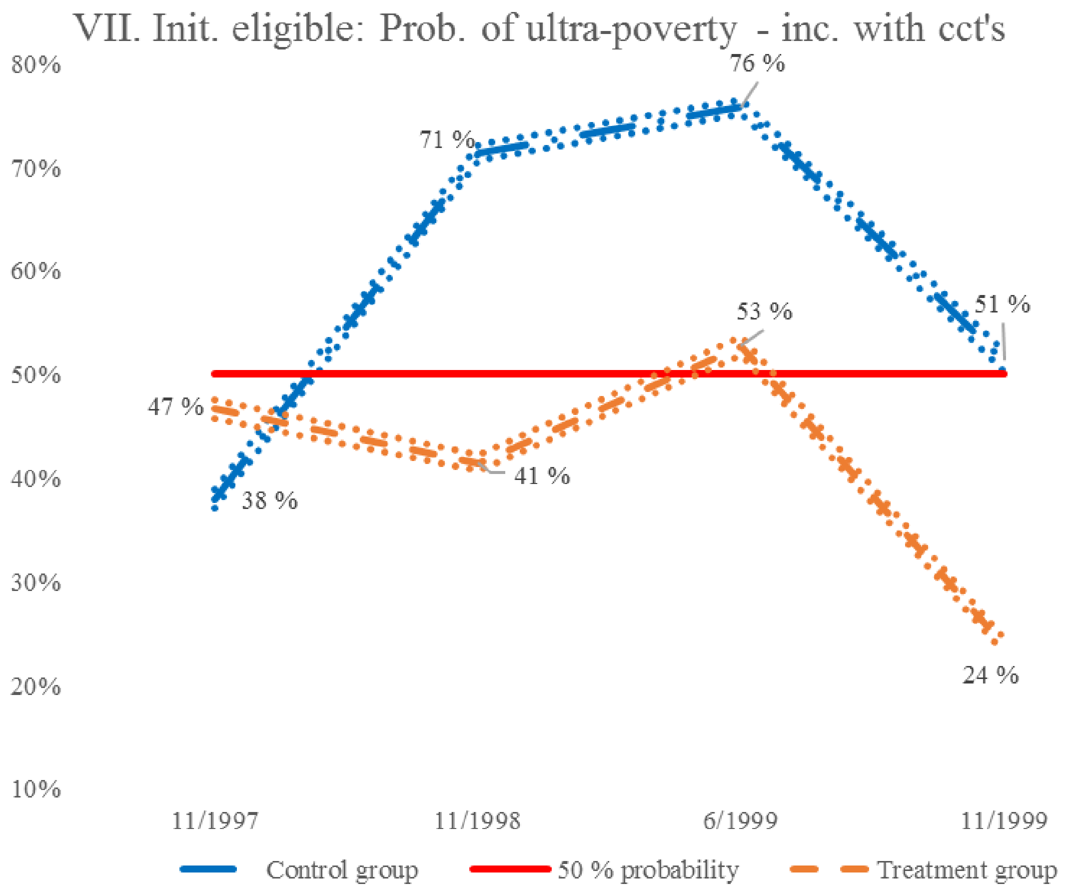
Initially eligible households



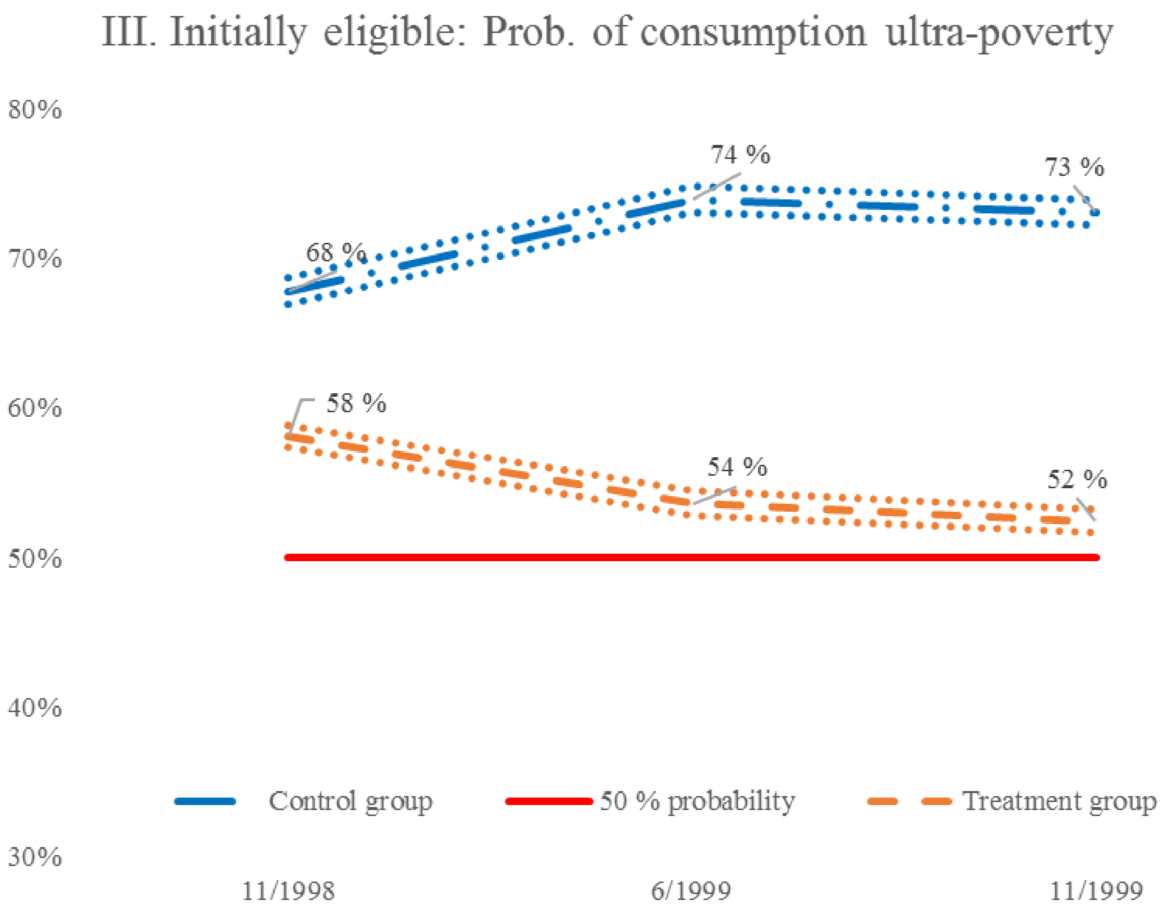
- Indirect effect on income production process small but significant in 11/1999

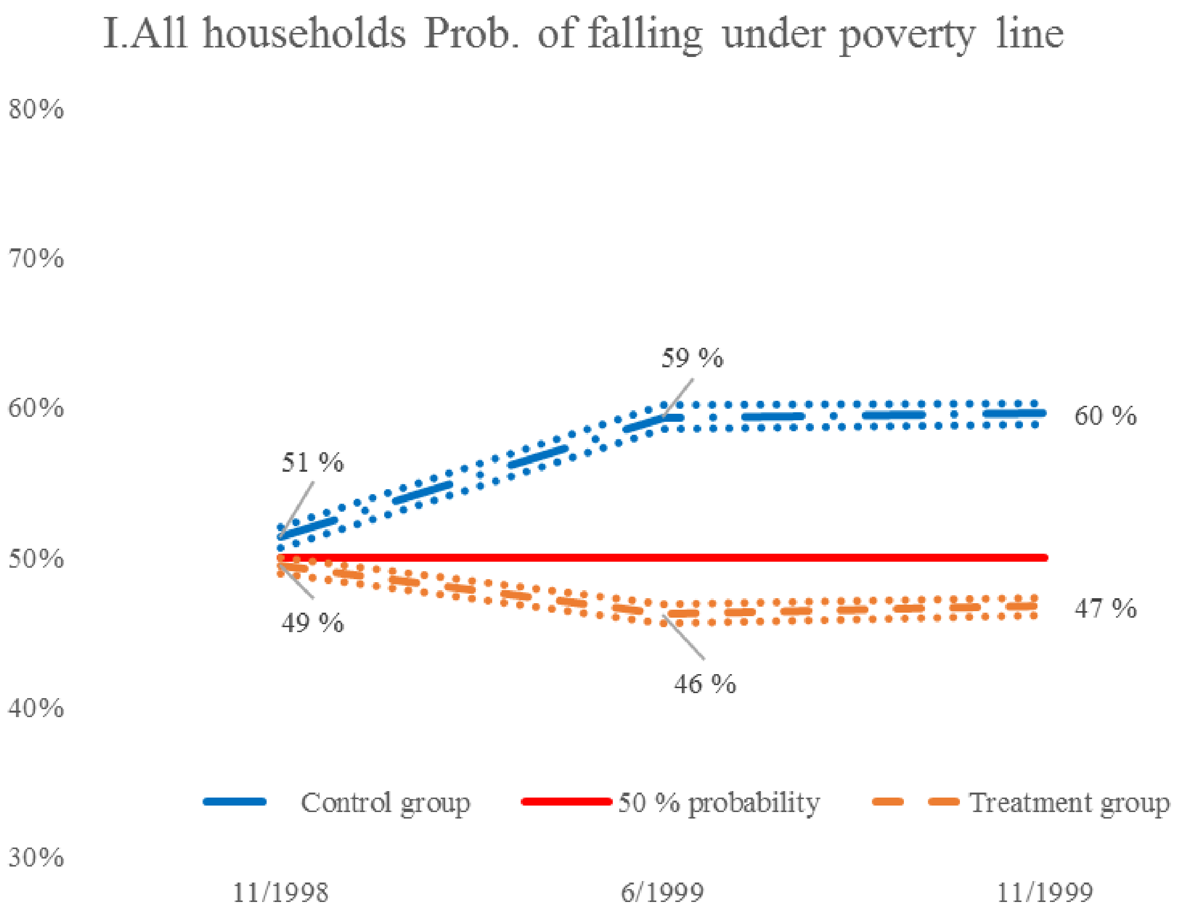
Magnitude of vulnerability to poverty



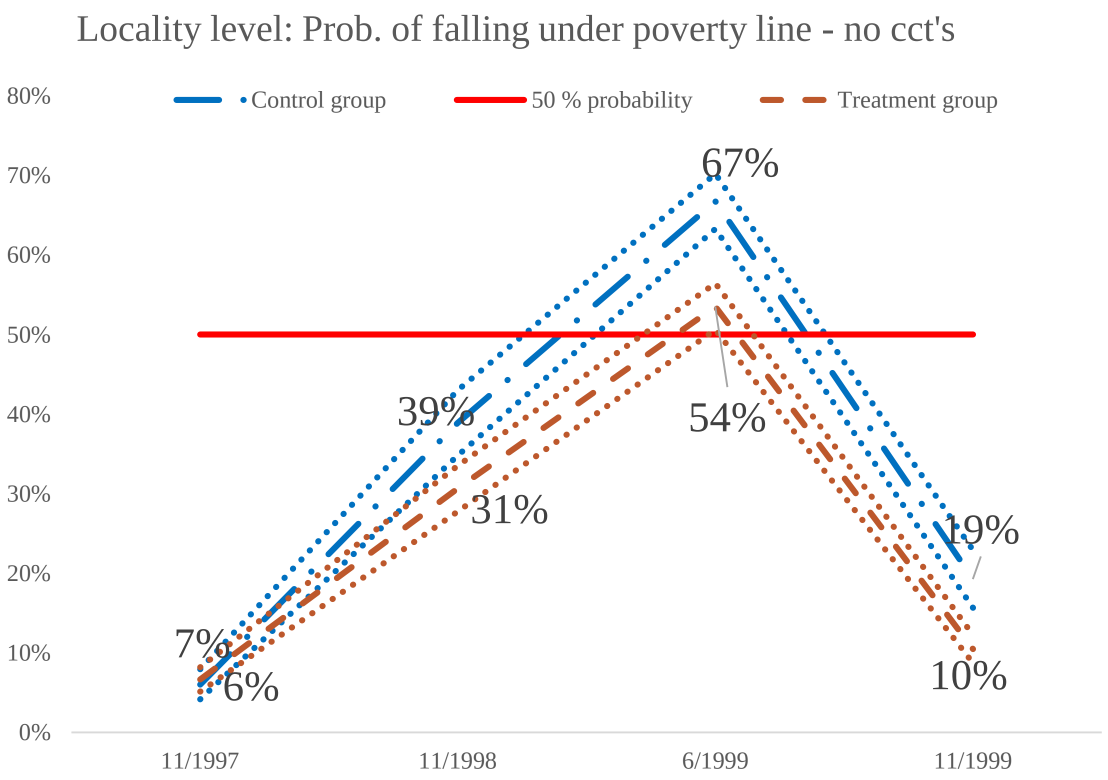


Vulnerability to ultra-consumption-poverty in control and treatment groups





Magnitude of vulnerability to income-ultra-poverty: locality level



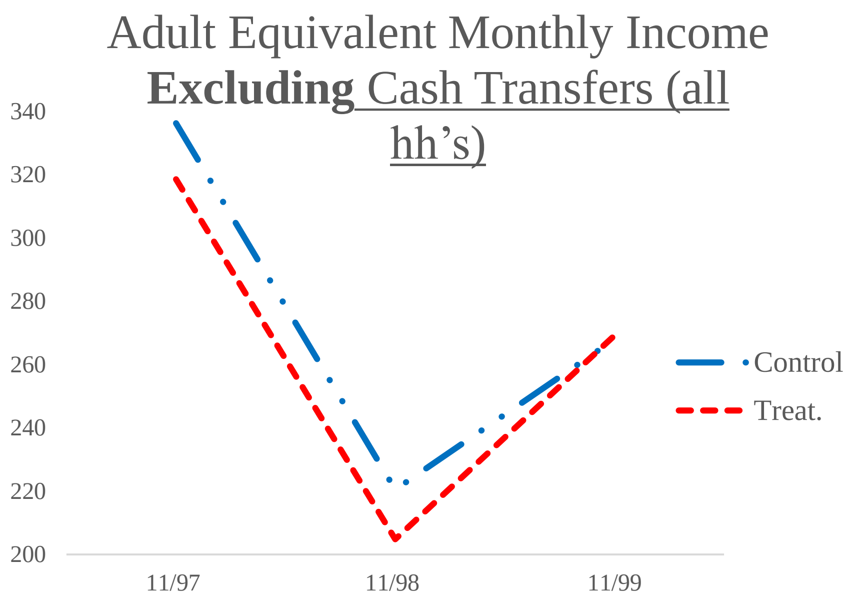
Locality level results reveal that VEP-vulnerability is lower for the treated localities after the intervention and at the baseline the groups are the same

The post-treatment effect is positive on average vulnerability to income ultra-poverty (no CCT's)

Results differ from household level results as the unit of observation is locality and not a household

Indirect program effects on incomes

- At baseline treatment group seems to have lower incomes
- Averages (excl. CCT's) show that treatment group reaches control group in 1999



- Differences-in-differences model (1st-stage):

$$\ln y_{ij,t+1} = \alpha + X_{ijt}\beta + \phi\tau_{ij} + \Sigma\lambda_t Round_t + \delta_1(\tau_{ij} \cdot Post_{ijt}) + \varepsilon_{ij,t+1}$$

Difference-in-Differences:"Indirect" Treatment Effect on Expected Income

Excluding cash transfers from income gives indication that most of the effect seems to come through higher expected labour income

ALL INCOME (excluding cash transfers)			
Differences in differences analysis - pooled	1st stage Conditional predicted: (Heteroscedasticity not FGLS corrected) Income	2nd stage Conditional predicted variance of: Income	3rd stage Conditional predicted: (heteroscedasticity corrected using FGLS) Income
	(1)	(2)	(3)
All data - ATE effect			
Treatment estimate	0.11**	-0.13*	0.14***
	(0.05)	(0.07)	(0.05)
Observations	52674	52674	52674
R^2	0.12	0.07	0.12
Sample of initially eligible households			
Treatment estimate	0.16***	-0.25***	0.19***
	(0.06)	(0.09)	(0.06)
Observations	28616	28616	28616
R^2	0.10	0.08	0.09
Sample of initially eligible, indigenous, large households			
Treatment estimate	0.33***	-0.37*	0.26**
	(0.12)	(0.20)	(0.10)
Observations	7200	7200	7200
R^2	0.10	0.08	0.07

How large effect on labour income?

Give indication that

1. Expected income is 19 percent higher for treated households after treatment
2. Treatment has a variance reducing effect – lowers uncertainty of future income
3. The effect is higher for population that belongs to a disadvantaged group

LABOUR INCOME (excluding cash transfers)

Differences in differences analysis - pooled	1st stage Conditional predicted: (Heteroscedasticity not FGLS corrected)	2nd stage Conditional predicted variance of:	3rd stage Conditional predicted: (heteroscedasticity corrected using FGLS)
	Income	Income	Income
	(1)	(2)	(3)
All data - ATE effect			
Treatment estimate	0.15*	-0.23***	0.14**
	(0.08)	(0.07)	(0.06)
Observations	52639	52639	52639
R^2	0.15	0.25	0.11
Sample of initially eligible households			
Treatment estimate	0.22**	-0.46***	0.19***
	(0.09)	(0.09)	(0.07)
Observations	28609	28609	28609
R^2	0.16	0.23	0.11
Sample of initially eligible, indigenous, large households			
Treatment estimate	0.38**	-0.41**	0.20
	(0.15)	(0.18)	(0.12)
Observations	7200	7200	7200
R^2	0.17	0.18	0.08

DD: Treatment Effect on Poverty Status

Predicting poverty status using DD-model :

$$\Pr(\text{poor} = 1 |\ \text{poor} = 0)\ =$$
$$\alpha + X_{ijt}\beta\ \ + \phi\tau_{ij} + \Sigma\lambda_t Round_t + \delta_1(\tau_{ij} \cdot Post_{ijt}) + \varepsilon_{ij,t+1}$$

Preliminary results

1. Poverty decreasing treatment effect on expected income ultra-poverty
2. Treatment effect on poverty is smaller than on expected income
3. Treatment has a variance reducing effect – lowers uncertainty of future income

I. POVERTY PROBABILITY (INCOME EXCLUDING CCT'S)		1st stage Condition Income	2nd stage Condition Income	3rd stage Condition Income
		(1)	(2)	(3)
	All data - ATE effect			
A.	Treatment estimate	-0.03**	-0.15**	-0.03*
		(0.02)	(0.07)	(0.02)
	Observations	52687	52687	52687
	R^2	0.15	0.11	0.15
	Sample of initially eligible households			
B.	Treatment estimate	-0.06***	0.07	-0.06***
		(0.02)	(0.07)	(0.02)
	Observations	28618	28618	28618
	R^2	0.13	0.13	0.14
II. POVERTY PROBABILITY (INCOME WITH CCT'S)				
	Sample of initially eligible households			
C.	Treatment estimate	-0.25***	-0.17***	-0.24***
		(0.02)	(0.06)	(0.02)
	Observations	22029	22029	22029
	R^2	0.13	0.06	0.13

Conclusion

First program impact study regarding the effects of conditional cash transfer (CCT) programs on vulnerability to expected poverty and expected consumption (income) ex-ante:

- Significant effects on vulnerability that appear larger than the program effects on poverty
- Vulnerability headcount is on a lower level (30%pt) among treated in treatment village
- Magnitude of vulnerability is 20 %pt lower in treatment villages among treated

First program impact study regarding the effects of conditional cash transfer (CCT) programs on expected income and poverty using difference-in-differences (DD) model for income with and without cash transfers

- Expected income, even without cash transfers seems to be affected by the Program
- Often also effects are larger for disadvantaged groups

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