



STRATEGIC
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2024 Capacity Development
IMPACT
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STRATEGIC
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DIFFERENCE-IN-DIFFERENCE

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Overview

- Quasi-experimental method to estimate causal effect of an intervention (policy/program)
- An option when randomization is not possible
- Often, we want to compare the outcome of interest for participants and non-participants to see if the program is effective

Problem: There may be unobserved factors that are affecting the outcomes

Example: Participants of a scholarship program may be more motivated to study compared with non-participants, even without intervention; comparing the two groups would lead to a “difference” that we can’t fully attribute to the scholarship program alone (overestimate)

Overview

- Recall the basic problem for IE: come up with a counterfactual
- Idea of DID: make two comparisons
 1. First difference –compare differences across time periods; this would remove time-invariant unobserved characteristics
 2. Second difference –compare differences between control and treatment group subject to same time-varying factors

Impact = average effect of an intervention to those who received the intervention (ATET)

- DID solves the problem of unobserved factors because it allows us to control for both time-invariant and time-varying factors

Data requirements

- Control and treatment group (composition is stable over time)
- Several periods of data (before and after intervention)
 - ✓ panel data
 - ✓ repeated cross sectional data

Period	Group	
Before intervention	Control	Treatment
After intervention	Control	Treatment

Assumptions

- Parallel trend
- Policy/program (intervention) is unrelated to the outcome of interest at the baseline
- No spillovers

Parallel trend assumption

- The most critical assumption of the DID approach to ensure internal validity
- Basic idea: in the absence of the policy intervention, the difference between the control and treatment group should remain constant (move in tandem)
- Note: Not required for treatment and control group to have the same levels at baseline

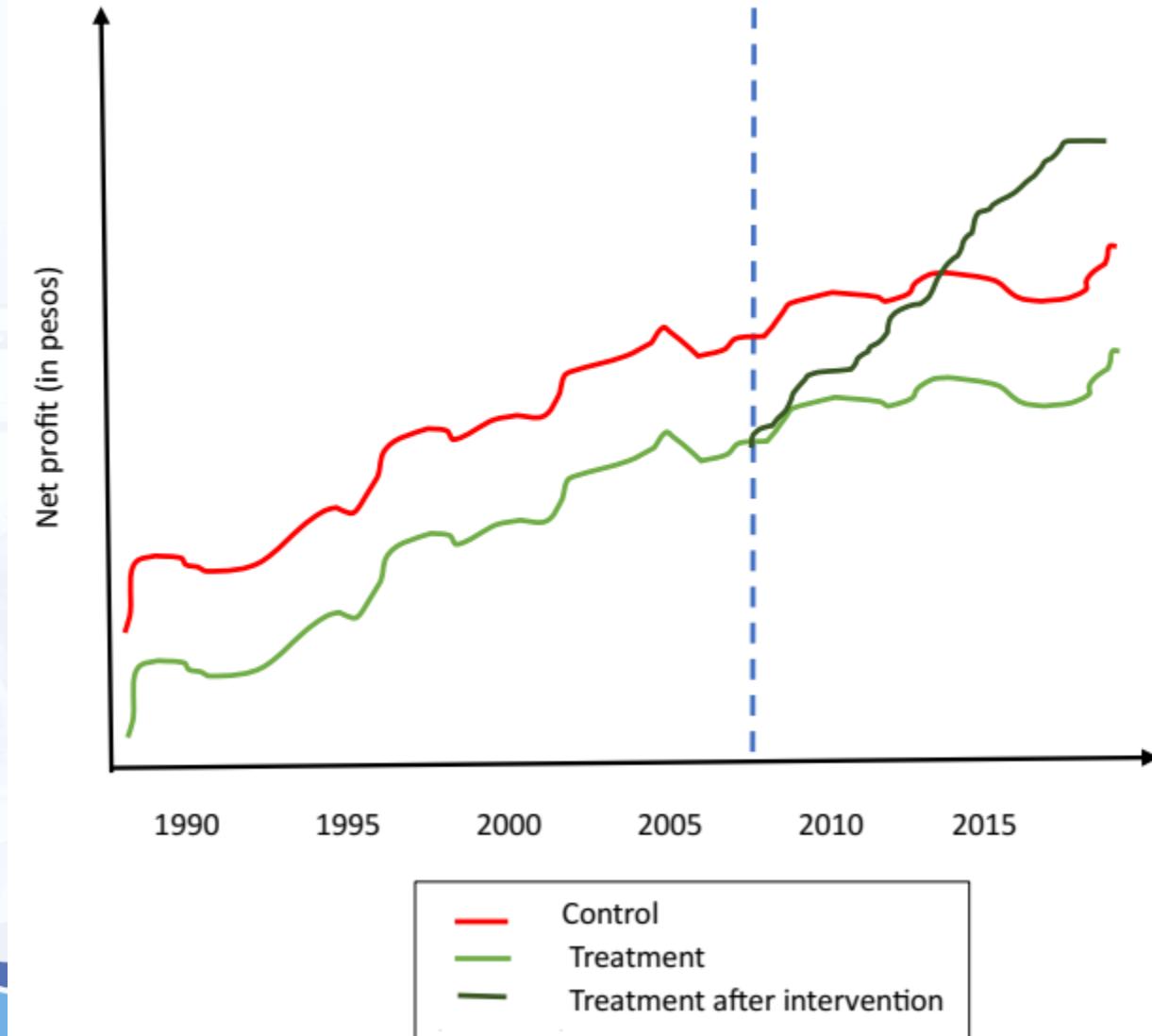
Policy intervention: 2007
(Mobile phone)

	Treatment ($T=1$)	Comparison ($T=0$)
After the program ($P=1$)	Y_{11}	Y_{01}
Before the program ($P=0$)	Y_{10}	Y_{00}

$$DID = (Y_{11} - Y_{10}) - (Y_{01} - Y_{00})$$

$$Y = \alpha_0 + \alpha_1 P + \alpha_2 T + \alpha_3 P * T + \varepsilon$$

$$DID = \alpha_3$$



Testing parallel trend assumption

- 1) Examine the trends in outcome of interest for control and treatment group prior to policy intervention
- 2) Perform a placebo test using:
 - fake group (those that are not affected by the policy)
 - fake outcome
- 3) Use other control groups (if control groups are both valid, estimates should be similar)

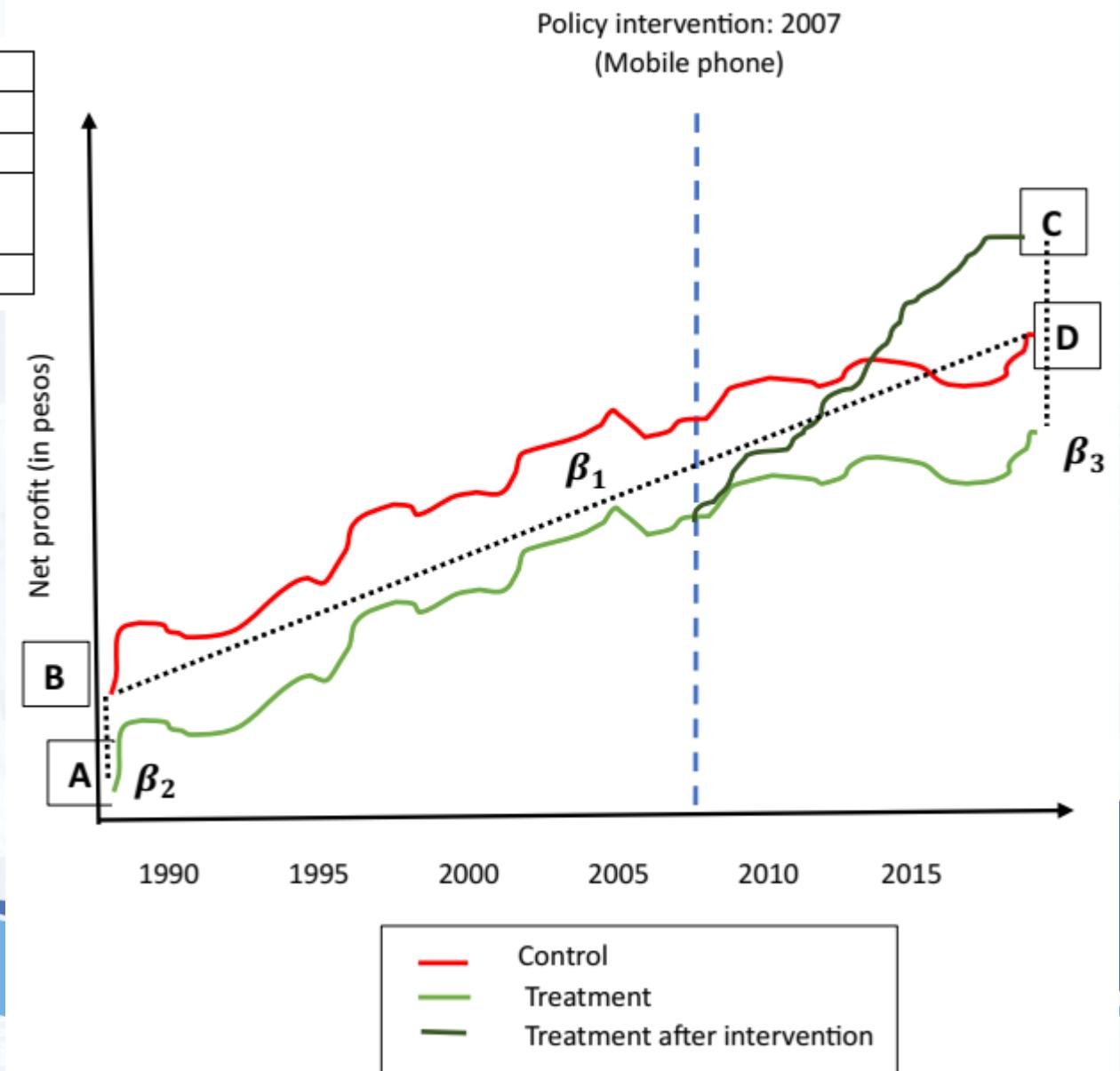
Mathematical representation of DID

- In a regression model, DID is usually implemented as an interaction between a dummy variable representing time and a dummy variable representing the treatment group

$$Y = \beta_0 + \beta_1[\text{time}] + \beta_2[\text{treatment}] + \beta_3[\text{time} * \text{treatment}] + \beta_4[\text{other factors}] + \varepsilon$$

$$Y = \beta_0 + \beta_1[\text{time}] + \beta_2[\text{treatment}] + \beta_3[\text{time} * \text{treatment}] + \beta_4[\text{other factors}] + \varepsilon$$

Coefficient	Representation	Interpretation
β_0	B	Baseline average
β_1	D - B	Time trend in control
β_2	A - B	Diff. between control and treatment before intervention
β_3	(C-A) - (D-B)	Diff. in changes over time



Pros:	Cons:
<ul style="list-style-type: none"> ✓ Suitable for assessing impact of policy shifts 	<ul style="list-style-type: none"> ✓ Requires more data (baseline, data for control and treatment group)
<ul style="list-style-type: none"> ✓ Results are easy to interpret 	<ul style="list-style-type: none"> ✓ Challenging to satisfy the parallel trend assumption
<ul style="list-style-type: none"> ✓ Permits individual/group level analysis 	<ul style="list-style-type: none"> ✓ There maybe serial correlation in the outcome of interest; need to use corrected standard errors
<ul style="list-style-type: none"> ✓ Controls for time-invariant and time-varying unobserved factors 	<ul style="list-style-type: none"> ✓ Complexities: <ul style="list-style-type: none"> ❑ Policy implementation is staggered (different timing) ❑ When there is spillover effect from other policy intervention



DID in practice

History of DID

- Early applications: Snow (1849), Snow (1855)
- Contrary to what was known during that period, Dr. Snow claimed that cholera was not transmitted through contaminated air or blood, but via contaminated water (polluted with sewage).
- Setup of the natural experiment:

There were 2 alleys that were close together; houses occupied by the poor are found on either side of the alley -the south side and the north side. Both sides are using the same drain and there is an open sewer passing the further end of both alleys. Cholera problem in the north side was more devastating than in the south side, where only one cholera-related death was recorded. The only difference between north and south side is a well where households in the north side obtain their water from.
- 1985 study: Dr. Snow collected data before and after the pump with contaminated water was closed

Example 1

Duflo (2001). Impact of a School Construction Program on Educational Achievements and Wage Earnings

- Policy background:
School construction program in Indonesia using resources from the oil boom, with 61,000 primary schools built in the period 1974-1978.
- Goal of the study:
Assess the impact of school construction on educational achievements (years of education) and later on wages earned.

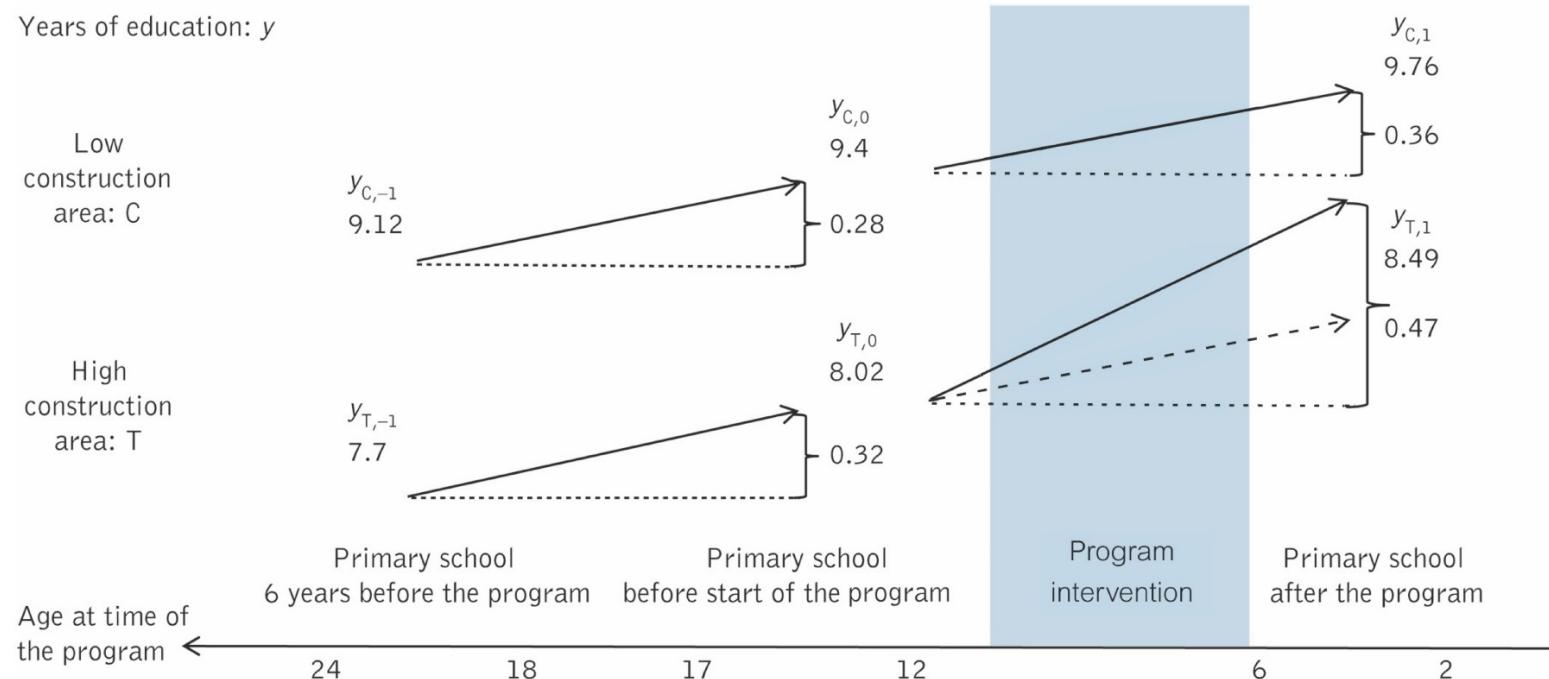
Duflo (2001). Impact of a School Construction Program on Educational Achievements and Wage Earnings

- Used the 1995 population census and looked at the educational and wage achievements of two different cohorts of people: the cohort of people who were of school age before the program and could not benefit from the program, and the cohort of people who attained school age after the program and could fully benefit from the program. People who were of school age during the program would only partially benefit and are not considered in the analysis.
- The "before" cohort is defined by the older group that was 12-17 years old in 1974, the "after" cohort by the younger group that was 2-6 years old in 1974. The contrast between the control and the treatment comes from the variation in program intensity across districts. The school construction program was high intensity in some regions but low intensity in others.

Impact of school construction program on years of education and verification of parallel trends hypothesis

Years of education	Level of program intensity		Difference in region of birth (T-C)
	Low (C)	High (T)	
Six years before (18–24 in 1974)	9.12	7.70	-1.42
Before (12–17 in 1974)	9.40	8.02	-1.38
After (2–6 in 1974)	9.76	8.49	-1.27
Pre-program changes	0.28	0.32	0.04
Before–after changes	0.36	0.47	0.11

Source: Duflo (2001)



Diff-in-diffs before the program
Test of parallel trends.
 $.32 - .28 = .04$ precise zero

Diff-in-diffs due to program
Impact of the program
 $.47 - .36 = .11^{**}$

Example 2

Card, D. and Krueger, A. (1994). Minimum Wages and Employment: A Case Study of the Fast-food Industry in New Jersey and Pennsylvania. American Economic Review, 84(4), 772-93.

➤ Policy background:

In Nov. 1989 a law was passed raising the Federal minimum wage from \$3.35 to \$3.80 per hour effective Apr. 1990, with a further increase to \$4. 25 per hour effective Apr. 1991. The New Jersey legislature then enacted a parallel increase in State minimum wage for 1990 and 1991, and an additional increase to \$5.05 per hour effective Apr 1992 –making New Jersey’s minimum wage the highest among all US States at the time (opposed by many business leaders).

➤ Goal of the study:

Assess the impact of minimum wage increase on establishment level employment outcomes (comparison of employment levels, wages and prices)

Card, D. and Krueger, A. (1994). Minimum Wages and Employment: A Case Study of the Fast-food Industry in New Jersey and Pennsylvania

- Strategy: compare employment outcomes of fast-food restaurants in New Jersey and Pennsylvania (a nearby State)
 - New Jersey is a relatively small State whose economy is closely linked to neighbor States
 - Seasonal patterns of employment in New Jersey and Eastern Pennsylvania are similar

Card, D. and Krueger, A. (1994). Minimum Wages and Employment: A Case Study of the Fast-food Industry in New Jersey and Pennsylvania

➤ Why fast-food chains?

- leading employer of low-wage workers (employs 25% of workers in restaurant industry)
- compliant with minimum wage regulations
- job requirements and products in fast-food restaurants are homogenous; easier to obtain reliable measure of employment, wages and product prices
- wage measurement is easier (no tips)
- sample frame construction is easy
- fast-food chains have high response rate to surveys

Card, D. and Krueger, A. (1994). Minimum Wages and Employment: A Case Study of the Fast-food Industry in New Jersey and Pennsylvania

- Sampling: 410 fast-food restaurants in New Jersey and Pennsylvania were interviewed
 - First wave of interview were conducted in February and March 1992 (just before the increase in minimum wage)
 - Second wave of interview conducted in November and December 1992 (7 to 8 months after the increase in minimum wage)
 - Questions about employment, starting wages, other store characteristics were asked
 - Data on store closings and employment changes were also gathered to capture overall effect

TABLE 1—SAMPLE DESIGN AND RESPONSE RATES

	All	NJ	PA	Stores in:
<i>Wave 1, February 15–March 4, 1992:</i>				
Number of stores in sample frame: ^a	473	364	109	
Number of refusals:	63	33	30	
Number interviewed:	410	331	79	
Response rate (percentage):	86.7	90.9	72.5	
<i>Wave 2, November 5–December 31, 1992:</i>				
Number of stores in sample frame:	410	331	79	
Number closed:	6	5	1	
Number under renovation:	2	2	0	
Number temporarily closed: ^b	2	2	0	
Number of refusals:	1	1	0	
Number interviewed: ^c	399	321	78	

TABLE 2—MEANS OF KEY VARIABLES

Variable	Stores in:		
	NJ	PA	<i>t</i> ^a
1. Distribution of Store Types (percentages):			
a. Burger King	41.1	44.3	-0.5
b. KFC	20.5	15.2	1.2
c. Roy Rogers	24.8	21.5	0.6
d. Wendy's	13.6	19.0	-1.1
e. Company-owned	34.1	35.4	-0.2
2. Means in Wave 1:			
a. FTE employment	20.4 (0.51)	23.3 (1.35)	-2.0
b. Percentage full-time employees	32.8 (1.3)	35.0 (2.7)	-0.7
c. Starting wage	4.61 (0.02)	4.63 (0.04)	-0.4
d. Wage = \$4.25 (percentage)	30.5 (2.5)	32.9 (5.3)	-0.4
e. Price of full meal	3.35 (0.04)	3.04 (0.07)	4.0
f. Hours open (weekday)	14.4 (0.2)	14.5 (0.3)	-0.3
g. Recruiting bonus	23.6 (2.3)	29.1 (5.1)	-1.0
3. Means in Wave 2:			
a. FTE employment	21.0 (0.52)	21.2 (0.94)	-0.2
b. Percentage full-time employees	35.9 (1.4)	30.4 (2.8)	1.8
c. Starting wage	5.08 (0.01)	4.62 (0.04)	10.8
d. Wage = \$4.25 (percentage)	0.0	25.3 (4.9)	—
e. Wage = \$5.05 (percentage)	85.2 (2.0)	1.3 (1.3)	36.1
f. Price of full meal	3.41 (0.04)	3.03 (0.07)	5.0
g. Hours open (weekday)	14.4 (0.2)	14.7 (0.3)	-0.8
h. Recruiting bonus	20.3 (2.3)	23.4 (4.9)	-0.6

Notes: See text for definitions. Standard errors are given in parentheses.

^aTest of equality of means in New Jersey and Pennsylvania.

TABLE 3—AVERAGE EMPLOYMENT PER STORE BEFORE AND AFTER THE RISE
IN NEW JERSEY MINIMUM WAGE

Variable	Stores by state			Stores in New Jersey ^a			Differences within NJ ^b	
	PA (i)	NJ (ii)	Difference, NJ – PA (iii)	Wage = \$4.25 (iv)	Wage = \$4.26–\$4.99 (v)	Wage ≥ \$5.00 (vi)	Low– high (vii)	Midrange– high (viii)
1. FTE employment before, all available observations	23.33 (1.35)	20.44 (0.51)	−2.89 (1.44)	19.56 (0.77)	20.08 (0.84)	22.25 (1.14)	−2.69 (1.37)	−2.17 (1.41)
2. FTE employment after, all available observations	21.17 (0.94)	21.03 (0.52)	−0.14 (1.07)	20.88 (1.01)	20.96 (0.76)	20.21 (1.03)	0.67 (1.44)	0.75 (1.27)
3. Change in mean FTE employment	−2.16 (1.25)	0.59 (0.54)	2.76 (1.36)	1.32 (0.95)	0.87 (0.84)	−2.04 (1.14)	3.36 (1.48)	2.91 (1.41)
4. Change in mean FTE employment, balanced sample of stores ^c	−2.28 (1.25)	0.47 (0.48)	2.75 (1.34)	1.21 (0.82)	0.71 (0.69)	−2.16 (1.01)	3.36 (1.30)	2.87 (1.22)
5. Change in mean FTE employment, setting FTE at temporarily closed stores to 0 ^d	−2.28 (1.25)	0.23 (0.49)	2.51 (1.35)	0.90 (0.87)	0.49 (0.69)	−2.39 (1.02)	3.29 (1.34)	2.88 (1.23)

TABLE 5—SPECIFICATION TESTS OF REDUCED-FORM EMPLOYMENT MODELS

Specification	Change in employment		Proportional change in employment	
	NJ dummy (i)	Gap measure (ii)	NJ dummy (iii)	Gap measure (iv)
1. Base specification	2.30 (1.19)	14.92 (6.21)	0.05 (0.05)	0.34 (0.26)
2. Treat four temporarily closed stores as permanently closed ^a	2.20 (1.21)	14.42 (6.31)	0.04 (0.05)	0.34 (0.27)
3. Exclude managers in employment count ^b	2.34 (1.17)	14.69 (6.05)	0.05 (0.07)	0.28 (0.34)
4. Weight part-time as $0.4 \times$ full-time ^c	2.34 (1.20)	15.23 (6.23)	0.06 (0.06)	0.30 (0.33)
5. Weight part-time as $0.6 \times$ full-time ^d	2.27 (1.21)	14.60 (6.26)	0.04 (0.06)	0.17 (0.29)
6. Exclude stores in NJ shore area ^e	2.58 (1.19)	16.88 (6.36)	0.06 (0.05)	0.42 (0.27)
7. Add controls for wave-2 interview date ^f	2.27 (1.20)	15.79 (6.24)	0.05 (0.05)	0.40 (0.26)
8. Exclude stores called more than twice in wave 1 ^g	2.41 (1.28)	14.08 (7.11)	0.05 (0.05)	0.31 (0.29)
9. Weight by initial employment ^h	—	—	0.13 (0.05)	0.81 (0.26)
10. Stores in towns around Newark ⁱ	—	33.75 (16.75)	—	0.90 (0.74)
11. Stores in towns around Camden ^j	—	10.91 (14.09)	—	0.21 (0.70)
12. Pennsylvania stores only ^k	—	-0.30 (22.00)	—	-0.33 (0.74)

TABLE 7—REDUCED-FORM MODELS FOR CHANGE IN THE PRICE OF A FULL MEAL

Independent variable	Dependent variable: change in the log price of a full meal				
	(i)	(ii)	(iii)	(iv)	(v)
1. New Jersey dummy	0.033 (0.014)	0.037 (0.014)	—	—	—
2. Initial wage gap ^a	—	—	0.077 (0.075)	0.146 (0.074)	0.063 (0.089)
3. Controls for chain and ^b ownership	no	yes	no	yes	yes
4. Controls for region ^c	no	no	no	no	yes
5. Standard error of regression	0.101	0.097	0.102	0.098	0.097

Example 3

Francisco, K. and Tanaka, M. (2019). Does Public Infrastructure Affect Human Capital? The Effect of Improved Transport Connectivity on Children's Education in the Philippines. Economics of Education Review 73, 101927.

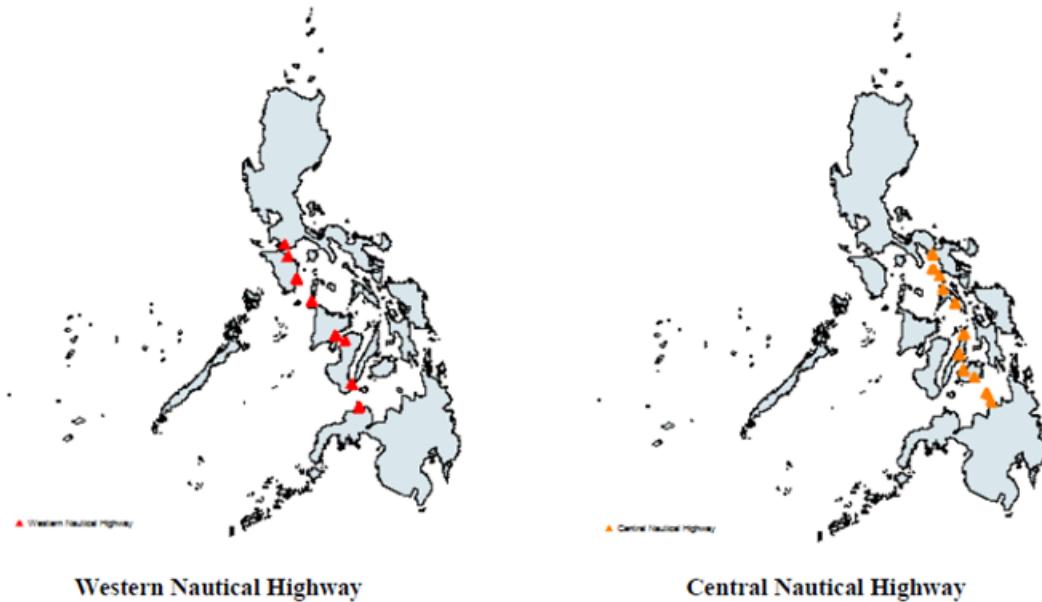
➤ Policy background:

A policy geared towards improving inter-island connectivity in the Philippines was implemented in 2003. Some ports were chosen to be part of the Roll-on/Roll-off (RORO) nautical highway, to allow for a more efficient intermodal connectivity via the RORO vessels. The RORO terminal system is composed of four nautical highways, covering the main islands of the country, Luzon, Visayas and Mindanao. The RORO policy was implemented in 2003 but the full roll-out of nautical highways was achieved in 2009.

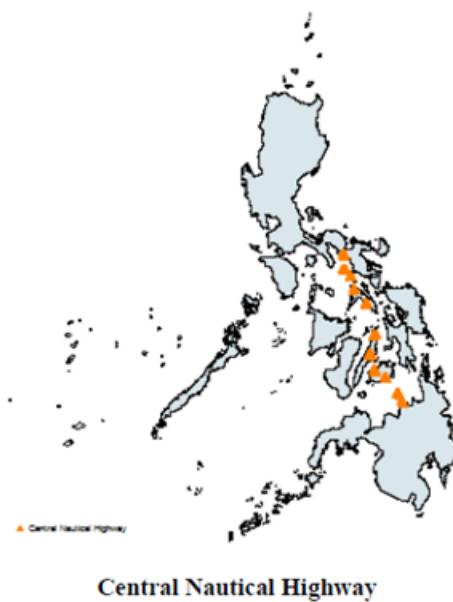
➤ Goal of the study:

Assess if the improvement in transport connectivity via RORO nautical highways affected children's education

Figure 1. Map of Philippine Nautical Highways



Western Nautical Highway



Central Nautical Highway



Pan-Philippine Highway



Eastern Nautical Highway

Note: list of Ro-Ro ports sourced from Philippine Ports Authority

Francisco, K. and Tanaka, M. (2019). Does Public Infrastructure Affect Human Capital? The Effect of Improved Transport Connectivity on Children's Education in the Philippines. Economics of Education Review 73, 101927.

➤ Strategy:

Analyze the change in school attendance in areas near the RORO ports; compare it with school attendance in areas near non-RORO ports, before and after policy implementation (municipality-level analysis).

➤ Why municipality-level?

- most likely to have at least one port
- initial changes caused by policy change may be more evident at the municipality level
- municipalities are easily identifiable using geographic data

Francisco, K. and Tanaka, M. (2019). Does Public Infrastructure Affect Human Capital? The Effect of Improved Transport Connectivity on Children's Education in the Philippines. Economics of Education Review 73, 101927.

➤ Treatment identification:

Compute distances using straight line distance formula; compare to which port the municipality is nearest to.

- Treatment group: municipalities closest to RORO port
- Control group: municipalities closest to non-RORO port

Francisco, K. and Tanaka, M. (2019). Does Public Infrastructure Affect Human Capital? The Effect of Improved Transport Connectivity on Children's Education in the Philippines. Economics of Education Review 73, 101927.

- Data:
 - Census of Population and Housing (CPH) 2000, 2010
 - Statement of Income and Expenditure from the Department of Finance's Bureau of Local Government Finance
 - List of RORO ports from Philippine Ports Authority
 - Inventory of Philippine Ports from Philippine Statistics Authority
 - Philippine Standard Geographic Code from Philippine Statistics Authority
 - Data Kit of Official Philippine Statistics from Philippine Statistics Authority

➤ Model specification:

$$y_{asmt} = \delta_a(D_m \cdot T_t \cdot S_s \cdot A_a) + \theta_a(D_m \cdot T_t \cdot A_a) + \beta_1 D_m + \beta_2 T_t + \beta_{3a} A_a + \beta_4 S_s + \phi_{asmt} + \mu_m + e_{asmt} \quad (2)$$

where:

$$\phi_{asmt} = \beta_{5a}(D_m \cdot A_a) + \beta_6(D_m \cdot S_s) + \beta_{7a}(S_s \cdot A_a) + \beta_{8a}(D_m \cdot S_s \cdot A_a) + \beta_9(T_t \cdot S_s) + \beta_{10a}(T_t \cdot A_a) + \beta_{11a}(T_t \cdot S_s \cdot A_a)$$

- DID estimator:

$$E(\hat{\gamma}_{as}) = (\delta_a + \theta_a + \beta_2 + \beta_9 + \beta_{10a} + \beta_{11a}) - (\beta_2 + \beta_9 + \beta_{10a} + \beta_{11a})$$

$$E(\hat{\gamma}_{as}) = \delta_a + \theta_a$$

Table 1
Characteristics of control and treatment group at pre-treatment period (Year 2000).

Variable	Mean		SD		Min.		Max	
	C	T	C	T	C	T	C	T
School attendance ratio	0.67305	0.65585	0.24499	0.25195	0.00	0.00	1.00	1.00
Employment-to-population ratio	0.36985	0.37048	0.24331	0.22451	0.00	0.00	1.00	1.00
Proportion of barangays with primary level school	0.76431	0.78449	0.20679	0.17193	0.00	0.05	1.00	1.00
Proportion of barangays with secondary level school	0.19806	0.17951	0.13521	0.10172	0.00	0.00	1.00	0.86
Proportion of barangays with tertiary level school	0.03838	0.03014	0.06470	0.04476	0.00	0.00	0.60	0.26
Log of tax revenue per capita (real value)	9.99481	9.79495	1.29003	0.92303	5.11584	6.02749	17.27475	13.08377

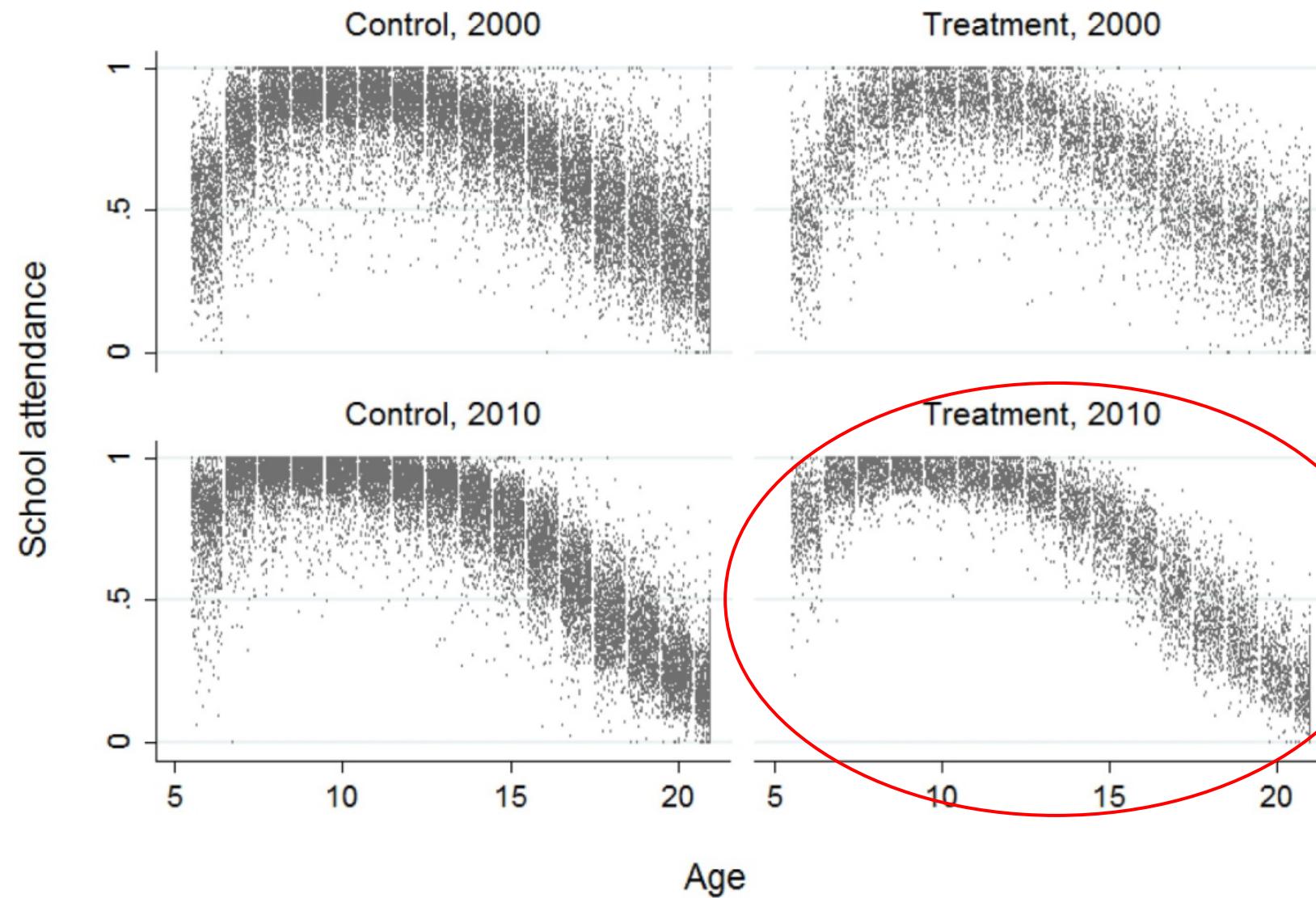


Fig. 4. Distribution of School Attendance for Males, 5 to 21 years old.

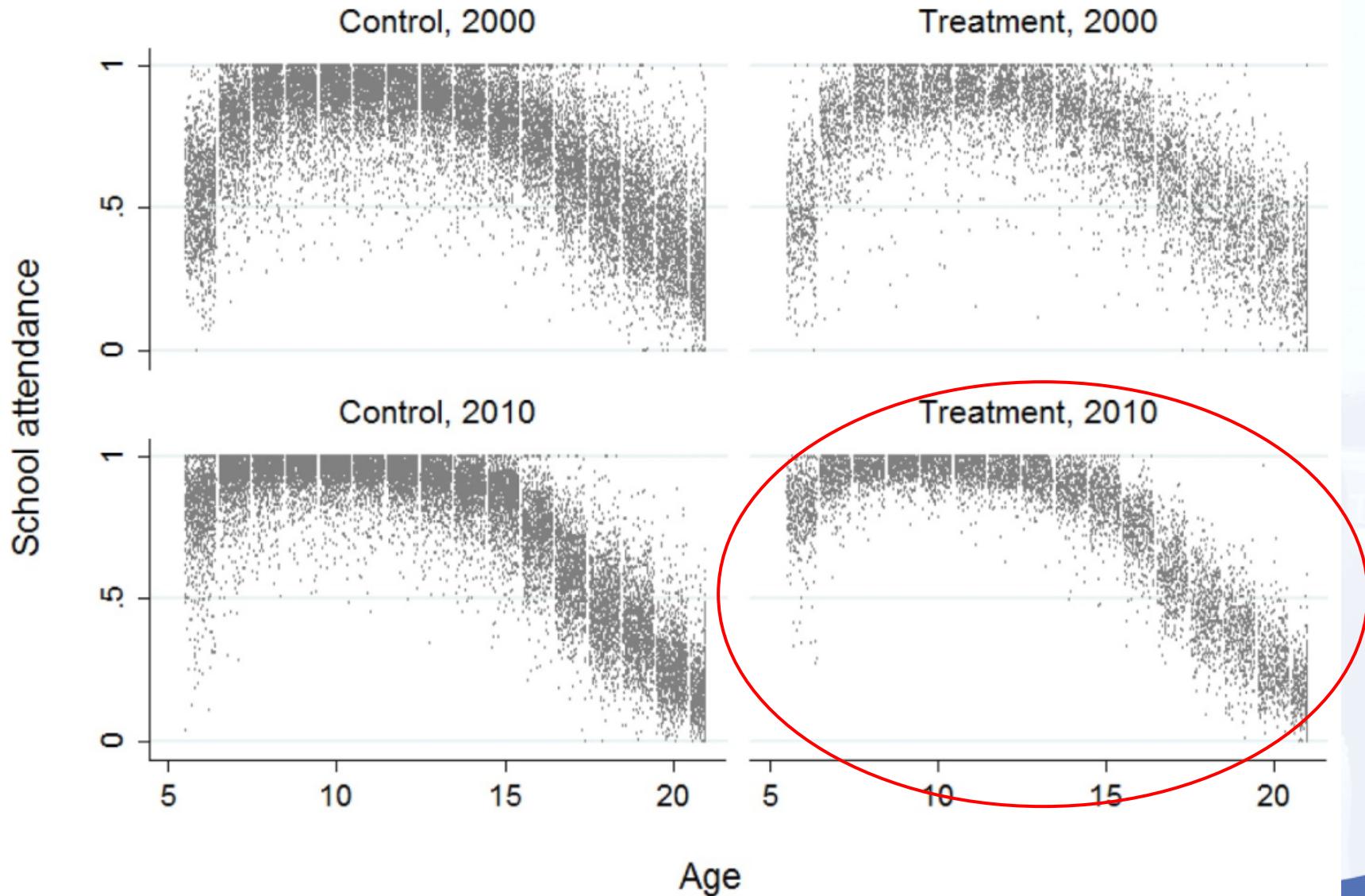


Fig. 5. Distribution of School Attendance for Females, 5 to 21 years old.

Table 2
Difference-in-differences estimates for school attendance.

	Male	Female
Pre-primary level		
Age 5	0.01610 (0.00991)	0.02016** (0.00977)
Primary level		
Age 6	0.03682*** (0.00957)	0.05557*** (0.00988)
Age 7	0.03910*** (0.00715)	0.02170*** (0.00650)
Age 8	0.01809*** (0.00591)	0.00910 (0.00571)
Age 9	0.01147** (0.00503)	0.00866 (0.00544)
Age 10	0.01285** (0.00529)	0.01271** (0.00521)
Age 11	0.01192** (0.00519)	0.00757 (0.00535)
Age 12	0.01727*** (0.00543)	0.00654 (0.00518)
Secondary level		
Age 13	0.01865*** (0.00644)	0.01790*** (0.00558)
Age 14	0.02185*** (0.00655)	0.02040*** (0.00582)
Age 15	0.03063*** (0.00687)	0.02886*** (0.00693)
Age 16	0.02929*** (0.00765)	0.02497*** (0.00785)
Tertiary level		
Age 17	0.01663** (0.00839)	0.03286*** (0.00863)
Age 18	0.02036** (0.00839)	0.02104** (0.00905)
Age 19	0.02854*** (0.00891)	0.01820** (0.00901)
Age 20	0.02233*** (0.00854)	0.02712*** (0.00872)
Age 21	0.01452 (0.00903)	0.02207** (0.00925)
N:		
observations	104,598	
groups	1539	
R-squared:		
within	0.8491	
between	0.0016	
overall	0.7965	

Table 3

Difference-in-differences estimates for child employment.

	Male	Female
Secondary level		
Age 15	-0.02848** (0.01149)	-0.00942 (0.01143)
Age 16	-0.03332*** (0.01176)	-0.01208 (0.01169)
Tertiary level		
Age 17	-0.02712** (0.01157)	-0.02462** (0.01150)
Age 18	-0.03302*** (0.01149)	-0.01990* (0.01180)
Age 19	-0.03714*** (0.01224)	-0.03265*** (0.01185)
Age 20	-0.04414*** (0.01166)	-0.02717** (0.01151)
Age 21	-0.03845*** (0.01119)	-0.03289*** (0.01238)
N:		
<i>observations</i>	43,070	
<i>groups</i>	1539	
R-squared:		
<i>within</i>	0.6146	
<i>between</i>	0.0062	
<i>overall</i>	0.5134	

Table 4
Estimates for log of tax revenue per capita.

Treatment	-0.19923*** (0.06039)
Year	0.28805*** (0.01996)
DID estimator	0.06925** (0.03465)
N:	
<i>observations</i>	2870
<i>groups</i>	1435
R-squared:	
<i>within</i>	0.2015
<i>between</i>	0.0041
<i>overall</i>	0.0195

Table 5

Estimates for school attendance and log of tax revenue per capita.

log of tax revenue per capita	0.01776*** (0.00177)
The model controls for:	
Year	Yes
Sex	Yes
Age	Yes
<i>Number of observations</i>	91,788
<i>R-squared</i>	0.8100
<i>Root MSE</i>	0.1106

Table 6

Estimates for school access.

	Prop. of barangays with primary level schools	Prop. of barangays with secondary level schools	Prop. of barangays with tertiary level schools
Treatment	0.01999*	-0.01860***	-0.00825***
	(0.01022)	(0.00630)	(0.00288)
Year	0.03085***	0.05788***	0.01186***
	(0.00392)	(0.00310)	(0.00171)
DID estimator	-0.00305	-0.01496***	-0.00240
	(0.00632)	(0.00510)	(0.00260)
N:			
<i>observations</i>	3076	3076	3076
<i>groups</i>	1538	1538	1538
R-squared:			
<i>within</i>	0.0565	0.2337	0.0437
<i>between</i>	0.0020	0.0083	0.0050
<i>overall</i>	0.0076	0.0429	0.0113

Table 7

Comparison of difference-in-differences estimates for school attendance.

	(a) Base Model I		(b) Controlling for domestic migration		(c) Controlling for foreign migration	
	Male	Female	Male	Female	Male	Female
Pre-primary level						
Age 5	0.01610 (0.00991)	0.02016** (0.00977)	0.01608 (0.00991)	0.02013** (0.00976)	0.01590 (0.00991)	0.01997** (0.00974)
Primary level						
Age 6	0.03682*** (0.00957)	0.05557*** (0.00988)	0.03679*** (0.00956)	0.05554*** (0.00988)	0.03662*** (0.00955)	0.05537*** (0.00986)
Age 7	0.03910*** (0.00715)	0.02170*** (0.00650)	0.03909*** (0.00715)	0.02167*** (0.00650)	0.03891*** (0.00719)	0.02150*** (0.00654)
Age 8	0.01809*** (0.00591)	0.00910 (0.00571)	0.01806*** (0.00591)	0.00907 (0.00571)	0.01789*** (0.00597)	0.00891 (0.00573)
Age 9	0.01147** (0.00503)	0.00866 (0.00544)	0.01146** (0.00502)	0.00863 (0.00544)	0.01128** (0.00507)	0.00846 (0.00550)
Age 10	0.01285** (0.00529)	0.01271** (0.00521)	0.01283** (0.00529)	0.01268** (0.00520)	0.01265** (0.00533)	0.01251** (0.00525)
Age 11	0.01192** (0.00519)	0.00757 (0.00535)	0.01189** (0.00519)	0.00755 (0.00535)	0.01172** (0.00523)	0.00738 (0.00537)
Age 12	0.01727*** (0.00543)	0.00654 (0.00518)	0.01724*** (0.00543)	0.00651 (0.00518)	0.01707*** (0.00544)	0.00634 (0.00522)
Secondary level						
Age 13	0.01865*** (0.00644)	0.01790*** (0.00558)	0.01862*** (0.00644)	0.01787*** (0.00558)	0.01846*** (0.00644)	0.01771*** (0.00561)
Age 14	0.02185*** (0.00655)	0.02040*** (0.00582)	0.02183*** (0.00655)	0.02037*** (0.00582)	0.02166*** (0.00654)	0.02020*** (0.00580)
Age 15	0.03063*** (0.00687)	0.02886*** (0.00693)	0.03060*** (0.00686)	0.02884*** (0.00693)	0.03043*** (0.00685)	0.02867*** (0.00694)
Age 16	0.02929*** (0.00765)	0.02497*** (0.00785)	0.02927*** (0.00765)	0.02494*** (0.00785)	0.02910*** (0.00761)	0.02477*** (0.00784)
Tertiary level						
Age 17	0.01663** (0.00839)	0.03286*** (0.00863)	0.01662** (0.00839)	0.03283*** (0.00863)	0.01644** (0.00836)	0.03266*** (0.00863)
Age 18	0.02036** (0.00839)	0.02104** (0.00905)	0.02034** (0.00839)	0.02101** (0.00905)	0.02016** (0.00835)	0.02085** (0.00899)
Age 19	0.02854*** (0.00891)	0.01820** (0.00901)	0.02853*** (0.00891)	0.01817** (0.00901)	0.02835*** (0.00886)	0.01800** (0.00896)
Age 20	0.02233*** (0.00854)	0.02712*** (0.00872)	0.02232*** (0.00854)	0.02709*** (0.00872)	0.02214*** (0.00850)	0.02692*** (0.00870)
Age 21	0.01452 (0.00903)	0.02207** (0.00925)	0.01451 (0.00903)	0.02205** (0.00924)	0.01433 (0.00898)	0.02187** (0.00922)
N:						
observations	104,598		104,598		104,598	
groups	1539		1539		1539	
R-squared:						
within	0.8491		0.8491		0.8495	
between	0.0016		0.0021		0.0803	
overall	0.7965		0.7963		0.8048	

Example 4

Abrigo, M. and Francisco, K. (forthcoming). Compulsory Kindergarten Education and Early Teenage Literacy in the Philippines. International Journal of Educational Development.

➤ Policy background:

In 2012, the Philippine government mandated compulsory kindergarten education, institutionalizing it as part of the country's basic education. Through the Kindergarten Education Act, all children set to enroll in the primary level (aged 5 years or older) are required to attend at least one year of pre-primary schooling.

➤ Goal of the study:

Assess the impact of compulsory kindergarten education on early teenage basic and functional literacy skills achievement.

Abrigo, M. and Francisco, K. (forthcoming). Compulsory Kindergarten Education and Early Teenage Literacy in the Philippines. International Journal of Educational Development.

➤ **Strategy:**

Compare the average literacy rates of those aged 11 to 13 years with older cohorts aged 14 to 16 years over the study period (2008, 2013, 2019). Those aged 11 to 13 years in the 2019 FLEMMS were required to attend kindergarten prior to entering primary level. They serve as the treatment group.

➤ **Data:**

- Philippine Functional Literacy, Education and Mass Media Survey (FLEMMS) 2008, 2013, 2019

➤ Model specification:

$$y_{iat} = \tau \cdot I(a \leq 13) \cdot I(t = 2019) + \mathbf{X}_{it}\boldsymbol{\beta} + \mu_t + \kappa_a + \gamma + \varepsilon_{iat},$$

where individuals aged a at period t are indexed by $i = 1, 2, \dots N_t$. The variable y corresponds to one of three possible dummy variables indicating literacy level attainment: Level 1, 2 or 3. The row vector \mathbf{X} are individual and household characteristics that we control in the model, and $\boldsymbol{\beta}$ is a conformable vector of regression coefficients. The parameters μ_t and κ_a are period- and age-fixed effects, respectively. The variable ε is the usual regression model residual. Our parameter of interest is τ , which captures the impact of the compulsory kindergarten education on the literacy level attainment of early teens.

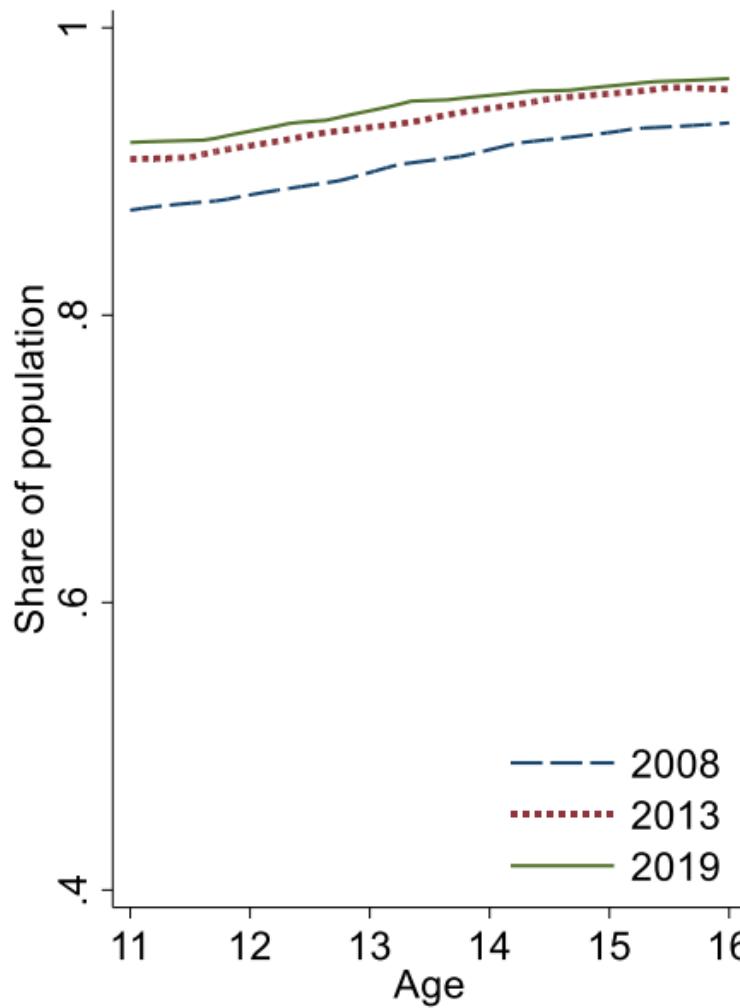
Table 2. Literacy distribution (%) among early teens by year and characteristics

	Basic Literacy			Functional Literacy					
	At least Level 1			At least Level 2			At least Level 3		
	2008	2013	2019	2008	2013	2019	2008	2013	2019
All sample	90.5	93.5	94.4	84.4	87.7	89.3	60.0	59.8	62.5
Age group									
11-13	88.1	91.9	92.9	80.9	84.4	86.2	55.2	54.3	58.8
14-16	92.9	95.1	96.0	88.0	91.1	92.5	65.1	65.6	66.2
Sex									
Male	88.0	91.9	92.9	81.3	85.7	87.5	55.3	56.5	59.3
Female	93.1	95.1	96.0	87.7	89.7	91.3	65.1	63.2	65.9
Highest education level in household									
Primary	70.5	78.3	76.0	58.7	68.6	67.2	32.5	34.2	39.3
Secondary	91.1	93.7	94.7	84.8	87.1	89.0	58.1	56.9	61.2
Tertiary	96.2	97.0	97.1	92.3	93.0	93.5	72.1	69.3	68.4
Broad region of residence									
NCR	95.6	97.1	97.3	90.9	90.1	93.7	74.5	65.6	69.8
Luzon, others	92.8	94.5	95.0	87.2	90.3	90.1	65.6	66.6	65.5
Visayas	87.1	91.9	93.3	79.5	83.3	86.4	52.0	53.2	58.3
Mindanao	87.1	91.8	93.5	80.8	85.3	88.7	51.2	51.8	59.2

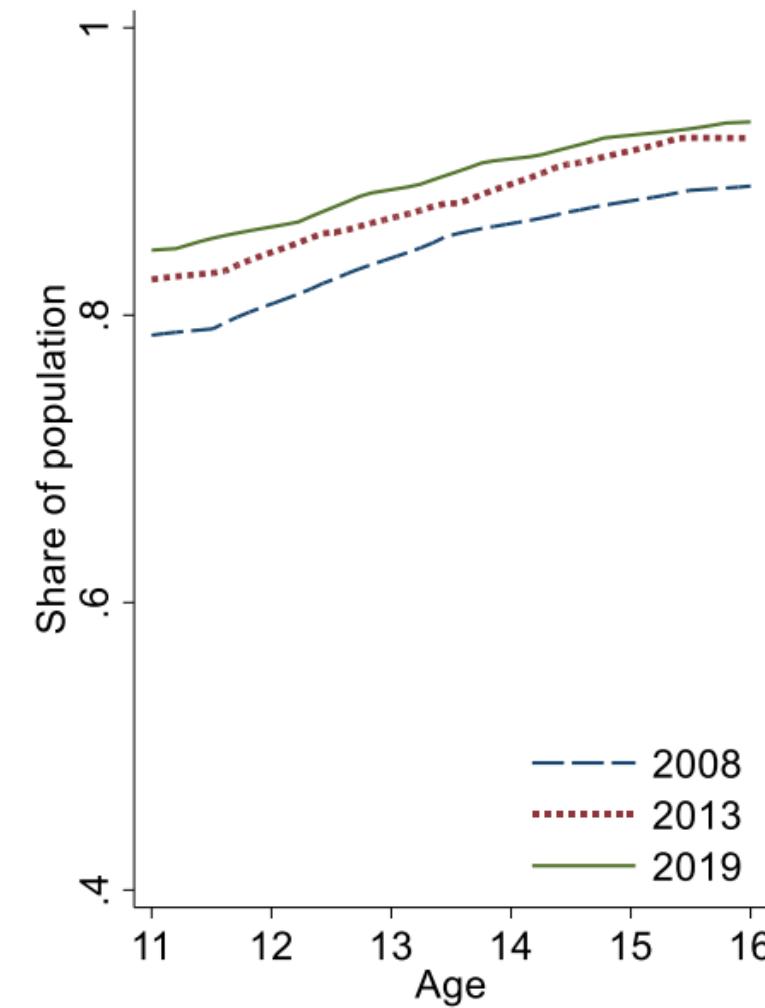
Source: Authors' estimates based on FLEMMS data, various years

Figure 2. Literacy rate by level and age

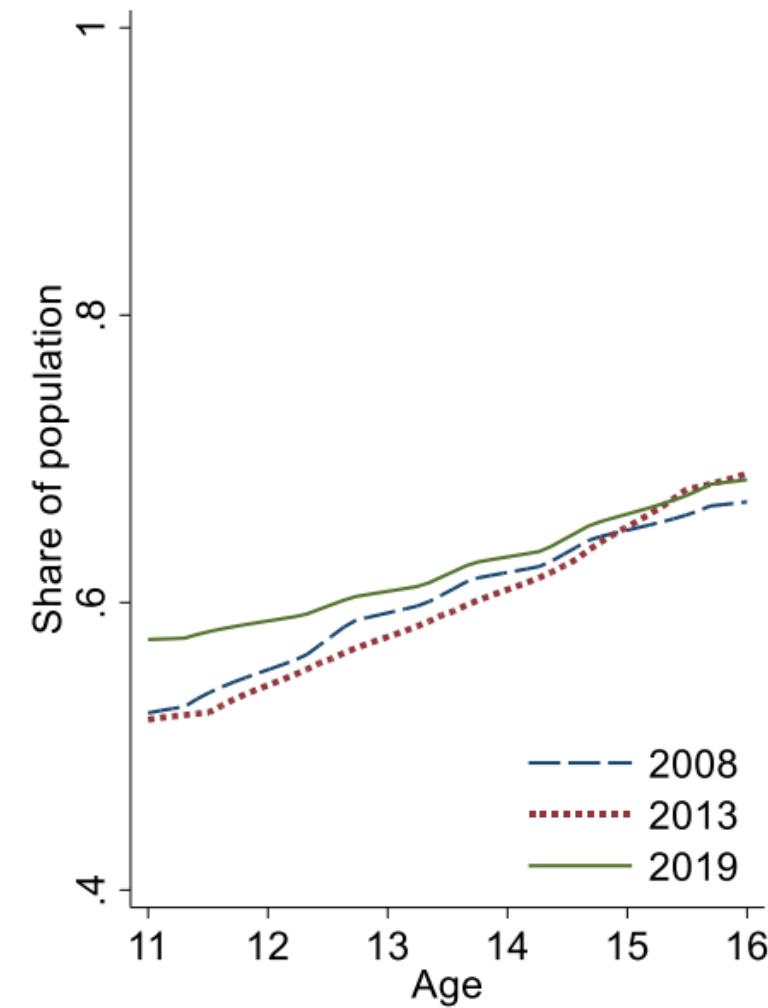
A. At least Level 1



B. At least Level 2



C. At least Level 3



Source: Authors' estimates based on FLEMMS data, various years

Appendix Table A. Covariate balance

	Age 11-13		Age 14-16		Std.	Var.
	Mean	SD	Mean	SD	Diff.	Ratio
A. All sample						
Household wealth index	-0.12	1.07	-0.21	1.09	0.08	0.97
Household head, college-educated (=1)	0.18	0.39	0.17	0.38	0.03	1.05
Household head, employed (=1)	0.11	0.31	0.11	0.31	0.01	1.02
Household head, female (=1)	0.15	0.36	0.14	0.35	0.04	1.08
Household with everyday reader (=1)	0.58	0.49	0.58	0.49	0.00	1.00
Household with everyday writer (=1)	0.14	0.35	0.14	0.35	0.00	1.01
Household with everyday arithmetic user (=1)	0.49	0.50	0.47	0.50	0.02	1.00
B. FLEMMS 2008 sample						
Household wealth index	-0.39	1.22	-0.29	1.21	-0.09	1.02
Household head, college-educated (=1)	0.11	0.31	0.12	0.32	-0.03	0.92
Household head, employed (=1)	0.09	0.29	0.11	0.31	-0.05	0.88
Household head, female (=1)	0.12	0.33	0.14	0.35	-0.05	0.89
Household with everyday reader (=1)	0.66	0.47	0.66	0.47	0.01	0.99
Household with everyday writer (=1)	0.18	0.38	0.18	0.38	0.00	0.99
Household with everyday arithmetic user (=1)	0.40	0.49	0.43	0.49	-0.05	0.98
C. FLEMMS 2013 sample						
Household wealth index	-0.25	1.10	-0.14	1.08	-0.10	1.04
Household head, college-educated (=1)	0.21	0.41	0.23	0.42	-0.06	0.92
Household head, employed (=1)	0.11	0.31	0.10	0.31	0.00	1.01
Household head, female (=1)	0.10	0.30	0.12	0.32	-0.05	0.88
Household with everyday reader (=1)	0.58	0.49	0.59	0.49	-0.02	1.01
Household with everyday writer (=1)	0.13	0.34	0.13	0.33	0.01	1.02
Household with everyday arithmetic user (=1)	0.37	0.48	0.37	0.48	0.00	1.00
D. FLEMMS 2019 sample						
Household wealth index	-0.05	0.96	-0.01	0.96	-0.05	1.01
Household head, college-educated (=1)	0.19	0.39	0.20	0.40	-0.01	0.99
Household head, employed (=1)	0.12	0.33	0.12	0.32	0.01	1.01
Household head, female (=1)	0.18	0.38	0.19	0.39	-0.02	0.96
Household with everyday reader (=1)	0.53	0.50	0.53	0.50	0.01	1.00
Household with everyday writer (=1)	0.12	0.32	0.12	0.33	-0.02	0.97
Household with everyday arithmetic user (=1)	0.59	0.49	0.59	0.49	-0.01	1.01

Note: Std. diff. – standardized difference; Var. ratio – variance ratio

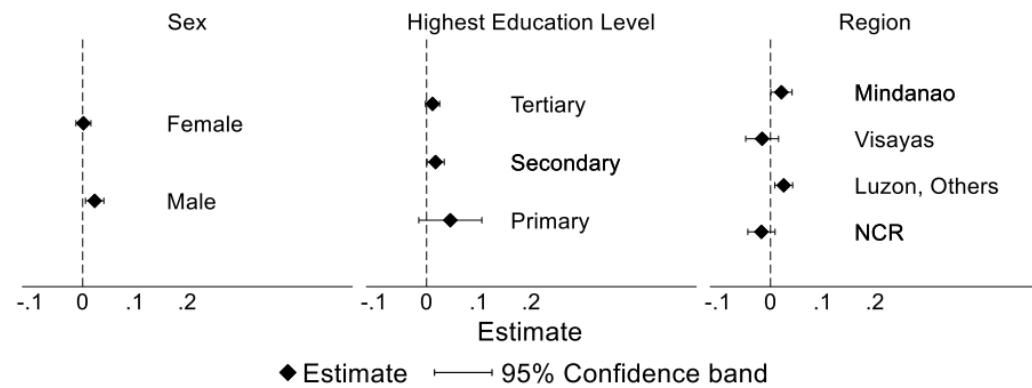
Table 3. ITT estimate of kindergarten impact on literacy level

	Basic Literacy			Functional Literacy					
	At least Level 1			At least Level 2			At least Level 3		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
I(a≤13) x I(t=2019)	0.002 (0.005)	0.000 (0.005)	0.000 (0.005)	0.003 (0.007)	0.000 (0.007)	0.000 (0.007)	0.039*** (0.011)	0.035*** (0.011)	0.035*** (0.010)
I(a≤13)	-0.032*** (0.004)	-0.021*** (0.004)	-0.021*** (0.004)	-0.067*** (0.006)	-0.052*** (0.006)	-0.053*** (0.006)	-0.112*** (0.009)	-0.095*** (0.008)	-0.097*** (0.008)
I(t=2019)	0.008** (0.004)	0.003 (0.003)	0.005 (0.003)	0.014*** (0.005)	0.010** (0.005)	0.014*** (0.005)	0.006 (0.008)	0.004 (0.008)	0.012 (0.008)
Child - female	Yes	Yes			Yes	Yes		Yes	Yes
Household head - employed	Yes	Yes			Yes	Yes		Yes	Yes
Household head - female	Yes	Yes			Yes	Yes		Yes	Yes
Household - highest education	Yes	Yes			Yes	Yes		Yes	Yes
Household - assets	Yes	Yes			Yes	Yes		Yes	Yes
Household - residence region		Yes				Yes			Yes
Observations	33,142	33,142	33,142	33,142	33,142	33,142	33,142	33,142	33,142
Adjusted R-square	0.005	0.052	0.065	0.011	0.052	0.066	0.009	0.040	0.057
BIC	-1,805	-3,372	-3,684	17,464	16,114	15,760	46,045	45,054	44,611

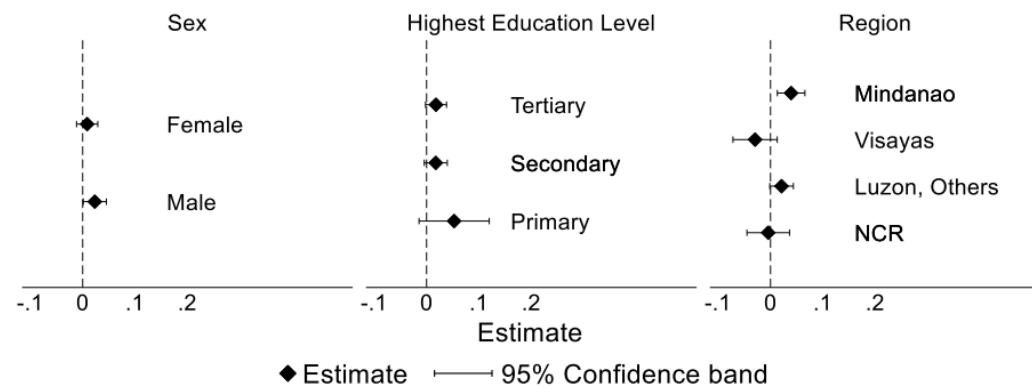
Note: *, **, *** signify statistical significance at the 10%, 5% and 1% alpha levels, respectively. Values in parentheses are heteroskedasticity-robust standard errors clustered at the household level. The sample includes children aged 11 to 16 years in the 2013 and 2019 FLEMMS. BIC – Bayesian information criterion.

Figure 3. ITT estimate of kindergarten impact on literacy level by characteristics

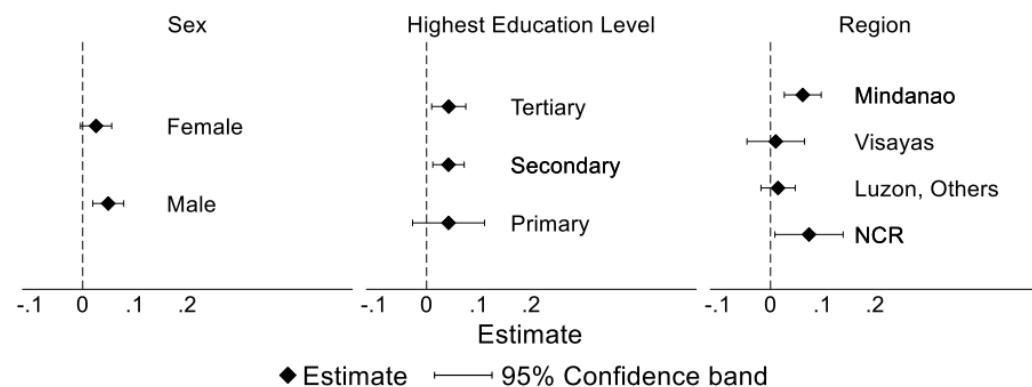
A. At least Level 1



B. At least Level 2



C. At least Level 3



Appendix Table B1. Falsification test: Pre-treatment trend

	Basic Literacy			Functional Literacy					
	At least Level 1			At least Level 2			At least Level 3		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
I(a≤13) x I(t=2008)	-0.016** (0.007)	-0.014** (0.006)	-0.015** (0.006)	-0.005 (0.008)	-0.002 (0.008)	-0.003 (0.008)	0.013 (0.012)	0.016 (0.012)	0.014 (0.011)
I(a≤13)	-0.032*** (0.004)	-0.019*** (0.004)	-0.020*** (0.004)	-0.067*** (0.006)	-0.050*** (0.006)	-0.051*** (0.006)	-0.112*** (0.009)	-0.092*** (0.008)	-0.094*** (0.008)
I(t=2008)	-0.022*** (0.004)	-0.018*** (0.004)	-0.014*** (0.004)	-0.031*** (0.006)	-0.024*** (0.006)	-0.019*** (0.006)	-0.004 (0.009)	0.007 (0.009)	0.010 (0.009)
Child - female	Yes	Yes			Yes	Yes		Yes	Yes
Household head - employed	Yes	Yes			Yes	Yes		Yes	Yes
Household head - female	Yes	Yes			Yes	Yes		Yes	Yes
Household - highest education	Yes	Yes			Yes	Yes		Yes	Yes
Household - assets	Yes	Yes			Yes	Yes		Yes	Yes
Household - residence region		Yes				Yes			Yes
Observations	25,434	25,434	25,434	25,434	25,434	25,434	25,434	25,434	25,434
Adjusted R-square	0.009	0.070	0.079	0.012	0.075	0.087	0.012	0.067	0.096
BIC	5,843	4,255	4,167	18,115	16,491	16,311	35,641	34,212	33,566

Note: *, **, *** signify statistical significance at the 10%, 5% and 1% alpha levels, respectively. Values in parentheses are heteroskedasticity-robust standard errors clustered at the household level. The sample includes children aged 11 to 16 years in the 2008 and 2013 FLEMMS. BIC – Bayesian information criterion.

Appendix Table B2. Falsification test: Placebo treatment group

	Basic Literacy			Functional Literacy					
	At least Level 1			At least Level 2			At least Level 3		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
I(a≥17) x I(t=2019)	-0.003 (0.004)	0.000 (0.004)	0.001 (0.004)	-0.007 (0.006)	-0.003 (0.006)	-0.001 (0.006)	0.004 (0.010)	0.012 (0.010)	0.014 (0.010)
I(a≥17)	0.014*** (0.004)	0.009** (0.004)	0.008** (0.004)	0.035*** (0.005)	0.026*** (0.005)	0.025*** (0.005)	0.162*** (0.008)	0.146*** (0.008)	0.143*** (0.008)
I(t=2019)	0.008** (0.004)	-0.001 (0.003)	0.000 (0.003)	0.014*** (0.005)	0.006 (0.005)	0.009* (0.005)	0.006 (0.008)	0.000 (0.008)	0.008 (0.008)
Child - female	Yes	Yes			Yes	Yes		Yes	Yes
Household head - employed	Yes	Yes			Yes	Yes		Yes	Yes
Household head - female	Yes	Yes			Yes	Yes		Yes	Yes
Household - highest education	Yes	Yes			Yes	Yes		Yes	Yes
Household - assets	Yes	Yes			Yes	Yes		Yes	Yes
Household - residence region		Yes				Yes			Yes
Observations	30,624	30,624	30,624	30,624	30,624	30,624	30,624	30,624	30,624
Adjusted R-square	0.001	0.081	0.089	0.004	0.071	0.080	0.035	0.094	0.108
BIC	-14,905	-17,392	-17,531	1,340	-737	-886	35,637	33,745	33,428

Note: *, **, *** signify statistical significance at the 10%, 5% and 1% alpha levels, respectively. Values in parentheses are heteroskedasticity-robust standard errors clustered at the household level. The sample includes children aged 14 to 19 years in the 2013 and 2019 FLEMMS. BIC – Bayesian information criterion.

Appendix Table B3. Falsification test: Placebo outcomes

	Everyday reader			Everyday writer			Everyday arithmetic user		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
I(a≤13) x I(t=2019)	0.012 (0.010)	0.008 (0.010)	0.007 (0.010)	-0.008 (0.007)	-0.010 (0.007)	-0.011 (0.007)	-0.005 (0.010)	-0.010 (0.010)	-0.009 (0.009)
I(a≤13)	-0.008 (0.008)	0.011 (0.007)	0.009 (0.007)	0.003 (0.005)	0.009* (0.005)	0.009* (0.005)	-0.002 (0.008)	0.014* (0.007)	0.014* (0.007)
I(t=2019)	-0.061*** (0.009)	-0.062*** (0.009)	-0.066*** (0.009)	-0.002 (0.006)	0.000 (0.006)	0.005 (0.006)	0.222*** (0.009)	0.228*** (0.009)	0.214*** (0.009)
Child - female	Yes	Yes			Yes	Yes		Yes	Yes
Household head - employed	Yes	Yes			Yes	Yes		Yes	Yes
Household head - female	Yes	Yes			Yes	Yes		Yes	Yes
Household - highest education	Yes	Yes			Yes	Yes		Yes	Yes
Household - assets	Yes	Yes			Yes	Yes		Yes	Yes
Household - residence region		Yes				Yes			Yes
Observations	34,698	34,698	34,698	34,698	34,698	34,698	34,698	34,698	34,698
Adjusted R-square	0.003	0.038	0.049	0.000	0.011	0.018	0.045	0.081	0.107
BIC	49,969	48,785	48,555	21,422	21,078	21,009	48,794	47,520	46,691

Note: *, **, *** signify statistical significance at the 10%, 5% and 1% alpha levels, respectively. Values in parentheses are heteroskedasticity-robust standard errors clustered at the household level. The sample includes children aged 11 to 16 years in the 2013 and 2019 FLEMMS. BIC – Bayesian information criterion.

Appendix Table B4. Falsification test: Alternative comparison group

	Basic Literacy			Functional Literacy					
	At least Level 1			At least Level 2			At least Level 3		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
I(a≤13) x I(t=2019)	0.004 (0.005)	0.000 (0.005)	-0.002 (0.005)	0.009 (0.007)	0.003 (0.007)	0.001 (0.007)	0.034*** (0.010)	0.023** (0.010)	0.021** (0.010)
I(a≤13)	-0.046*** (0.004)	-0.029*** (0.004)	-0.028*** (0.004)	-0.101*** (0.006)	-0.078*** (0.005)	-0.077*** (0.005)	-0.275*** (0.008)	-0.239*** (0.008)	-0.238*** (0.008)
I(t=2019)	0.006* (0.003)	0.003 (0.003)	0.006* (0.003)	0.008** (0.004)	0.007* (0.004)	0.013*** (0.004)	0.011 (0.007)	0.017** (0.007)	0.026*** (0.007)
Child - female	Yes	Yes			Yes	Yes		Yes	Yes
Household head - employed	Yes	Yes			Yes	Yes		Yes	Yes
Household head - female	Yes	Yes			Yes	Yes		Yes	Yes
Household - highest education	Yes	Yes			Yes	Yes		Yes	Yes
Household - assets	Yes	Yes			Yes	Yes		Yes	Yes
Household - residence region		Yes				Yes			Yes
Observations	31,020	31,020	31,020	31,020	31,020	31,020	31,020	31,020	31,020
Adjusted R-square	0.010	0.063	0.075	0.026	0.075	0.088	0.076	0.123	0.140
BIC	-4,284	-5,949	-6,192	12,847	11,297	11,014	37,910	36,350	35,903

Note: *, **, *** signify statistical significance at the 10%, 5% and 1% alpha levels, respectively. Values in parentheses are heteroskedasticity-robust standard errors clustered at the household level. The sample includes children aged 11-13 and 17-19 years in the 2013 and 2019 FLEMMS. BIC – Bayesian information criterion.

2024

CAPACITY DEVELOPMENT ON IMPACT EVALUATION

CHAPTER BREAK

Subtitle

Exercises



Exercise 1: Impact evaluation of a land certification program using a double difference approach: Procede in Mexico

- During the period running from 1993 to 2006, Mexico engaged in a major land certification program called Procede that gave property rights to some 2.5 million farm households over half of the country's agricultural land. The program was rolled out gradually across localities. Before certification, these farm households only had the right of use of the land (not ownership) and could be expropriated if they did not farm the land productively. One research question is whether having a land title giving households security of land ownership creates opportunities for migration since they no longer risk losing the land if they do not farm it productively. To test this, we use data from the population censuses by localities in 1980, 1990, and 2000. Net migration would be seen in the change in population in localities that were treated (certified between 1993 and 1999) and not treated (certified in 2000 or after). In worksheet “Procede”, we give you data on the average population size (number of persons) in 10,924 localities that were certified between 1993 and 1999, and in 6,828 localities that were certified in 2000 or after.

Exercise 1: Population in localities associated with ejidos, by period of certification

	Number of localities	1980	Average Locality Population	
			1990	2000
Certified between 1993 and 1999	10924	122	95	83
Certified in 2000 or after	6828	128	101	92

Source: data used in Table 2 of de Janvry, Emerick, Gonzalez-Navarro, Sadoulet

Exercise 1 (questions)

- Calculate the average change in population between the censuses for the treated and control localities.
- By double difference, measure what was the impact of land certification on average change in population. Did granting property rights increase or decrease net in-migration and by how much?
- How would you verify that the diff-in-diffs methodology applies to measuring the impact of certification on migration during the 1990-2000 period: explain what the test is and what it means.
- Show in the table below and on a graph the results of the test you proposed in response to the previous question.

Exercise 1

Report your results in the following table:

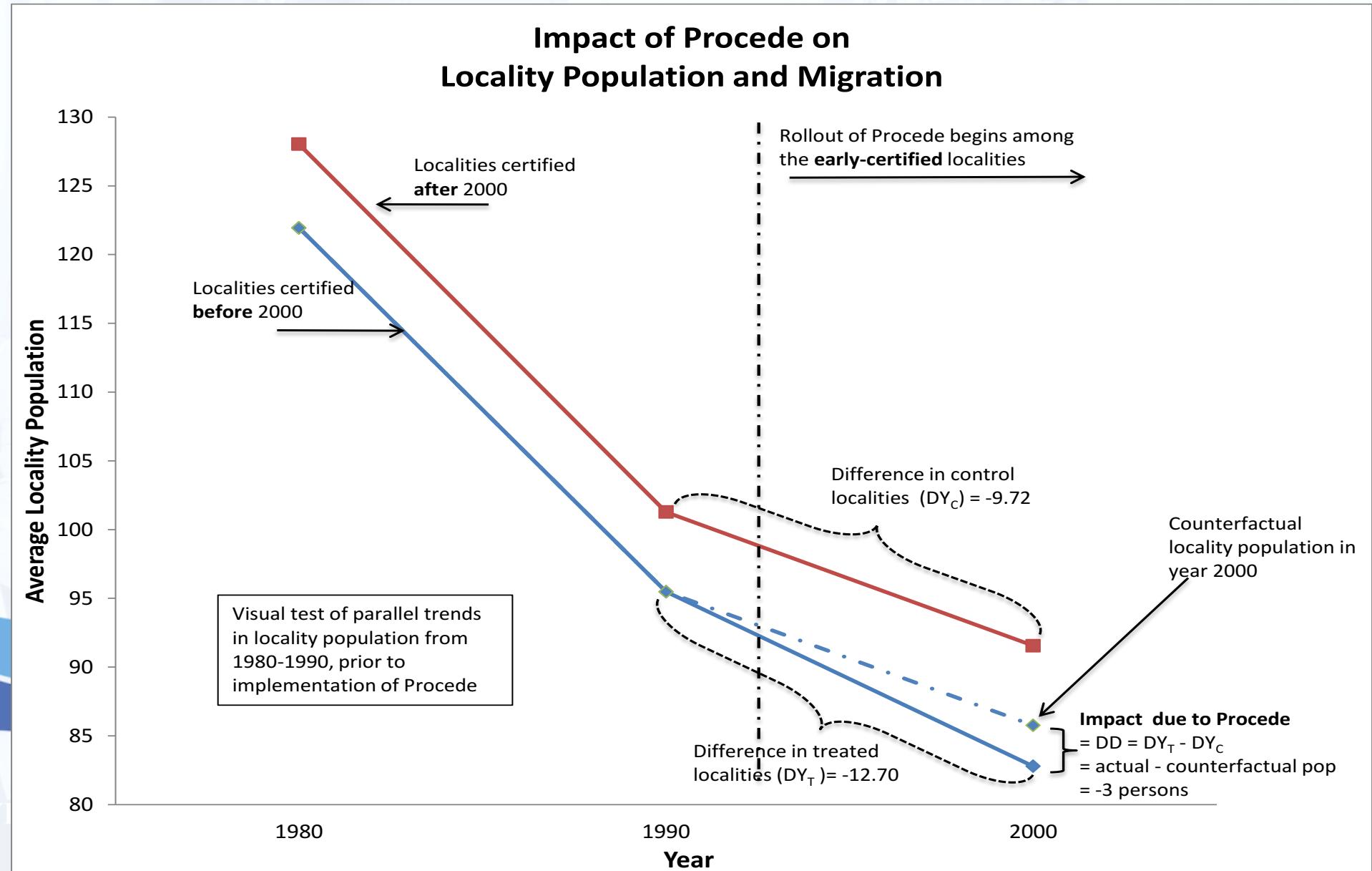
	Difference in treated localities	Difference in control localities	Double difference
Impact of PROCEDE			
Test of parallel trends			

Exercise 1

Report your results in the following table:

	Difference in treated localities	Difference in control localities	Double difference
Impact of PROCEDE	-12.70	-9.72	-2.98
Test of parallel trends	-26.46	-26.76	0.30

Exercise 1



Exercise 2

Exercise 2: HISP Evaluation data

- Let's assume that we have data only from localities where the program has been offered. In these localities, we have data both for households that participate in the program, as well as households that do not participate.
- Data are available for a baseline survey collected before the program, and a follow-up survey collected after the program.
- To obtain the difference-in-differences estimates, we first create a new variable(enrolled round), which is the interaction between participation in the program and the time at which the data are measured. The outcome variable is then regressed on this new variable, along with dummy variables capturing whether or not the household participated in the program, and the time at which each data point is observed.
- The coefficient of the new interaction variable is our difference-in-differences impact estimate.

```
out_did <- lm_robust(health_expenditures ~ round * enrolled,  
                     data = df %>% filter(treatment_locality == 1),  
                     clusters = locality_identifier)  
out_did_wcov <- lm_robust(health_expenditures ~ round * enrolled +  
                           age hh + age_sp + educ hh + educ_sp +  
                           female hh + indigenous + hhszie + dirtfloor +  
                           bathroom + land + hospital_distance,  
                           data = df %>% filter(treatment_locality == 1),  
                           clusters = locality_identifier)
```

```
htmlreg(list(out_did, out_did_wcov), doctype = FALSE,  
       custom.coef.map = list('enrolled' = "Enrollment",  
                             'round' = "Round",  
                             'round:enrolled' = "Enrollment X Round"),  
       caption = "Evaluating HISP: Difference-in-Differences with  
       Regression",  
       caption.above = TRUE,  
       custom.model.names = c("No Covariate Adjustment", "With  
       Covariate Adjustment"))
```

Evaluating HISP: Difference-in-Differences with Regression

	No Covariate Adjustment	With Covariate Adjustment
Enrollment	-6.30 [*] [-6.69; -5.91]	-1.51 [*] [-1.77; -1.25]
Round	1.51 [*] [0.79; 2.24]	1.45 [*] [0.73; 2.17]
Enrollment X Round	-8.16 [*] [-8.81; -7.52]	-8.16 [*] [-8.81; -7.52]
R ²	0.34	0.55
Adj. R ²	0.34	0.55
Num. obs.	9919	9919
RMSE	7.91	6.54
N Clusters	100	100

* Null hypothesis value outside the confidence interval.

Exercise 3

DECEMBER 2018

DISCUSSION PAPER SERIES NO. 2018-42

Devolution of Health Services, Fiscal Decentralization, and Antenatal Care in the Philippines

Michael Ralph M. Abrigo and Danica Aisa P. Ortiz

Abrigo, M. and Ortiz, D. (2018). Devolution of Health Services, Fiscal Decentralization, and Antenatal Care in the Philippines. Philippine Institute for Development Studies DP 2018-42.

➤ Policy background:

The delivery of healthcare in the country has been devolved to local governments for more than 25 years. However, studies examining the impact of decentralization on the demand for healthcare in the Philippines remain limited.

➤ Goal of the study:

Assess how an exogenous expansion in income of governments (through cityhood) affect household antenatal care decisions

Abrigo, M. and Ortiz, D. (2018). Devolution of Health Services, Fiscal Decentralization, and Antenatal Care in the Philippines. Philippine Institute for Development Studies DP 2018-42.

- Strategy:
- Data:
 - LGU finance statistics from DILG and BLGF
 - National Demographic Health Survey 2003, 2008, 2013

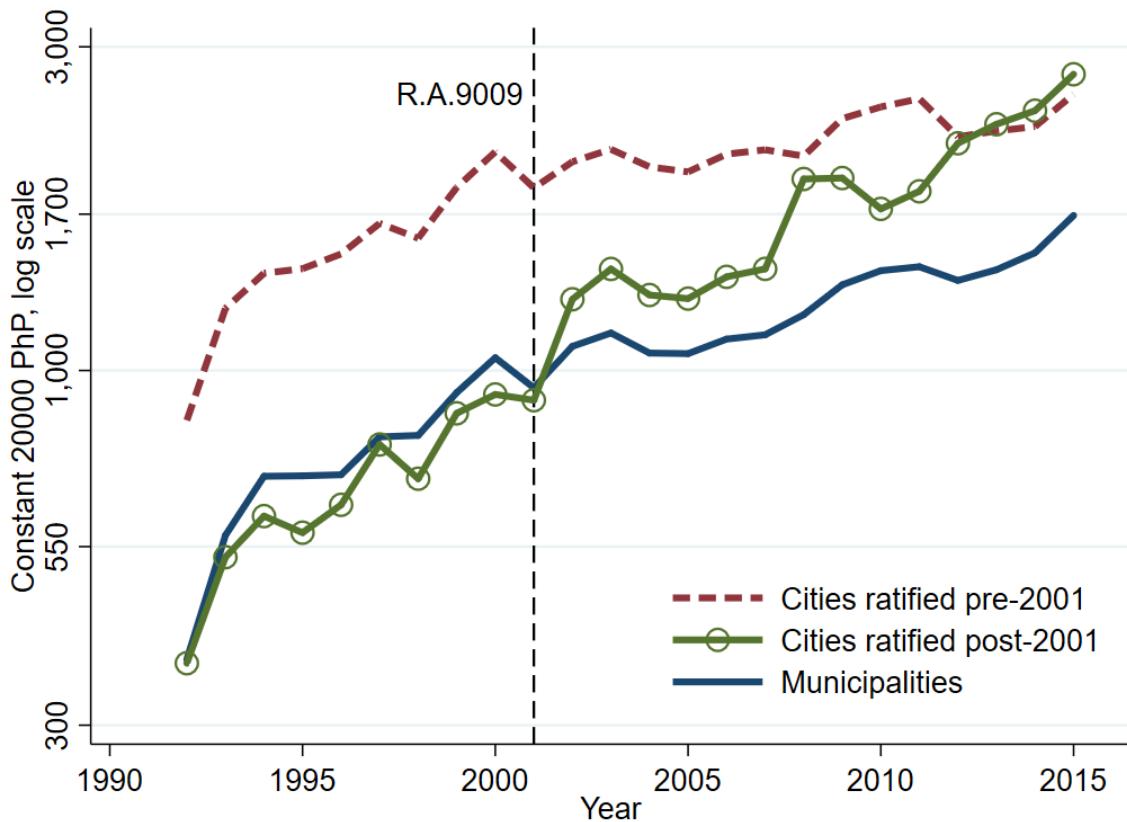
➤ Model specification:

We first evaluate how city-status affects local government incomes and expenditures using difference-in-differences (DID) by estimating the following regression model:

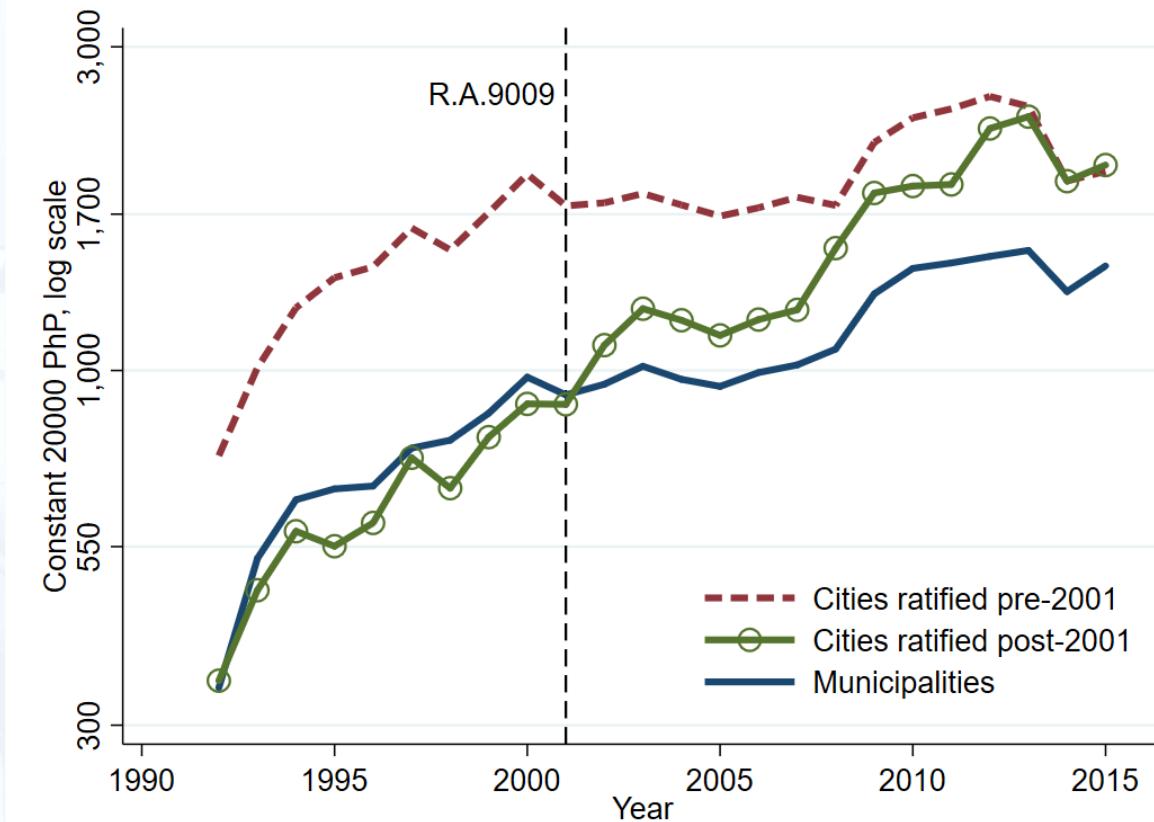
$$Y_{it} = \tau C_{it} + \alpha N_{it} + \beta L_{it} + \gamma_i + \gamma_t + \epsilon_{it}, \quad (1)$$

where Y_{it} is either log-transformed per capita income or per capita expenditure of local government unit i at period t . The variable C_{it} is a dummy variable for city status that takes on a value of unity if the LGU is a city, and zero if otherwise. The variables N_{it} and L_{it} correspond to (log-transformed) population and (log-transformed) past three-year average locally sourced income, with their corresponding parameters α and β , respectively. The LGU- and period-fixed effects γ_i and γ_t , respectively, capture invariant characteristics within-LGU, such as land features, and within-period, such as equal-share provisions in IRA. We are interested in the DID coefficient τ , which describes how much local government incomes or expenditures have changed as a result of the local government being conferred a city status.

➤ Parallel trend assumption:



Per capita Income



Per capita Expenditure

➤ Basic DID:

year	evercity	
	0	1
1992	5.927306	5.914218
2015	7.433907	7.913204

```
. display (7.913204-5.914218)-(7.433907-5.927306) // between 1992 and 2015!  
.492385
```

. reg lninc_pcr i.year##i.evercity if inlist(year, 1992, 2015) & !(cyear<=2000)						
Source	SS	df	MS	Number of obs	=	2,937
Model	1710.19247	3	570.064158	F(3, 2933)	=	2750.81
Residual	607.820132	2,933	.207234958	Prob > F	=	0.0000
Total	2318.01261	2,936	.78951383	R-squared	=	0.7378
				Adj R-squared	=	0.7375
				Root MSE	=	.45523
lninc_pcr	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year 2015	1.506601	.0170783	88.22	0.000	1.473115	1.540088
1.evercity	-.0130878	.0682256	-0.19	0.848	-.1468628	.1206872
year#evercity 2015 1	.4923846	.0959481	5.13	0.000	.3042522	.6805169
_cons	5.927306	.0122323	484.56	0.000	5.903321	5.95129

➤ Full sample:

	(1)	(2)
	lninc_pcr	lninc_pcr
1.cityx	0.562*** (0.055)	0.604*** (0.048)
3.tx		
6.tx		
9.tx		
10.tx		
lninclo_r3		0.067*** (0.009)
lnpopx3		-0.710*** (0.073)
N	38042	32439
r2_a	0.739	0.665
testF		
testFpval		

Standard errors in parentheses

➤ Placebo test: Early ratification by 3 years

	(1) lninc_pcr	(2) lninc_pcr	(3) lnexp_pcr	(4) lnexp_pcr	(5) lnrain_pcr	(6) lnrain_pcr
1.cityx3	-0.017 (0.022)	0.039 (0.026)	-0.029 (0.023)	0.036 (0.027)	-2.688 (1.866)	-1.828 (1.736)
N	35523	33555	35512	33550	36289	34232
r2_a	0.747	0.722	0.710	0.672	0.613	0.622

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

➤ Placebo test: Random assignment

	(1) lninc_pcr	(2) lninc_pcr	(3) lnexp_pcr	(4) lnexp_pcr	(5) lnrain_pcr	(6) lnrain_pcr
1.city_rand	0.000 (0.054)	0.035 (0.051)	-0.010 (0.052)	0.023 (0.046)	-2.838 (2.292)	-1.803 (2.322)
N	38042	36008	38031	36003	38938	36815
r2_a	0.718	0.687	0.685	0.642	0.614	0.621

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

➤ Placebo test: unrelated outcome (rainfall)

	(1) precip_dlr	(2) precip_dlr
1.cityx	-3.989** (2.004)	-2.691 (1.810)
N	38938	36815
r2_a	0.614	0.621

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01