Impact of English instruction on labor market outcomes

The case of Mexico

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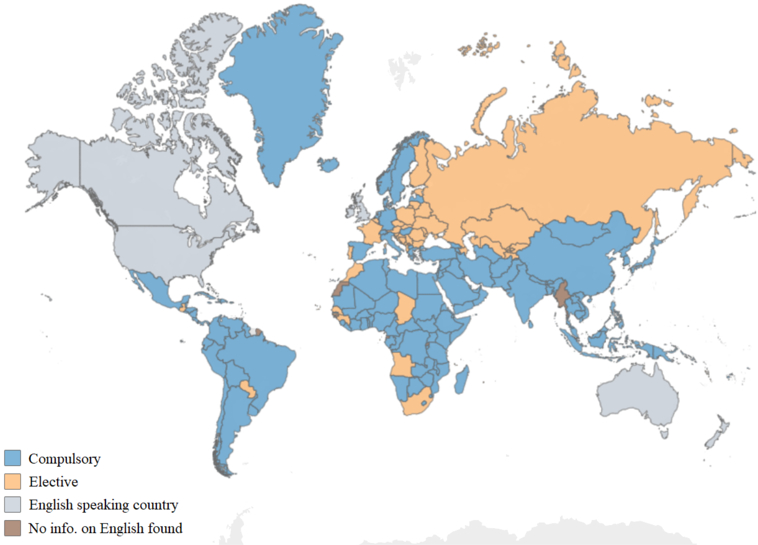
Motivation: Global English education policy



Source: Ives, P., Bale, J., and Haque, E. (2020). How States Promote Global English: Shifting Priorities in Education Policy. Social Sciences and Humanities Research Council of Canada.

Motivation

The value of English language skills in non-English speaking countries

- Globalization: trade and culture (internet, news, social media, etc.)
- Mobility and labor market outcomes

I will study the expansion of English instruction in Mexico

Related literature

Most related to this literature:

- Returns to English language skills
  - In English-speaking countries: Bleakley and Chin (2004); Chiswick and Miller (2015)
  - In non English-speaking countries: Lang and Siniver (2009); Azam, Chin and Prakash (2013)
- English instruction in schools
  - Policy change in the medium of instruction: Angrist, Chin and Godoy (2008); Eriksson (2014)
  - Exposure in a former British colony: Chakraborty and Bakshi (2016)

I study English instruction as a subject in Mexican public primary schools

Main contributions of this paper

Research question

- What is the effect of exposure to English instruction on labor market outcomes in a non-English speaking country?

Empirical strategy

- Variation in exposure driven by a policy change in Mexico
- Rich data connecting individuals first observed in primary school to their labor market outcomes
- Use school by cohort variation for very narrow cohort span

Key findings

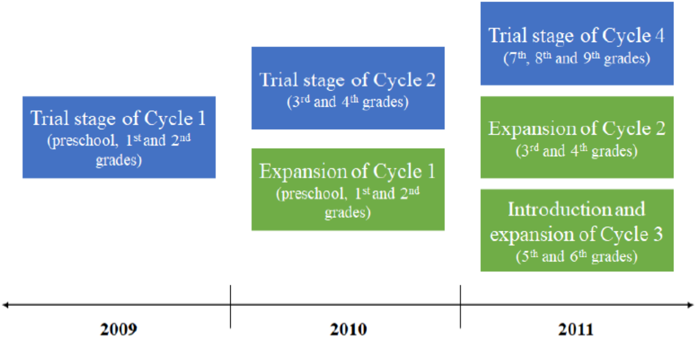
- No average effect on wages, but positive effect among high-achieving individuals
- Shifts between and within industries

Policy background

National English Program in Basic Education (NEPBE) launched in 2009 in Mexico

- Introduced English instruction in public primary schools
- Funded by the central government
- Implemented gradually

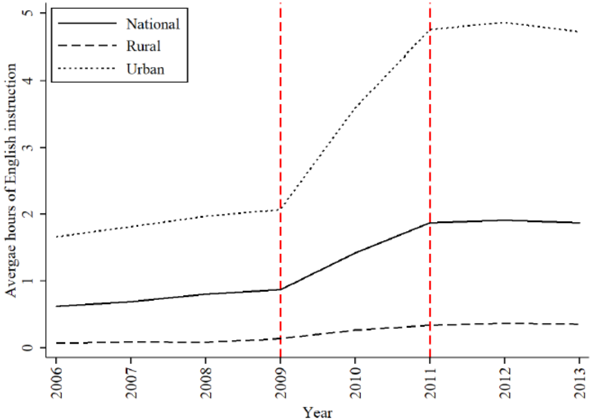
Policy background: English program stages



Note: NEPBE was launched in 2009 as a trial stage with the called Cycle 1. In 2010 the program continued the trial stage with the Cycle 2 and expanded Cycle 1. Finally, in 2011 the program introduced for the first time and expanded Cycle 3, benefiting fifth and sixth graders.

Exposure

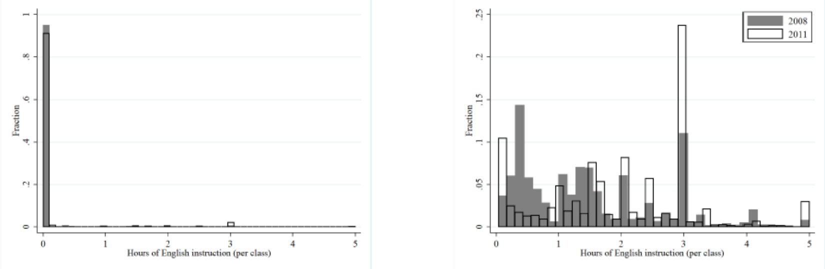
Policy background: English instruction over time



Source: Own elaboration with data from the Mexican school census, Ministry of Public Education (SEP). *Note:* Hours of English instruction are measured as the weekly hours average over the universe of Mexican elementary schools. Similarly, the number of English teachers refers to the average number of English teachers across elementary schools. The vertical dotted line in 2009 highlights the implementation year of the NEPBE's trial stage, while the dotted line in 2011 highlights the expansion of the program.

Hours of Eng

Policy background: Distribution of hours of English instruction (2008 vs 2011)



(a) Hours of English instruction

(b) Hours of English instruction (w/o zeros)

Note: Frequency of the indicated variables are plotted. Histograms at the right do not show zeros, which capture most of the distribution. Hours of English instruction are calculated by dividing the average weekly hours in a school by the total number of classes.

▸▸ Hours of Eng ▸▸ Proportion of schools

Human capital framework

How might English instruction in primary school affect labor market outcomes?

- English language skills
  - Expand the set of jobs individuals can get
  - Possible complementarity with cognitive skills
- Other skills
  - Reduces time on other subjects or school activities
  - Possible complementarities with other subjects

Empirical strategy

- Challenging to estimate the effect of exposure to English instruction on labor market outcomes

- Key concern: schools that offered English instruction are systematically different from those that did not
  - Likely to have positive selection bias, e.g., schools offering English instruction located in richer neighborhoods

- I address this by using a school FE approach
  - Intuition: compare students from the same school, some with more English instruction and some with less
  - Data of the universe of primary school students, able to connect to their labor market outcomes

Measure of exposure to English instruction ⏩ Hrs ⏩ Stages

Birth cohort	Primary school					
	1st	2nd	3rd	4th	5th	6th
1997	2003	2004	2005	2006	2007	2008
1998	2004	2005	2006	2007	2008	2009
1999	2005	2006	2007	2008	2009	2010
2000	2006	2007	2008	2009	2010	2011
2001	2007	2008	2009	2010	2011	2012
2002	2008	2009	2010	2011	2012	2013

- Using the Mexican school census, I calculate weekly hours of English instruction (per class), for each school-year
- For each school-cohort, I average the hours of English instruction from 1st to 6th grade
  - I assume students enter school at age 6 and had normal progression until 6th grade

Impact on labor market outcomes

I estimate the following equation to get the effect of exposure to English instruction on labor market outcomes:

$$y_{isc} = \alpha + \beta \cdot ExpEng_{sc} + \boldsymbol{X_{isc}\gamma} + \zeta_c + \nu_s + \tau_t + \varepsilon_{isc}$$

where y_{isc} is the labor market outcome of individual i, who attended school s and belongs to cohort c

Descriptive

Data

I construct a unique data set connecting restricted-use administrative data of students and their labor market outcomes for birth cohorts 1997-2002

- ENLACE (2006-2013): universe of primary school students
  - I know what school they attended
  - Reading and mathematics test scores
- Mexican school census (2003-2013)
  - School characteristics: weekly hours of English instruction
- Social Security data (2018-2021)
  - I use individual ID to match students to their labor market outcomes
  - Formal sector
  - Individuals between 16-24 years old

Data: Labor market outcomes

I investigate the effect of exposure to English instruction on four main labor market outcomes:

1. Works in formal sector
   - Dummy for being in social security data among the universe of students
2. Wages (average monthly wage) IMSS
3. Geographical mobility
   - Distance from home to working county
   - Moving from home state
4. Industries (NAICS) codes
   - Dummies for agriculture, construction, manufacturing and services industries

Estimation results: Sample selection

Table 2: Exposure to English instruction and labor market outcomes (Social Security data)

	(1) Formal sector	(2) ln(wage)	(3) ln(distance)	(4) Move state
Panel A: Full sample				
Hrs English	$\boxed{\begin{matrix}-0.013^{***} \\ (0.001)\end{matrix}}$	$\boxed{\begin{matrix}-0.015^{***} \\ (0.002)\end{matrix}}$	-0.035***	-0.004***
			(0.008)	(0.001)
Observations	16,938,183	4,055,434	4,055,434	4,055,434
Adjusted R^2	0.105	0.270	0.477	0.555

- Concern about selection into social security data
- Possibly because individuals are still enrolled in school
- Use counties where it is less likely that they are enrolled

Statuses Test scores

Proposed solution: Construction of low-enrollment sample

1. Using the 2020 Mexican Population Census, I construct a county-enrollment rate variable
   - Enrollment rates in first year of college (2002 cohort)
2. I keep the data with 38 percent (or less) of individuals enrolled in school
3. The low-enrollment sample represents 6.4% of the full sample

Statuses How?

Labor market outcomes with low-enrollment sample

Table 2: Exposure to English instruction and labor market outcomes (Social Security data)

	(1) Formal sector	(2) ln(wage)	(3) ln(distance)	(4) Move state
Panel B: Low enrollment sample				
Hrs English	$\boxed{-0.012}$	-0.005	-0.058	0.015**
	$\boxed{(0.008)}$	(0.011)	(0.044)	(0.007)
Observations	1,554,827	259,666	259,666	259,666
Adjusted R^2	0.123	0.312	0.677	0.727
Mean of dep. var.	0.17	8.68	3.69	0.45

Labor market outcomes with low-enrollment sample

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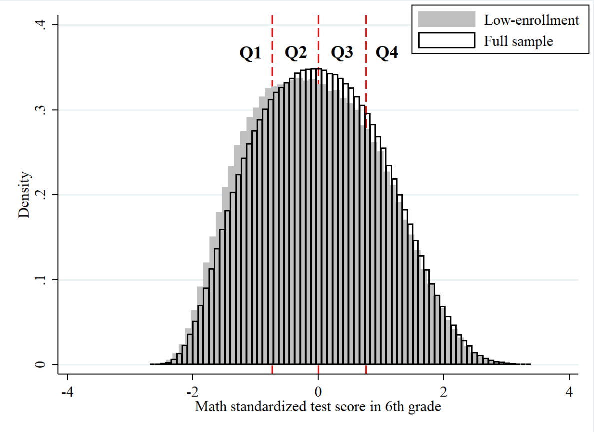
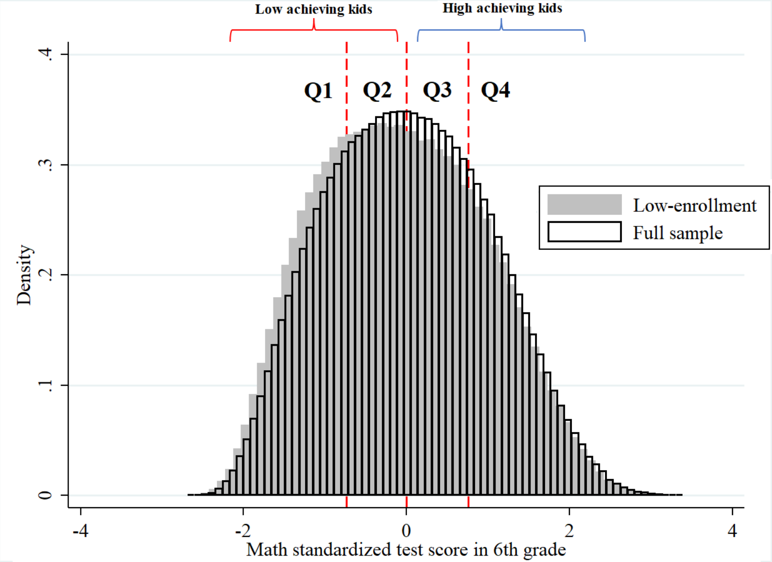
Labor market outcomes by cognitive abilities

Now let us allow the effect to vary by cognitive abilities

- I am able to explore this because I observe test scores in primary school



Labor market outcomes by cognitive abilities



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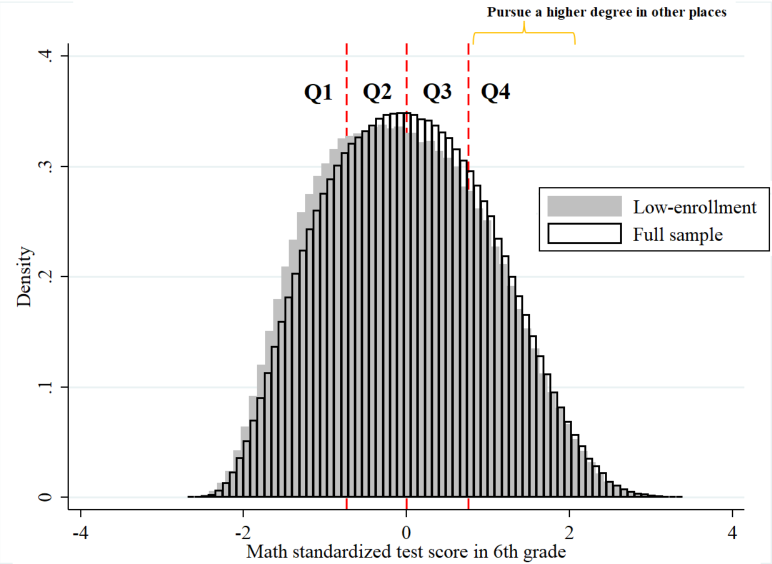
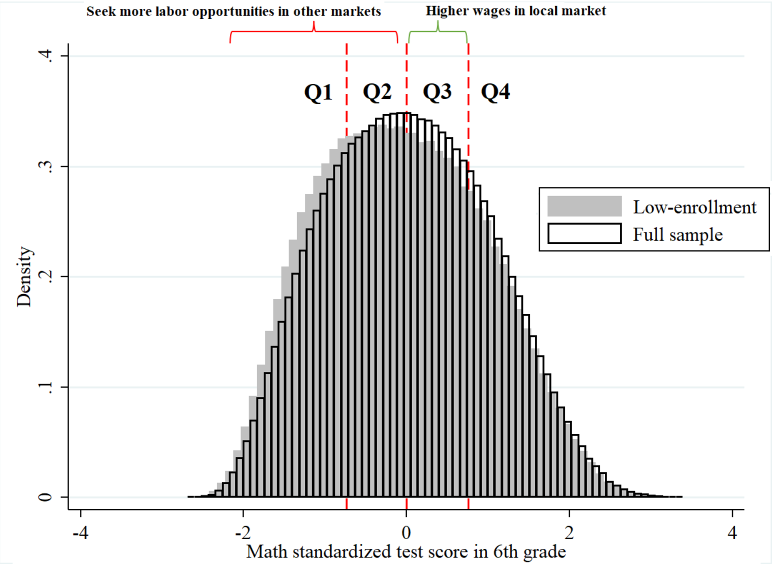


Labor market outcomes by cognitive abilities



Labor market outcomes by cognitive abilities

Table 3: Exposure to English instruction and labor market outcomes by abilities (Social Security data)

	(1) Formal sector	(2) ln(wage)	(3) ln(distance)	(4) Move state
Panel A: Low enrollment sample				
Hrs English	-0.007	-0.013	-0.079	0.021**
	(0.009)	(0.012)	(0.049)	(0.010)
Eng×Q2	-0.003	-0.003	-0.018	-0.011
	(0.006)	(0.009)	(0.047)	(0.008)
Eng×Q3	-0.005	0.031***	0.012	-0.017
	(0.006)	(0.009)	(0.036)	(0.011)
Eng×Q4	-0.013**	0.012	0.106***	0.001
	(0.006)	(0.012)	(0.040)	(0.012)
Observations	1,554,827	259,666	259,666	259,666
Adjusted R^2	0.123	0.312	0.677	0.727

Low achieving kids

Note: The quartile Q4 contains the top part of the abilities' distribution with individuals obtaining the highest Math test scores.

Labor market outcomes by cognitive abilities

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Eng×Q4	-0.013**	0.012	0.106***	0.001
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Eng×Q2	-0.003	-0.003	-0.018	-0.011
	(0.006)	(0.009)	(0.047)	(0.008)
Eng×Q3	-0.005	0.031***	0.012	-0.017
	(0.006)	(0.009)	(0.036)	(0.011)
Eng×Q4	-0.013**	0.012	0.106***	0.001
	(0.006)	(0.012)	(0.040)	(0.012)
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Adjusted R^2	0.123	0.312	0.677	0.727

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Note: The quartile Q4 contains the top part of the abilities' distribution with individuals obtaining the highest Math test scores.

English instruction and economic industries

Table 4: Exposure to English instruction and economic industries (Social Security data)

	(1) Agri-culture	(2) Con-struction	(3) Manu-facturing	(4) Serv-ices
Panel B: Low enrollment sample				
Hrs English	-0.012**	-0.025**	0.040**	-0.003
	(0.006)	(0.010)	(0.017)	(0.016)
Observations	259,666	259,666	259,666	259,666
Adjusted R^2	0.402	0.388	0.342	0.292
Mean of dep. var.	0.11	0.16	0.39	0.34

We observe shifts across industries (consistent with more mobility). Implications and potential causes:

- Different career path
- More employment opportunities?
- Individuals perceive a broader choice set?

Abilities Heterogeneous

Exploring mechanisms

- Mechanism 1: English abilities
  - I cannot test directly this mechanism because my data set does not have a measure of English abilities
  - Evidence I will show:
    - (a) Galvez-Soriano (2023) shows that exposure to English instruction in primary school increases the probability of speaking English
    - (b) Workers are systematically moving to economic industries requiring English abilities
- Mechanism 2: Other cognitive abilities
  - Language (Spanish)
  - Mathematics

Mechanism 2: Cognitive abilities

Effect of exposure to English instruction on student achievement:

$$test\_score_{isc} = \theta + \phi \cdot ExpEng_{sc} + \boldsymbol{X_{isc}}\gamma + \zeta_c + \nu_s + \varepsilon_{isc}$$

where $test\_score_{isc}$ is the 6th grade test score of student i, who attended school s and belongs to cohort c

Data

Mechanism 2: Cognitive abilities

Full sample

Table 7: Exposure to English instruction and student achievement

	(1) Language 6th	(2) Math 6th
Low enrollment sample		
Hrs English	0.0476	0.0094
	(0.0470)	(0.0344)
Observations	259,666	259,666
Adjusted R^2	0.351	0.381

- Exposure to English instruction does not affect other cognitive abilities
- English skills?
- Industries requiring English skills?

Mechanism 1a: English abilities (Galvez-Soriano, 2023)

Data

- I use the 2014 Subjective Well-being Survey (BIARE)
- Representative at national and state level
- Asks if the respondent speaks English
- Only 3% reported they speak English

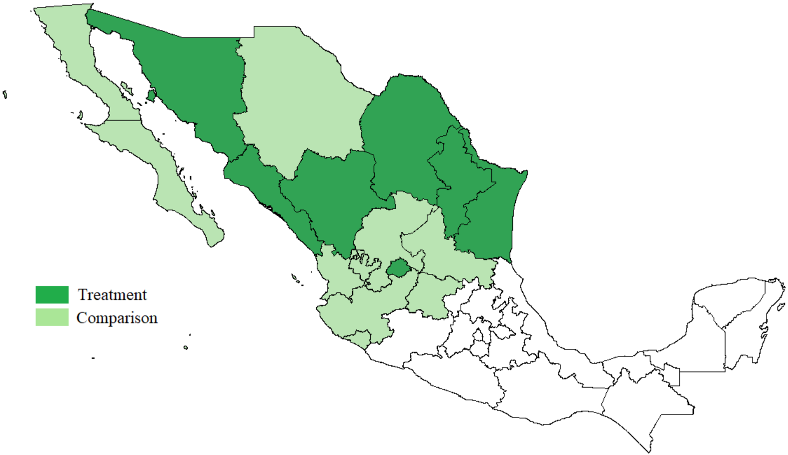
Empirical strategy

Take advantage of state policy changes in English instruction

$$y_{isc} = \theta + \psi \cdot HadPolicy_{sc} + \delta_s + \kappa_c + \boldsymbol{X_{isc}}\boldsymbol{\Psi} + \varepsilon_{isc}$$

where $HadPolicy_{sc}$ takes the value of one if individual i lives in a treated state and he/she belongs to one of the affected cohorts (zero otherwise)

Mechanism 1a: English abilities (Galvez-Soriano, 2023)



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where $HadPolicy_{sc}$ takes the value of one if individual i lives in a treated state and he/she belongs to one of the affected cohorts (zero otherwise) PTA

Mechanism 1a: English abilities (Galvez-Soriano, 2023)

Table: Intention to Treat effect of offering English instruction at school (SDD estimate)

	(1) Hrs Eng	(2) Speak Eng
Panel A: Full sample		
Had Policy	$\boxed{0.308^{***}}$	$\boxed{0.015^{**}}$
	(0.046)	(0.008)
Observations	13,131	13,131
Adjusted R^2	0.596	0.075

Mechanism 1b: Workers moving to jobs requiring English skills

- Same social security data I use in the labor market analysis
- Use BIARE to I construct an index of economic industries by English skills
  - According to the NAICS at four-digit code
- For each manufacturing and services, I form dummy variables indicating if job requires English
  - Dummy for high-English manufacturing jobs indicating industries with more than 8% of English speakers
  - Dummy for low-English manufacturing jobs indicating industries with less than 8% of English speakers
  - Similarly for services

Mechanism 1b: Workers moving to jobs requiring English skills

Table 6: Exposure to English instruction and economic industries (Social Security data)

	(1)	(2)	(3)	(4)
	Manufacturing		Services	
	High English	Low English	High English	Low English
Panel B: Low enrollment sample				
Hrs English	0.060***	-0.026**	0.046***	-0.039***
	(0.013)	(0.012)	(0.014)	(0.011)
Observations	259,666	259,666	259,666	259,666
Adjusted R^2	0.175	0.189	0.145	0.116

Manu Ind Svcs Ind Abilities

Robustness Checks

- Concern about TWFE estimator in the presence of heterogeneous treatment effects TWFE
- Concern about differential cohort trends across labor markets State by cohort
- Different exposure variable Exposure
- Different enrollment thresholds Threshold Test scores
- No-changes in private school enrollment Private enrollment
- No-effects on other resources Teachers

Discussion

- Exposure to English instruction in Mexican primary schools
  - Has, on average, no significant effect on wages
    - But positive returns among high-achieving kids
  - Across industries: shifts workers out of agriculture and construction
  - Within industries: shifts workers to jobs requiring English abilities

- Consistent with English skills mediating these effects of English instruction
  - Evidence from previous state English programs (Galvez-Soriano, 2022)
  - No effect on other cognitive skills

Thank you!

For more about me and my research, please scan here:

Measuring hours of English instruction

Benito Juarez Elementary School

Weekly hours of English instruction	18
Number of classes	6
Hours of English instruction (per class)	3

Eng over time | Exposure | Distribution

Descriptive statistics (matched data sets)

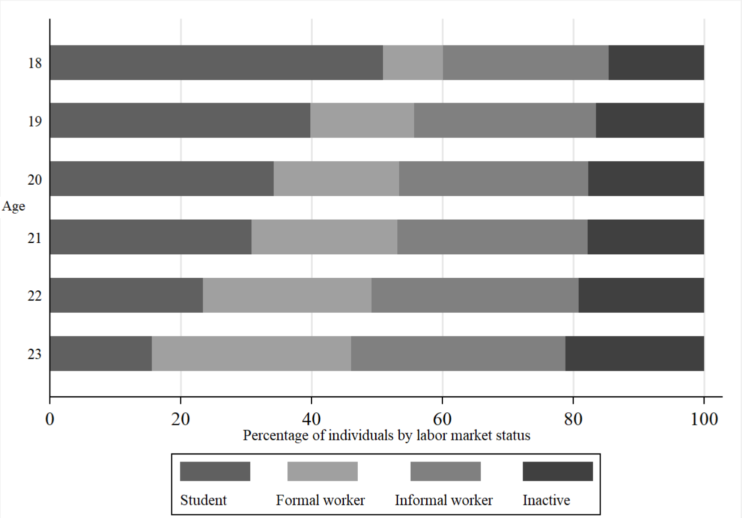
Table 1: Descriptive statistics

Variable	Mean	SD	Min	Max
Individual characteristics				
Female	0.39	0.49	0	1
Age	20.88	1.51	16	24
Language test score	-0.06	0.97	-2.84	3.53
Math test score	-0.04	0.97	-2.69	3.40
School characteristics				
Hours of English instruction	0.23	0.60	0	9.41
English teachers	0.02	0.05	0	1
Number of students (6th grade)	28.87	9.49	1	119
Number of teachers with college	0.87	0.20	0	2.15
Number of teachers with masters	0.05	0.07	0	0.91
Rural (%)	0.27	0.44	0	1
Labor market characteristics				
Wage (monthly pesos)	6,586	3,383	2,510	67,215
Permanent job	0.81	0.39	0	1
Number of jobs (in a year)	1.48	0.83	1	17
Number of permanent jobs	1.20	0.83	0	14
Company size (workers)	1,922	5,456	1	92,972
Distance home-work (km)	107	265	0	2,029
Observations	4,055,434			

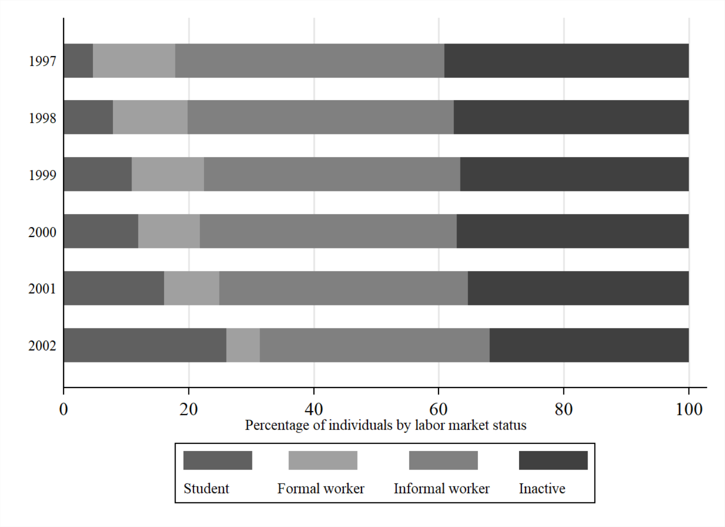
Empirical strategy

Potential problem: many 16-24 year olds are enrolled in school (2020 Mexican census)

Back

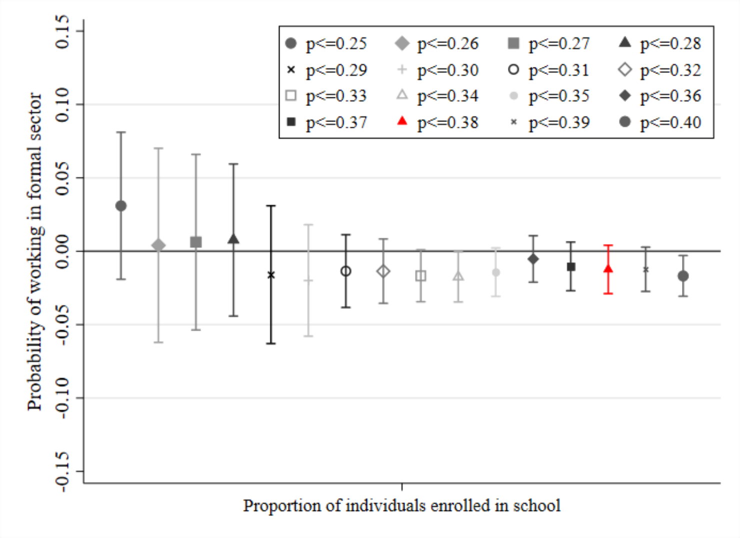


Statuses with low-enrollment sample



Low Enrollment

How I chose the 38 percent enrollment rate?



Low Enrollment

High-English intensive manufacturing industries

Table A.6: Economic Manufacturing Industries

4-digit code	Industry name	5-digit code	Industry name
3110	Animal food manufacturing	31131	Sugar and confectionery product manufacturing
		31141	Fruit and vegetable preserving manufacturing
		31151	Dairy product manufacturing
		31161	Animal slaughtering and processing
3120	Beverage and tobacco industries	31211	Beverage manufacturing
3150	Apparel manufacturing	31511	Apparel knitting mills
		31521	Cut and sew apparel manufacturing
3160	Leather and hide tanning and finishing	31611	Leather and hide tanning and finishing
		31621	Footwear manufacturing
3220	Paper industry	32211	Pulp, paper, and paperboard mills
3250	Chemical industry	32511	Basic chemical manufacturing
		32521	Resin, synthetic rubber, and artificial and synthetic fibers
		32541	Pharmaceutical and medicine manufacturing
		32551	Paint, coating, and adhesive manufacturing
		32591	Other chemical product and preparation manufacturing
3270	Nonmetallic mineral products	32711	Clay product and refractory manufacturing
		32731	Cement and concrete product manufacturing
3320	Metal products manufacturing	33241	Boiler, tank, and shipping container manufacturing
		33251	Hardware manufacturing
		33281	Coating, engraving, heat treating, and allied activities
3340	Manufacturing of computer	33461	Manufacturing and reproducing magnetic and optical media
3350	Electric appliances and electric power generation	33511	Electric lighting equipment manufacturing
		33521	Household appliance manufacturing
		33531	Electrical equipment manufacturing
3360	Transportation equipment	33611	Motor vehicle manufacturing
		33641	Aerospace product and parts manufacturing
		33651	Railroad rolling stock manufacturing
		33661	Ship and boat building
3370	Household furniture	33710	Nonupholstered wood household furniture manufacturing

Back

Services that require English abilities

Table A.7: Economic Services Industries

4-digit code	Industry name	5-digit code	Industry name
4310	Wholesale trade of groceries, food, beverages and tobacco	43111	Grocery merchant wholesalers
		43112	Tobacco and alcoholic beverage merchant wholesalers
4350	Wholesale trade of industrial machinery and equipment	43522	Wholesale trade of manufacturing machinery and equipment
		43541	Computer and software merchant wholesalers
4620	Retail trade in self-service shops and department stores	46211	Retail trade in self-service shops
		46221	Retail trade in department stores
4641	Retail trade of health care items	46412	Optical goods and other health care stores
4651	Retail trade of perfumery and jewelry	46511	Cosmetics, beauty supplies, and perfume stores
4661	Retail trade of household furniture	46611	Furniture stores
4682	Automotive parts and accessories	46821	Automotive parts, accessories, and tire stores
4841	Freight truck transportation	48410	General freight trucking
4931	Warehousing services	49310	Warehousing and storage
5170	Telecommunications	51731	Wired and wireless telecommunications carriers
5324	Commercial and industrial machinery	53242	Office machinery and equipment rental and leasing
5610	Administrative and support services	56160	Investigation and security services
		56170	Services to buildings and dwellings
7100	Artistic, cultural and sporting services	71121	Spectator sports
		71311	Amusement parks and arcades
7211	Traveler accommodation	72111	Hotels and motels
7223	Special food services	72231	Food and beverage preparation services
7224	Drinking places (alcoholic beverages)	72241	Nightclubs, bars and similar drinking places
8114	Personal and household goods repair	81140	Personal and household goods repair and maintenance
8131	Religious organizations	81311	Religious organizations
9314	Justice, public order, and safety	93141	Justice, public order, and safety activities

Back

NAICS codes in my classification

Industries	NAICS code	Industry Title
Agriculture	11	Agriculture, Forestry, Fishing and Hunting
Construction	21	Mining
	22	Utilities
	23	Construction
Manufacturing	31-33	Manufacturing
Services	42	Wholesale Trade
	44-45	Retail Trade
	48-49	Transportation and Warehousing
	51	Information
	52	Finance and Insurance
	53	Real Estate Rental and Leasing
	54	Professional, Scientific, and Technical Services
	55	Management of Companies and Enterprises
	56	Administrative and Support and Waste Management
	61	Educational Services
	62	Health Care and Social Assistance
	71	Arts, Entertainment, and Recreation
	72	Accommodation and Food Services
	81	Other Services (except Public Administration)
	92	Public Administration

Labor market outcomes

Data: Student achievement

1. I look at test scores as one of the mechanisms

2. I standardize test scores, ts_{isct}, of each student i in school s at time t using the following formula:

$$test\_score_{isc} = \frac{ts_{isct} - \mu_t}{\sigma_t}$$

where $test\_score_{isc}$ is the standardized test score, while μ_t and σ_t are the mean and standard deviation of test scores, respectively, pooling all Mexican students by grade and by each observed year

Back

Estimation results: exposure to Eng and test scores

Table 7: Exposure to English instruction and student achievement

	(1) Language 6th	(2) Language 6th	(3) Math 6th	(4) Math 6th
Panel A: Full sample in ENLACE database				
Hrs English	0.0335***	0.0099*	0.0155***	-0.0081
	(0.0033)	(0.0054)	(0.0036)	(0.0062)
Observations	16,938,183	16,938,183	16,938,183	16,938,183
Adjusted R^2	0.426	0.472	0.429	0.482
Panel B: Full sample in Social Security data				
Hrs English	0.0284***	-0.0015	0.0105***	-0.0225***
	(0.0033)	(0.0075)	(0.0037)	(0.0086)
Observations	4,055,434	4,055,434	4,055,434	4,055,434
Adjusted R^2	0.404	0.453	0.413	0.470

Robustness checks Test scores Wages

Gender heterogeneous effects

Table 2: Exposure to English instruction and labor market outcomes (Social Security data)

	(1) Formal sector	(2) ln(wage)	(3) ln(distance)	(4) Move state
Panel C: Low enrollment sample (Men)				
Hrs English (β^M)	-0.016	-0.002	-0.130**	0.004
	(0.011)	(0.016)	(0.057)	(0.012)
Observations	750,812	166,165	166,165	166,165
Adjusted R^2	0.149	0.315	0.680	0.729
Panel D: Low enrollment sample (Women)				
Hrs English (β^W)	-0.010	-0.022	0.063*	0.033**
	(0.010)	(0.015)	(0.034)	(0.012)
Observations	804,015	93,501	93,501	93,501
Adjusted R^2	0.107	0.363	0.700	0.756
$\beta^M = \beta^W$ [p-value]	[0.012]	[0.448]	[0.190]	[0.090]
State of work FE	NO	YES	YES	YES

Back

Gender heterogeneous effects

Table 3: Exposure to English instruction and labor market outcomes by abilities (Social Security data)

	(1) Formal sector	(2) ln(wage)	(3) ln(distance)	(4) Move state
Panel B: Low enrollment sample (Men)				
Hrs English	-0.014	-0.010	-0.145**	0.008
	(0.012)	(0.018)	(0.064)	(0.014)
Eng×Q2	0.007	-0.001	-0.023	-0.005
	(0.009)	(0.011)	(0.060)	(0.010)
Eng×Q3	-0.006	0.040***	0.008	-0.014
	(0.011)	(0.014)	(0.049)	(0.012)
Eng×Q4	-0.013	0.010	0.104*	-0.001
	(0.011)	(0.017)	(0.058)	(0.014)
Observations	750,812	166,165	166,165	166,165
Adjusted R^2	0.149	0.315	0.680	0.729
Panel C: Low enrollment sample (Women)				
Hrs English	-0.007	-0.030*	0.029	0.042**
	(0.010)	(0.016)	(0.084)	(0.017)
Eng×Q2	-0.006	-0.007	-0.002	-0.024**
	(0.007)	(0.012)	(0.065)	(0.012)
Eng×Q3	-0.000	0.017*	0.017	-0.020
	(0.006)	(0.010)	(0.087)	(0.017)
Eng×Q4	-0.008	0.017	0.109	0.004
	(0.007)	(0.017)	(0.080)	(0.019)
Observations	804,015	93,501	93,501	93,501
Adjusted R^2	0.107	0.363	0.701	0.756

Gender heterogeneous effects

Table 4: Exposure to English instruction and economic industries (Social Security data)

	(1) Agri-culture	(2) Con-struction	(3) Manu-facturing	(4) Serv-ices
Panel C: Low enrollment sample (Men)				
Hrs English (β^M)	-0.005	-0.026*	0.040**	-0.010
	(0.008)	(0.014)	(0.020)	(0.020)
Observations	166,165	166,165	166,165	166,165
Adjusted R^2	0.424	0.424	0.352	0.273
Panel D: Low enrollment sample (Women)				
Hrs English (β^W)	-0.024***	-0.006	0.043**	-0.012
	(0.008)	(0.006)	(0.021)	(0.024)
Observations	93,501	93,501	93,501	93,501
Adjusted R^2	0.446	0.139	0.383	0.383
$\beta^M = \beta^W$ [p-value]	[0.055]	[0.000]	[0.003]	[0.974]
Shares	0.04	0.08	0.35	0.53

Back

Gender heterogeneous effects

Table 6: Exposure to English instruction and economic industries (Social Security data)

	(1)	(2)	(3)	(4)
	Manufacturing		Services	
	High English	Low English	High English	Low English
Panel C: Low enrollment sample (Men)				
Hrs English (β^M)	0.075***	-0.035**	0.033**	-0.035**
	(0.016)	(0.016)	(0.015)	(0.014)
Observations	166,165	166,165	166,165	166,165
Adjusted R^2	0.175	0.202	0.163	0.111
Panel D: Low enrollment sample (Women)				
Hrs English (β^W)	0.038*	-0.011	0.047*	-0.039*
	(0.020)	(0.018)	(0.027)	(0.023)
Observations	93,501	93,501	93,501	93,501
Adjusted R^2	0.226	0.229	0.191	0.173
$\beta^M = \beta^W$ [p-value]	[0.058]	[0.070]	[0.454]	[0.594]
Shares	0.17	0.17	0.29	0.24

Back

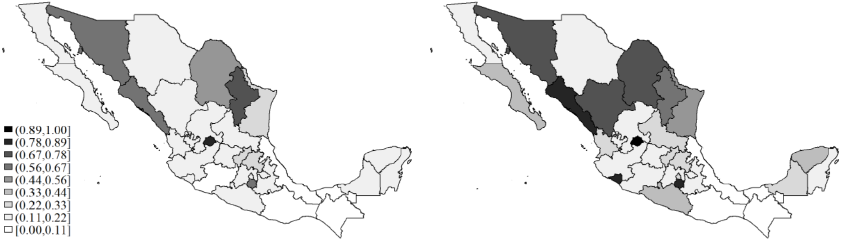
Proportion of **rural** schools with English instruction (2008 vs 2011)

(a) Rural schools in 2008

(b) Rural schools in 2011

Back

Proportion of **urban** schools with English instruction (2008 vs 2011)



(c) Urban schools in 2008 **(d)** Urban schools in 2011

Back

English instruction and industries by abilities

Table 5: Exposure to English instruction and economic industries by abilities (Social Security data)

	(1) Agri-culture	(2) Con-struction	(3) Manu-facture	(4) Serv-ices
Panel A: Low enrollment sample				
Hrs English	-0.005	-0.035***	0.049***	-0.008
	(0.007)	(0.010)	(0.018)	(0.018)
Eng×Q2	-0.014***	0.006	-0.010	0.017
	(0.004)	(0.005)	(0.011)	(0.011)
Eng×Q3	-0.011*	0.020***	-0.008	-0.001
	(0.006)	(0.006)	(0.012)	(0.012)
Eng×Q4	-0.005	0.022***	-0.022*	0.004
	(0.006)	(0.007)	(0.013)	(0.010)
Observations	259,666	259,666	259,666	259,666
Adjusted R^2	0.402	0.388	0.342	0.292

Industries Gender

Industries requiring English skills by abilities

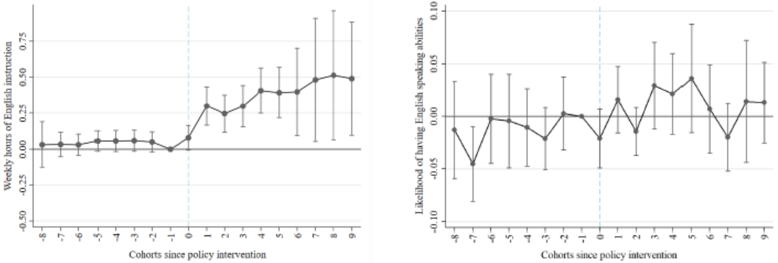
Table A.2: Exposure to English instruction and economic industries by abilities (Social Security data)

	(1)	(2)	(3)	(4)
	Manufacturing		Services	
	High English	Low English	High English	Low English
Panel A: Low enrollment sample				
Hrs English	0.065***	-0.020	0.040***	-0.037***
	(0.014)	(0.015)	(0.015)	(0.012)
Eng×Q2	0.001	-0.012	0.021*	-0.005
	(0.009)	(0.010)	(0.011)	(0.008)
Eng×Q3	-0.007	0.000	0.001	-0.003
	(0.011)	(0.011)	(0.010)	(0.007)
Eng×Q4	-0.012	-0.014	0.004	0.000
	(0.011)	(0.014)	(0.009)	(0.008)
Observations	259,666	259,666	259,666	259,666
Adjusted R^2	0.175	0.189	0.145	0.116

Back

Mechanism 1a: English abilities (Galvez-Soriano, 2023)

$$y_{isc} = \theta + \sum_{c} \psi_c \cdot I_{(treatment_{sc}=c-c_s^*)} + \delta_s + \kappa_c + \boldsymbol{X_{isc}\Psi} + \varepsilon_{isc}$$



(a) Hours of English **(b)** Speak English

Back

TWFE correction (Callaway, Goodman-Bacon and Sant'Anna (2021))

Table 8: Solutions for TWFE with heterogeneous treatment effects (Social Security data)

	(1) Formal sector	(2) ln(wage)	(3) ln(distance)	(4) Move state
Panel A: Binary treatment				
Eng	-0.009	0.000	-0.020	0.014*
	(0.006)	(0.011)	(0.042)	(0.008)
Observations	1,554,827	259,666	259,666	259,666
Adjusted R^2	0.125	0.292	0.675	0.726
Panel B: Binary treatment w/o always treated				
Eng	-0.011*	0.002	-0.016	0.016*
	(0.006)	(0.011)	(0.043)	(0.009)
Observations	1,531,834	254,287	254,287	254,287
Adjusted R^2	0.125	0.292	0.675	0.726

Back

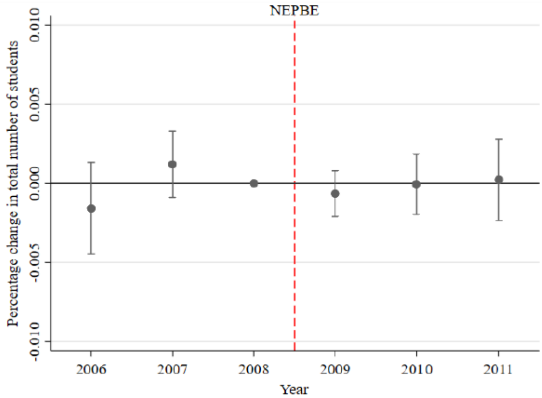
Differential cohorts trends across labor markets?

Table 10: Exposure to English instruction and labor market outcomes (with state-by-cohort FE, Social Security data)

	(1) Formal sector	(2) ln(wage)	(3) ln(distance)	(4) Move state
Panel B: Low enrollment sample				
Hrs English	-0.007	0.008	-0.045	$\boxed{0.012}$
	(0.010)	(0.013)	(0.051)	$\boxed{(0.010)}$
Observations	1,554,827	259,666	259,666	259,666
Adjusted R^2	0.124	0.313	0.677	0.728

Back

No-changes in private school enrollment



Back

Different exposure variable

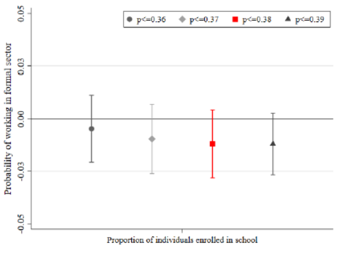
Table 9: English instruction and labor market outcomes (Alternative exposure variable)

	(1) Formal sector	(2) ln(wage)	(3) ln(distance)	(4) Move state
Panel B: Low enrollment sample				
Eng Teachers	-0.202*	-0.127	-0.772	0.072*
	(0.120)	(0.196)	(0.751)	(0.040)
Observations	1,554,827	259,666	259,666	259,666
Adjusted R^2	0.123	0.312	0.677	0.727

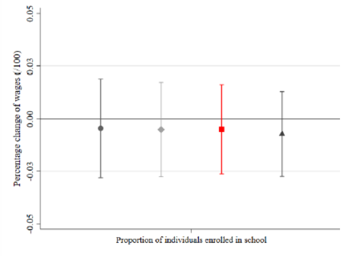
Back

Solution to sample selection

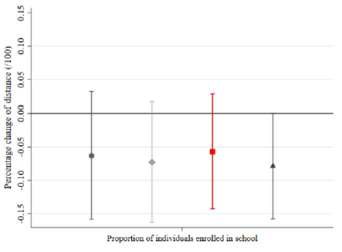
Back



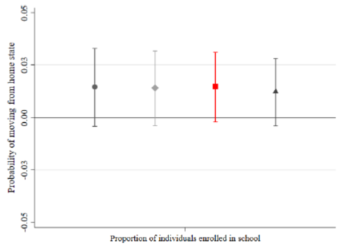
(a) Formal sector



(b) Ln(monthly wage)

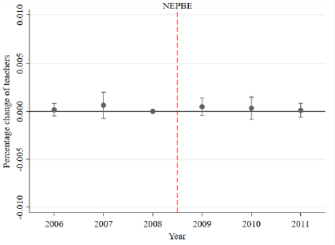


(c) Distance home-job county

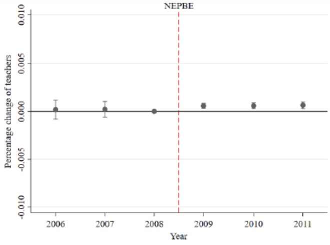


(d) Moves from home county

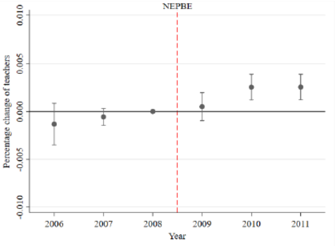
More teachers? Back



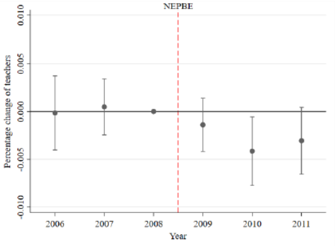
(a) With elementary school



(b) With middle school



(c) With high school



(d) With college degree

Gender heterogeneous effects

- Increase in mobility is driven by women ⏩ Labor mkt
  - Women move away from rural areas ⏩ Industries
- Positive effect on wages is driven by men ⏩ High achieving
  - High achieving men substitute proportionally more agricultural than construction jobs for manufacturing ones ⏩ Abilities

Wages in IMSS data ⏩ Back

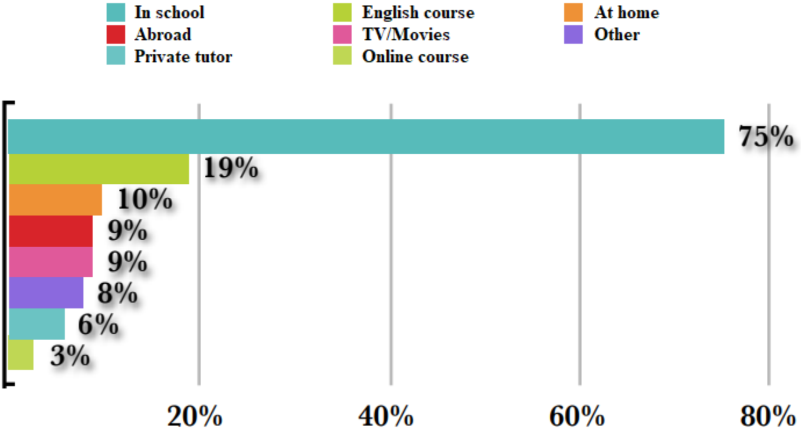
The social security data has a monthly frequency, and each month could have more than one observation for the same worker because some workers have more than one job

1. I take the average of the wages reported over one year, by worker, by economic sector and by employer
2. When a worker has multiple jobs, I drop the jobs with the lowest wages if those are non-permanent jobs
3. If there are individuals with permanent and non-permanent jobs, I only use permanent jobs
4. For individuals who have more than one job with the same wage I choose the job in which they have worked most part of the year

I assume that an employee works 30 days, on average

Where did you learn English?

Back



Note: This question was answered only by individuals who reported having English abilities. The answers are independent, i.e. do not sum 100 percent.

Source: CIDAC (2008). Encuesta CIDAC sobre Capital Humano en México. México.