

# An Evaluation of the Effect of Quality of Education on Violence: Evidence from Colombia

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- This paper on the other hand examines the **impact of quality of education on violence**

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  - Efforts to improve school quality over the long run would potentially imply an extraordinary rate of return
  - Education quality is essential for researchers to understand the existence and persistence of violence and conflicts

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  - Quantitative analysis of this causal link at a dis-aggregated level (lacking from the existing literature)

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- This is consistent with the opportunity cost effect
  - High quality education increases higher expectations of being absorbed by the labor market or of future returns in the labor market, discouraging engaging in criminal activities

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    - Discourages *presence of illegal armed groups*
    - Increases the *surrender rate*
    - Correlation between presence and ambushes is positive - is it an 'attraction effect'?

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  - Data
  - Empirics
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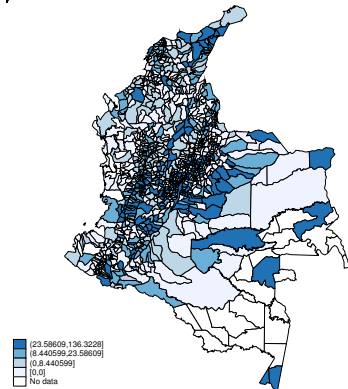
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- Control variables: demographic and economic variables

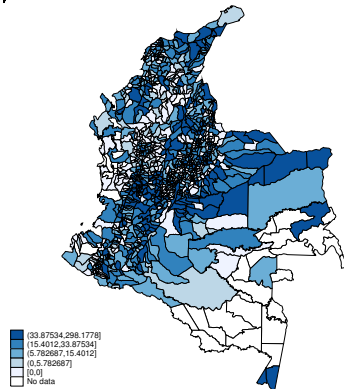
# About Colombia

Commerce Theft Rate 2007



Source: CEDE

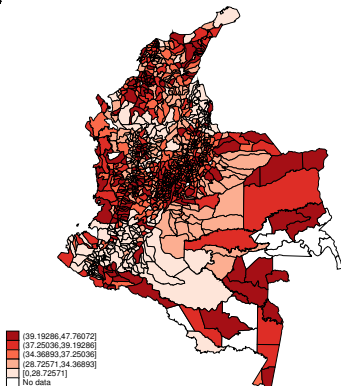
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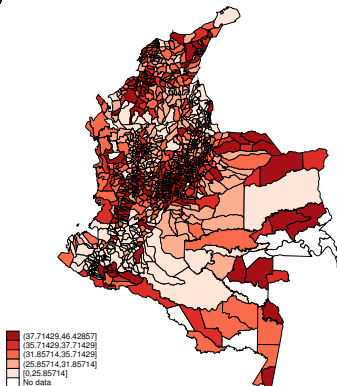
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Average Score in Subjects 2007



(Source: ICFES, IPUMS, and authors' calculations)

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- Empirics

## 2 Results

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# Econometric Model

- Estimate the following model to identify a causal impact of quality of education on crime

$$Y_{mt} = \beta_0 + \beta_1 EducationQuality_{mt} + \beta_2 X_{mt} + \mu_m + \eta_t + \varepsilon_{mt} \quad (1)$$

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  - $\varepsilon_{mt}$  the mean zero error term in equation
- Parameter of interest is  $\beta_1$  giving us the causal impact of education quality on violence

- Also estimate following model to identify the causal impact of quality of education on presence of illegal armed groups

$$Presence_{mt} = \beta_0 + \beta_1 EducationQuality_{mt} + \beta_2 X_{mt} + \mu_m + \eta_t + \varepsilon_{mt} \quad (2)$$

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  - Shift-share instruments

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# Results: Impact of Education Quality on Violence

	Homid	Tot Kidnapp	Pol Kid	Nonpol Kid	Terror	Amushes	Car theft	Comm theft	Person	Household
Average Score in Subjects	2.714 (1.872)	-0.666* (0.394)	0.064 (0.140)	-0.730* (0.377)	0.178 (0.224)	0.067* (0.035)	-1.490 (1.096)	-1.969 (1.321)	-10.223** (4.800)	-1.087 (1.300)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Underidentification	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Weak Identification	53.257	53.299	53.299	53.299	53.299	53.299	92.053	52.620	53.249	46.267
Overidentification	0.850	0.895	0.237	0.880	0.599	0.186	0.204	0.153	0.136	0.667
Endog. test	0.154	0.038	0.731	0.020	0.131	0.362	0.224	0.151	0.234	0.433
N	6134	6213	6213	6213	6213	6213	4586	5962	6130	6036

Notes: \*\*\* denotes statistical significance at the 1% level, \*\* at the 5% level, and \* at the 10% level, all for two-sided hypothesis tests.

## Results: Impact of Education Quality on on Violence

- Increase in average median test scores in all subjects by 1 standard deviation results in a marginal decline of approximately
  - 1.8 standard deviations of total kidnappings
  - 3 standard deviations of political kidnappings
- We also find 1 standard deviation increase in test scores leads to statistically significant decline of
  - 1.9 standard deviation in the rate of theft on persons
- These results remain consistent when we use other measures of quality of education

# Indoctrination Effect?

- According to theoretical framework: a positive effect on violence measures would imply an indoctrination effect
  - We find that 1 S.D. increase in test scores leads to a 1.4 standard deviations rise in the ambush rates
- This impact is statistically significant implying a positive causal link between education quality and a conflict outcome since ambushes are caused largely by conflict in Colombia
  - However, we cannot say for certain at this point if this positive causal impact is in fact suggestive of an indoctrination effect of education quality

## Results: Impact of Education Quality on Presence

	FARC	ELN	Any illegal armed group
Average Score in Subjects	-0.079*** (0.013)	-0.075*** (0.011)	-0.081*** (0.011)
Control	Yes	Yes	Yes
Control_Mean	Yes	Yes	Yes
N	6215	6215	6215

Notes: \*\*\* denotes statistical significance at the 1% level, \*\* at the 5% level, and \* at the 10% level, all for two-sided hypothesis tests.

## Results: Impact of Education Quality on Presence

- Better quality of education lowers the likelihood of presence of the illegal armed groups in the municipalities
  - 1 standard deviation increase in test scores leads to a decline in probability that
    - FARC is present in the municipality by 2.9 percent
    - ELN by 2.2 percent
    - Either FARC or ELN by approximately 3 percent
- These marginal effects are found to be statistically significant.

# Results: Impact of Education Quality on Surrender rate

Surrender rate	(1)	(2)	(3)	(4)	(5)
Average Score in Subjects	1.249*** (0.405)				
Subjects Median Z Score		17.799*** (5.766)			
Average Score in Cognitive Areas			1.192*** (0.390)		
Language Median Score				0.868*** (0.264)	
Math Median Score					1.687** (0.731)
Control	Yes	Yes	Yes	Yes	Yes
N	4136	4136	4136	4136	4136

## Results: Impact of Education Quality on Surrender rate

- Better education quality has a statistically significant positive impact on the surrender rates
- 1 standard deviation increase in test scores causes an increase of
  - 1.5 standard deviation in the surrender rates in the municipality
- Better quality of education
  - discourages engaging in violent acts of conflict
  - acts as a catalyst to discourage continuation in such armed groups
- Results are consistent through all other measures of education quality as well

## Results: Impact of Education Quality on Surrender rate

- As a consequence of the above models, we assert that
  - the results are indicative of a 'pacifying effect'
    - decline in the likelihood of presence of the illegal armed groups
    - increase in the surrender rates by their members is found
- Thus, the positive ambush rates we find in our baseline model may not be an indoctrination effect as suggested by theory since Colombia is not a theocratic country
  - positive effect could simply be due to greater presence of mobile police and military units in the municipalities that attract higher ambushes



# Robustness checks

Results are robust to

- Different measures of quality of education
- Sub-sample analyses
  1. Excluding Bogota from the sample [here](#)
  2. Excluding all capital cities from the full sample [here](#)
    - quality of education has a negative and statistically significant impact on commerce theft after excluding the state capitals

# Robustness checks

- (cont'd)
  3. Municipalities with population less than 200,000 [here](#)
  4. Urban areas: we find that the effects are similar to the baseline results in terms of statistical significance as well as direction of impact [here](#)
  5. Rural areas: we do not find statistically significant results for theft rates in this case [here](#)

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# Conclusions

- We find that the higher the average selection-corrected median scores in the exam, the lower the car theft rates and thefts on persons one period hence
- We also find that better education quality leads to a statistically significant but marginal decline in non-political kidnappings
- We find better education quality to consistently reduce the presence of illegal armed groups in the municipalities
- As well as increase the surrenders by the members of these groups
- It is noteworthy that we find some positive impact of education on ambush rates
  - The definitive cause for higher ambushes needs to be explored further

Thank you!

# Robustness checks: No Bogotá [back](#)

	Homid	Tot Kidnapp	Pol Kid	Nonpol Kid	Terror	Amushes	Car theft	Comm theft	Person	Household
Average Score in Subjects	2.714 (1.872)	-0.666* (0.394)	0.064 (0.140)	-0.730* (0.377)	0.178 (0.224)	0.067* (0.035)	-1.490 (1.096)	-1.969 (1.321)	-10.223** (4.800)	-1.087 (1.300)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Underidentification	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Weak Identification	53.257	53.299	53.299	53.299	53.299	53.299	92.053	52.620	53.249	46.267
Overidentification	0.850	0.895	0.237	0.880	0.599	0.186	0.204	0.153	0.136	0.667
Endog. test	0.154	0.038	0.731	0.020	0.131	0.362	0.224	0.151	0.234	0.433
N	6134	6213	6213	6213	6213	6213	4586	5962	6130	6036

Notes: \*\*\* denotes statistical significance at the 1% level, \*\* at the 5% level, and \* at the 10% level, all for two-sided hypothesis tests.

# Robustness checks: No state capitals [back](#)

	Homid	Tot Kidnapp	Pol Kid	Nonpol Kid	Terror	Amushes	Car theft	Comm theft	Person	Household
Average Score in Subjects	3.223 (2.041)	-0.701 (0.527)	0.076 (0.150)	-0.777 (0.501)	0.087 (0.257)	0.071* (0.037)	-1.044 (1.512)	-2.455 (1.510)	-2.859 (4.030)	-0.059 (1.464)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Underidentification	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Weak Identification	30.038	30.086	30.086	30.086	30.086	30.086	51.335	29.649	29.898	25.840
Overidentification	0.293	0.659	0.152	0.815	0.199	0.403	0.688	0.235	0.569	0.225
Endog. test	0.146	0.023	0.965	0.064	0.672	0.700	0.361	0.153	0.738	0.756
N	5954	6033	6033	6033	6033	6033	4424	5782	5950	5856

Notes: \*\*\* denotes statistical significance at the 1% level, \*\* at the 5% level, and \* at the 10% level, all for two-sided hypothesis tests.

# Robustness checks: Population < 200 thousand [back](#)

	Homid	Tot Kidnapp	Pol Kid	Nonpol Kid	Terror	Amushes	Car theft	Comm theft	Person	Household
Average Score in Subjects	3.251 (2.039)	-0.706 (0.527)	0.079 (0.150)	-0.785 (0.501)	0.090 (0.257)	0.071* (0.037)	-1.045 (1.510)	-2.561* (1.512)	-2.989 (4.028)	-0.144 (1.473)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Underidentification	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Weak Identification	30.064	30.115	30.115	30.115	30.115	30.115	51.931	29.694	29.919	25.887
Overidentification	0.303	0.686	0.148	0.796	0.193	0.404	0.689	0.236	0.549	0.229
Endog. test	0.142	0.023	0.973	0.066	0.665	0.699	0.360	0.135	0.721	0.716
N	5984	6063	6063	6063	6063	6063	4436	5812	5980	5886

Notes: \*\*\* denotes statistical significance at the 1% level, \*\* at the 5% level, and \* at the 10% level, all for two-sided hypothesis tests.



# Robustness checks: Rural areas [back](#)

	Homid	Tot Kidnapp	Pol Kid	Nonpol Kid	Terror	Amushes	Car theft	Comm theft	Person	Household
Average Score in Subjects	3.339 (2.211)	-0.274 (0.368)	0.044 (0.153)	-0.318 (0.357)	-0.003 (0.288)	0.076* (0.041)	0.012 (1.262)	-1.094 (1.481)	2.753 (2.160)	2.052* (1.173)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Underidentification	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Weak Identification	24.807	24.638	24.638	24.638	24.638	24.638	61.934	24.606	24.368	23.294
Overidentification	0.298	0.114	0.183	0.561	0.458	0.488	0.581	0.344	0.677	0.446
Endog. test	0.133	0.128	0.911	0.154	0.763	0.522	0.812	0.554	0.211	0.122
N	3961	4029	4029	4029	4029	4029	2668	3805	3946	3858

Notes: \*\*\* denotes statistical significance at the 1% level, \*\* at the 5% level, and \* at the 10% level, all for two-sided hypothesis tests.

# Robustness checks: Urban areas [back](#)

	Homid	Tot Kidnapp	Pol Kid	Nonpol Kid	Terror	Amushes	Car theft	Comm theft	Person	Household
Average Score in Subjects	-2.963 (2.933)	-0.095 (0.838)	0.575 (0.542)	-0.670 (0.647)	1.110** (0.458)	-0.040 (0.063)	0.327 (1.804)	-8.473*** (2.386)	-32.079*** (11.361)	-2.146 (5.854)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Underidentification	0.046	0.047	0.047	0.047	0.047	0.047	0.125	0.051	0.047	0.105
Weak Identification	16.098	16.056	16.056	16.056	16.056	16.056	7.448	17.066	16.056	6.596
Overidentification	0.060	0.073	0.276	0.056	0.824	0.736	0.644	0.082	0.298	0.028
Endog. test	0.428	0.810	0.982	0.402	0.038	0.597	0.924	0.304	0.030	0.770
N	2165	2175	2175	2175	2175	2175	1912	2148	2175	2169

Notes: \*\*\* denotes statistical significance at the 1% level, \*\* at the 5% level, and \* at the 10% level, all for two-sided hypothesis tests.