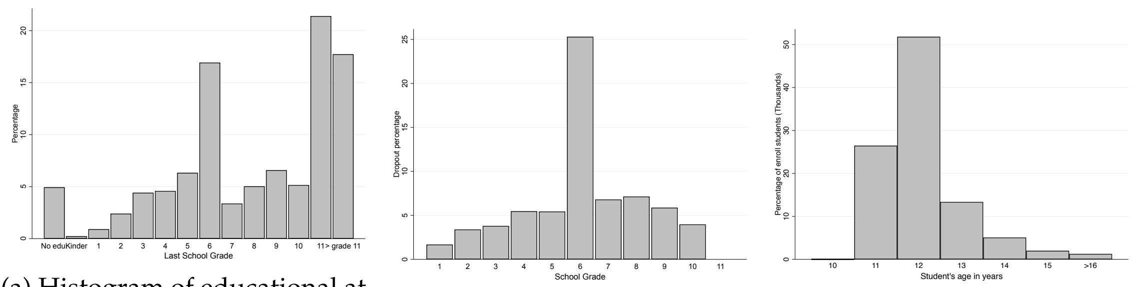
Online Appendix

A Additional Descriptive Figures and Tables

Figure A1: Ages of exposure



(a) Histogram of educational attainment from 2007 Census

(b) Dropout rates 2013

(c) Ages at transition grades 6-7

Figure A2: Age distribution of incarcerated individuals in 2015

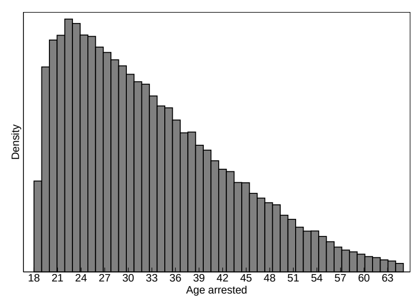
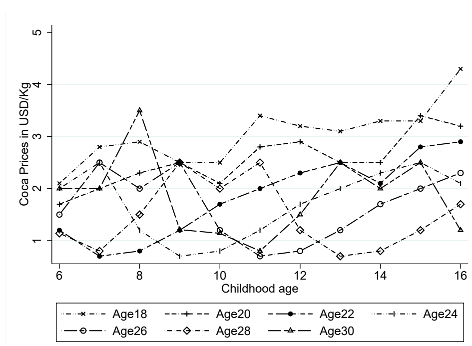


Figure A3: Variation in coca prices during childhood across cohorts



Notes: This figure shows the different coca prices experienced at all ages in childhood for a sub-sample of cohorts.

Table A1: Summary statistics of main variables

	Unit	Obs	Mean	Std. Dev.
Panel level variables				
Child labor (6-21)	Individual	413174	0.369	0.483
Child labor (6-14)	Individual	242593	0.298	0.458
Child labor (6-10)	Individual	131689	0.232	0.422
Child labor (11-14)	Individual	110904	0.377	0.485
Adult labor (15-18)	Individual	106287	0.422	0.494
Adult labor (19-21)	Individual	64294	0.548	0.498
Incarceration rate	District-Cohort	23853	3.365	23.501
District level variables				
Dropout rate (6-10)	School	289499	0.060	0.103
Dropout rate (11-14)	School	365115	0.080	0.142
Dropout rate (15-18)	School	100944	0.080	0.092
Fail rate (6-10)	School	427928	8.465	9.185
Fail rate (11-14)	School	514878	6.863	12.067
Fail rate (15-18)	School	125505	5.117	7.442
High age for grade (6-10)	School	434160	0.187	0.171
High age for grade (11-14)	School	516107	0.273	0.274
High age for grade (15-18)	School	129851	0.230	0.215
Coca intensity, thousands of hectares, 1994	District	1825	0.013	0.122
Gold deposits, 1970	District	1825	0.092	0.678
Coffee intensity, thousands of hectares, 1994	District	1825	3.070	9.996
Cotton intensity, thousands of hectares, 1994	District	1825	1.414	4.709
Sugar intensity, thousands of hectares, 1994	District	1825	2.495	8.848
Cacao intensity, thousands of hectares, 1994	District	1825	2.640	9.373
Time level variables				
Log internal coca price	Year	34	0.739	0.461
Log coca hectares in Colombia, hundred thousands of hectares	Year	26	-0.392	0.459
Log international coffee price	Year	34	1.175	0.375
Log international gold price	Year	34	1.756	0.423
Log international cacao price	Year	34	0.750	0.349
Log international sugar price	Year	34	0.311	0.153
Log international cotton price	Year	34	1.971	0.537

B Additional Analysis and Robustness checks

B.1 Additional analysis: the effects of shocks to other commodities on child labor

Table A2: Controlling for price shocks to other commodities

	Labor
$PriceShock_{d,t}$	0.201**
	(0.092)
$PriceShock_{d,t} \times 6x10$	0.056**
	(0.027)
$PriceShock_{d,t} \times 11x14$	0.144***
	(0.026)
$PriceShock_{d,t} \times 15x18$	0.074**
	(0.036)
$PriceShockGold_{d,t}$	0.035
	(0.025)
$PriceShockGold_{d,t} \times 6x10$	0.012*
	(0.006)
$PriceShockGold_{d,t} \times 11x14$	0.015**
	(0.006)
$PriceShockGold_{d,t} \times 15x18$	-0.007*
	(0.004)
$PriceShockCoffee_{d,t}$	0.003***
	(0.001)
$PriceShockCoffee_{d,t} \times 6x10$	-0.001
	(0.001)
$PriceShockCoffee_{d,t} \times 11x14$	0.003
	(0.002)
$PriceShockCoffee_{d,t} \times 15x18$	0.000
	(0.001)
$PriceShockCotton_{d,t}$	0.009***
	(0.003)
$PriceShockCotton_{d,t} \times 6x10$	-0.006**
	(0.003)
$PriceShockCotton_{d,t} \times 11x14$	-0.003
	(0.003)
$PriceShockCotton_{d,t} \times 15x18$	-0.001
	(0.002)
$PriceShockCacao_{d,t}$	-0.004***
	(0.001)
$PriceShockCacao_{d,t} \times 6x10$	0.001
	(0.002)
$PriceShockCacao_{d,t} \times 11x14$	-0.004
	(0.003)
$PriceShockCacao_{d,t} \times 15x18$	0.002**
	(0.001)
$PriceShockSugar_{d,t}$	-0.002*
	(0.001)
$PriceShockSugar_{d,t} \times 6x10$	0.001
	(0.001)
$PriceShockSugar_{d,t} \times 11x14$	0.001*
	(0.001)
$PriceShockSugar_{d,t} \times 15x18$	0.002***
	(0.000)
Observations	412,026
Number of districts	1,469
Dep. var. mean	0.369
District FE	✓
Year FE	✓

Notes: Building upon the specification presented in Equation 1, this table also includes price shocks to gold, coffee, cacao, cotton and sugar. $PriceShock_{d,t}$ is the interaction between log coca prices and the number of coca hectares in the district in 1994. $6x10$, $11x14$ and $15x18$ are dummy variables corresponding to each age bin. The omitted category is ages 19 to 21. $PriceShockGold_{d,t}$ is the interaction between log gold prices and mineral gold deposits in the district in 1970. $PriceShockCoffee_{d,t}$ is the interaction between log coffee prices and the average coffee suitability in the district for the period 1960-1990. $PriceShockCotton_{d,t}$ is the interaction between log cotton prices and the average cotton suitability in the district for the period 1960-1990. $PriceShockCacao_{d,t}$ is the interaction between log cacao prices and the average cacao suitability in the district for the period 1960-1990. $PriceShockSugar_{d,t}$ is the interaction between log sugar prices and the average sugar suitability in the district for the period 1960-1990. It includes district and year fixed effects. The dependent variable is labor participation (whether an individual in a given district-year had worked in the previous week). The sample is defined at the individual-household-year level. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

B.2 Robustness checks: child labor

Table A3: Robustness checks, labor participation by ages

	(1) Labor	(2) Labor	(3) Labor	(4) Labor	(5) Labor	(6) Labor
$PriceShock_{d,t}$	0.191**	0.186**	0.163*	0.168	0.241***	0.264***
	(0.091)	(0.091)	(0.091)	(0.156)	(0.091)	(0.088)
$PriceShock_{d,t} \times 6x10$	0.002	0.001	0.041	0.037	0.042	0.043
	(0.028)	(0.028)	(0.029)	(0.029)	(0.029)	(0.030)
$PriceShock_{d,t} \times 11x14$	0.079***	0.076***	0.139***	0.135***	0.144***	0.143***
	(0.026)	(0.026)	(0.028)	(0.027)	(0.028)	(0.028)
$PriceShock_{d,t} \times 15x18$	0.003	0.002	0.067*	0.065*	0.070*	0.069*
	(0.028)	(0.028)	(0.036)	(0.035)	(0.036)	(0.036)
Observations	399,246	398,935	412,026	412,026	401,941	412,026
Number of districts	1,442	1,442	1,469	1,469	1,469	1,469
Dep. var. mean	0.370	0.370	0.369	0.369	0.369	0.369
District FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Post 2001	✓	✓				
Covariates		✓				
Departament trends			✓			
DepYear FE				✓		
Baseline characteristics					✓	
Coca time trends						✓

Notes: Column (1) presents the results from Equation 1 using only the observations from the post period (2001-2013). Column (2) includes controls for poverty at the household level. Column (3) includes department time trends as a regressor. Column (4) includes department-by-year fixed effects. Column (5) further controls for baseline characteristics interacted with year such as the proportion of villages affected by conflict in the 1980s and malnutrition rates, variables that are in general used to assign social programs. Column (6) also includes linear trends specific to coca-suitable areas as regressors. The dependent variable is labor participation (whether an individual in a given district-year had worked in the previous week). The sample is defined at the individual-household-year level. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

B.3 Validity of the instrument

Table A4: First stage

	(1) $PriceShock_{d,t}$	(2) $PriceShock_{d,t}$
$Coca_d \times CocaColombia_t$	-0.418***	-0.412***
	(0.123)	(0.121)
Observations	412,026	401,941
Kleiberg-Paap F-stat	1409.095	1466.590
District FE	✓	✓
Year FE	✓	✓
Baseline trends		✓

Notes: This table presents the first stage associated with Equation 1. $Coca_d \times CocaColombia_t$ is the interaction between the number of hectares dedicated to coca in Peru in 1994 (the coca suitability measure) and the log number of hectares in Colombia. The dependent variable is $PriceShock_{d,t}$ which is the interaction between log coca prices and the coca suitability measure. Column (1) includes district and year fixed effects. Column (2) further controls for baseline characteristics interacted with year. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Figure A4: Coca eradication in Peru and Colombia

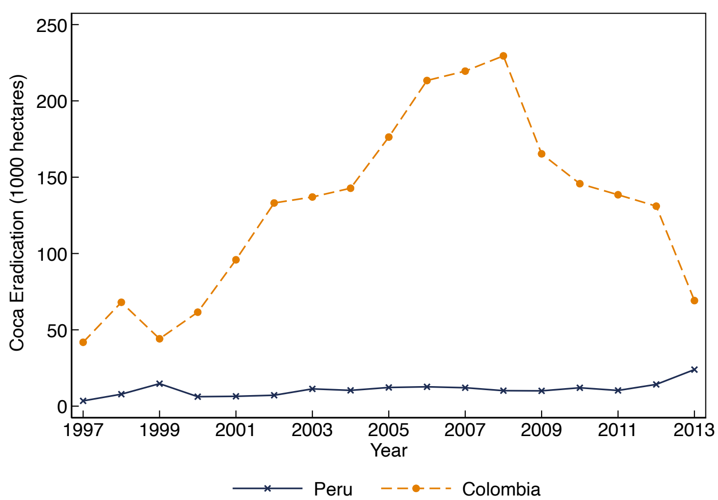


Table A5: Validity of the exclusion restriction

	(1) Taxes	(2) Property taxes	(3) Contributions	(4) Other non-tax revenues	(5) Customs	(6) Other transfers
$Coca_d \times CocaColombia_t$	0.038	0.004	0.001	-0.214	0.022	-0.467
	(0.128)	(0.121)	(0.003)	(0.376)	(0.016)	(0.434)
Observations	23,702	23,702	23,702	23,702	18,286	18,286
Number of districts	1,831	1,831	1,831	1,831	1,831	1,831
Dep. var. mean	0.674	0.575	0.005	0.971	0.072	0.586
Magnitude of the effect	0.51%	0.06%	2.30%	-1.99%	2.73%	-7.18%
District FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

Notes: This table presents the estimates from the reduced form specification of Equation 1 where $Coca_d \times CocaColombia_t$ is the interaction between the coca suitability measure and the log number of hectares dedicated to coca in Colombia. All dependent variables are expressed in real values per million. All specifications control for district and year fixed effects, as well as department time trends. Column (1) presents as dependent variable the total municipal revenues, which are composed of tax revenues (taxes and contributions), non-tax revenues (sale of goods, provision of services, fees, among others), transfers and capital revenues; Column (2), the total property taxes collected by the municipality, which include building and vehicular taxes; Column (3), the income received by the municipalities for the execution of government activities; Column (4), the total non-tax revenue of the municipality that includes income from fees, sale of goods, provision of services, property rentals, penalties, among others; Column (5), the transfer received by municipalities for income collected by maritime, air, river, lake and terrestrial ports located in their jurisdiction (this variable is only available for the period 2001-2011); and Column (6), special transfers received by the municipality for the Municipal Compensation Fund. and other transfers received by municipalities in addition to transfers for royalties, and fees (this variable is only available for the period 2001-2011). The magnitudes of the effects are calculated for a district with 0.3 hectares of coca and for an average increase of 30% in the number of hectares in Colombia during the period of analysis. The sample is at the district-year level. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Table A6: OLS and reduced form estimates

	(1) Labor	(2) Labor	(3) Labor	(4) Labor	(5) Labor
$PriceShock_{d,t}$	0.009	0.004			
	(0.043)	(0.043)			
$PriceShock_{d,t} \times 6x10$	0.032	0.032			
	(0.034)	(0.034)			
$PriceShock_{d,t} \times 11x14$	0.098**	0.098**			
	(0.042)	(0.042)			
$PriceShock_{d,t} \times 15x18$	0.021	0.021			
	(0.022)	(0.022)			
$Coca_d \times CocaColombia_t$			-0.009	-0.006	0.007
			(0.049)	(0.049)	(0.063)
$Coca_d \times CocaColombia_t \times 6x10$			-0.063	-0.063	-0.122
			(0.052)	(0.052)	(0.081)
$Coca_d \times CocaColombia_t \times 11x14$			-0.242***	-0.242***	-0.380***
			(0.048)	(0.048)	(0.065)
$Coca_d \times CocaColombia_t \times 15x18$			-0.121*	-0.121*	-0.298***
			(0.063)	(0.063)	(0.041)
Observations	412,026	401,941	412,026	401,941	153,017
Number of districts	1,469	1,469	1,469	1,469	1,077
Dep. var. mean	0.369	0.369	0.369	0.369	0.322
District FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Baseline trends		✓		✓	
Period	94-13	94-13	94-13	94-13	94-05

Notes: This table presents the OLS and reduced form estimates associated with Equation 1. The dependent variable is labor participation (whether an individual in a given district-year had worked in the previous week). $PriceShock_{d,t}$ is the interaction between log coca prices and the number of hectares dedicated to coca in the district in 1994. $6x10$, $11x14$ and $15x18$ are dummy variables corresponding to each age bin. The omitted category is the age 19 to 21. $Coca_d \times CocaColombia_t$ is the interaction between the coca suitability measure and the log number of hectares in Colombia. Columns (1) and (3) include district and year fixed effects. Columns (2) and (4) further include baseline characteristics such as poverty and violence interacted with year. Column (5) restricts the analysis to pre-2005. The sample is at the individual-household-year level. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Table A7: Growing status in 1994 and coca production growth in 2002-2013

	(1) Coca growth	(2) Coca growth	(3) Coca growth
Growing status in 1994 (=1)	331.043***	509.135***	197.879***
	(24.032)	(29.265)	(18.803)
Constant	4.258	4.258	4.258
	(8.026)	(7.397)	(4.713)
Observations	1,847	1,753	1,751

Notes: This table analyzes whether production in 1994 predicts coca growth during the period of analysis. Growing status in 1994 takes the value of 1 if the district has coca production in 1994 and 0 otherwise. Columns (2) and (3) divide the sample between high and low coca suitable districts in 1994. The sample is at the district level. Significant at $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

B.4 Additional analysis: the effects of coca price shocks on test scores

Table A8: The effect of coca prices on test scores for second grade students (aprox. ages 7-9)

	(1) Math	(2) Level 1 Math	(3) Reading	(4) Level 1 Reading
$PriceShock_{d,t}$	-12.389*	4.502	-7.919	-3.006
	(6.847)	(3.696)	(5.935)	(3.393)
Observations	95,039	70,847	95,034	70,759
Dep. var. mean	514.847	49.934	518.897	21.739
School FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Notes: This table presents the estimates from Equation 2, where $PriceShock_{s,t}$ is the interaction of log coca prices and the coca density associated with the school. The dependent variables in Column (1) and (3) are the average scores in math and reading at the national exam. The dependent variables in Column (2) and (4) are the proportion of students that got the lowest score in math and reading. The sample is at the school-year level. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

B.5 Robustness checks: schooling outcomes

Table A9: Robustness checks, schooling outcomes: including department time trends; and department-by-year fixed effects and school level covariates

	Panel A: Dropout rate					
	Dep. time trends			Dep-by-year FE and school cov.		
	(1) 6-10	(2) 11-14	(3) 15-18	(4) 6-10	(5) 11-14	(6) 15-18
$PriceShock_{s,t}$	0.001	0.007**	-0.007	-0.000	0.007**	-0.008
	(0.003)	(0.004)	(0.006)	(0.003)	(0.003)	(0.006)
Observations	287,629	362,130	100,039	263,325	324,624	85,223
Number of schools	33,849	42,933	11,385	30,759	38,295	9,622
Dep. var. mean	0.060	0.080	0.080	0.063	0.083	0.084
	Panel B: Failed grade					
	Dep. time trends			Dep-by-year FE and school cov.		
$PriceShock_{s,t}$	0.711***	0.256	-0.448	0.595***	0.041	-0.496
	(0.218)	(0.281)	(0.416)	(0.186)	(0.266)	(0.405)
Observations	425,606	513,334	125,006	383,337	452,880	103,636
Number of schools	36,825	47,651	12,476	33,244	42,232	10,484
Dep. var. mean	8.480	6.871	5.126	8.925	7.140	5.294
	Panel C: High age for grade					
	Dep. time trends			Dep-by-year FE and school cov.		
$PriceShock_{s,t}$	0.021***	0.005	-0.012	0.021***	0.007	-0.004
	(0.004)	(0.007)	(0.010)	(0.004)	(0.007)	(0.009)
Observations	433,408	514,551	129,340	389,956	453,846	107,322
Number of schools	36,840	47,145	12,487	33,267	41,790	10,497
Dep. var. mean	0.187	0.273	0.230	0.198	0.291	0.254
School FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Department Trend	✓	✓	✓			
DepYear FE				✓	✓	✓
School cov.				✓	✓	✓

Notes: Building upon the specification presented in Equation 2, this table also includes department specific time trends, department-by-year fixed effects, and school covariates as regressors. The sample is at the school-year level. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Table A10: Robustness checks, schooling outcomes: including coca specific time trends; and district-by-year fixed effects.

	Panel A: Dropout rate					
	Coca trends			District-by-Year FE		
	(1)	(2)	(3)	(4)	(5)	(6)
	6-10	11-14	15-18	6-10	11-14	15-18
$PriceShock_{s,t}$	-0.001	0.007**	-0.008	0.000	0.012**	0.008
	(0.003)	(0.003)	(0.006)	(0.004)	(0.006)	(0.012)
Observations	283,103	356,492	98,539	285,400	360,908	92,718
Number of schools	33,328	42,268	11,234	33,737	42,867	10,889
Dep. var. mean	0.060	0.079	0.080	0.060	0.080	0.079
	Panel B: Failed grade					
	Coca trends			District-by-Year FE		
$PriceShock_{s,t}$	0.621***	0.109	-0.499	-0.135	-0.580	-0.747
	(0.186)	(0.264)	(0.394)	(0.280)	(0.395)	(1.011)
Observations	417,862	504,177	123,108	424,383	512,766	117,780
Number of schools	36,242	46,899	12,315	36,754	47,628	12,015
Dep. var. mean	8.397	6.785	5.081	8.483	6.872	5.084
	Panel C: High age for grade					
	Coca trends			District-by-Year FE		
$PriceShock_{s,t}$	0.019***	0.005	-0.007	0.011*	0.012	-0.003
	(0.004)	(0.006)	(0.009)	(0.006)	(0.009)	(0.016)
Observations	425,185	505,176	127,366	432,195	513,962	122,284
Number of schools	36,261	46,402	12,328	36,769	47,119	12,026
Dep. var. mean	0.185	0.270	0.228	0.187	0.273	0.225
School FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
DepYear	✓	✓	✓			
Coca Trends	✓	✓	✓			
DistYear FE				✓	✓	✓

Notes: Building upon the specification presented in Equation 2, this table also includes coca specific time trends and baseline time trends; and district-by-year as regressors. The sample is at the school-year level. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

B.6 Additional analysis: heterogeneity by ages at incarceration

Table A11: Coca prices during childhood and subsequent criminal behavior

	(1) All crimes	(2) All crimes	(3) By age at incarceration
$PriceShockAge6to7_{d,c}$	1.029	-0.308	
	(0.716)	(0.847)	
$PriceShockAge8to9_{d,c}$	1.564*	1.661**	
	(0.848)	(0.840)	
$PriceShockAge10to11_{d,c}$	2.455**	1.614	
	(1.003)	(1.037)	
$PriceShockAge12to13_{d,c}$	4.559**	1.972***	
	(1.981)	(0.686)	
$PriceShockAge14to15_{d,c}$	7.309**	1.346**	
	(3.177)	(0.650)	
$PriceShockAge16to17_{d,c}$	2.812	0.293	
	(2.391)	(0.324)	
$PriceShockAge18to19_{d,c}$		0.497	
		(0.796)	
$PriceShockAge11to14_{d,c} \times 18x19$			4.607**
			(1.816)
$PriceShockAge11to14_{d,c} \times 20x29$			5.401***
			(1.853)
$PriceShockAge11to14_{d,c} \times 30x39$			0.274
			(1.428)
Observations	23,853	22,028	38,541
Dep. var. mean	4.565	4.256	4.360
Age sample	18-30	28-39	18-39
District of birth FE	✓	✓	✓
Year of birth FE	✓	✓	✓

Notes: This table presents the estimates from Equation 3 where *PriceShock Age* $x_{d,c}$ is the interaction between the coca suitability in the district of birth and log average coca prices at different ages. Column (1) restricts the sample to those aged 18-30 in the incarceration data. Column (2) restricts the sample to those aged 28-39. Column (3) includes interaction of the main explanatory variable with (mutually exclusive) dummies indicating the current age category of the cohorts. The sample is defined at the district and year of birth level. All specifications control for district and year of birth fixed effects, as well as district specific time trends. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

B.7 Robustness checks: crime

Table A12: Robustness checks, coca prices during childhood and subsequent criminal behavior

	(1)	(2)	(3)	(4)	(5)
$PriceShockAge11to14_{d,c}$	3.405***	0.129***	0.007**	2.878***	3.859***
	(0.907)	(0.033)	(0.003)	(1.105)	(1.021)
Observations	23,853	667,884	1,295,788	23,853	23,853
Dep. var. mean	4.565	0.159	0.018	4.565	4.565
Department by yob FE	✓				
Year of Arrest FE		✓			
District by yob FE			✓		
Control for victims in civil conflict				✓	
Control for sentence length					✓

Notes: This table presents the estimates from Equation 3 where *PriceShock Age11to14*$_{d,c}$ is the interaction of log average price of coca between 11 to 14 years old and coca suitability measure of the district or village of birth. Column (1) further controls for department-by-year fixed effects. The sample is at the district and year of birth level. Column (2) includes year of arrest fixed effects as a regressor. The sample is at the year of birth, year of arrest and district of birth level. Column (3) uses 2016 census to obtain information on the village of birth and classifies the treatment status of the village of birth using the coca density maps. In particular, it replaces the coca suitability measure at the district level with a dummy indicating if the village is located in a coca geographic cell (identified by satellite images). The sample is at the village and year of birth level and allows to include district-by-year fixed effects. Column (4) controls for the number of victims during the civil conflict in each district of birth. Column (5) controls for the average sentence length. The sample in Columns (4) and (5) is at the district and year of birth level. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

C Mechanisms

C.1 Violence, Enforcement and Governance

In this section, I explore the effect of changes in coca prices on violence and enforcement in order to understand whether exposure to violence during childhood may explain the results on future criminality. First, I briefly review the theoretical and empirical literature. Second, I provide a description of the Peruvian context, which is relevant for understanding whether violence may be driving the main results. Third, I analyze the effects of the high coca prices on short-run violence using different datasets and measures of crime, violence, and conflict. I show that violence did not increase when coca prices increased. Finally, to further understand whether the long-term effects are driven by violence (for example, violence that I am not able to observe with my data), I discuss previous literature on the long-term effects of violence as well as several pieces of evidence from my analysis that suggest that the results could not be mainly driven by violence.

Literature and background: from a theoretical point, previous literature has suggested that there could be ambiguous effects on the role of illegal commodity booms on violence (Kalyvas 2006; Snyder and Duran-Martinez 2009; Castillo and Kronick 2020; Mesquita 2020). The sign of the effects mainly depends on the opportunity cost of committing violence, the number of groups competing for the control of the extra resources, and the law enforcement against illegal activity. Hence, the literature distinguishes between four different scenarios. Depending on the scenario, opportunity cost effects are more or less likely to dominate contestation effects, driving a net positive or negative effect on violence (Snyder and Duran-Martinez 2009; Gehring et al. 2020): A. High enforcement and multiple groups competing, B. High enforcement and no competition, C. Low enforcement and multiple groups competing , D. Low enforcement and no competition.

In scenario A, since the contestation effects dominate the opportunity cost of committing violence, we expect shocks to illegal commodities to raise violence. This resource-conflict curse is common in the empirical literature, especially in countries like Colombia (Angrist and Kugler 2008; Mejía et al. 2017; Ibanez and Carlsson 2010; Ibanez and Martinsson 2013; Wright 2016), Mexico and El Salvador (Dell 2015; Sobrino 2019; Sviatschi 2019).[72] Moreover, in the case of Mexico, Dell (2015) shows that while there is an increase in violence from government suppression since 2007, the paper also documents a non-violent equilibrium with extensive drug trafficking before the 2007 election (when there was no government suppression).

On the one hand, scenario B describes dominance and enforcement from the incumbent government. Hence, we expect weak opportunity cost, but also low contestation effects. This case resembles the evidence for Afghan Districts under the rule of the Afghan government (Gehring et al. 2020). On the other hand, in scenario C, we expect not only a strong contestation, but also strong opportunity costs, since more farmers benefit from higher prices. Thus, opportunity costs offset contestation effects. Finally, scenario D describes a context with low enforcement and lack of contestation. In this case, booms to illegal commodities may reduce the violence, since the opportunity cost effects related to higher prices outperform the weak contestation effects. This case resembles the evidence for Afghan Districts under the rule of the Taliban (Gehring et al. 2020), and according to my interviews and other anecdotal evidence, it describes the Peruvian context.[73]

The case of Peru during my period of analysis is closer to this last case because of the weak level of law enforcement prevailing then and the lack of competition among armed groups by the time cocaine expanded in the 2000s. This is mainly because the two armed groups (the main one, the Shining Path, which was controlling cocaine production and instigating violent confrontations with state officials, and the Tupac Amaru Revolutionary Movement) had already been defeated by state officials when coca prices increased during my period of analysis (Palmer 1994; Brienen and

[72] When cocaine expanded in Colombia in the 1990s, armed groups were already involved in the ongoing civil conflict: a left-wing guerrilla known as FARC (the Spanish acronym for Revolutionary Armed Forces of Colombia) and right-wing paramilitary groups known as AUC (the Spanish acronym for United Self-Defense Forces of Colombia). These groups took advantage of the boom and engaged in the coca sector to fund their criminal operations. Following the increase in the cocaine supply, in 1999, the Colombian and the US governments announced a top-down joint strategy to crack down on illegal markets and strengthen the security conditions in the coca-growing regions, known as Plan Colombia. This strategy consisted of such coercive actions as an increased military presence and the aerial spraying of coca crops with glyphosate (see Mejía (2015), for a thorough description of Plan Colombia).

[73] In these insurgent-controlled districts, the Taliban behaves like a stationary bandit (Sánchez de la Sierra 2020). They are the only insurgent group controlling the drug trade by providing security to the opium farmers and traffickers in exchange for rents or "taxation."

Rosen 2015). This was part of the presidents' policy of reducing conflict and armed groups in rural areas.[74] Thus, from mid 1990s to today there have not been large violent confrontations. Furthermore, anecdotal evidence from my field interviews as well as from Peruvian anthropologists and sociologists suggests that drug trafficking today is managed by a few Peruvian family clans (called *firmas*), which are not contesting territory as in the case of Colombian or Mexican cartels. Instead, the *firmas* rely on local networks of long-lasting relationships and operate with the support of the inhabitants and, in most of the cases, the local authorities. Hence, as opposed to the Colombian or Mexican context, the cocaine industry, in either Huallaga Valley or the Peruvian Amazonian Borderlands, has infiltrated all aspects of everyday social relations in the coca-growing communities (Van Dun 2012, 2014, 2016; Vizcarra 2018, 2019).[75] A quote from a coca farmer in Huallaga: "We live peacefully here as long as nobody gets involved with other peoples' businesses. It is not like in the TV shows and movies where you see different cartels fighting and many people being killed. We manage to keep violence low since fighting will only call the attention of authorities and damage the business." In fact, while Colombia had a homicide rate of over 38 per 100,000 inhabitants in 2007 and over 80 at the peak of cocaine production (Policia Nacional de Colombia), Peru has only 3 homicides per 100,000 inhabitants. In Peru, violence has been mainly used, if at all, to enforce contracts.[76] Violent episodes associated with the contestation of territories are scarce due to the relevance of the social bonds between *firmas* and the communities (Van Dun 2012, 2014, 2016).

Further, Peru, unlike Colombia, did not have a strong eradication or enforcement policy during the period being studied, which in general tends to increase violence (as seen with the evidence in Mexico and Colombia). In the case of Peru, eradication efforts were only manual and very small in scale. Figure A4 presents the number of eradicated coca hectares in Peru and Colombia. It shows that eradication did not increase during the period of analysis, and that it was very small in scale compared to Colombia. The minor eradication efforts in Peru were mainly due to the social mobilization and the bargaining power of *cocalero* peasant movements. Before the 2000s, the central government feared that crackdowns on the coca farms would increase the collaboration between *cocaleros* and Shining Path. Hence, eradication campaigns ceased, and the central government presented itself as an ally of the farmers instead of an enemy, to gain their hearts and minds.

[74]Under the Fujimori administration, the struggle against the left-wing insurgent movements through militarization was the primary concern. The capture of Abimael Guzman, head of the Shining Path, resulted in a significant reduction in insurgent activities and the subsequent disintegration of the group due to organizational matters and disagreements among the remaining insurgents (Waynee 2008).

[75] In addition, coca production is not associated with violence in general, given the Peruvian history of the crop, which again is very different from its history in Colombia. In Colombia, the first coca leaf crops were found on the farms and properties of the "emeralds," organizations in charge of controlling the smuggling of emeralds, which already had private security forces. These organizations became the first drug traffickers, forcing Colombian peasants to grow the leaf, replacing their previous crops (Escobedo 2011). In contrast, the production of coca leaf in Peru is legal if it is grown for medicinal purposes or for chewing the leaves, a traditional practice among indigenous communities. For this reason, coca leaf cultivation dates back to well before the nineteenth century. It was not illegal, but instead represented the cultivation of a plant with high personal and medicinal value for the general population. It was therefore easy for cartels to convince farmers to produce coca without exerting violence or linking it to an illegal activity.

[76]Disputes and contestation among local firmas are scarce. According to (Van Dun 2016), drug barons usually agree on *pactos de caballeros* (gentlemens agreements) that define property rights on the territories.

Anecdotal evidence suggests, moreover, that the family clans that control the business have preferred not to confront the police and instead pay bribes. As one of my interviewers mentioned: "Peru has long eluded the levels of bloodshed that have fueled displacement and indiscriminate violence in Colombia and Mexico. Peruvian drug traffickers prefer bribes to bullets." Nevertheless, since it is an illegal industry, violence could still occur, for example, as a means of enforcing contracts. Thus, in the following analysis, I estimate the contemporaneous effects of coca prices on violence using different datasets.

Empirical analysis: to analyze the effects on enforcement and violence, I use data on 1) the number of officers, 2) the perception of violence, 3) victimization, 4) major criminal records from different sources, and 5) conflict, criminal organizations and terrorist events. I analyze the contemporaneous effects of the coca price shock on these measures.[77] First, I use data from the *Ministerio del Interior* in Peru on the number of patrolling rural officers per district per year for the period 2004-2014. Second, I use data from the National Registry of Municipalities (RENAMU), which is an administrative registry completed by all the districts of the country on an annual basis since 2001. It contains general information on municipalities, as well as information on human resources, competencies and functions, public infrastructure, and local public services, including citizen security. Among the questions on citizen security, I used the dichotomous question on problems that affect the safety of the district during the year, such as robbery, prostitution, drug trafficking, and terrorism. Third, I use data from the module of victimization and security from the Peruvian National Household Survey (ENAHO), where individuals are asked whether they were victims of any violent crime and whether insecurity or corruption is a main problem in their neighborhood (2002-2017). Fourth, I use confidential data from Affidavit and Veritas which have information on the criminal records of all mayors and candidates in each district in Peru during the period of analysis.

Tables A13 to A14 present the results. Column (1) and (2) in Table A13 show that an increase in coca prices in coca districts did not affect the probability of having police patrols in the district nor did it increase the number of officers. Moreover, I find no evidence that individuals living in coca areas are more likely to perceive drug trafficking, terrorism, and crime as a threat to their own safety as coca prices increase. Table A14 also shows that higher coca prices do not increase the likelihood of being a victim of violence in coca districts. Further, results from the survey in Column (2) show that the probability of considering crime the main problem decreases as coca prices increase in coca-suitable districts. This decline could be explained by the opportunity cost channel (when there is a boom in the cocaine sector, there are fewer incentives to be involved in robberies) as well as the fact that the drug business provides some social order and reduces other types of crimes (Van Dun 2014; Vizcarra 2019).[78] While violent crime may not have increased,

[77] In particular I estimate the following equation:

$$Y_{d,t} = \beta \underbrace{(PriceCoca_t \times Coca_d)}_{PriceShock_{d,t}} + \alpha_d + \phi_t + \epsilon_{i,d,t} \tag{5}$$

[78] Indiscriminate violence and other types of crime (robbery, kidnapping, extortion, rape, etc.) are harmful to the

it is still possible that because of the coca boom, changes in governance may occur at the local level. However, Columns (3)-(6) in Table A14 show that the number of individuals reporting corruption at the district level as a leading problem did not increase due to the increase in coca prices. Moreover, Columns (7) and (8) show the effects on the probability that a municipality has a mayor with a criminal record and of the number of candidates with criminal records. I find no evidence that the rise in coca prices increases the criminality of the mayor and candidates. These results are consistent with the lack of contestation and the degree of alignment between the local governments and the coca sector in the coca-growing communities.[79]

Finally, while the incidence of armed conflict plummeted in 1990, there were still remnants of armed groups in rural areas in Peru, who may have exerted violence due to the boom in coca prices. Thus, to analyze the effects on armed conflict, I used information on the number of terrorist events by department. I used terrorist events because terrorist groups were the ones managing the drug trafficking in the 1980s, and were the ones that historically generated violence and conflict in Peru (Palmer 1994; Brienen and Rosen 2015). Moreover, the measure of terrorist events is the number of armed conflict events.[80] Thus, I used the variable terrorist events as a proxy of violence to show that it did not increase during the period of the paper (see Figure A5). Nevertheless, to analyze whether new criminal groups arose and contested the area, following Sobrino (2019)'s methodology, I scraped all news that mentioned the presence of a cartel and homicide per district per year since 2002 (when newspapers began to have online editions). Using this proxy, Columns (1)-(3) in Table A15 show no change in the number of cartels per district per year when coca prices increased. In addition, I use UCPD-GED data for Peru that has the number of deaths related to conflicts geocoded for the years 1987 to 2017 and I find no increase in the number of deaths due to conflict, ruling out that an increase in the return of coca increased conflict in coca suitable districts (see Columns (4)-(8) in Table A15).

Childhood exposure to violence and future criminality: There could still be a concern that children growing up could be exposed to a type of violence I cannot measure in the datasets presented above. However, existing literature has suggested that the long-term effects of exposure to violence/conflict on human capital and future criminality are concentrated on individuals who were exposed in early childhood (before age 5) whereas I find the effects concentrated in 11-14 years old.[81] Moreover, Figure A6 shows that prices before the age of five do not affect future

functioning of the *firmas*, because they quickly attract the attention of the national authorities and the media. Hence, leaders of *firmas* (also known as *patrones*) use selective violence to maintain tranquility in their communities.

[79] Unlike the central government, the independent local parties actively advocated the right to cultivate coca. Beyond that, the mayors and candidates often rely on local *patrones* to fund their political campaigns (see Van Dun (2014), for a thorough description of the bonds and relations of *firmas* with mayors and local politicians). The entrenchment of the cocaine industry in the communities and the lack of violence around it therefore makes the entry of violent candidates unlikely.

[80] In Peru, the conflict was among the government and the leftist insurgent groups (the Shining Path and the Tupac Amaru Revolutionary Movement). According to the Truth and Reconciliation Commission, the Shining Path has been responsible for most of the casualties during the conflict.

[81] See for example Shaw and Gross (2008); Akresh and de Walque (2008); Akresh et al. (2017); Leon (2012); Duque (2019); Couttenier et al. (2019). Moreover, a recent paper on the Peruvian civil war in the 1980s shows that exposure to civil war in Peru has no effects on future criminality for those who were older than 11 (Sara 2020).

criminality.

Table A13: The effect of coca prices on enforcement and perceived safety

	Police enforcement		Perceived Safety				
	(1) Patrolling (=1)	(2) Patrolling officers pc.	(3) Robb.	(4) Gang	(5) Narco	(6) Terror.	(7) Prost.
$PriceShock_{d,t}$	0.400	-0.219	0.010	0.333	0.196	-0.082	0.348***
	(0.362)	(0.201)	(0.381)	(0.318)	(0.240)	(0.291)	(0.133)
Observations	19,814	19,814	20,002	20,002	20,002	20,002	20,002
Dep. var. mean	0.245	0.340	0.682	0.166	0.047	0.019	0.119

Notes: This table presents the estimates from Equation 5 on several outcomes. The dependent variable in Column (1) is a dummy variable indicating whether the district has police patrolling in a given year, and in Column (2) is the number of police officers per district and year. In Columns (3)-(7), the dependent variable is a dummy indicating whether the individual considers that in a given year robbery, gang, drug trafficking, terrorism or prostitution as a threat for the local community in the district. $PriceShock_{d,t}$ is the interaction between log coca prices and the number of coca hectares in the district in 1994. The sample is at the district-year level, and all specifications include district and year fixed effects. Conley standard errors presented in parentheses. Significant at $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Table A14: Perceived problems; and mayor and candidates criminal records

	Perceived problems						Mayor and cand.	
	(1) Victim	(2) Crime Prob.	(3) Corrup Prob.	(4) Bribe.	(5) +Corrup	(6) -Corrup	(7) Mayor offender	(8) Cand. offender
$PriceShock_{d,t}$	0.026	-0.256***	-0.040	0.013	-0.311*	0.040	-0.019	0.065
	(0.026)	(0.062)	(0.070)	(0.014)	(0.171)	(0.088)	(0.173)	(0.315)
Observations	13,287	11,269	12,130	10,657	8,815	8,815	6,446	6,446
Dep. var. mean	0.039	0.118	0.167	0.024	0.416	0.102	0.233	0.444

Notes: This table presents the estimates from Equation 5. In Column (1), the dependent variable is a dummy variable indicating if the respondent was a victim of crime in the district. In Columns (2) and (3), the dependent variable is a dummy variable indicating if the respondent considers crime and corruption as a main problem in the district. In Column (4), the dependent variable indicates whether the respondent has paid a bribe. In Columns (5) and (6), the dependent variable is a dummy variable indicating if the individual considers that corruption has increased or declined in the last year. In Column (7), the dependent variable is a dummy variable indicating if the mayor elected had a criminal record and in Column (2) the dependent variable is the share of election candidates with criminal records. $PriceShock_{d,t}$ is the interaction between log coca prices and the number of coca hectares in the district in 1994. The sample is at the individual-district-year levell, and all specifications include district and year fixed effects. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Figure A5: Number of terrorist events

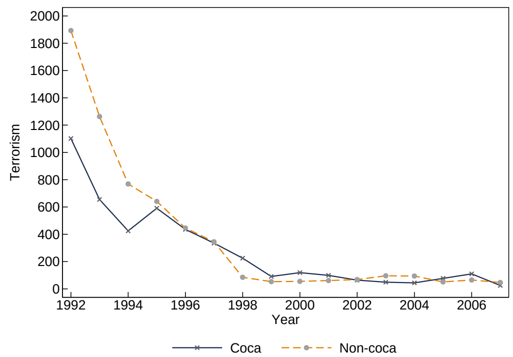
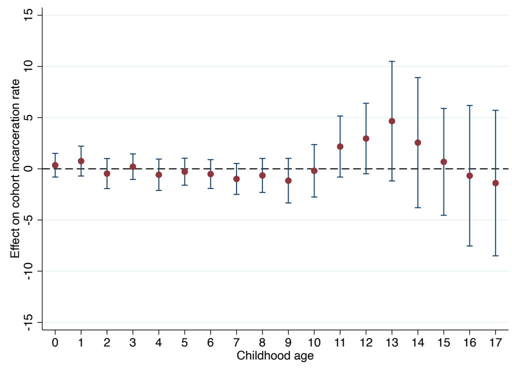


Table A15: Presence of cartels and homicides; and conflicts and deaths

	Cartel violence			Deaths and conflicts				
	(1) Cartel and Hom.	(2) Cartel	(3) Hom.	(4) Num. conflicts	(5) Total deaths	(6) Guerilla deaths	(7) Gov. deaths	(8) Civil. deaths
$PriceShock_{d,t}$	-0.032	-0.029	-0.003*	-4.312	-42.675	-42.808	-36.629	-5.990
	(0.026)	(0.025)	(0.001)	(4.880)	(46.142)	(46.153)	(39.224)	(6.967)
Observations	18,720	18,720	18,720	46,775	46,775	46,775	46,775	46,775
Dep. var. mean	0.002	0.002	0.000	0.015	0.118	0.115	0.105	0.014

Notes: The first part of this table presents the estimates from Equation 5. The dependent variable for each of these columns uses the number of news related to cartels and homicides per district and year using newspaper data. In particular, Column (1) indicates if there was any news related to homicides and cartel in that year for a particular district; and Columns (2) and (3) indicate the presence of homicide or cartel respectively. The second part presents the estimates from Equation 5. The dependent variables in each column are: the number of conflicts (Column 4), total deaths (Column 5), guerrilla deaths (Column 6), government officials deaths (Column 7) and civilian deaths (Column 8). $PriceShock_{d,t}$ is the interaction between log coca prices and the number of coca hectares in the district in 1994. All specifications include district and year fixed effects. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

Figure A6: Incarceration rate effects by age



C.2 Supply of Education

Table A16: The effect of coca prices on the supply of education

	(1) Log teachers	(2) Log teachers with post secundary education
$PriceShock_{d,t}$	-0.009	0.006
	(0.030)	(0.031)
Observations	749,621	700,122
Dep. var. mean (levels)	6.660	6.134

Notes: This table presents the estimates from Equation 2 on the log number of teacher in Column (1) and on the log number of teachers with post secondary education in Column (2). The sample is at the school-year level. All specifications include school and year fixed effects. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

C.3 Migration

As discussed in Section 5.1.3, migration could bias my results if high coca prices alter the composition of out-migrants in highly coca-suitable areas. For example, higher coca prices may deter poorly educated and criminal-type families from migrating, but have no impact on the migration decisions of highly educated families. Thus, the average criminality of non-migrants would then increase due to the reduced out-migration of criminal or poorly educated families.

To analyze the extent to which migration may be affecting the results, I conducted the following analysis. First, I test whether higher coca prices between the ages 11 to 14 increase the size of the sample cohort. I estimate the same model as in the long-term analysis in specification 3. There is no evidence that cohort size responds positively to changes to coca prices at the key ages of exposure. In fact, the specification finds a small non-significant decline in cohort size (Column 1 in Table A17). Second, to test out-migration, I directly estimate how contemporaneous coca prices may have affected the proportion of migrants (people who left per district by year) in coca-suitable districts using the ENCO survey. This survey asks about the number of people in the family who left per year of migration. I can also, using ENCO, get an estimate of the number of people who left by year of birth by district and analyze the effect of coca prices at key ages of exposure on the probability of migrating out of the district by cohort. To test this hypothesis, I replace cohort incarceration with cohort out-migration in specification 3. Columns (2) and (3) in Table A17 present the results and show no effects on out-migration.

In addition, I also test how in-migration may generate heterogeneity in the impact of high coca prices in highly coca-suitable areas. At the extreme, if the cocaine sector only employs migrants, then higher coca prices should have no impact on the local children (children born in the affected district). Column (1) in Table A18 tests this hypothesis using the household surveys, for which I have information on the migrant status of individuals. In particular, I am able to determine whether the individual was born in the district of the interview or came from another district. Thus, I restrict the analysis to non-migrants, and I still find effects on child labor, suggesting that the results are not entirely driven by migrant families.

Next, I also test whether negatively selected families that may have decided to stay due to the increase in coca prices explain all of the effects on child labor. I test this by analyzing the effects on children of non-migrant parents who have low levels of education attainment. Column (2) shows that, among non-migrants, there are no differential effects on child labor for children whose parents are poorly educated. Further, to provide evidence that non-migrants are not a selected sample affected by coca prices, I also test directly how coca prices in coca suitable districts may affect the proportion of non-migrant families and I find no significant effects in Column (3). Moreover, I do not find differential effects on migration based on the parent's education. These results are in line with the results from the household fixed effects specification, which also deals with the negative selection of families.[82]

C.4 General human capital channel

As discussed in Section 5.2.2, it could be the case that criminality effects are merely driven by a reduction in human capital independently of children working on illegal activities and gaining criminal capital. In this section, I address this mechanism in the following way. First, I further estimate the effects on crimes where a decline in general human capital is more likely to have an effect. Second, I estimate the effects on child labor and criminality for other relevant commodities in Peru. Third, I study the characteristics of compliers to shed light on whether those affected by the shock have characteristics that are related to working in the cocaine industry as children.

[82] In addition, using incarceration data I also examine whether incarcerated individuals who were exposed to price changes in their early teens were more or less likely to migrate (using as proxy the location of jails) and whether this probability differed by individuals' observable characteristics such as education and occupation. In particular, I estimate the effects of high coca prices on migration as well as interactions between coca prices and the individual's education and occupation. Overall, I find no evidence that the probability of migrating is associated with changes in coca prices during childhood (for brevity these estimates are not shown). Moreover, I do not find differential responses across individuals, for instance, those in jail who have less than primary education or were unemployed are not less likely to migrate in response to changes in coca prices in their childhood.

Table A17: Coca price shocks and migration

	(1) Log Cohort size	(2) Cohort out-migration	(3) Contemporaneous out-migration
$PriceShockAge11to14_{d,c}$	-0.051	0.169	
	(0.064)	(0.159)	
$PriceShock_{d,t}$			0.106
			(0.146)
Observations	23,853	23,777	21,952

Notes: Columns (1) and Columns (2) present the estimates from Equation 3 on the log of the cohort size and the number of people who left by year of birth in each district. Column (3) presents the estimates from Equation 5 on the number of people in the family that left per year of migration and district. All specifications include district and year fixed effects. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

Table A18: Coca price shocks and migration

	(1) Labor	(2) Labor	(3) Non-migrant	(4) Non-migrant
$PriceShock_{d,t}$	0.198	0.186	-0.107	-0.124
	(0.167)	(0.168)	(0.106)	(0.112)
$PriceShock_{d,t} \times 11x14$	0.148***	0.132***	0.008	0.006
	(0.042)	(0.045)	(0.022)	(0.030)
$PriceShock_{d,t} \times HighEduParent$		0.037		0.039
		(0.038)		(0.036)
$PriceShock_{d,t} \times HighEduParent \times 11x14$		0.036		0.002
		(0.052)		(0.033)
Observations	185,517	185,517	401,107	401,107
Dep. var. mean	0.449	0.449	0.663	0.663
Sample	Non-migr.	Non-migr.	All sample	All sample

Notes: This table presents the estimates of Equation 1 in Columns (1) and (2) keeping only non-migrant families. For these specifications, the dependent variable is labor participation (whether an individual in a given district-year had worked in the previous week). In Columns (3) and (4), the dependent variable is a dummy variable indicating whether an individual was born in the district of the interview. $PriceShock_{d,t}$ is the interaction between log coca prices and the number of coca hectares in the district in 1994. $11x14$ is a dummy variable corresponding to the ages 11 to 14. $HighEduParent$ is a dummy variable indicating whether the head of the household has more than a high school education. The sample is at the individual-household-year level. All specifications include district and year fixed effects. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

General human capital specific crimes: Table A19 presents the results for the type of crimes that are more likely to be affected by the general human capital mechanism and for homicides where this mechanism is less likely to play a role. I find that the price shock has no effect for property and white collar crimes. Moreover, the effects are positive and significant for homicides, which are crimes specific to the cocaine industry.

Table A19: Other crimes

	(1) Property Crimes	(2) White Collar Crimes	(3) Homicides
$PriceShockAge11to14_{d,c}$	0.068	-0.025	0.252***
	(0.113)	(0.097)	(0.076)
Observations	23,853	23,853	23,853
Dep. var. mean	0.231	0.142	0.289

Notes: This table presents the estimates from Equation 3 where *PriceShock Age11to14*$_{d,c}$ is the interaction of log average price of coca between 11 to 14 years old and the coca suitability measure of the district or village of birth. The dependent variable is the propensity to crime of a cohort in a given district by different types of crime. The sample is defined at the district of birth and year of birth level. All specifications include district of birth and year of birth fixed effects. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

Shocks to coca in the legal sector: I exploit shocks to coca in the legal sector for two main reasons. First, the first stages of production are exactly the same as in coca for the illegal sector. However, in these areas, there is no processing of coca into cocaine paste and thus, less likely that children will be in involved in the illegal chain of production and gain relevant criminal capital. Second, prices in the legal sector follow trends similar to those followed by the coca price in the illegal sector (but at different levels). By looking at the data on coca prices in the legal sector since 1998, we can see that the trends are very similar (see Figure A7 below), allowing me to exploit shocks to the illegal sector. Tables A20 and A21 show a significant increase in child labor and dropout rates at the key ages of exposure 11-14. For an average coca district when prices double, child labor increases by about 30% in the legal sector. However, as shown in the main paper, there is no increase in future criminality for individuals born in districts where coca production is legal.

Figure A7: Coca prices in the legal sector

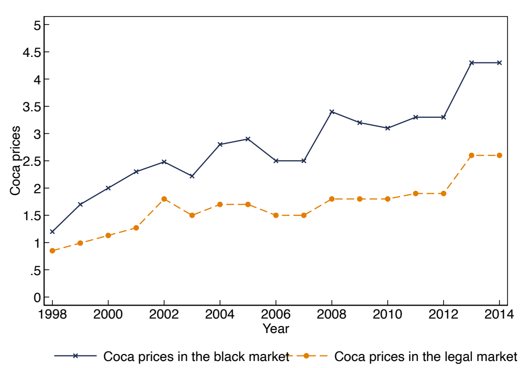


Table A20: Child labor and price shock in coca legal districts

	(1) Labor
$PriceShock_{d,t}$	0.178**
	(0.076)
$LegalCoca \times 6x10$	0.110***
	(0.043)
$LegalCoca \times 11x14$	0.232***
	(0.049)
$LegalCoca \times 15x18$	0.132*
	(0.072)
Observations	412,026
Number of districts	1,469
Dep. var. mean	0.369

Notes: This table presents the estimates from Equation 1. $PriceShock_{d,t}$ is the interaction between log coca prices and the number of coca hectares in districts that produce coca for the legal sector. $6x10$, $11x14$ and $15x18$ are dummy variables corresponding to each age bin. The omitted category is the age 19 to 21. It includes district and year fixed effects. The dependent variable is labor participation (whether an individual in a given district-year had worked in the previous week). This specification includes district and year fixed effects. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

Table A21: Dropout and price shock in coca legal districts

	Dropout rate		
	(1) 6-10	(2) 11-14	(3) 15-18
$PriceShock_{s,t}$	0.011***	0.010***	-0.000
	(0.004)	(0.004)	(0.005)
Observations	287,629	362,130	100,039
Number of schools	33,849	42,933	11,385
Dep. var. mean	0.060	0.080	0.080

Notes: This table presents the estimates from Equation 2, where $PriceShock_{s,t}$ is the interaction of coca prices and the coca density associated with the school in legal coca districts. The dependent variable is the proportion of students that drop out from school in a given level of education. In line with the evidence presented in Section 2.2, Columns (1)-(3) present the analysis for different levels of education: primary school (ages 6-10), the transition between primary and secondary education (ages 11-14), and last years of secondary education (ages 15-18). All specifications include school and year fixed effects. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

Shocks to other commodities: Table A22 presents the impacts on dropout rates of price changes in sugar, cotton, cacao, coffee and gold. In particular, shocks to gold increase the dropout rate from school at the key ages of exposure 11-14, consistent with previous results in Table A2 showing an increase in child labor in gold districts. However, when looking at incarceration rates, I find that none of the shocks increase future criminality (Table 5). These results suggest that future criminality may not be fully explained by just a reduction in human capital.

Table A22: The effects of price shocks to other commodities on dropout rates

	Dropout rate		
	(1)	(2)	(3)
	6-10	11-14	15-18
$PriceShock_{s,t}$	-0.000	0.007**	-0.006
	(0.003)	(0.003)	(0.006)
$GoldPriceShock_{s,t}$	0.000	0.002*	0.000
	(0.001)	(0.001)	(0.002)
$CoffeePriceShock_{s,t}$	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
$CacaoPriceShock_{s,t}$	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)
$CottonPriceShock_{s,t}$	-0.000	-0.001*	0.000
	(0.000)	(0.000)	(0.000)
$SugarPriceShock_{s,t}$	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)
Observations	287,629	362,130	100,039
Number of schools	33,849	42,933	11,385
Dep. var. mean	0.060	0.080	0.080

Notes: Building upon the specification presented in Equation 2, this table also includes price shocks to other commodities such as gold, coffee, cacao, cotton and sugar. The dependent variable is the proportion of students that drop out from school in a given level of education. In line with the evidence presented in Section 2.2, Columns (1)-(3) present the analysis for different levels of education: primary school (ages 6-10), the transition between primary and secondary education (ages 11-14), and last years of secondary education (ages 15-18). The sample is at the school-year level. All specifications include school and year fixed effects. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

Compliers characteristics: to gain insight into whether individuals who are more likely to be incarcerated due to high coca prices during childhood (i.e. compliers) were the ones who were affected by child labor in coca farms, I investigate the labor, schooling, and family characteristics of offenders. I can compute the proportion of compliers who have characteristic X using two-stage least squares:

$$D_{c,d} = \phi Treated_{c,d} + \kappa_d + \nu_c + \pi_d c + \chi_t + \mu_{c,d} \tag{6}$$

$$X_{c,d} \times D_{c,d} = \beta D_{c,d} + \alpha_d + \delta_c + \sigma_d c + \gamma_t + \epsilon_{c,d} \tag{7}$$

where $D_{c,d}$ is the number of individuals who are in prison per cohort and district of birth. For ease of interpretation, I redefine the treatment as a discrete variable. I define $Treated_{c,d}$ for those whose average prices in the key ages were above the median and who were born in a district with coca. I also check the robustness of the results using the continuous treatment variable (the interaction of coca prices at specific ages and coca suitability). Note that $X_{c,d} \times D_{c,d}$ is the number of individuals per cohort who are in prison and have characteristic X (e.g., less than a high school degree). The coefficient β gives the proportion of compliers with characteristic X. Results for the characteristics of compliers can be found in Column 1 in Table A23. About 80% of those who were affected by the shock had less than a high school degree. I also repeat the analysis using an indicator for whether each offender's occupation was farming and find that about 60% of affected individuals declared farming as their main previous occupation.[83] When comparing these proportions to the proportions in the actual population in column (2), about 80% of compliers had participated in illicit activities before the age of 18 and 43% had at least one of their family or friends in prison. In the general population, those percentages are 50% and 31%, respectively.

Table A23: Complier characteristics

	(1) Compliers	(2) Population
Has less than high school education	0.819***	0.585
	(0.219)	[0.493]
Had farming as last occupation	0.598**	0.333
	(0.264)	[0.471]
Participated in illicit activities before age 18	0.776**	0.500
	(0.381)	[0.500]
Had friends in illicit activities before age 18	0.425	0.372
	(0.340)	[0.484]
Had a family member in jail	0.425	0.314
	(0.263)	[0.464]
Experienced gangs in neighborhood during childhood	0.466	0.505
	(0.337)	[0.5]

Notes: Column (1) presents the β estimates from Equation 7, which represents the proportion of individuals in prison due to the shock that have a particular characteristic. All specifications control for district and year of birth, as well as district specific time trends. Standard errors clustered at the district of birth level are in parentheses. Standard deviations are presented in brackets. Significant at *** p<0.01, ** p<0.05, * p<0.1.

[83]Notice that in coca-growing areas, there is also coffee and cacao production as well as services, trade, manufacturing and construction. For example, the agriculture sector employs 69% of the labor force. The remaining 31% of the labor force is employed in other sectors such as services (15%), trade (9%), manufacturing (3%), construction (3%), and others (1%). In the general population of the incarceration sample about 33% reported farming which contrast with the 60% of affected individuals.

C.5 Adult exposure

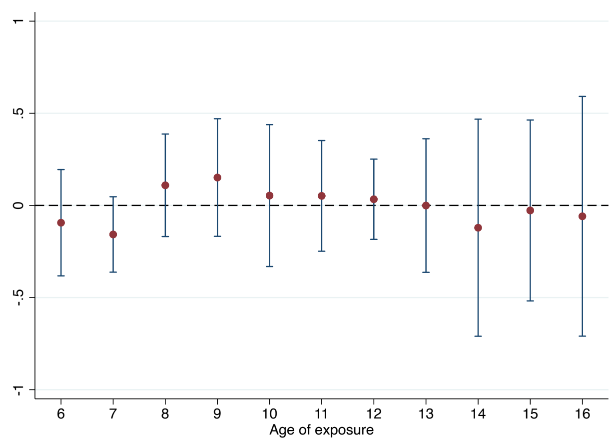
Table A24: Prisons in non-coca districts

	(1) All	(2) Drugs	(3) Violent	(4) Sexual	(5) Family	(6) Other
$PriceShockAge11to14_{d,c}$	2.253***	1.275*	0.881***	-0.136	0.062	0.172
	(0.809)	(0.701)	(0.319)	(0.201)	(0.079)	(0.263)
Observations	23,853	23,853	23,853	23,853	23,853	23,853
Dep. var. mean	4.516	0.607	2.255	0.395	0.088	1.170

Notes: This table presents the estimates from Equation 3 where *PriceShock Age11to14*$_{d,c}$ is the interaction of log average price of coca between 11 to 14 years old and the coca suitability measure of the district or village of birth. The dependent variable is the propensity to crime of a cohort in a given district by different types of crime. The sample is defined at the district of birth and year of birth level and includes the total of individuals in prisons located in non-coca districts. All specifications include district of birth and year of birth fixed effects. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1$

C.6 Differential mortality

Figure A8: Effects on victims of homicides by age using police data



Notes: This graph plots the coefficients obtained from a regression of the victimization rate on the interaction between the coca suitability in the district of birth and price at different childhood ages. The regressions control for district of birth, district time trends, and cohort fixed effects. The Y-axis shows the estimated coefficients and the X-axis shows the ages. The confidence intervals are at 95%. Standard errors are adjusted for spatial and time correlation using Conley standard errors.

D Additional Results, CCTs

Table A25: CCTs and coca price shocks on schooling

	(1) Dropout rate: 11-14	(2) Failed the grade: 6-10	(3) High age for grade: 6-10
$PriceShock_{d,t}$	0.013***	1.069***	0.033***
	(0.004)	(0.300)	(0.006)
$PriceShock_{d,t} \times CCT$	-0.003*	-0.194**	-0.006***
	(0.002)	(0.097)	(0.002)
Observations	362,130	425,606	433,408
Number of schools	42,933	36,825	36,840
Dep. var. mean	0.080	8.480	0.187

Notes: This table presents the estimates of Equation 2, including interactions with $CCT_{d,t}$, a dummy that equals 1 if the district d had a CCT in year t and 0 otherwise. All specifications include school and year fixed effects as well as department time trends. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

Table A26: CCTs and coca price shocks on crime

	(1)
$PriceShockAge6to10_{d,c}$	1.781
	(1.672)
$PriceShockAge11to14_{d,c}$	5.555**
	(2.611)
$PriceShockAge15to17_{d,c}$	-0.345
	(2.171)
$PriceShockAge6to10_{d,c} \times CCTsAge6to10$	-1.669
	(1.302)
$PriceShockAge11to14_{d,c} \times CCTsAge11to14$	-1.176
	(0.891)
$PriceShockAge15to17_{d,c} \times CCTsAge15to17$	-0.348
	(0.251)
Observations	23,853
Dep. var. mean	4.565

Notes: This table presents the estimates of Equation 3 with interactions with *CCTs*, a dummy indicating whether cohort c was exposed to CCTs at different ages and 0 otherwise. This specification includes district of birth and year of birth fixed effects. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

E Coca Agro-Ecological Index

Figure A9: Coca agro-ecological index across Peru

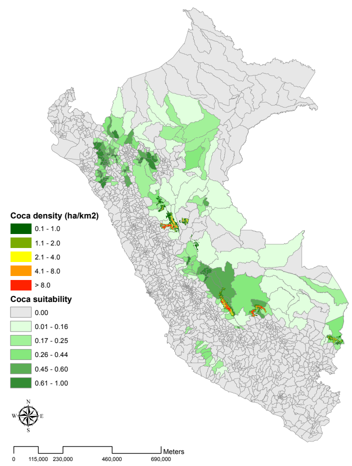


Table A27: Main regressions using coca agro-ecological index

	(1) Child Labor	(2) Dropout rate: 11-14	(3) Failed the grade: 6-10	(4) High age for grade: 6-10	(5) Crime
$PriceShock_{d,t} \times 11to14$	0.128**				
	(0.059)				
$PriceShock_{s,t}$		0.011	1.517***	0.027***	
		(0.007)	(0.306)	(0.006)	
$PriceShockAge11to14_{d,c}$					0.633***
					(0.217)
Observations	410,896	362,130	425,606	433,408	23,671
Dep. var. mean	0.369	0.080	8.480	0.187	4.581

Notes: Column (1) presents the estimates associated to the total effect at ages 11-14 from Equation 1 including price interactions with other age bins, where the dependent variable is a dummy indicating if the individual worked in a given district last week. $PriceShock_{d,t}$ is the interaction of coca prices and the coca agro-ecological index associated with the district. This specification includes district and year fixed effects. Columns (2)-(4) present the estimates from Equation 2, where the dependent variable for each column is the proportion of students that drop out from school in the transition, the share of students that failed the grade and the share of students that have high age for grade, respectively. $PriceShock_{s,t}$ is the interaction of coca prices and the coca agro-ecological index associated with each school. All theses specifications include school and year fixed effects. Column (5) presents the estimates from Equation 3, where the dependent variable is adult criminality. $PriceShockAge11to14_{d,c}$ in the interaction of the average coca prices at ages 11-14 and the coca agro-ecological index associated to the district. This specification includes district of birth and year of birth fixed effects. Conley standard errors are presented in parenthesis. Significant at $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

F Qualitative Data Appendix

Since this paper studies an illegal industry, it is difficult to obtain data on the type of activities per each age group in the cocaine industry. Thus, during April and July 2015, I conducted interviews to understand what factors influence child labor decisions in Peru's coca areas. In addition in January 2020, I went back to some of the coca villages to better understand the production process and how child labor demand works at different ages. I conducted interviews in 6 districts: Monzon, Rupa-Rupa, Daniel Alomia Robles, Mariano Damaso Beraun, and Jose Crespo y Castillo. Since the interviews' objective was to understand how individuals started in the business, the sample mainly included individuals who are still participants or were part of the business at some point. These interviews were between 20 to 30 minutes each, and to get access to participants, I hired a local consultant who grew up in the area and was also a coca farmer in the past. For this sample, we used a snowball sampling procedure. We started with 30 individuals that the local guide knew well and then asked them to nominate other participants who met the eligibility criteria and potentially would contribute to the project. For all the interviews, we took care to preserve the participants' anonymity and freedom to consent. Indeed, the strategy for maintaining trust and safety was to be extremely clear to all participants that the purpose of the survey was only academic. As recording the conversations might have discouraged participants from speaking freely, an assistant typically took detailed notes. Whenever possible, we verified our observations from the interviews with multiple sources such as other relatives in the household or friends in the village that the local guide knew.

The survey mainly consisted of talking about their childhood experience and thus did not involve or increase participants' risk. In particular, I asked how they started being involved in the business, the grade and age at which individuals dropped out of school, and their main activity at different ages of childhood. Tables A28 and A29 present the results. Most of participants dropped out of school during the transition from primary to secondary school (Column 1 in Table A28). If I restrict the sample to individuals that today were involved in the illegal stages of production (Column 2), the share of individuals that dropped out in that transition is even larger. In terms of the main activities per age range, Table A29 shows that most of the participants started mainly collecting coca leaves while also attending school between the ages of 6 and 10. After dropping out of school (ages 11 to 14), they also started doing other activities such as processing coca into cocaine and transporting it. Moreover, if I restrict the sample further to those that drop out from school in the transition between primary and secondary education, 90% of them were involved in other stages of production such as processing coca into cocaine and transporting it. Although this is mainly qualitative, it shows the intensity of labor at different ages, given that the vast majority of participants were combining school with harvesting coca leaves. Below, I highlight some quotes from the field that convey a sense of the employment cycle in the cocaine industry:

> "I left school because my high school was too far. That's when I decided to obtain easy money by dedicating myself full time to the coca business."

> "Since I was 8 years old, when I was in primary school, I used to work in coca helping my father, and since very little, I had in my mind that once I grew up, I could generate money with drugs. Thus, when I dropped out of school, since I did not have anybody to guide me, I thought why should I not follow that path in the business? I have had this idea in my mind since very little as I started seeing people making lots of money with drugs. So once I was out of school, I decided to be fully in the business turning coca into cocaine."

> "Since I was 6, I helped in the farm growing subsistence crops, and then when I was 11, I started helping my uncle, who had coca farms. I had a clear contract where they paid me by arroba of coca, and then he taught me how to harvest. As I was carrying the leaves to maceration pits, I met several chemists [people

who process the leaves], and by just seeing what they were doing, I started very early quemiqueando (using chemicals to transform coca into cocaine paste). I learned just by being there. As a chemist, they paid me a lot per kilogram."

"I was starting high school, and at that point, I couldn't continue since it was far and I also needed to work. During my primary school, I worked helping my father harvesting coca and subsistence crops, and then at 11, when my father passed away, I dropped out and started processing coca into cocaine."

"When I was 5 years old, I helped my grandparents with coca production, and they gave me a tip by harvesting. When I was older, between 12 and 13, I went to live with my father, and he helped to dry the coca and put it in bags and many other things. For example, I got the chance to do the processing, and only once I did a delivery abroad, but I stopped because it didnt go well, that drug delivery."

"When I was in primary school, I mainly studied and worked in coca on the weekends. As I grew older, I helped in preparing the coca leaves in bags to take them to the processing centers."

"I started working in the business when I dropped out of school at the age of 14 to earn money. I liked that life and I stayed since then. I ended up having my own plot at an early age where I could harvest and also process part of the coca into cocaine."

Table A28: Dropout rates (%)

Sample	All	Illegal stages
Primary (1 grade)	2.86	1.56
Primary (2 grade)	1.90	3.13
Primary (3 grade)	4.76	7.81
Primary (4 grade)	0	0
Primary (5 grade)	0.95	1.56
Primary (6 grade)	16.19	23.44
Secondary (1 grade)	8.57	12.5
Secondary (2 grade)	14.29	23
Secondary (3 grade)	0.95	1.56
Secondary (4 grade)	0	0
Secondary (5 grade)	43.8	21.88
University	5.71	3.13
Total observations	105	48

Table A29: Activities per age range (%)

	6-10	11-14	>14
Main activity			
Study only	5.66	7.55	0
Work and study	91.51	66.98	50.94
Work only	2.83	25.47	49.06
Main work activity			
Collecting coca	88.99	44.76	36.89
Transforming coca	11.01	21.90	29.13
Transporting coca/cocaine		23.81	33.01
Non-coca related		9.52	0.97