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Illegal Mining and Human Capital Accumulation: Evidence from the Colombian Gold Rush

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Illegal Mining and Human Capital Accumulation: Evidence from the Colombian Gold Rush

Leonardo Bonilla-Mejía*

Abstract

This paper assesses the local effects of gold mining on human capital accumulation in contexts where illegal mining is prevalent. Evidence is based on high-resolution geographic information of gold mining and schools, and rich administrative data from Colombia. I exploit a boom in international gold prices and the exogenous geographic distribution of gold deposits to assess the causal effects of mining. Results indicate that mining increases enrollment in primary school and reduces dropout rates throughout the school cycle. However, mining also reduces standardized test scores and college enrollment, particularly in academic degrees and STEM fields. The estimated effects are considerably larger when both legal and illegal mining are accounted for. I then assess some of the potential mechanisms through which the commodity price shock can affect human capital. While child labor is overall unaffected, young adults between 19 and 25 are more likely to work in the mining sector. Evidence also indicates that mining increases royalties and public investment, with mixed results in terms of school inputs. Mining also intensifies conflict and violence, with potential large negative effects on human capital accumulation.

Keywords: Natural resource curse, mining, human capital, Colombia
JEL Classification: Q32, Q33, J13, J24

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Minería ilegal y acumulación de capital humano: Evidencia del boom minero en Colombia

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Resumen

Este trabajo estudia el efecto local de la minería de oro sobre la acumulación de capital humano en contextos en los cuales predomina la minería ilegal. La evidencia está basada en información geográfica de alta resolución de minería y registros administrativos detallados del sistema educativo de Colombia. Para estimar los efectos causales de la minería se explota la variación exógena en los precios internacionales del oro y la distribución geográfica de los depósitos de mineral. Los resultados indican que la minería incrementa la matrícula escolar en primaria y reduce la deserción a lo largo del ciclo escolar. Sin embargo, la minería también tiene efectos negativos sobre el aprendizaje y reduce las probabilidades de acceder al sistema de educación superior, particularmente en carreras STEM. Los efectos estimados son considerablemente más grandes cuando se tiene en cuenta tanto la minería legal como la ilegal. En la última sección se prueban distintos mecanismos a través de los cuales el boom minero puede afectar la acumulación de capital humano. Mientras que no hay evidencia de mayor trabajo infantil, los adultos jóvenes entre 19 y 25 años tienen mayores probabilidades de trabajar en el sector minero. La evidencia también muestra que las regalías y la inversión pública aumentaron en los municipios mineros, con resultados mixtos para la provisión de educación escolar. Finalmente, el boom de precios intensifica el conflicto y la violencia en estas regiones, con efectos negativos potencialmente importantes sobre la acumulación de capital humano.

Palabras clave: Maldición de recursos naturales, minería, capital humano, Colombia
Clasificación JEL: Q32, Q33, J13, J24

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1 Introduction

Natural resources impact economic development through multiple channels. Commodity price booms increase consumption and investment but also appreciate local currencies and increase volatility, with detrimental effects to non-mining sectors and long-term growth (Sachs and Warner, 2001; Auty, 2007). Resource-dependent countries and regions are also more prone to corruption and violence, which comes at a high price in terms of institutional and economic development (Ross, 2004; Mehlum et al., 2006; Robinson et al., 2006; Brückner and Ciccone, 2010; Sala-i Martin and Subramanian, 2013; Dube and Vargas, 2013; Boschini et al., 2013; Asher and Novosad, 2018).

An alternative mechanism through which natural resources affect long-term economic development is human capital accumulation. Higher wages could boost private investment in education, however, they can also increase the opportunity cost of studying. Aggregate factors, such as public investment or violence, may also mediate the effect of mining on human capital. Cross-country evidence on the human capital mechanism is mixed. While Gylfason (2001), Birdsall et al. (2001), and Papyrakis and Gerlagh (2004) show negative relationships between natural resources and education attainment and learning, Stijns (2006) and Smith (2015) find positive or insignificant effects. Ebeke et al. (2015) find that mining rents can influence career choices, however, the effects vary according to the quality of political institutions. In low income countries, with weaker institutions, oil booms increase enrollment in professions that are more prone to rent-seeking. The opposite happens in well-governed countries, where students are more attracted to careers in science and technology.

At the sub-national level, evidence based on large-scale mining consistently shows that education spending and school attendance increases near mining sites (Aragón and Rud, 2013; Caselli and Michaels, 2013; Chuhan-Pole et al., 2015; Ahlerup et al., 2017). However, most of the gold mining in developing countries takes place in small-scale and illegal mines and there is still little evidence on the effect of this type of mining on human capital accumulation. One of the few papers addressing this issue is Santos (2018). Based on census samples from 1985 to 2005, the author finds that during the first years of the price boom, child labor increased and school attendance dropped in municipalities with gold mining.

This paper provides new evidence on the local effects of mining on human capital accumulation. Evidence is based on Colombia, where gold production tripled between 2001 and 2014, as a result of a sharp rise in international prices. Unlike other countries in which large-scale mining is prevalent, the 2010 mining census indicates that approximately 87% of the Colombian gold is extracted in small-scale and illegal mines. I use high-resolution geographic information on gold mining and schools and rich administrative data from the education sector. I also use household surveys and aggregate data on public investment, corruption, and violence, to assess alternative mechanisms through which mining can affect human capital decisions.

I exploit the exogeneity of international gold prices and the geographic distribution of gold deposits to assess the causal effects of mining. The identification strategy relies on the assumption that gold prices disproportionately affect areas with potential for gold mining. I also assess the differential effect of legal and illegal mining with two time-varying measures of mining. The first one, area covered by active mining titles, captures the expansion of legal mining. The second one is the deforestation in areas with identified gold deposits. Since mining is one of the main sources of deforestation in the region of study, this is a proxy for all mining activities, whether they are legal or not. The potential measurement error and endogeneity problems are addressed by instrumenting these measures with the interaction between time-invariant gold deposits and international prices.

The main results show that the gold boom increases school enrollment in primary school and reduces dropout rates at all school levels. I also find that mining booms are followed by an increase in promotion rates in primary and lower secondary. These improvements at the extensive margin contrast with the negative effects on learning. In fact, mining has negative and significant effects on the exit exam, and grade 9 proficiency tests. Students in mining areas are also less likely to enroll in college, and to opt for academic degree (4-years) and a Science, Technology, Engineering, and Mathematics (STEM) fields. Since the number of students taking the exam and the age of the students is unaltered, these results do not seem to be driven by selection. The estimated effects have the same sign and are statistically significant for mining titles and mining deforestation. However, they are considerably larger when I use the deforestation-based measure, reflecting the importance of illegal mining in Colombia.

Mining could affect human capital accumulation through multiple channels, including the labor participation of children and young adults, public investment, and violence. I use a relatively simple child labor model to incorporate all these factors in a single framework and estimate the effect of mining on each of these potential mechanisms. Results indicate that the price shock reduced the labor participation of children between 10 and 14 in the mining sector. In contrast, young adults between 19 and 25, and particularly males, are more likely to work in mining during the boom period. Aggregate factors affecting learning might have also mediated the effect of mining on human capital. First, royalties and public investment increased in mining municipalities during the boom years. This is not reflected in improvements in primary school inputs. At the secondary level, I find that mining regions hire less teachers but invest more in their training. Second, mining could also boost corruption and affect local institutions. However, I find no significant effects on disciplinary prosecutions or corruption-related criminal investigations. Third, the commodity price shock fueled conflict and violence in the mining regions, significantly increasing homicide and forced displacement rates.

The paper contributes to the literature in at least three ways. First, the analysis is based on satellite imagery and detailed geographic information allowing to measure mining at a high-spatial resolution. Previous studies are in most cases based on municipal-level analysis (Aragón and Rud, 2013; Santos, 2018), and the few papers to use such granular geographic information focus exclusively on large-scale mining (Chuhan-Pole et al., 2015; Ahlerup et al., 2017). Moreover, I use deforestation in cells with identified gold deposits to account for illegal mining. Results indicate that previous studies based exclusively on mining titles could be underestimating the effect of mining.

Second, I measure human capital accumulation using administrative records capturing both intensive and extensive margin outcomes. While the existing literature has focused almost exclusively on school attainment, I find that natural resource shocks also have an impact on long-term development through learning and college enrollment. Moreover, the negative impact on STEM degrees is in line with Ebeke et al. (2015) in that natural resource shocks can contribute to the misallocation of talent in contexts where institutions are weak.

Third, I assess alternative mechanisms through which mining can affect human capital accumulation. My results contrast with a number of previous studies on commodity-price booms and child labor as I find that gold mining has negative or null effects on labor participation among children (Kruger, 2007; Dammert, 2008; Cogneau and Jedwab, 2012; Santos, 2018). In this context, most of the effects of mining on labor participation are concentrated on young adults, which is consistent with the lower enrollment in higher education. I also test the effect of mining on a number of aggregate mechanisms including public investment and violence. While public investment increased, there are no detectable improvements on school inputs. Mining also intensified violence and conflict quite dramatically, with potential negative effects on human capital accumulation.

The remainder of this paper is organized as follows. The next section introduces the theoretical framework. Section 3 characterizes the Colombian gold mining sector. Sections 4 and 5 describe the data and empirical strategy. Section 6 presents the main results and section 7 assesses some of the potential mechanisms. The last section concludes.

2 Gold mining in Colombia

Colombia experienced a gold rush during the past decade. According to official statistics, gold production grew from 21 tons in 2001, to near 60 tons in 2014 (Panel a of Figure 1). In its peak year of 2012, the country was the 11th largest producer of gold in the world, with

approximately 2% of the total production, surpassing Brazil and Indonesia (USGS, 2015). The boom was driven by a sharp rise in international prices; For the first time since the eighties, the price of gold surpassed 600 USD per troy ounce, reaching a maximum of 1,900 USD in September 2011. This was mostly caused by the financial crisis, during which gold was used as a safe haven for financial assets (Baur and McDermott, 2010; Reboredo, 2013).
Colombia also witnessed an accelerated growth of mining titles.[1] The surface covered by approved gold titles increased by over 700%, from 3,583 km^2 in 2001, to 29,361 km^2 in 2014 (Panel b of Figure 1). Although this boom was mostly driven by sharp increases in gold prices, there were also generous tax incentives and legislative reforms designed to attract foreign investors, who now own most of the titles.[2] The title expedition process, however, was far from transparent. Corruption scandals and lack of administrative capacity forced the government to stop the application process between 2011 and 2013, and restructure the title expedition process and the Mining Cadastre.[3]

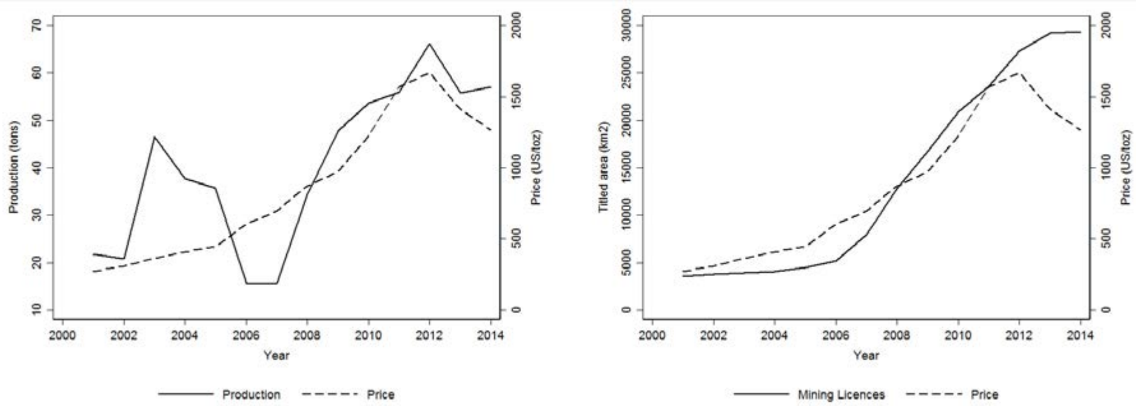
In spite of the rapid growth of mining titles, Colombia's gold sector is still dominated by artisanal and illegal mining. The 2010-2011 Mining Census indicates that 87% of the gold mines operate without a title, and only 3% have mandatory environmental permits. Reality is probably worse than statistics reflect; compliance with the Census was not mandatory, and officers failed to visit mines in conflict regions. This highlights two failures of the Colombian mining policy. On one hand, the various plans to formalize artisanal, small-scale, miners have consistently failed (Echavarria, 2014; Gonzalez et al., 2013; Defensoría del Pueblo, 2010). On the other hand, illegal alluvial mining, which is highly mechanized and causes enormous environmental impact, has rapidly spread. Identifying how much of the reported production comes from illegal mining is difficult since most of the gold is laundered through local traders and exporting companies, that pay royalties and export it legally. Moreover, there are serious

[1]Colombian subsoil resources are the property of the State and mining firms are granted titles to exploit them. Since 2001 (Mining Code, Law 685 of 2001), Concession Agreements are the only legal form of contracting. These titles, granted for up to 30 years, contemplate three phases: exploration, construction, and exploitation. The exploration phase period is 3 years and can be extended up to 11 years. Environmental permits are required to begin the construction and exploitation phases. During the initial phases, firms pay a yearly fee that is determined by the surface area. Once the exploitation phase begins, mining companies pay royalties over the reported production (4% for gold and silver, and 6% for alluvial gold). Royalties are collected by the central government, and mining departments and municipalities receive a fraction of them. The 2012 tax reform reduced the share of royalties received by producing departments and municipalities and redistributed them nationwide based on poverty levels.

[2]Between 2002 and 2005, Congress approved sector-specific income tax breaks, tax deductions for investments, and legal stability contracts. Also, the new Mining Code simplified the institutional framework for doing business.

[3]The corruption scandals included several cases of bribery, titles in protected areas, and speculation with mining titles. By 2011, there were 19,000 accumulated requests, most of which were eventually rejected by the new National Mining Agency (The Economist, 2013).

Figure 1
The Colombian Gold Rush



(a) Reported Prodution **(b)** Titled Area

Source: Author's calculations based data from World Bank, SIMCO, SIGOT and Tierraminada.
Notes: Gold production is expressed in tons and titled area in km^2. International prices are expressed in US dollars per Troy Once.

traceability issues. According to Goñi et al. (2014), 23% of the gold is not sold and therefore reported, in the municipality where it was extracted.

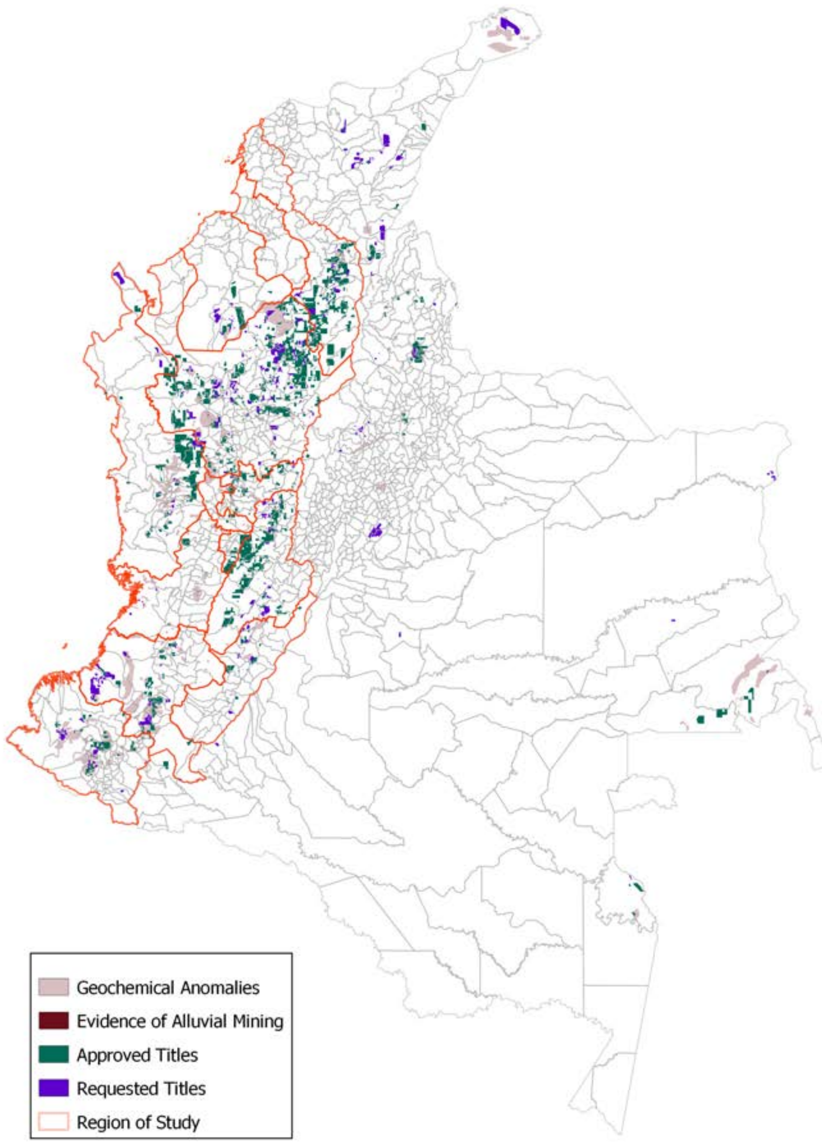
This study focuses on 13 departments from the Pacific, Central and Caribbean regions, which account for 99.3% of the reported gold production and 91.2% of the titled area (Figure 2).[4] Most of these departments have had gold mines since the colonial period. According to Acemoglu et al. (2012), the resulting extractive institutions have significantly affected their long-run economic growth. These regions have traditionally combined underground mining in the mountains and alluvial mining in the river beds. However, during the period of study underground mining has grown at a relatively slow pace, while alluvial mining has exploded under the lead of illegal actors (Rettberg and Ortiz, 2014; UNODC, 2015). There are some large-scale projects in the Central region, however, none of them has reached the production phase.[5]

The mining boom has also had devastating effects on the environment. Alvarez-Berríos and Aide (2015) show that the impact of mining on deforestation in South America has significantly increased over the last decade. Forest loss in gold mining areas reached 116,000 Ha between 2007 and 2013, and one of the hotspots is located in the central-west region of Colombia. Consistently, official statistics indicate that mining is nowadays one of the main

[4] Pacific region: Cauca, Chocó, Nariño, and Valle del Cauca; Central region: Antioquia, Caldas, Huila, Quindío, Risaralda, and Tolima; and Caribbean region: Bolívar, Córdoba, and Sucre.

[5] In particular, two of the largest ongoing open-pit projects in the country are *Mandé Norte* and *La Colosa*. Given the multiple legal actions that were taken by local communities, including a referendum, both projects are currently suspended (El Tiempo, 2010; Reuters, 2017).

Figure 2
Geography of Gold Mining



Source: Author's calculations based data from SIMCO, SIGOT, Tierraminada, UNODC, and SGC.
Notes: The geochemical anomalies and evidence of alluvial mining are measured in 2009 and 2014, respectively. Approved titles include all gold mining titles that were active at some point between 2000 and 2014. Requested titles include all pending requests by the end of 2014. The red line delimits the region of study.

causes of deforestation in the area of study (IDEAM, 2015). Abundant evidence has also shown that mercury contamination of water sources has increased, and so have the number of reported cases of mercury poisoning and newborn complications (Cordy et al., 2011; Güiza and Aristizabal, 2013; Romero and Saavedra, 2015). Rozo (2016) finds that gold mining has also increased the incidence of malaria, mostly due to the growing availability of stagnant water surfaces.

Abundant literature has also shown that gold mining has fueled conflict in Colombia (Dube and Vargas, 2013; Idrobo et al., 2014). In fact, mining has become an important source of financing for illegal armed groups, intensifying violence in the region of study.[6] Official reports also indicate that forced displacement and human rights violations have increased in municipalities with large-scale mining projects (Garay et al., 2013). Besides, illegal mining is a constant source of corruption and tax fraud. Local authorities are in charge of monitoring gold production and receive a share of the royalties. This creates incentives for local authorities to participate in gold laundering schemes (Garay et al., 2013; Rettberg and Ortiz-Riomalo, 2014).[7] Consistently, Saavedra and Romero (2017) show that the 2012 tax reform, which cut the share of royalties transferred back to the municipality, increased illegal mining, especially in areas where law enforcement is weak. The Colombian Government has since increased the number of raids and introduce legislative reforms facilitating the enforcement of law.[8] The efficacy of these policies is still to be proven.

3 Conceptual framework

One of the main mechanism through which a commodity price boom can affect human capital accumulation is the labor participation of children and young adults. When mining wages are attractive and jobs are available, children and young adults have incentives to work, often neglecting their education. Even if they stay in school and graduate, mining can affect preferences for higher education when the shift in the opportunity cost of studying is perceived as permanent. In this case, students might study less, opt-out of college, or choose less selective degrees. Environmental factors may also mediate the effect of mining on human capital. For instance, evidence shows that commodity price booms fuel violence and conflict

[6]Qualitative evidence suggests that most miners and traders pay extortions in conflict areas, and that illegal armed groups are in many cases actively involved in mining activities.

[7]There is also evidence of royalties fraud schemes, where mafias falsely report gold as produced in municipalities where they have control on local authorities and public spending (El Espectador, 2013). Moreover, ongoing investigations indicate that gold has been used as part of a massive drug-related money laundering schemes (The Telegraph, 2014; Bloomberg, 2015).

[8]For instance, the Law 1453 of 2011 increases the penalty for illegal mining and environmental damage. Likewise, Decision 774 of 2012 of the Andean Community (CAN) restricts machinery commerce, creates a unified mining register, and allows authorities to seize or destroy machinery in absence of mining titles.

(Ross, 2004; Brückner and Ciccone, 2010; Dube and Vargas, 2013; Idrobo et al., 2014). Wars and violence can, in turn, affect school enrollment and learning (Akresh and De Walque, 2008; Shemyakina, 2011; Chamarbagwala and Morán, 2011; Leon, 2012; Rodriguez and Sanchez, 2012; Minoiu and Shemyakina, 2014). Mining booms can also improve education through an increase in local revenue and public investment. However, the gains from additional revenue and investment could be undermined if the mining increases corruption and weakens the quality of local institutions (Martınez, 2016; Asher and Novosad, 2018).

I use a relatively simple child labor model in the spirit of Ravallion and Wodon (2000) and Kruger (2007) to incorporate all these mechanisms in a single framework. Suppose a representative household with a single offspring who allocates a unit of time to either study (s) or work (l): $1 = s + l$. The household utility function is additive in consumption (c) and children human capital (h):

$$U(c, h) = u(c) + \alpha v(h) \tag{1}$$

Functions u and v are twice continuously differentiable, increasing in c and h, and strictly concave. α is a positive coefficient reflecting family and individual preferences for education. Human capital is the product of study time and a positive education technology coefficient (β) that captures all environmental factors, such as school quality and violence, affecting learning: $h = \beta s$. The budget constraint is such that each household consumes the total labor income of parents (I) and offspring (wl):

$$c = I + wl \tag{2}$$

In the interior solution, the marginal rate of substitution between human capital and consumption is positively related to wages, and negatively to education technology and preferences for education:

$$-\frac{\partial v}{\partial h} / \frac{\partial u}{\partial c} = \frac{w}{\alpha\beta} \tag{3}$$

Commodity price booms can raise the opportunity cost of schooling by increasing wages. Mining can also affect human capital choices through education technology. For instance, public investments that improve school quality reduce the opportunity cost of education, while violence and corruption have the opposite effect. Families and individuals might also increase the opportunity cost of studying by reducing their preferences for education.

The effect of an increase in wages on human capital can be decomposed into income and substitution effects using the Slutsky equation:

$$\frac{\partial h}{\partial w} = \frac{\partial h}{\partial \bar{I}} l + \frac{\partial h^*}{\partial w}\bigg|_{u=\bar{u}} \tag{4}$$

Where h and h^* are the Walrasian and Hicksian demand functions of human capital, respectively. Given the assumptions of the model, the income effect (first term of the right-hand side) is always positive and the substitution effect (second term of the right-hand side) is negative. Therefore, positive shocks in children wages reduce human capital accumulation if the substitution effect is larger than the income effect, and increase it if the opposite happens.

4 Data

4.1 Gold mining

One of the practical consequences of the prevalence of artisanal and illegal mining is that the existing measures of gold production are limited and unreliable (Goñi et al., 2014). For instance, official production statistics, based on royalties, not only fail to account for an unknown fraction of the illegal mining but are also distorted by royalties frauds and money laundering schemes. Besides, production is aggregated at the municipal level, and there is no way to track it to a specific mine. The Mining Cadastre, registering all approved and requested titles, has also several limitations. Notably, there is no information about the production of each mine. Moreover, approval dates are not always good predictors of gold production. In fact, there are some areas where artisanal and illegal miners have operated long before the license was requested. There are also large areas with approved titles which have not reached the production phase.

I begin my analysis by identifying areas with high probability of having gold deposits. I do this by combining three different data sources. First, the geochemical anomalies associated with the presence of gold mineralization provided by the Colombian Geological Service (SGC, for its acronym in Spanish). The agency uses historic geochemical anomalies, on-site sampling, and cluster analysis to identify high potential areas for gold mining (SGC, 2009). Second, the remote-sensing evidence of alluvial gold exploitation from the United Nations Office on Drugs and Crime (UNODC). The evidence is generated using remote sensing analysis based on the 2014 Landsat imagery and on-site monitoring and is available at a 1 km^2 resolution.[9] Third, the approved and requested gold mining titles registered in the Mining Cadastre.[10] Given the

[9] UNODC monitors illicit crops in Colombia since the year 2001. Given the growing intensity of illegal mining, it started monitoring alluvial mining in 2014. For more details on the remote sensing methodology, see UNODC (2016).

[10] Most of the approved titles information, including type of mineral, date of approval, and detailed GIS data is provided by the Mining Information System of Colombia (SIMCO) and the Colombian Geographic Information

costs of requesting and holding a title, firms have few incentives to invest in areas without potential. Therefore, it is reasonable to assume that titles reflect firms' private information regarding gold deposits. This is consistent with the fact that most titles were requested in areas traditionally exploited by artisanal miners (Goñi et al., 2014; Gonzalez et al., 2013). Between 2001 and 2014, the government approved 3,114 titles for gold mining and there were 429 pending requests in December 2014. As can be seen in Figure 2, the three data sources tend to overlap in the main mining clusters and are complementary in other areas. Evidence of alluvial mining and geochemical anomalies are particularly useful to detect gold deposits in areas surrounding mining titles and within national parks and collective lands, where titles are restricted.[11]

Based on these three sources of information, I create a time-invariant raster that takes value 1 if there is any evidence of gold deposits and 0 otherwise. The raster has a spatial resolution of approximately 1 km^2, providing a detailed picture of gold mining potential in the vicinity of schools and households. While 43% of the municipalities in Colombia have some evidence of gold deposits, less than 5% of the cells actually match these criteria. This reflects the heterogeneous distribution of gold deposits, a variation that will be exploited as a source of exogenous variation. More details on the identification strategy are presented in Section 5.

To further study the differential effects of illegal mining, I propose two time-varying measures of gold mining. The first one is the area covered by *active* mining titles. A title is considered active in year t if it was approved before or during that year, and has not expired. This measure is intended to capture the expansion of legal mining, independently of the stage of the project. Based on the mining titles polygons, I create a raster with a spatial resolution of 1 km^2 for each year, in which cells take value one if there is an active mining title, and zero otherwise. The second measure is the annual forest loss in cells with identified gold deposits, capturing both legal and illegal mining. Since mining is one of the main sources of deforestation in the region of study, deforestation in cells with high potential for mining is a good proxy for this activity (Alvarez-Berríos and Aide, 2015; IDEAM, 2015).[12] I use the Hansen et al. (2013) high-resolution forest cover maps to calculate the annual deforestation in each cell.[13]

System for Planning (SIGOT). Requested titles are based on data from *TierraMinada*, an NGO overseeing mining activity in Colombia.

[11] Mining is strictly forbidden in National Parks and requires prior consultation in indigenous or Afro-Colombian collective lands, both legal instruments that have effectively halted large-scale mining projects in the region (El Tiempo, 2010).

[12] Gold mining impacts forest through vegetation removal from mining areas, settlements, and roads. Wood is also extensively used for building the mining structures and settlements.

[13] Annual forest loss data is available at a spatial resolution of 30 meters for the period 2001-2016. Between 2001 and 2014, the country lost over 3 million hectares of forest. The expansion of the agricultural frontier in the Amazon region accounts for more than half of it. The second largest deforestation hotspot is located in the northeast mining cluster (Figure A.2).

Annual deforestation in cells with gold deposits, hereafter referred as mining deforestation, is expressed in hectares per squared kilometer.

4.2 Education outcomes

Human capital accumulation is measured at the extensive and intensive margin using annual school censuses, standardized test scores, and higher education administrative records. Given that mining represents only a small share of the economy in large cities, I discard municipalities over 200,000 inhabitants.[14] I focus on public schools, which represent 95.6% of schools in the sample. The coordinates of the schools are provided by the Ministry of Education and local authorities (Figure A.1). I was able to geocode 88,7% of the schools in the sample.

The annual school censuses are collected by the National Statistics Department (DANE, for its acronym in Spanish) and the Ministry of Education (MEN, for its acronym in Spanish). Principals report basic information of the schools, including ownership, calendar, rurality status, teachers' training, and the number of students that enrolled, dropped-out, repeated a grade or transferred by grade and gender. This information is available for all years between 2004 and 2014.[15] Schools may have multiple shifts, in which case they are treated separately. In order to have enough within-school variation and discard schools that were created during the mining boom, I further restrict the sample schools with at least 8 years of information. The final sample includes 16,602 schools, of which 79.3% are rural. In addition to students enrollment and progress throughout the year, I also collect detailed information on teachers training from school censuses.

I measure intensive margin effects using three standardized tests administered by the Colombian Institute for the Promotion of Higher Education (ICFES, for its acronym in Spanish). The most important one is the national exit exam –SABER 11, a high stake exam determining college acceptance and funding opportunities. Individual scores for different area subjects, along with basic student characteristics including date of birth and gender. The sample includes over 872,750 students who graduated from schools in the final sample and took the exit exam between 2001 and 2014. Additional self-reported characteristics, such as parents' education and labor status, were collected in some years, but not others.[16] SABER 5 and 9 exams measure mathematics and language proficiency at the end of primary and lower secondary, respectively. Comparable tests were administered in 2009, 2012, 2013, and 2014 to randomly selected samples of students in each school. Schools are classified based on the number

[14]Colombia has 1,122 municipalities, of which only 26 have more than 200.000 inhabitants.

[15]While school censuses exist since 2000, enrollment information was not collected in 2003 and dropout and school transfers can only be differentiated since 2004. Therefore, I focus on the period 2004-2014.

[16]In particular, questions on parents' education and labor participation were not asked between 2004 and 2007.

of students who score above the satisfactory cutoff. For comparability, all individual and school-level proficiency measures are normalized with respect to national mean and standard deviation of the corresponding year.

Additionally, I measure higher education enrollment using administrative records from MEN's Higher Education Dropout Prevention System (SPADIES, for its acronym in Spanish). I follow all students who took the exit exam between 2001 and 2014 and enrolled in college up to two years after graduation. I measure the effect of mining on overall enrollment and accredited -high quality- colleges. Academic (4-year) and STEM degrees have particularly high wage premiums, which is why I also assess the effect on these specific choices.[17]

Table 1 reports summary statistics of schools and standardized tests. Colombian schools usually combine different education levels. Primary schools, which are predominantly rural, enroll on average 82.2 students per year. The dropout and grade retention rates are 6.7% and 7.5%, respectively. Lower and upper secondary schools tend to have more students and lower retention rates. Dropout rates reach a peak in lower (7.5%) and fall in upper secondary (4.8%), reflecting that students who self-select into high school are likely to graduate. Standardized test scores are negative, which implies that students in the sample are below the national average, particularly in mathematics. 6.5% of the exam takers reported working in their senior high school year. Finally, only 12.8% of the students who took the exit exam enrolled in higher education within two years of graduation. Of these, 6% enrolled in an accredited college, 10.4% opted for an academic (4-year) degree, and 6.8% for a STEM degree.

[17]There are 563 colleges in Colombia, of which 120 are accredited. I measure the wage premium of accredited universities, academic (4-year), and STEM degrees, using data from the Labor Observatory of the Ministry of Education on entry-wage of students graduating from college in 2011. The unconditional wage differences are 17.0%, 33.4%, and 7.9%, respectively. When I estimated them jointly, the premiums are 10.4%, 33.7%, and 13.6%, respectively.

Table 1
Summary Statistics of Education Outcomes

	Mean	sd	Obs.
A. Primary			
Rural	0.819	0.385	173239
School Enrollment	84.818	112.679	146148
Dropout Rate	6.771	8.866	145868
Retention Rate	7.489	9.800	145868
Promotion Rate	81.601	14.597	145868
Language Proficiency*	-0.078	0.949	25683
Mathematics Proficiency*	-0.084	0.943	25553
B. Lower Secondary			
Rural	0.635	0.482	45573
School Enrollment	220.732	194.770	32807
Dropout Rate	7.538	8.126	32746
Retention Rate	7.100	7.785	32746
Promotion Rate	81.873	12.443	32746
Language Proficiency*	-0.149	0.787	7010
Math Proficiency*	-0.114	0.825	6963
C. Upper Secondary			
Rural	0.529	0.499	30129
School Enrollment	187.343	172.908	21452
Dropout Rate	4.843	6.090	21385
Retention Rate	4.847	5.870	21385
Promotion Rate	87.811	9.923	21385
Exam Takers*	48.736	40.617	21054
Age*	17.801	2.222	1082517
Language Score*	-0.196	0.924	1085548
Mathematics Score*	-0.161	0.907	1085533
Total Score*	-0.219	0.844	1085389
Student Works*	0.065	0.246	792636
D. College Enrollment			
College Enrollment*	0.128	0.335	1041992
Accredited College*	0.060	0.238	1041992
Academic Degree*	0.104	0.306	1041992
STEM Degree*	0.068	0.252	1041992

Source: Author's calculations based data from MEN, DANE, and ICFES.
Note: Statistics are based on a quasi-balanced panel of public schools from 2004 to 2014. Variables with an asterisk are based on the SABER 5, 9, and 11 standardized tests and higher education administrative records. Enrollment refers to the number of students registered at the beginning of the school year. Dropout and grade retention and promotion rates correspond to the share of enrolled students who dropout or fail grade at the end of the school year. School proficiency measures for primary and lower secondary are given by the share of students who score above the satisfactory cutoff in the SABER 5 and 9 tests from 2009, 2012, 2013, and 2014. Upper secondary proficiency measures are based on individual SABER 11 test scores from 2001 to 2014. College Enrollment is based on SPADIES, for students taking the SABER 11 test between 2001 and 2014. All learning measures are normalized with respect to national mean and standard deviation of the corresponding year.

4.3 Additional data sources

I use National Household Surveys (GEIH, for its acronym in Spanish) administer by DANE, to study labor participation of children and young adults. I focus on the 2007-2011 rounds, which include households' municipality and rural district, allowing to geocode with precision both urban and rural households.[18] The sample includes 403,481 households living in 310 municipalities (Figure A.1). These surveys provide detailed information on school attendance between ages 6 and 18, and labor participation of individuals aged 10 or more.

I also collect municipal level information on public finances, corruption, and violence. Royalties and investment are provided the National Planning Department between 2004 and 2014 (DNP for its acronym in Spanish). Corruption measures are based on two data sources. First, public records of disciplinary prosecutions to local governments from the national watchdog agency (*Procuraduría General de la Nación*) between 2008 and 2014. Second, public records of corruption-related criminal investigation from the General Attorney's Office (*Fiscalía General de la Nación*) between 2006 and 2014. Homicide and forced displacement rates between 2004 and 2014 are provided by CEDE and National Police.

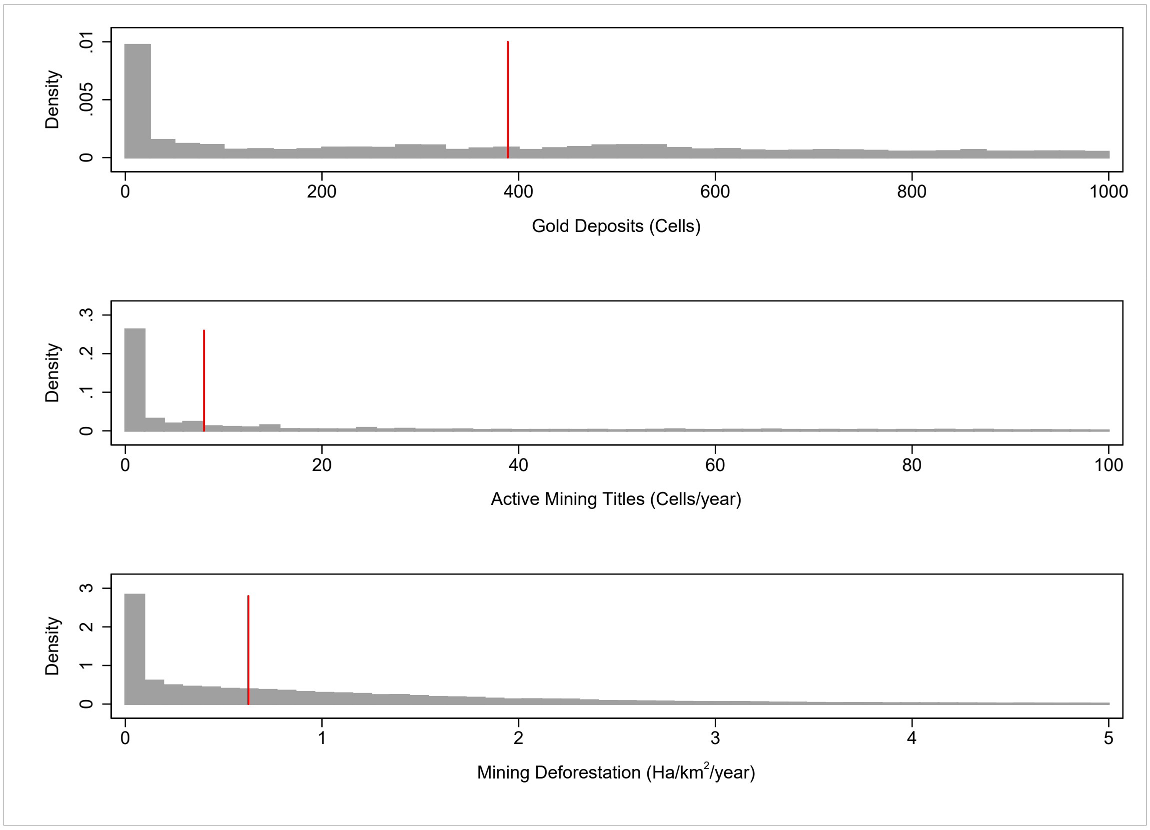
5 Emprical Strategy

This paper estimates the causal effect of gold mining on human capital accumulation. The first step in doing so is to measure the geographical variation of mining in the vicinity of schools. Using school coordinates and detailed geographic information on gold mining, I create fixed-distance buffers around each school and calculate three measures of mining intensity: number of cells with evidence of gold deposits, number of cells with active mining titles, and forest loss in cells with evidence of gold deposits. While gold deposit intensity is time-invariant, active mining titles and mining deforestation are calculated on a yearly basis. The same measures are used for household surveys, using the rural district centroids as a reference point.

Benchmark regressions are based on 30 km buffers, and sensibility tests use buffers ranging from 10 to 50 km. The median school has 389 cells with evidence of gold deposits within 30 km vicinity, equivalent to 13.7% of the total area. In comparison, active mining titles are more spatially concentrated; 37.2% of the year-cells take value zero and the median schools/year has only 8 cells with active mining titles in the 30km vicinity. Likewise, the median mining deforestation within 30 km of the schools is 0.62 Ha/km^2/year.

[18]The 1,122 municipalities are divided into 35,168 rural districts. While most of the administrative information in Colombia is available at a municipal level, the 2007-2011 rounds of GEIH also include the rural district code.

Figure 3
Mining Intensity in the 30 km Vicinity of Schools



Source: Author's calculations based data from SIMCO, SIGOT, Tierraminada, UNODC, SGC, Hansen et al. (2013), MEN, and DANE.
Note: The red line represents the median value of the corresponding mining intensity measure.

The effect of mining is estimated using a difference-in-differences approach that exploits the spatial and temporal variation of gold mining. The first measure I use to capture these variations is the interaction between the (time-invariant) intensity of gold deposits in the vicinity of schools and the logarithm of international gold prices. The intuition is that gold price shocks should disproportionately affect areas with high potential for gold mining.[19] To assess the differential effects of illegal mining, I also estimate the model using two alternative measures of mining: active mining titles and mining deforestation. While active mining titles reflect the expansion of legal mining, mining deforestation is a proxy for both legal and illegal mining.

The specification of the model depends on the unit of analysis. For school-level outcomes (e.g. enrollment, dropout rate), I estimate panel fixed-effects models as described in Equation

[19] Examples of studies following a similar approach to estimate the causal effect of the external shock on a specific economic activity include Black et al. (2002); Angrist and Kugler (2008); Dube and Vargas (2013).

5. The outcome y_{st} and the gold mining measure $Gold_{st}$ vary by school s and year t. In both models, errors are clustered at the school level. For ease of interpretation, all mining intensity measures are normalized with mean zero and standard deviation equal to one. Estimated coefficients should, therefore, be interpreted as the effect of a one standard deviation increase in mining intensity in the vicinity of schools. Regressions include school fixed effects (μ_s) that control for observed and unobserved school characteristics, including geographic features determining gold deposits in the area. I also include year fixed effects (τ_t) and quadratic time trends for each education district ($\eta_{d\times}t$) that account for common shocks and common trends in education policy.

$$y_{st} = \gamma Gold_{st} + \mu_s + \tau_t + \eta_d \times t + \epsilon_{st} \tag{5}$$

The effect of mining on individual educational outcomes based on standardized test scores or household surveys is estimated with repeated cross-section models that include school and year fixed effects and education district-specific time trends, and also control for students' age and gender (Equation 6).[20]

$$y_{ist} = \gamma Gold_{st} + \beta X_{ist} + \mu_s + \tau_t + \eta_d \times t + \epsilon_{ist} \tag{6}$$

The estimated effect of the interaction between the intensity of gold deposit and international gold prices can be interpreted as causal. In fact, gold deposits depend exclusively on geographical features and therefore are strictly exogenous to human capital decisions. The location of the schools and settlements could be endogenous, however, we focus on schools created before the gold boom and school fixed-effects account for all factors determining their location decisions. As for international prices, Colombia produces less than 2% of the world's gold and is a price-taker in the international gold market (USGS, 2015). Therefore, prices are exogenous as well.

Mining titles and mining deforestation have at least three potential sources of bias. First, observed and unobserved factors can simultaneously affect mining intensity and human capital decisions. For instance, conflict escalation may increase illegal mining and worsen the quality of public education. Second, there could be reverse causality if changes in the education system affect the probability of working in any activity related to mining. Third, gold mining is measured with error, which could lead to attenuation bias. In fact, mining titles do not necessarily reflect the stage of the project and deforestation in cells with potential for gold deposits may be caused by other activities. To address these issues, I instrument the alternative

[20]Other individual characteristics, such as parents' education, are not observed every year and therefore are not included in the benchmark specification.

mining intensity measures with the interaction between gold deposits and international gold prices. The main assumption is that conditional on the model covariates and fixed effects, the interaction between gold deposits and international prices only affect human capital decisions through gold mining. The identification strategy also requires the instrument to be highly correlated with mining. As will be seen in the next section, this is, in fact, the case.

6 Main Results

6.1 School enrollment and progress

I begin my analysis by estimating the reduced form effects of gold mining on schools enrollment and progress in Table 2. At the primary level, mining increases enrollment and promotion rates and reduces dropouts. These effects are statistically and economically significant. An additional standard deviation in mining increases enrollment by 2.564 students, equivalent to 1.4% of the average enrollment. Mining also reduces the dropout rate by 0.308 pp and increases promotion rate by 0.302 pp. At the lower secondary level, the effects on enrollment, dropout, and retention are similar in magnitude but statistically insignificant. However, there is a significant increase in promotion rates of 0.523 pp. Something similar happens in upper secondary, where the only significant coefficient is dropout rates, with an estimated effect of -0.489 pp.

Table 2
Reduced Form Effect of Gold Mining on School Enrollment and Progress

	School Enrollment (1)	Dropout Rate (2)	Retention Rate (3)	Promotion Rate (4)
A. Primary				
Gold Deposits × Price	2.564***	-0.308***	0.049	0.302**
	(0.692)	(0.093)	(0.104)	(0.148)
Mean(y)	81.623	6.832	7.455	81.732
Observations	146024	145743	145743	145743
B. Lower Secondary				
Gold Deposits × Price	2.198	-0.307	-0.181	0.523*
	(2.443)	(0.198)	(0.192)	(0.305)
Mean(y)	212.216	7.593	6.972	82.051
Observations	32523	32462	32462	32462
C. Upper Secondary				
Gold Deposits × Price	1.302	-0.489**	0.087	0.369
	(2.689)	(0.215)	(0.179)	(0.327)
Mean(y)	178.620	4.885	4.704	87.965
Observations	21254	21211	21211	21211

Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. Each coefficient corresponds to a separate panel regression that controls for school and year fixed effects, and education district-specific time trends. The independent variable is the interaction between the intensity of gold deposits in the 30 km vicinity of schools (normalized with mean zero and standard deviation equal to one) and the logarithm of international gold prices. Standard errors are clustered at the school level.

The instrumental variable estimations for mining titles and mining deforestation are presented in Table 3. The first thing to notice is that the instrument is a good predictor of both time-varying measures, with Kleibergen-Paap F statistics oscillating between 114.6 and 23,256.4. The effects of mining titles on primary enrollment and progress are similar to the reduced form. However, they are significantly larger for mining deforestation. For instance, at the primary level, the estimated effect of mining titles and mining deforestation are 2.787 and 8.524 students, respectively. Likewise, the effects on dropout rates in primary and upper secondary are 2 to 4 times larger when I use the mining deforestation measure.

Table 3
Instrumental Variable Effect of Gold Mining on School Enrollment and Progress

	School Enrollment (1)	Dropout Rate (2)	Retention Rate (3)	Promotion Rate (4)
A. Primary				
Mining Titles	2.787***	-0.335***	0.054	0.328**
	(0.750)	(0.101)	(0.113)	(0.161)
Kleibergen-Paap F	23259.360	23205.315	23205.315	23205.315
Mining Deforestation	8.524***	-1.024***	0.165	1.004**
	(2.264)	(0.316)	(0.346)	(0.497)
Kleibergen-Paap F	1199.102	1195.651	1195.651	1195.651
Mean(y)	81.623	6.832	7.455	81.732
Observations	146024	145743	145743	145743
B. Lower Secondary				
Mining Titles	2.171	-0.304	-0.178	0.517*
	(2.414)	(0.194)	(0.190)	(0.301)
Kleibergen-Paap F	4468.151	4461.275	4461.275	4461.275
Mining Deforestation	8.104	-1.133	-0.666	1.927*
	(8.856)	(0.753)	(0.715)	(1.155)
Kleibergen-Paap F	171.075	170.906	170.906	170.906
Mean(y)	212.216	7.593	6.972	82.051
Observations	32523	32462	32462	32462
C. Upper Secondary				
Mining Titles	1.232	-0.462**	0.083	0.349
	(2.541)	(0.203)	(0.170)	(0.308)
Kleibergen-Paap F	2531.228	2526.508	2526.508	2526.508
Mining Deforestation	4.453	-1.678**	0.300	1.268
	(9.104)	(0.760)	(0.621)	(1.124)
Kleibergen-Paap F	115.593	114.649	114.649	114.649
Mean(y)	178.620	4.885	4.704	87.965
Observations	21254	21211	21211	21211

Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. Each coefficient corresponds to a separate instrumental variable regression that controls for school and year fixed effects, and education district-specific time trends. The independent variables are mining titles and mining deforestation in the 30 km vicinity of schools. The instrument is the interaction between the intensity of gold deposits in the 30 km vicinity of schools and the logarithm of international gold prices. All mining intensity measures are normalized with mean zero and standard deviation one. Standard errors are clustered at the school level.

The effect of mining on enrollment and progress is similar for male and female students. As can be seen in Appendix Table A.1, there are some cases in which females react differently than males. For instance, the estimated effect for enrollment in primary school is slightly larger for female students. However, these differences are economically small and in most of the outcomes with significant effects, the subgroup difference tests indicate that the coefficients are equivalent between genders.

These findings are robust to alternative vicinity definitions. In Appendix Table A.2 I replicate the reduced form estimates with buffers ranging from 10 to 50 km. The primary school enrollment and dropout rate effects are significant with all buffers. Primary and lower secondary promotion rate and upper secondary dropout are significant from 30 to 50 km. Some of the outcomes failing to reject the null with 30 km buffers, may be significant with alternative definitions. In particular, I find negative and significant effects on lower secondary dropout rates with 10, 40 and 50 km buffers.

Estimates based on household surveys are in line with these results. Appendix Table A.3 presents the effect of mining on school attendance and overage for the grade. For ease of interpretation, children are classified into three age groups: 6-9, 10-14, and 15-18. While all coefficients are positive, mining has no significant effect on school attendance. However, there is a significant reduction in the number of children between 6 and 9 who are overage for the grade. This suggests that children are entering the school system earlier, which is consistent with an increase in enrollment in primary school. The overage coefficients are also negative for the group 15-18, although statistically insignificant. This reflects the lower upper secondary dropout rates in mining areas.

6.2 Learning and college enrollment

Gold mining can also affect education on the intensive margin. Table 4 presents the effect on the SABER 11 (exit exam) test scores. Results consistently show that mining is detrimental to students' academic performance. The reduced form estimates for language and mathematics are -0.019 standard deviations. The effect on the total scores is -0.024 standard deviations. Instrumental variable estimates are similar in magnitude for mining titles, and approximately three times larger when I use the mining deforestation measure instead.

These results could be driven by selection. However, the effect on the number of exam takers is relatively small and statistically insignificant. Consistently, there are no effects on school enrollment or attendance in upper-secondary (Tables 2 and A.3). Since mining reduces grade retention in upper secondary, it might also be the case that students are younger. However, there are no detectable effects on the age of exam takers. Therefore, the observed changes in tests scores are not driven by age composition either.

Table 4
Effect of Gold Mining on SABER 11 (Exit Exam)

	Test Score			Exam Takers	
	Language (1)	Mathematics (2)	Total (3)	Number (4)	Age (5)
A. Reduced Form					
Gold Deposits × Price	-0.019***	-0.019***	-0.024***	-0.649	-0.005
	(0.006)	(0.007)	(0.007)	(0.906)	(0.031)
B. Instrumental Variable					
Mining Titles	-0.021***	-0.020***	-0.025***	-0.660	-0.006
	(0.007)	(0.007)	(0.007)	(0.922)	(0.033)
Kleibergen-Paap F	229.712	229.737	229.700	441.161	229.674
Mining Deforestation	-0.061***	-0.059***	-0.074***	-2.173	-0.016
	(0.022)	(0.022)	(0.024)	(2.990)	(0.095)
Kleibergen-Paap F	28.380	28.380	28.377	70.741	28.380
Mean(y)	. -0.196	-0.161	-0.219	46.955	17.801
Observations	1023279	1023264	1023138	20574	1023282

Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. Coefficients in Panel A correspond to separate OLS regression that control for school and year fixed effects, and education district-specific time trends. Individual-level regressions also control for the students' age and gender. The independent variable is the interaction between the intensity of gold deposits in the 30 km vicinity of schools and the logarithm of international gold prices. Coefficient in Panel B correspond to separate instrumental variable regressions that control for school and year fixed effects, and education district-specific time trends. The independent variables are mining titles and mining deforestation in the 30 km vicinity of schools. The instrument is the interaction between the intensity of gold deposits in the 30 km vicinity of schools and the logarithm of international gold prices. All mining intensity measures are normalized with mean zero and standard deviation one. Standard errors are clustered at the school level.

Evidence suggests that mining impacts academic performance from earlier stages of the school cycle. I estimate the effect of mining on school-level mathematics and language proficiency scores in grade 5 and 9 in Appendix Table A.4. Results indicate that mining has negative and significant effects on the grade 9 mathematics, with estimated effects oscillating -0.326 and -0.401 standard deviations. In contrast, there are some positive, although small, effects on the mathematics scores in grade 5. This is could be explained by the reduction of overage students at the primary level. The effects on language are statistically and economically small for both levels.

Mining also has negative effects on higher education enrollment, particularly in academic (4-year) and STEM degrees. The effects of mining on college enrollment of students taking the exit exam are presented in Table 5. The estimated effect of mining on college enrollment oscillates between 0.8 pp and 2.9 pp. The effect on accredited colleges and STEM degrees is also negative and significant, although smaller in magnitude. The reduced form estimates for these two choices are -0.7 pp and -0.6 pp, respectively. While coefficients are also negative, the estimated effects on accredited colleges are smaller and statistically insignificant. As for school enrollment and test scores, the estimated effects are considerably larger when using the mining deforestation measure, which takes into account both legal and illegal mining.

Table 5
Effect of Gold Mining on College Enrollment

	College Enrollment (1)	Accredited College (2)	Academic Degree (3)	STEM Field (4)
A. Reduced Form				
Gold Deposits × Price	-0.010***	-0.003	-0.007**	-0.006***
	(0.003)	(0.002)	(0.003)	(0.002)
B. Instrumental Variable				
Mining Titles	-0.008***	-0.002	-0.006**	-0.005***
	(0.003)	(0.001)	(0.002)	(0.002)
Kleibergen-Paap F	244.792	244.792	244.792	244.792
Mining Deforestation	-0.029**	-0.008	-0.021**	-0.017**
	(0.012)	(0.005)	(0.011)	(0.008)
Kleibergen-Paap F	34.227	34.227	34.227	34.227
Mean(y)	0.132	0.060	0.106	0.070
Observations	859474	859474	859474	859474

Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. Coefficients in Panel A correspond to separate OLS regression that control for gender and age, school and year fixed effects, and education district-specific time trends. The independent variable is the interaction between the intensity of gold deposits in the 30 km vicinity of schools and the logarithm of international gold prices. Coefficient in Panel B correspond to separate instrumental variable regressions that control for school and year fixed effects, and education district-specific time trends. The independent variables are mining titles and mining deforestation in the 30 km vicinity of or schools. The instrument is the interaction between the intensity of gold deposits in the 30 km vicinity of schools and the logarithm of international gold prices. All mining intensity measures are normalized with mean zero and standard deviation one. Standard errors are clustered at the school level.

The effects of mining on learning and college enrollment are similar across gender, age, and parents' education. I test this by estimating the heterogeneous effects of mining on these outcomes in Appendix Tables A.5 and A.6. In most cases, coefficients are comparable and the t-tests confirm that there are no statistical differences. The SABER 11 and college enrollment results are also robust to alternative vicinity definitions. I test this in Appendix Tables A.7 and A.8 with buffers ranging from 10 to 50 km. In all cases, the sign and significance of the coefficients remain unaltered when the buffer is changed.

Overall, these results indicate that students in mining areas not only learn less but also have smaller probabilities of enrolling in college and opting for high-earning degrees. Moreover, the lower enrollment in STEM degrees is consistent with Ebeke et al. (2015) in that mining booms fail to attract talent to productive activities.

7 Mechanisms

This section tests some of the potential mechanisms through which mining can affect human capital accumulation. The first set of results focuses on labor participation of children and young adults. I then assess the effect on more aggregate factors, such as public investment, corruption, and violence, that can potentially affect how students learn.

7.1 Labor participation

Natural resources shocks can directly affect human capital accumulation if students quit school to join the labor force. I use the labor questionnaire of the household surveys, applied to all individuals aged 10 or older, to test this mechanism. Table 6 presents the estimated effect of mining on labor participation in the mining and non-mining sector. Since the legal working age in Colombia is 15, I split the sample into three groups: 10-14, 15-18, and 18-25.

For children between 10 and 14, the probability of working in mining drops during mining booms. The estimates coefficients oscillate between -0.002 and -0.004 pp. The effects are also negative, although statistically insignificant, between ages 15 and 18. This could be the results of public policy interventions. In fact, mining has been classified as one of the worst forms of child labor, and child labor eradication policies have explicitly targeted mining activities in recent years (DPS, 2015).

In contrast, young adults between 19 and 25 are more likely to join the mining sector. The estimated coefficients go from 1.7 pp with the mining titles measure to 4.7 pp with mining deforestation. The probability of working in the non-mining sector is unaltered. Results are similar for the intensive margin of labor supply. While estimates are negative or insignificant for all children under 18, the effect on the number of hours worked in mining is positive and significant for young adults between 19 and 25, with coefficients between 0.970 and 2.680 (Appendix Table A.9).

Table 6
Effect of Gold Mining on Labor Participation of Children and Young Adults

	Mining Sector			Non-Mining Sectors		
	10-14	15-18	19-25	10-14	15-18	19-25
	(1)	(2)	(3)	(4)	(5)	(6)
A. Reduced Form						
Gold Deposits × Price	-0.004*	-0.013	0.036**	0.016	-0.004	-0.012
	(0.002)	(0.014)	(0.016)	(0.017)	(0.037)	(0.044)
B. Instrumental Variable						
Mining Titles	-0.002*	-0.006	0.017**	0.007	-0.002	-0.006
	(0.001)	(0.006)	(0.007)	(0.008)	(0.017)	(0.021)
Kleibergen-Paap F	265.370	287.181	255.459	265.370	287.181	255.459
Mining Deforestation	-0.004*	-0.015	0.047***	0.019	-0.005	-0.015
	(0.002)	(0.012)	(0.018)	(0.020)	(0.042)	(0.058)
Kleibergen-Paap F	20.477	17.700	23.633	20.477	17.700	23.633
Mean(y)	0.001	0.004	0.008	0.048	0.206	0.480
Observations	57403	44592	60076	57403	44592	60076

Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. Coefficients in Panel A correspond to separate OLS regression that control for gender, age, parents' education level, rural district fixed effects, year, and month fixed effects, and education district-specific time trends. The independent variable is the interaction between the intensity of gold deposits in the 30 km vicinity of rural district centroids and the logarithm of international gold prices. Coefficient in Panel B correspond to separate instrumental variable regressions that control for gender, age, parents' education level, rural district fixed effects, year and month fixed effects, and education district-specific time trends. The independent variables are mining titles and mining deforestation in the 30 km vicinity of rural district centroids. The instrument is the interaction between the intensity of gold deposits in the 30 km vicinity of rural district and the logarithm of international gold prices. All mining intensity measures are normalized with mean zero and standard deviation one. Standard errors are clustered at the rural district level.

I estimate the heterogeneous effects of mining on labor participation in Appendix Table A.10. Mining has larger effects for males and there are no detectable differences by parents' education. Estimates based on the SABER 11 survey tend to confirm these results. The effect of mining on labor participation is significantly larger for males and overage students. The difference between parental education groups is statistically significant but economically small (column 4 of Appendix Table A.5).

These changes in labor participation are consistent with the observed wage premiums. I estimate the wage gap between mining and non-mining sector for different sub-samples of children and young adults in Appendix Table A.11. Estimates are based on rural districts with at least one cell with gold deposits within 30km. For young adults between 19 and 25, wages are 6% higher in the mining sector than in the non-mining sector. The difference is statistically insignificant for younger children. The premium is particularly large for males, with an estimated coefficient of 15.6%. Interestingly, females tend to have larger wages in the non-mining sector, with a premium that is close to -25%. This could partially explain why they are less likely to join the mining sector during the boom period. Wage premiums are similar for children with more and less-educated parents. Consistently, there are no differential effects on labor participation by parental education.

7.2 Public investment, corruption, and violence

Mining can also impact human capital accumulation through local revenue and public investment. I test this in Table 7 by estimating the effects of mining on municipal royalties and investment. Results based on the 2004-2014 period confirm that mining increases royalties and investment, with reduced form estimates of 13.4% and 15.8%, respectively. IV estimates are similar in magnitude but less precise. This seems to be the results of the 2012 tax reform, which assigned fewer royalties to mining municipalities in favor of the poorest ones. When I exclude the last two years from the analysis I find statistically significant IV effects for royalties as well.

Table 7
Effect of Gold Mining on Royalties and Public Investment

	2004-2014		2004-2012	
	Royalties (1)	Investment (2)	Royalties (3)	Investment (4)
A. Reduced Form				
Gold Deposits × Price	0.126*	0.147**	0.187**	0.150**
	(0.076)	(0.061)	(0.078)	(0.063)
B. Instrumental Variable				
Mining Titles	0.132	0.153**	0.192**	0.154**
	(0.081)	(0.068)	(0.084)	(0.071)
Kleibergen-Paap F	64.848	64.848	62.035	62.035
Mining Deforestation	0.599	0.696*	0.707*	0.567*
	(0.454)	(0.420)	(0.366)	(0.323)
Kleibergen-Paap F	8.799	8.799	11.559	11.559
Mean(y)	3.291	8.816	2.682	8.688
Observations	7057	7057	6156	6156

Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. Royalties and investment are expressed in logarithms. Coefficients in Panel A correspond to separate OLS regression that control for municipal and year fixed effects. The independent variable is the interaction between the intensity of gold deposits in the municipality and the logarithm of international gold prices. Coefficient in Panel B correspond to separate instrumental variable regressions that control for municipal and year fixed effects. The independent variables are mining titles and mining deforestation in the municipality. The instrument is the interaction between the intensity of gold deposits in the municipality and the logarithm of international gold prices. All mining intensity measures are normalized with mean zero and standard deviation one. Standard errors are clustered at the municipal level.

These investments may translate into better school inputs. To further explore this mechanism, I assess the effect of mining on students per teacher and teachers' training, in Table 8. While there are no detectable effects at the primary level, the results for secondary schools are mixed. On one hand, mining regions tend to hire fewer teachers in secondary, which is reflected in a positive and significant effect on the students to teacher ratio. the estimated coefficients oscillate between 0.799 and 2.837, equivalent to changes of 3.02% and 10.73%, respectively. It is worth noting that the effect on enrollment is positive but insignificant (Table 2). Therefore, the increase in the students to teacher ratio is not entirely driven by enrollment. On the other hand, mining has positive effects on secondary teachers' training. Specifically, there is a positive and significant effect on the percentage of teachers with a masters degree. The estimated effects oscillate between 1.022 and 3.629 pp. While qualitative evidence suggests that royalties have also been used to financed school infrastructure, it is not possible to test this mechanism with the available data.

Table 8
Effect of Gold Mining on School Inputs

	Students per Teacher		Teachers' Highest Degree			
			Bachelor's		Masters	
	Primary (1)	Secondary (2)	Primary (3)	Secondary (4)	Primary (5)	Secondary (6)
A. Reduced Form						
Gold Deposits × Price	0.003	0.799***	0.068	-0.082	0.076	1.022*
	(0.097)	(0.225)	(0.469)	(0.534)	(0.334)	(0.590)
B. Instrumental Variable						
Mining Titles	0.003	0.725***	0.070	-0.074	0.079	0.928*
	(0.099)	(0.206)	(0.482)	(0.485)	(0.343)	(0.541)
Kleibergen-Paap F	4338.760	881.268	4338.760	881.268	4338.760	881.268
Mining Deforestation	0.011	2.837***	0.231	-0.290	0.258	3.629*
	(0.327)	(0.910)	(1.585)	(1.894)	(1.128)	(2.176)
Kleibergen-Paap F	513.733	78.050	513.733	78.050	513.733	78.050
Mean(y)	25.211	26.427	65.769	89.468	15.811	25.034
Observations	141419	30289	141419	30289	141419	30289

Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. Coefficients in Panel A correspond to separate OLS regression that control for or school and year fixed effects, and education district-specific time trends. The independent variable is the interaction between the intensity of gold deposits in the 30 km vicinity of schools and the logarithm of international gold prices. Coefficient in Panel B correspond to separate instrumental variable regressions that control for school and year fixed effects, and education district-specific time trends. The independent variables are mining titles and mining deforestation in the 30 km vicinity of schools. The instrument is the interaction between the intensity of gold deposits in the 30 km vicinity of schools and the logarithm of international gold prices. All mining intensity measures are normalized with mean zero and standard deviation one. Standard errors are clustered at the school level.

Previous evidence has also shown that commodity price booms can increase corruption and affect the provision of public goods (Garay et al., 2013; Rettberg and Ortiz-Riomalo, 2014; Saavedra and Romero, 2017). I test this is in columns 1 and 2 of Table 9. While the effects on disciplinary prosecutions and corruption-related criminal investigations are positive and economically large, they are consistently insignificant. Therefore, evidence does not allow to conclude that the gold boom has harmed local governments or crippled its capacity to provide public goods.

Finally, the last set of results confirms that the gold boom intensified conflict and violence in Colombia (Dube and Vargas, 2013; Idrobo et al., 2014). I estimate the effect of mining on the municipal homicide and forced displacement rates in columns 3 and 4 of Table 9. Mining significantly increases both of these measures, with reduced form coefficients of 9.938 and

275.010 pp, respectively. The difference between legal and illegal mining is quite large in this case. For instance, when it comes to homicides, the effect of a one standard deviation increase in mining is 10.342 pp for mining titles, and 47.751 pp for mining deforestation. Violence has, in turn, large negative effects on schooling in Colombia (Rodriguez and Sanchez, 2012).

Table 9
Effect of Gold Mining on Corruption and Violence

	Corruption		Violence	
	Disciplinary Prosecution (1)	Criminal Investigation (2)	Homicide (3)	Forced Displacement (4)
A. Reduced Form				
Gold Deposits × Price	0.133	4.458	9.938***	275.010*
	(0.391)	(3.670)	(1.775)	(153.101)
B. Instrumental Variable				
Mining Titles	0.077	2.524	10.342***	286.183*
	(0.226)	(1.942)	(2.354)	(165.169)
Kleibergen-Paap F	68.199	69.774	66.659	66.659
Mining Deforestation	0.464	24.604	47.751***	1321.417
	(1.392)	(30.398)	(17.260)	(835.911)
Kleibergen-Paap F	1.255	1.299	8.706	8.706
Mean(y)	1.218	23.999	45.093	1935.622
Observations	3654	4698	7308	7308

Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. All outcomes are expressed as rate per 100,000 inhabitants. Coefficients in Panel A correspond to separate OLS regression that control for municipal and year fixed effects. The independent variable is the interaction between the intensity of gold deposits in the municipality and the logarithm of international gold prices. Coefficient in Panel B correspond to separate instrumental variable regressions that control for municipal and year fixed effects. The independent variables are mining titles and mining deforestation in the municipality. The instrument is the interaction between the intensity of gold deposits in the municipality and the logarithm of international gold prices. All mining intensity measures are normalized with mean zero and standard deviation one. Standard errors are clustered at the municipal level.

8 Conclusions

This paper estimates the local effects of gold mining on human capital accumulation in a context where illegal mining is prevalent. Evidence is based on Colombia, where I combine high-resolution geographic information on gold mining and rich administrative data on education. Mining increases enrollment in primary school and reduces dropout rates throughout the school cycle. There are also positive effects on the promotion rate in lower secondary. These improvements at the extensive margin contrast with the negative effects on learning and college enrollment. I find consistent negative and significant effects on test scores and college enrollment. I also find that the estimated effects are consistently larger when using the mining deforestation measure, which accounts for both legal and illegal mining. This suggest that previous studies based exclusively on mining titles could be underestimating the effect of mining.

I assess alternative mechanisms through which mining can affect human capital accumulation. While there are no effects on labor participation among children and adolescents, the probability that young adults between 18 and 25 work in mining increased during boom periods. I also assess the effects of mining on aggregate factors that might affect learning. On one hand, royalties and public investment increased in mining regions, with mixed effects in terms of school inputs. On the other hand, mining dramatically increased violence and forced displacement, with potentially negative effects on human capital accumulation.

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Online Appendix
(Not for publication)

Table A.1
Reduced Form Effect of Gold Mining on School Enrollment and Progress by Gender

	School Enrollment (1)	Dropout Rate (2)	Retention Rate (3)	Promotion Rate (4)
A. Primary				
Female	1.364***	-0.312***	0.035	0.331**
	(0.346)	(0.094)	(0.104)	(0.149)
Male	1.201***	-0.304***	0.041	0.313**
	(0.347)	(0.094)	(0.105)	(0.150)
Female=Male (p-value)	0.002	0.270	0.442	0.165
Observations	292296	291030	291030	291030
B. Lower Secondary				
Female	1.401	-0.403**	-0.009	0.425
	(1.234)	(0.197)	(0.184)	(0.300)
Male	0.796	-0.409**	-0.162	0.593*
	(1.222)	(0.198)	(0.187)	(0.306)
Female=Male (p-value)	0.020	0.727	0.000	0.000
Observations	65614	64832	64832	64832
C. Upper Secondary				
Female	0.604	-0.480**	0.204	0.219
	(1.353)	(0.222)	(0.182)	(0.331)
Male	0.698	-0.502**	0.054	0.398
	(1.351)	(0.223)	(0.183)	(0.333)
Female=Male (p-value)	0.756	0.127	0.000	0.000
Observations	42904	42423	42423	42423

Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. Each set of coefficients correspond to a separate panel regression that controls for school and year fixed effects, and education district-specific time trends. The main independent variables are the interaction between gender, the intensity of gold deposits in the 30 km vicinity of schools (normalized with mean zero and standard deviation equal to one), and the logarithm of international gold prices. The p-value of a subgroup difference test is also reported. Standard errors are clustered at the school level.

Table A.2

Reduced Form Effect of Gold Mining on School Enrollment and Progress: Buffer Sensibility

	10 *km* (1)	20 *km* (2)	30 *km* (3)	40 *km* (4)	50 *km* (5)
A. Primary					
School Enrollment	1.910***	2.486***	2.564***	2.789***	2.728***
	(0.559)	(0.625)	(0.692)	(0.763)	(0.813)
Dropout Rate	-0.149*	-0.241***	-0.308***	-0.337***	-0.316***
	(0.085)	(0.089)	(0.093)	(0.097)	(0.099)
Retention Rate	0.084	0.120	0.049	0.008	-0.050
	(0.091)	(0.098)	(0.104)	(0.108)	(0.111)
Promotion Rate	0.086	0.186	0.302**	0.409***	0.464***
	(0.135)	(0.142)	(0.148)	(0.155)	(0.160)
B. Lower Secondary					
School Enrollment	0.998	0.962	2.198	2.604	2.594
	(2.198)	(2.310)	(2.443)	(2.534)	(2.627)
Dropout Rate	-0.312*	-0.287	-0.307	-0.376*	-0.377*
	(0.186)	(0.190)	(0.198)	(0.208)	(0.213)
Retention Rate	-0.160	-0.132	-0.181	-0.184	-0.202
	(0.189)	(0.182)	(0.192)	(0.204)	(0.211)
Promotion Rate	0.504*	0.442	0.523*	0.613*	0.630*
	(0.300)	(0.293)	(0.305)	(0.322)	(0.333)
C. Upper Secondary					
School Enrollment	1.576	0.760	1.302	2.184	2.634
	(2.678)	(2.618)	(2.689)	(2.798)	(2.971)
Dropout Rate	-0.322	-0.330	-0.489**	-0.513**	-0.566**
	(0.207)	(0.204)	(0.215)	(0.230)	(0.237)
Retention Rate	0.019	0.038	0.087	0.113	0.108
	(0.171)	(0.165)	(0.179)	(0.194)	(0.196)
Promotion Rate	0.312	0.298	0.369	0.339	0.408
	(0.321)	(0.310)	(0.327)	(0.352)	(0.362)

Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. Each coefficient corresponds to a separate panel regression that controls for school and year fixed effects, and education district-specific time trends. The independent variable is the interaction between the intensity of gold deposits in the vicinity of schools (normalized with mean zero and standard deviation equal to one) and the logarithm of international gold prices. Vicinity buffers range from 10 to 50 km. Standard errors are clustered at the school level.

Table A.3
Effect of Gold Mining on School Attendance and Overage
(Household Surveys)

	School Attendance			Overage		
	6-9	10-14	15-18	6-9	10-14	15-18
	(1)	(2)	(3)	(4)	(5)	(6)
A. Reduced Form						
Gold Deposits × Price	0.007	0.002	0.027	-0.039*	0.048	-0.053
	(0.020)	(0.020)	(0.039)	(0.023)	(0.031)	(0.039)
B. Instrumental Variable						
Mining Titles	0.004	0.001	0.013	-0.019*	0.022	-0.025
	(0.010)	(0.009)	(0.019)	(0.011)	(0.014)	(0.018)
Kleibergen-Paap F	152.840	162.759	147.795	152.840	162.759	147.795
Mining Deforestation	0.008	0.003	0.032	-0.040	0.059	-0.061
	(0.021)	(0.024)	(0.047)	(0.028)	(0.045)	(0.052)
Kleibergen-Paap F	17.702	21.860	19.887	17.702	21.860	19.887
Mean(y)	0.955	0.937	0.686	0.065	0.308	0.520
Observations	45490	57403	44592	45490	57403	44592

Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. Coefficients in Panel A correspond to separate OLS regression that control for gender, age, parents' education level, rural district fixed effects, year, and month fixed effects, and education district-specific time trends. The independent variable is the interaction between the intensity of gold deposits in the 30 km vicinity of rural district centroids and the logarithm of international gold prices. Coefficient in Panel B correspond to separate instrumental variable regressions that control for gender, age, parents' education level, rural district fixed effects, year, and month fixed effects, and education district-specific time trends. The independent variables are mining titles and mining deforestation in the 30 km vicinity of rural district centroids. The instrument is the interaction between the intensity of gold deposits in the 30 km vicinity of rural district centroids and the logarithm of international gold prices. All mining intensity measures are normalized with mean zero and standard deviation one. Standard errors are clustered at the rural district level.

Table A.4
Effect of Gold Mining on SABER 5 and 9

	SABER 5		SABER 9	
	Language (1)	Mathematics (2)	Language (3)	Mathematics (4)
A. Reduced Form				
Gold Deposits × Price	-0.025	0.114*	0.004	-0.401**
	(0.074)	(0.068)	(0.060)	(0.173)
B. Instrumental Variable				
Mining Titles	-0.023	0.105*	0.003	-0.326**
	(0.069)	(0.063)	(0.049)	(0.142)
Kleibergen-Paap F	1001.567	998.554	272.671	267.291
Mining Deforestation	-0.041	0.172	0.009	-0.901
	(0.119)	(0.105)	(0.136)	(0.550)
Kleibergen-Paap F	52.086	57.537	6.126	5.993
Mean(y)	-0.086	-0.091	-0.162	-0.115
Observations	22125	21991	6141	6100

Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. Coefficients in Panel A correspond to separate OLS regression that control for school and year fixed effects, and education district-specific time trends. The independent variable is the interaction between the intensity of gold deposits in the 30 km vicinity of schools and the logarithm of international gold prices. Coefficient in Panel B correspond to separate instrumental variable regressions that control for school and year fixed effects, and education district-specific time trends. The independent variables are mining titles and mining deforestation in the 30 km vicinity of schools. The instrument is the interaction between the intensity of gold deposits in the 30 km vicinity of schools and the logarithm of international gold prices. All mining intensity measures are normalized with mean zero and standard deviation one. Standard errors are clustered at the school level.

Table A.5
Effect of Gold Mining on SABER 11 (Exit Exam) and Labor Participation by Gender, age, and Parents' Education

	Test Score			
	Language	Mathematics	Total	Works
	(1)	(2)	(3)	(4)
A. Gender				
Female	-0.020***	-0.019***	-0.024***	0.004*
	(0.006)	(0.007)	(0.007)	(0.002)
Male	-0.019***	-0.018**	-0.023***	0.007***
	(0.006)	(0.007)	(0.007)	(0.002)
Female=Male (p-value)	0.082	0.615	0.671	0.000
Mean(y)	-0.196	-0.161	-0.219	0.065
Observations	1023279	1023264	1023138	746101
B. Age				
Under (<=18)	-0.019***	-0.018***	-0.023***	0.005**
	(0.007)	(0.007)	(0.007)	(0.002)
Over (>18)	-0.018**	-0.017**	-0.020***	0.007***
	(0.007)	(0.007)	(0.008)	(0.002)
Under=Over (p-value)	0.543	0.446	0.220	0.000
Mean(y)	-0.196	-0.161	-0.219	0.065
Observations	1023279	1023264	1023138	746101
C. Parents' Education				
Low	-0.019***	-0.017**	-0.023***	0.006**
	(0.006)	(0.007)	(0.007)	(0.002)
High	-0.020***	-0.018**	-0.026***	0.005**
	(0.006)	(0.007)	(0.007)	(0.002)
Low=High (p-value)	0.170	0.683	0.105	0.001
Mean(y)	-0.196	-0.161	-0.219	0.065
Observations	743616	743605	743545	732433

Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. Each set of coefficients correspond to separate OLS regression that control for age and gender, school and year fixed effects, and education district-specific time trends. The main independent variables are the interaction between gender, age, or parents'education level, the intensity of gold deposits in the 30 km vicinity of schools (normalized with mean zero and standard deviation equal to one), and the logarithm of international gold prices. The p-value of a subgroup difference test is also reported. Standard errors are clustered at the school level.

Table A.6
Reduced Form Effect of Gold Mining on College Enrollment by Gender, age, and Parents' Education

	College Enrollment (1)	Accredited College (2)	Academic Degree (3)	STEM Field (4)
A. Gender				
Female	-0.006**	-0.001	-0.005**	-0.003*
	(0.002)	(0.001)	(0.002)	(0.002)
Male	-0.006***	-0.001	-0.005**	-0.003*
	(0.002)	(0.001)	(0.002)	(0.002)
Female=Male (p-value)	0.172	0.172	0.905	0.508
Mean(y)	0.124	0.058	0.100	0.066
Observations	1023282	1023282	1023282	1023282
B. Age				
under (<=18)	-0.006**	-0.001	-0.005**	-0.003*
	(0.002)	(0.001)	(0.002)	(0.002)
over (>18)	-0.006**	-0.003*	-0.005**	-0.003**
	(0.002)	(0.001)	(0.002)	(0.002)
Under=Over (p-value)	0.937	0.001	0.494	0.333
Mean(y)	0.124	0.058	0.100	0.066
Observations	1023282	1023282	1023282	1023282
C. Parents' Education				
Low	-0.006**	-0.002	-0.006***	-0.002
	(0.002)	(0.001)	(0.002)	(0.002)
High	-0.007***	-0.001	-0.007***	-0.002
	(0.003)	(0.002)	(0.002)	(0.002)
Low=High (p-value)	0.394	0.021	0.240	0.813
Mean(y)	0.124	0.058	0.100	0.066
Observations	743618	743618	743618	743618

Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. Each set of coefficients correspond to separate OLS regression that control for school and year fixed effects, and education district-specific time trends. The main independent variables are the interaction between gender or parents'education, the intensity of gold deposits in the 30 km vicinity of schools (normalized with mean zero and standard deviation equal to one), and the logarithm of international gold prices. The p-value of a subgroup difference test is also reported. Standard errors are clustered at the school level.

Table A.7
Reduced Form Effect of Gold Mining on SABER 11 (Exit Exam) and Labor Particiaption: Buffer Sensibility

	10 *km* (1)	20 *km* (2)	30 *km* (3)	40 *km* (4)	50 *km* (5)
A. Test Scores					
Language	-0.013**	-0.017***	-0.019***	-0.018***	-0.016**
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
Mathematics	-0.015**	-0.018***	-0.019***	-0.018**	-0.014*
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
Total Score	-0.015**	-0.022***	-0.024***	-0.021***	-0.017**
	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
B. Exam Takers					
Number	-0.582	-0.472	-0.649	-0.482	-0.262
	(0.717)	(0.787)	(0.906)	(1.012)	(1.065)
Age.	-0.011	0.002	-0.005	0.003	0.014
	(0.029)	(0.031)	(0.031)	(0.031)	(0.032)
C. Labor Participation					
Works	0.004*	0.005**	0.005**	0.004*	0.004*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)

Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. Each coefficient corresponds to a separate OLS regression that control for school and year fixed effects, and education district-specific time trends. Individual-level regressions also control for the students' age and gender. The independent variable is the interaction between the intensity of gold deposits in the vicinity of schools (normalized with mean zero and standard deviation equal to one) and the logarithm of international gold prices. Vicinity buffers range from 10 to 50 km. Standard errors are clustered at the school level.

Table A.8
Reduced Form Effect of Gold Mining on College Enrollment: Buffer Sensibility

	10 *km* (1)	20 *km* (2)	30 *km* (3)	40 *km* (4)	50 *km* (5)
College Enrollment	-0.005***	-0.006***	-0.006***	-0.006**	-0.006**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Accredited College	0.000	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Academic Degree	-0.005***	-0.005***	-0.005**	-0.005**	-0.005**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
STEM Degree	-0.002	-0.002	-0.003*	-0.003*	-0.003*
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)

Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. Each coefficient corresponds to a separate OLS regression that control for gender and age, school and year fixed effects, and education district-specific time trends. The independent variable is the interaction between the intensity of gold deposits in the vicinity of schools (normalized with mean zero and standard deviation equal to one) and the logarithm of international gold prices. Vicinity buffers range from 10 to 50 km. Standard errors are clustered at the school level.

Table A.9
Effect of Gold Mining on Hours Worked by Children and Young Adults

	Mining Sector			Non-Mining Sectors		
	10-14 (1)	15-18 (2)	19-25 (3)	10-14 (4)	15-18 (5)	19-25 (6)
A. Reduced Form						
Gold Deposits × Price	-0.161**	-0.590	2.077***	-0.175	-1.534	-0.693
	(0.074)	(0.448)	(0.788)	(0.392)	(1.575)	(2.125)
B. Instrumental Variable						
Mining Titles	-0.073**	-0.277	0.970***	-0.080	-0.719	-0.324
	(0.034)	(0.203)	(0.363)	(0.181)	(0.744)	(0.993)
Kleibergen-Paap F	3957.176	3054.306	3549.835	3957.176	3054.305	3549.836
Mining Deforestation	-0.190**	-0.664*	2.680***	-0.208	-1.724	-0.894
	(0.086)	(0.380)	(0.780)	(0.483)	(1.809)	(2.831)
Kleibergen-Paap F	131.351	66.310	131.029	131.351	66.310	131.029
Mean(y)	0.022	0.145	0.394	1.143	7.680	22.303
Observations	57403	44592	60076	57403	44592	60076

Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. Coefficients in Panel A correspond to separate OLS regression that control for gender, age, parents' education level, rural district, year and month fixed effects, and education district-specific time trends. The independent variable is the interaction between the intensity of gold deposits in the 30 km vicinity of rural district centroids and the logarithm of international gold prices. Coefficient in Panel B correspond to separate instrumental variable regressions that control for gender, age, parents' education level, rural district, year and month fixed effects, and education district-specific time trends. The independent variables are mining titles and mining deforestation in the 30 km vicinity of rural district centroids. The instrument is the interaction between the intensity of gold deposits in the 30 km vicinity of rural district and the logarithm of international gold prices. All mining intensity measures are normalized with mean zero and standard deviation one. Standard errors are clustered at the rural district level.

Table A.10
Reduced Form Effect of Gold Mining on Labor Participation of Children and Young Adults by Gender and Parents' Education

	Mining Sector			Non-Mining Sectors		
	10-14	15-18	19-25	10-14	15-18	19-25
	(1)	(2)	(3)	(4)	(5)	(6)
A. Gender						
Female	-0.004*	-0.014	0.034**	0.024	0.005	0.002
	(0.002)	(0.014)	(0.016)	(0.018)	(0.040)	(0.047)
Male	-0.003*	-0.012	0.040**	0.018	-0.019	-0.039
	(0.002)	(0.013)	(0.016)	(0.018)	(0.039)	(0.046)
Female=Male (p-value)	0.121	0.038	0.003	0.000	0.000	0.000
Mean(y)	0.001	0.004	0.008	0.048	0.206	0.480
Observations	57403	44592	60076	57403	44592	60076
B. Parents' Education						
Low	-0.003*	-0.013	0.037**	0.016	-0.004	-0.022
	(0.002)	(0.014)	(0.016)	(0.018)	(0.039)	(0.044)
High	-0.004*	-0.014	0.037**	0.018	0.004	-0.021
	(0.002)	(0.014)	(0.016)	(0.018)	(0.039)	(0.044)
Low=High (p-value)	0.145	0.415	0.793	0.038	0.000	0.304
Mean(y)	0.049	0.210	0.489	0.048	0.206	0.480
Observations	57403	44592	60076	57403	44592	60076

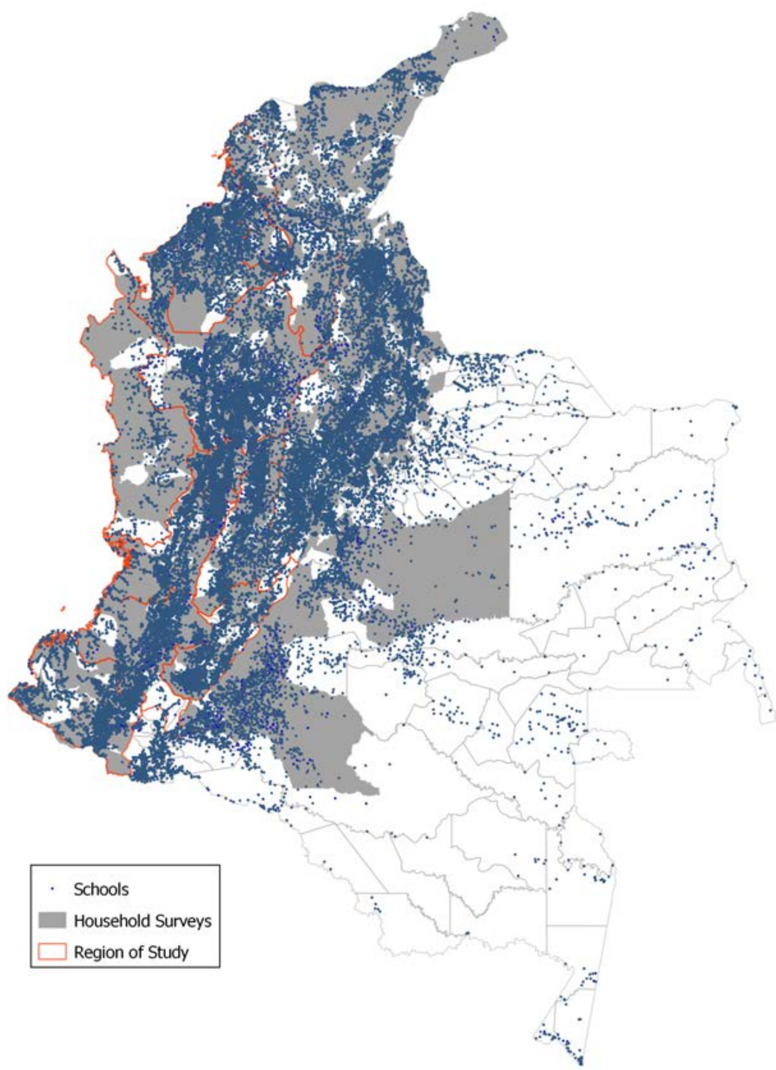
Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. All Coefficients correspond to separate OLS regression that control for gender, age, parents' education level, rural district fixed effects, year, and month fixed effects, and education district-specific time trends. The independent variable is the interaction between gender and parents' education, the intensity of gold deposits in the 30 km vicinity of rural district centroids, and the logarithm of international gold prices ((normalized with mean zero and standard deviation equal to one). The p-value of a subgroup difference test is also reported. Standard errors are clustered at the rural district level.

Table A.11
Mining Sector Wage Premium for Children and Young Adults by Gender and Parents' Education

	10-14 (1)	15-18 (2)	19-25 (3)
A. Full sample			
Mining	0.175	-0.082	0.060*
	(0.252)	(0.064)	(0.033)
Mean(y)	7.981	8.345	8.764
Observations	895	5599	22311
B. Gender			
Female	-0.185	0.080	-0.249***
	(0.762)	(0.226)	(0.079)
Male	0.231	-0.084	0.156***
	(0.257)	(0.067)	(0.036)
Female=Male (p-value)	0.593	0.481	0.000
Mean(y)	7.981	8.345	8.764
Observations	895	5599	22311
C. Parents' Education			
Low	0.292	-0.009	0.077*
	(0.259)	(0.067)	(0.040)
High	-1.289	-0.635***	0.118**
	(1.181)	(0.199)	(0.054)
Low=High (p-value)	0.192	0.002	0.518
Mean(y)	7.981	8.345	8.764
Observations	895	5599	22311

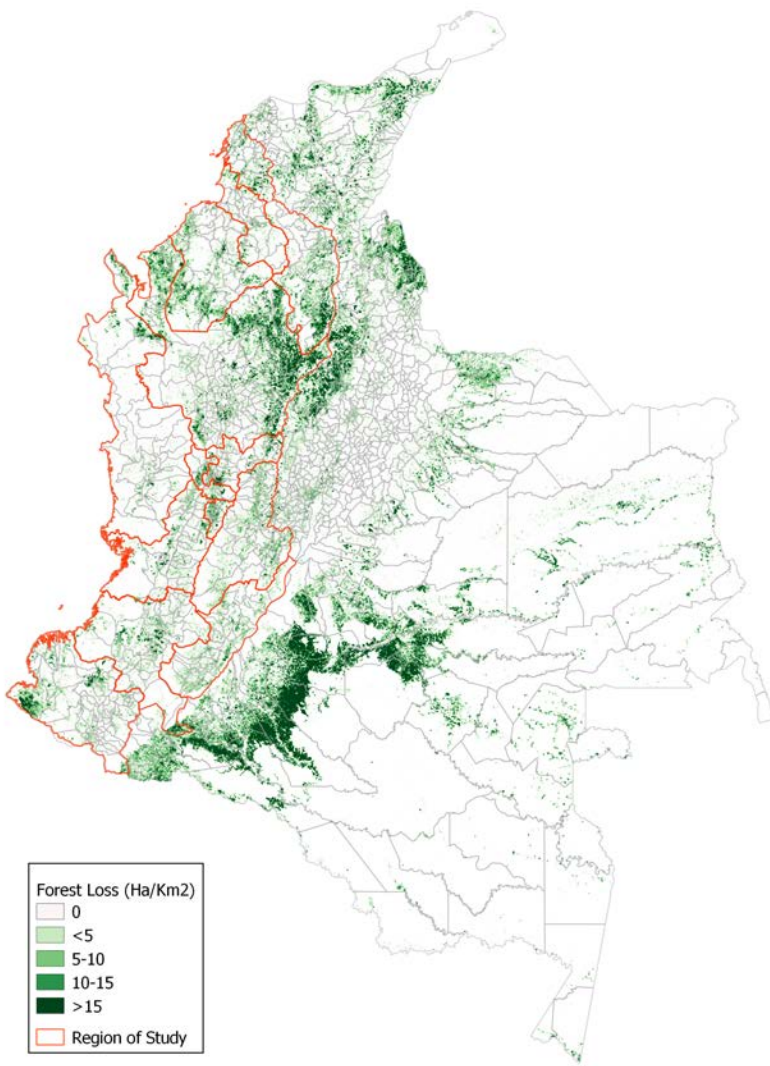
Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. All coefficients correspond to separate OLS regression that control for gender, age, parents and children education level, rural district fixed effects, and year and month fixed effects. The independent variable is the interaction between gender and parents' education and a mining sector indicator. The p-value of a subgroup difference test is also reported.

Figure A.1
Geographic Distribution of Public Schools and Household Surveys



Source: Author's calculations based data from MEN and DANE. Each blue point represents a school. The grey area corresponds to municipalities with household surveys. The red line delimits the region of study.

Figure A.2
Forest Loss (2001-2014)



Source: Author's calculations based data from SIGOT and Hansen et al. (2013).
Notes: Accumulated Forest loss between 2001 and 2014 is aggregated at a spatial resolution of 1 km^2 and expressed in Ha/km^2. The red line delimits the region of study.