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The Local Human Capital Costs of Oil Exploitation*

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Abstract

This paper explores the impacts of oil exploitation on human capital accumulation at the local level in Colombia, a resource-rich developing country. We provide evidence based on detailed spatial and temporal data on oil exploitation and education, using the number of wells drilled as an intensity treatment at the school level. To find causal estimates we rely on an instrumental variable approach that exploits the exogeneity of international oil prices and a proxy of oil endowments at the local level. Our results indicate that oil has a negative impact on human capital since it reduces enrollment in higher education. Furthermore, it generates a delay in the decision to enroll in higher education and leads students to prefer technical areas of study and programs in social science, business, and law. However, we do not find any effects on quality or tertiary education completion. Our results are robust to a number of relevant specification changes and we stress the role of local markets and spillovers as the main transmission channel. In particular, we find that higher oil production causes an increase in formal wages but that there is no premium to tertiary education enrollment.

Keywords: Natural Resource Exploitation, Human Capital, Colombia.

JEL classification: I23, Q32, Q35.

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1 Introduction

Natural resource exploitation and its effect on the economic performance of countries has been extensively studied. Some scholars argue that human capital accumulation is one of the mechanisms through which the natural resource curse might operate. However, consensus has yet to be reached as to whether natural resource exploitation hinders or fosters human capital accumulation. Certain studies find a negative relationship between natural resource exploitation and human capital accumulation (Birdsall et al., 2001; Gylfason, 2001; Papyrakis and Gerlagh, 2004), while others provide compelling evidence of a positive relationship (Smith, 2015; Stijns, 2006). The quality of the institutions (Ebeke et al., 2015) and the type of natural resource measures used (Stijns, 2006) may drive these differences. While much research has been done at the country level, we still know surprisingly little about the effects of natural resources at the subnational level (Aragón et al., 2015). Findings at this level indicate that natural resource exploitation causes lower school attendance (Santos, 2018), educational attainment (Ahlerup et al., 2020), education quality (Bonilla, 2020), promotion rates (Cascio and Narayan, 2020), and tertiary education enrollment (Bonilla, 2020). However, results on this front are also mixed as there is evidence of natural resource exploitation increasing promotion rates, high school enrollment (Bonilla, 2020) and education quality (Agüero et al., 2021).

In this paper we explore the impacts of oil exploitation on human capital accumulation at the local level. Specifically, we study the case of Colombia, a developing and highly oil-dependent country, using administrative data from 2002 to 2014 on all high school students in the country. The data captures education quality (as measured with performance in a national exam), tertiary education decisions and the exact location of schools. We also use data from the National Hydrocarbons Agency (ANH), which contains the location and spud date of every oil well ever drilled in Colombia.[1]

We exploit the exogeneity of international oil prices and the location of oil endowments, relying on an instrumental variable approach to find causal estimates. As a proxy of school-level oil production, we use the number of wells drilled within a certain distance of the school. As this measure is potentially biased due to endogeneity issues, we instrument it with the interaction between international oil prices and an oil suitability measure at the school level. The latter is measured as the total number of wells drilled in the buffer around the school for a given year before the first year of our analysis. The basic intuition behind our instrument is that international oil prices and the oil endowments of the school should affect human capital accumulation decisions only as they change the year-to-year oil production at the school level.

In our context, the results suggest that oil operates as a curse in terms of human capital accumulation at the local level. First, we find that an increase in oil exploitation reduced the enrollment rate in higher education programs. An increase of one standard deviation in the number of wells generated a decrease of 2.81 pp in the enrollment rate in our benchmark model. Second, our results show that oil exploitation affects the talent allocation decisions of students. An increase in the number of nearby wells causes a higher proportion of students to

[1]The spud date indicates the day the drilling process began.

enroll in technical degree programs. This is consistent with the structure of oil production in Colombia, which employs a larger amount of non-trained workers and those with a technical training than professional workers, which we term the "talent allocation effect". Likewise, oil activity increases the proportion of students and the probability of enrolling in higher education programs in business, economics, law, social sciences and related programs, as compared to STEM. We also find evidence of what we call a "delay effect". In line with Emery et al. (2012), our findings indicate that oil exploitation changes the timing of tertiary education decisions, generating a delay in students' enrollment of about three months.

These findings are robust to a number of relevant transformations, including changing the definition of school vicinity, adjusting for the life cycle of oil wells, and using different thresholds to measure our instrument. Moreover, our results are not driven by selection, as there is no effect on the number of students, or on education quality. This is in line with our identification strategy, which stresses the fact that schools are unable to directly benefit from rents derived from oil exploitation in their vicinity. Focusing our analysis at the school and individual level allows us to disentangle the higher rent effect from a local economic activity and labor market effect. Using data on formal wages for a subset of the students in our sample, we show that the latter mechanism is most likely operating in our setting. We find that a one standard deviation increase in the number of wells rises annual income by approximately 4 current minimum wages.

In conducting this analysis, we contribute to the literature on the dynamics of natural resource exploitation. Very little research has explored the effects of oil exploitation on educational outcomes at the subnational level. Cascio and Narayan (2020) estimate that fracking increased high school dropout rates in production areas while James (2017) finds lower graduation rates during oil booms in resource-rich states in the US. Tangential evidence shows that public expenditures on education are higher in oil-producing states or municipalities (Caselli and Michaels, 2013; James, 2017), though this does not necessarily translate into higher welfare (Caselli and Michaels, 2013), perhaps due to patronage (Robinson et al., 2006). Other studies focus on the effects on corruption (Brollo et al., 2013; James and Rivera, 2019; Vicente, 2010), civil conflict and democracy (Brückner and Ciccone, 2010; Dube and Vargas, 2013; Tsui, 2011), wages (Kearney and Wilson, 2018), and general local economic indicators (Bartik et al., 2019). We build on this body of work by carrying out our assessment at a non-administrative local level (schools and individuals). This allows us to identify one of the main mechanisms of transmission of the resource curse (or blessing), namely the local market spillover effect.

We also join a nascent strand of literature that uses resource endowments and exploitation measures to overcome certain challenges in identifying the causal effects of natural resources on different scenarios. Most such studies rely on an instrumental variable approach to deal with selection, measurement error, or omitted variable biases. Examples include using some measures of oil or gas shale formations and gas well drilling (Maniloff and Mastromonaco, 2017), production (Brown, 2014), employment (Feyrer et al., 2017), gas property taxes (Weber et al., 2016), and gold deposits and gold mining titles (Bonilla, 2020). Yet, to the best of our knowledge, our paper is the first to use conventional oil wells as a treatment measure at a non-administrative local level and fully exploit the temporal and spatial variation in well drilling.

In addition, our study is tangentially related to the conflict literature, in particular that of armed conflict in Colombia. Conflict in this country has been measured with war-related episodes (*e.g.* Dube and Vargas, 2013; Prem et al., 2020) or self-reported violence victims (*e.g.* Ibáñez and Vélez, 2008). We contribute to this work by proposing a new, local measure of violence using detailed data on the location of all accidents involving landmines. The data, collected by the High Commissioner for Peace (OACP), allows us to control for violence shocks at a very granular level, that of schools and individuals.

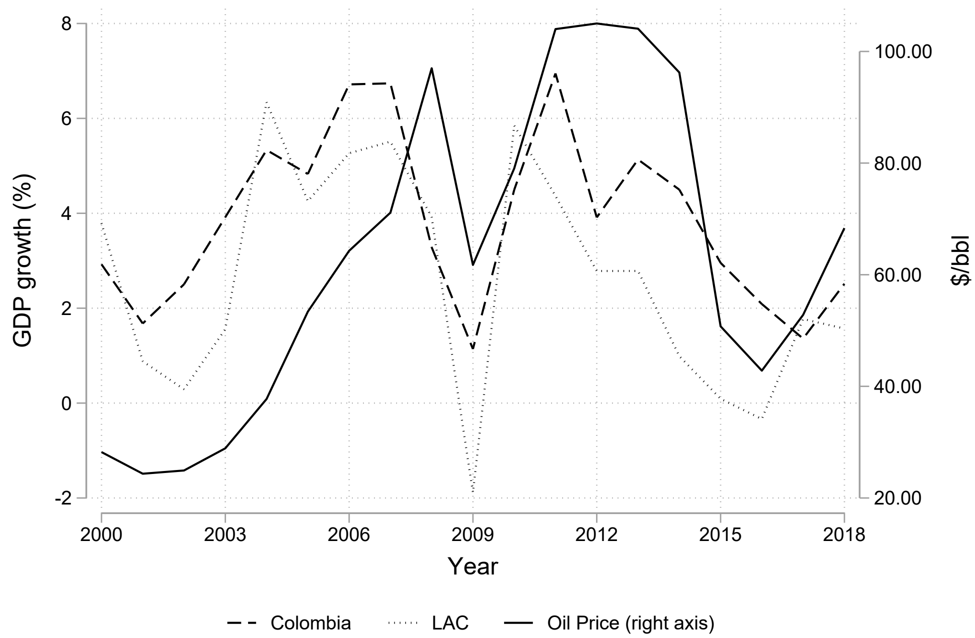
The rest of the paper is organized as follows. Section 2 gives an overview of oil exploitation in the Colombian context while Section 3 describes the data. Section 4 then presents our empirical strategy. Section 5 shares the results of the study and Section 6 discusses the robustness checks. Section 7 presents evidence of our main mechanism and, finally, Section 8 concludes with a discussion and a reflection on the policy implications of our findings.

2 Oil Exploitation in Colombia

Natural resource exploitation has played a central role in the economic performance of many countries in Latin American and the Caribbean (LAC), constituting one of the key pillars of regional economies for many decades. Oil, gas, and mining rents alone accounted, on average, for 5% of LAC countries' GDP and nearly 27% of the region's total exports in the last decade. The extractive sector is particularly important in Colombia. Oil, gas, and mining represented nearly 60% of the total exports and the rents accounted for nearly 6% of the national GDP in that same period.[2] Furthermore, economic growth in Colombia and the region is highly correlated with the international oil price (see Figure 1). During the global financial crisis of 2008, oil prices plummeted but quickly returned to record-high levels in 2010.

[2] Authors' calculations based on data from the World Bank and the Atlas of Economic Complexity at Harvard University.

Figure 1: Dependence on Oil Performance



The oil price shown is an equally weighted measure of the Brent, Dubai and WTI spot prices.
Source: Authors' calculations based on the World Bank's pink sheet and development indicators.

The Colombian oil sector, once dominated by the public sector, has seen major efforts to increase private participation since 2000. For instance, State participation in oil exploration and exploitation activities was mandatory until 2003, when the requirement was dropped. In return, private firms must pay royalties based on reported production.[3] Nevertheless, the State is the majority shareholder of Ecopetrol, one of Colombia's biggest oil companies. Since 2003, the ANH has been in charge of regulating and managing the State participation in the Colombia oil sector. Changes to Ecopetrol and the creation of the ANH were an additional component of the policies seeking to ensure efficiency in the oil sector Balza and Espinasa (2015); Gómez (2013).

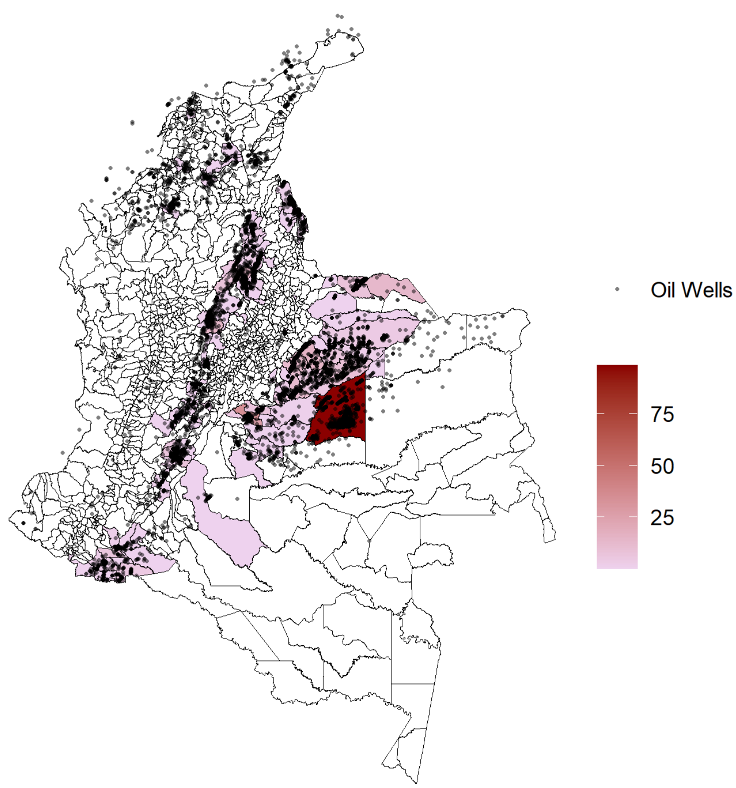
Exploration activities in Colombia's offshore fields have been largely unsuccessful and, to this day, the vast majority of the country's production occurs in onshore oil fields. Oil production is scattered throughout the country, with particularly high levels of production in some regions. Figure 2 shows the mean oil production between 2011 and 2016 for all municipalities and the location of every oil well ever drilled in the country. While oil production is concentrated in the country's western, production sites are also present along the northern coast, the central region and the south. The overlap between oil-producing regions

[3]Before 2012 only oil-producing municipalities and departments received those royalties. Since then, all municipalities are eligible to receive part of the royalties derived from natural resource exploitation. See Bonet-Morón et al. (2018) for a full account on the history of the fiscal regime in Colombia.

and the locations of oil wells is evident and natural, since wells are a necessary part of the oil production infrastructure.

Oil exploitation activities in Colombia do not require a large professional workforce. In fact, there is a higher demand for non-qualified and technical workers at most stages of the oil exploitation process. Table 1 shows the relative demand for different types of workers at some of the most important stages of the oil exploitation process, as calculated by Gómez (2013) for Colombia, where we see that the demand for professional workers is lower than non-professional workers at every stage. Furthermore, demand for non-professional workers appears to be highest during the exploration and production stages. The basic features of labor demand in the oil sector oil could affect students' decisions related to higher education. Specifically, since oil exploitation activities create a larger demand for non-professional workers, the oil sector might generate incentives for students not to enroll in higher education or to prefer technical programs. As oil is, by nature, a spot commodity, the local labor market might see larger demand increases.

Figure 2: Mean Oil Production (2011-2016) and Oil Wells Location



This figure shows the mean oil production (million barrels) between 2011 and 2016 in Colombian municipalities and the location of all the oil wells ever drilled in the country. Source: Authors' calculation using data from ANH.

Table 1: Oil-sector Workers' Level of Training

Stage	Professional	Technical	Non-Qualified
Exploration	6%	41%	53%
Evaluation and Development	44%	31%	25%
Drilling and Testing	18%	23%	59%
Development and Production	3%	43%	54%

Note: Gómez (2013) calculations. This table shows the proportion of professional, technical and non-trained workers at different upstream stages in the oil sector.

3 Data

Oil Activity

For the purposes of this paper, we exploit data on oil exploitation and exploration with a rarely seen level of spatial and temporal variation. We use the location and the spud date of every oil well ever drilled in Colombia to create a measure of oil production at the local level. Data on oil wells location and drilling dates is reported by the ANH, the national agency in charge of regulating the oil sector in Colombia. According to our data, the first oil well in Colombia was drilled in 1918 and, as of April 2020, a total of 21,115 oil wells had been drilled in the country. Unfortunately, the data does not allow us to differentiate between producing and non-producing wells. Given confidentiality concerns and political pressure, there is often a lack of reliable data on oil exploitation and reserves (Laherrère, 2003). Our paper is the first, to the best of our knowledge, to use data with this level of granularity to explore the impacts of oil production.

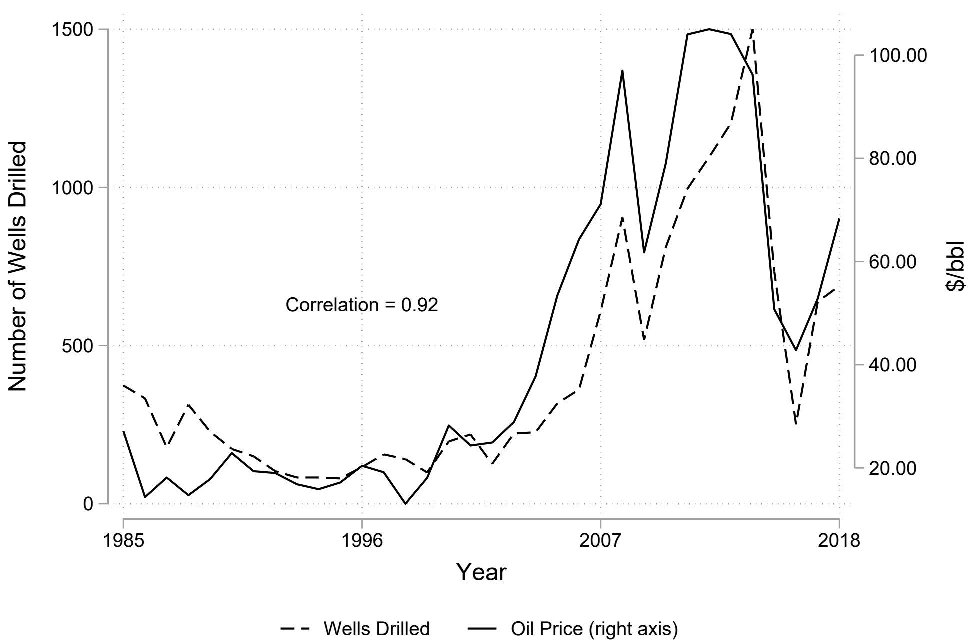
As the most basic infrastructure needed for oil production, oil well drilling reacts very quickly to changes in international oil prices. This is clear in Figure 3, where the number of oil wells drilled is quite responsive to the international price of oil, with a Parson's correlation of 0.92. At the same time, the number of oil wells drilled is strongly correlated with total oil production. Unfortunately, the data does not include information on the production levels of each well, nor does it have information on the success of the well or the well type (exploratory or productive well). However, using available information from the ANH we show in Table 2 that there is a statistically significant correlation between the number of wells and oil production both at the field concession and municipality levels. Even though we cannot differentiate between producing and non-producing oil wells, this stylized fact shows that our data are the best proxy available for oil production at the local level, allowing us to measure the intensity of oil exploitation in every possible polygon within the country.

Table 2: Correlation between Number of Wells and Oil Production

	Barrels (Thousands)	
	Field Concession	Municipality
Wells	11.26***	12.22***
	(1.39)	(0.29)
Observations	112	4312
Adjusted R^2	0.22	0.99
Mean Production	28.99	322.08

Note: This table presents the results of a simple OLS exercise using the number of wells and oil production. Municipality-level data is from 2004 to 2018, while field concession data is only available from 2011 until 2019. Wells are the cumulative total number of wells drilled in the location every year. Results are presented at the field-concession level and at the municipality level. Year fixed effects were included. Municipality fixed effects were only included for the correlation at the municipality level. Robust standard errors in parentheses; *** $p < 0.01$

Figure 3: Oil Well Drilling in Colombia

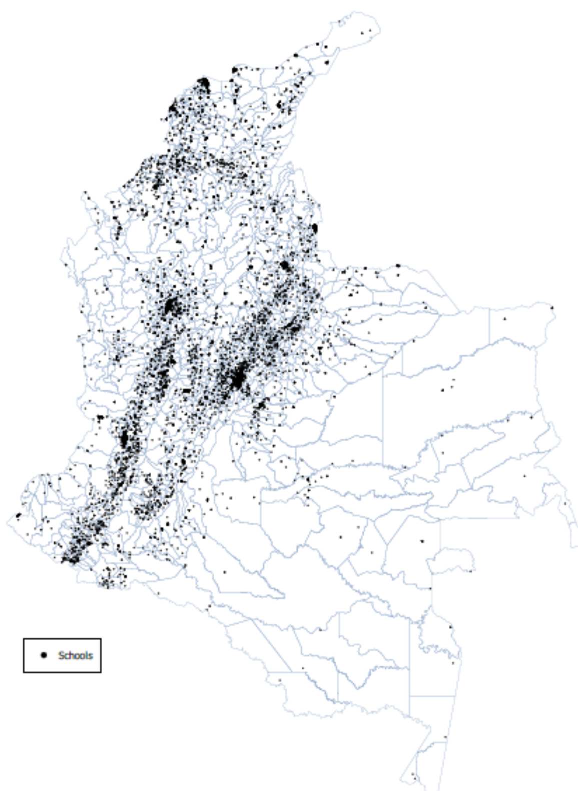


Note: Authors' calculations based on data from the World Bank and ANH. Oil price is an equally weighted measure of Brent, Dubai and WTI spot prices. We show the total number of wells drilled every year in the country.

Education

We employ administrative data that allows us to capture crucial dimensions of human capital accumulation from 2002 until 2014 and to track secondary school graduates into higher education. For the purpose of this paper, we only consider students who graduated from high school in a city with fewer than 200,000 inhabitants. Colombia has 1,122 municipalities in total, only 26 of which were excluded from our sample. This was done as natural resource exploitation activities are unlikely to have an impact in big cities.[4] We use the school coordinates provided by the Ministry of Education (see Figure 4). Since some schools can have more than one shift (*e.g.*, morning or afternoon), we consider each shift to be a separate school. That is, we regard a given school not as a set of buildings, but rather as a group of norms and institutions (*i.e.*, teachers, students). Our sample consists of 7,668 schools, of which 78% are public and 58% are rural.

Figure 4: Location of Secondary Schools



Note: Authors' plot based on data from the Ministry of Education. This figure indicates the location of all high schools in Colombia included in our study. Schools located in municipalities with more than 200,000 inhabitants were excluded.

[4]Actually, Bonilla (2020) takes the same approach when studying the case of gold mining in Colombia.

We use the secondary school exit exam (ICFES) as a measure of general student quality. The ICFES is required for college enrollment and is often used as a threshold for scholarship programs.[5] Since tests change over time and reported scores are not comparable, we use students' percentile score rather than the raw test score. Our sample includes information on 2,855,798 students who graduated between 2002 and 2014. In addition, we track all of the students into higher education using the higher education dropout prevention system database (SPADIES), which also reports basic information on the program in which students enrolled.

Related studies argue that natural resource rents cause a displacement of individuals from the productive sector of the economy to the rent-seeking sector (Mehlum et al., 2006). Even more, Ebeke et al. (2015) find that oil rents push students to pursue degrees in areas related to economics, business and law as opposed to those related to engineering, manufacturing and construction. The former group are regarded as grabber-friendly, while the latter group are seen as producer-friendly. Following this strand of the literature, we create a measure indicating whether students enrolled in a program related to economics, business or law, or in a STEM program (natural sciences and engineering).

For every student in our sample we know the semester in which the student took the ICFES and the semester when the student started a higher education program. A student might decide not to enroll in higher education if the returns are not high enough to compensate for the opportunity cost (Becker, 1964). Nevertheless, students could also simply delay their decision to enroll in higher education programs and benefit in the short term from the rents derived from resource exploitation. In fact, previous evidence suggests that an oil boom may simply change the timing of schooling rather than the enrollment decision itself (Emery et al., 2012). Thus, we measure the number of semesters that passed between a student's high school graduation and higher education enrollment.[6]

In Table 3 we present the descriptive statistics of our human capital measures. Approximately 46% of our sample enrolled in some higher education program. Furthermore, 78% of those who enrolled in higher education did so in a professional program rather than a technical one, 44% enrolled in a program related to economics, business, law or social sciences, and 30% in a STEM program. The average student took 4.5 semesters–a delay of two full years– to enroll in a higher education program.

Next, we build an intensity measure to capture whether there are more students choosing a professional program. We define the Professional intensity as the difference between enrollment in professional programs (4+ year degrees) minus enrollment in technical programs expressed as a proportion of total enrollment in higher education. By nature, this variable and the enrollment rate can only be defined at the school level.

[5] One of the most ambitious education programs in Colombia, called Ser Pilo Paga, provides financial aid for higher education based on students' scores on the ICFES exam. For the interested reader, Londoño-Vélez et al. (2020) offer an extensive analysis of the program.

[6] Students in Colombia can enter a higher education program either in January or July.

Table 3: Basic Descriptive Statistics

Outcome	Mean	Std. Dev.	Obs
A. Individual Level			
ICFES percentile	46.04	27.97	2,855,798
Enrolled in HE	0.46	0.49	2,855,798
Business-related program	0.44	0.49	1,315,277
STEM programs	0.33	0.47	1,315,277
Other programs	0.22	0.41	1,315,277
Semesters to enrollment	4.52	4.67	1,245,263
Professional program	0.78	0.42	1,183,820
Completion	0.42	0.49	547,756
B. School Level			
Enrollment rate	43.65	20.39	69,050
Professional intensity	46.07	38.10	67,058

Note: Authors' calculations based on data from SPADIES and ICFES. Following Ebeke et al. (2015), rent-accessible programs are defined as programs related to economics, business, law and social sciences. STEM programs are those of engineering and the natural sciences. Professional program intensity is defined as the difference between enrollment in professional and technical programs as a proportion of total higher education enrollment.

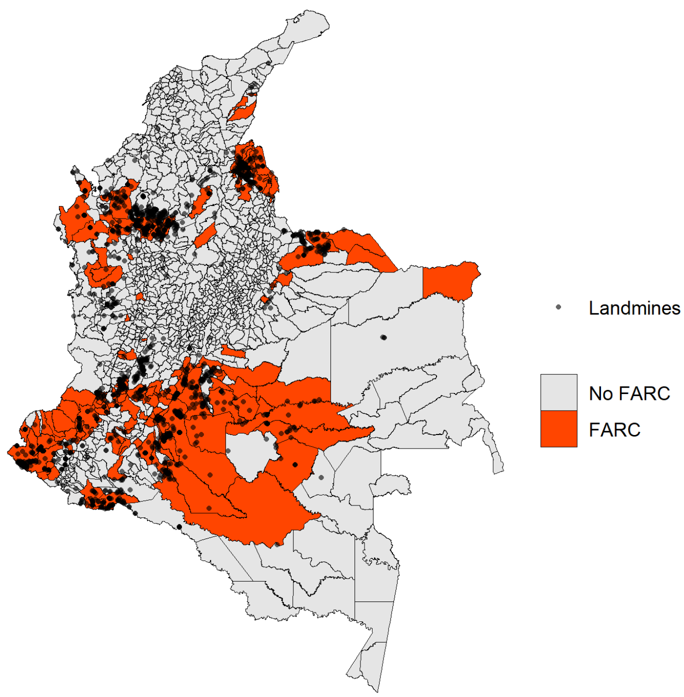
Local Violence

We use data on the exact location and year of detonation of every landmine accident in Colombia to capture violence at the local level. The information is gathered by the High Commissioner for Peace (OCAP), with assistance from local authorities. Every reported accident is verified, which takes between one and three months according to OCAP official website.

Landmines were extensively used throughout the country by guerrilla groups, primarily as a mechanism to defend against and attack the military, but also to protect their coca plantations (Ruiz and Pinto, 2017). In Figure 5 we show the location of all the landmines that exploded after 2010. There is a clear overlap with municipalities where the FARC, Colombia's largest guerilla group, was present between 2011 and 2016. We use the same definition of FARC presence as Prem et al. (2020), and their open data. Appendix Figure A1 shows the distribution of all the landmine events in Colombia's history according to OCAP.

As far as we are aware, ours is the first paper to employ this source of information for the case of Colombia. Doing so allows us to measure the intensity of civil conflict every year at the local level. Indeed, future studies on conflict in Colombia might benefit from the ability to measure violence shocks at this granular level. OCAP's strict verification procedures represent a considerable advantage over conflict measures based on self-reporting. The data also has the advantage of being spatially flexible since it allows conflict to be measured over time in any area of the country. Measures at the municipality level are, by nature, less flexible and usually show little spatial variation over time.

Figure 5: Landmines and FARC Presence



Landmines accidents after 2010.
Source: FARC presence data made available by Prem et al. (2020) and collected and edited by Restrepo et al. (2004) and the Universidad del Rosario. Landmine accidents reports were collected by the *Oficina del Alto Comisionado para la Paz (OACP)*

Other

In addition to the above-described information, we also have data on income for a subset of the students in our sample. Specifically, we draw from the PILA database, which records all payments to social security in the formal sector and the number of days worked per year, as well as the main ISIC code of the industry in which the student was employed. It thus covers the salaries and worked days from 2008 until 2014 for all students who joined the formal labor force. Annual income is simply the sum of the reported contributions to social security and is normalized by the legal minimum wage in a given year.

4 Identification Strategy

To estimate the impact of oil activity on different dimensions of human capital accumulation, we propose a school-level measure of oil production using information on the number of wells drilled in the vicinity of the educational institution. As discussed in section 3, the number of oil wells is the best proxy for oil production at the local level. Measuring the number of oil wells drilled within a buffer around the school allows us to use the most detailed available information on oil production in Colombia and its distribution over space and time. Using school coordinates and detailed information on oil wells locations for every year in our study, we can count the number of wells that are drilled around each school in the country in a given year, allowing us to capture the effect of higher oil activity. In our benchmark model we count wells that are within a 10km buffer around the school, though our results are also robust to buffers ranging from 5km to 30km. The average school has 12.9 wells within the 10km buffer, but this figure is quite variable, with a standard deviation of 105.05 wells (see Table 4). Table 5 shows the number of schools that had at least one oil well drilled within these buffers by the year 2000. Naturally, as the buffer size increases, the number of schools with at least one oil well within the buffer area rises as well.

Table 4: Wells and Landmines at the School Level

Variable	Mean	Std. Dev.	Max	Obs.
Wells	12.9	105.05	1,993	69,050
Landmines	0.25	1.16	26	69,050

Note: Authors' calculations based on data from ANH, Ministry of Education, and OCAP. Values are calculated using a buffer of 10km around every school, which corresponds to our benchmark model.

Table 5: Schools with Nearby Wells Prior to 2000

Buffer	5 km	10 km	20 km	30 km
Schools	851	1,946	3,450	4,394

Note: Authors' calculations based on data from ANH and Ministry of Education. Number of schools that have at least one well drilled nearby prior to the year 2000 using different buffers.

We estimate the impact of oil activity on educational outcomes by using the number of wells drilled around the school as an intensity treatment. Since our data allows for aggregation at the school level, the model specification depends on the unit of analysis. For educational outcomes at the school level (*e.g.*, enrollment rate), we estimate a fixed effects panel as in Equation 1. y_{st} measures a dimension of human capital in school s and year t. $Wells_{st}^{k}$ is our variable of interest, measuring the total number of wells that have ever been drilled around the school s by year t within a buffer of k kilometers. γ_s are school level fixed effects, λ_{dt} captures department-time trends, and X_{st}^{k} controls for the total number of landmine accidents in the vicinity of s in year t. When using individual measures of human capital accumulation (*e.g.*, test scores), we estimate a repeated cross-section as in Equation 2. The model also includes school fixed effects, department-time trends, and controls for landmine accidents and student's gender and age. Since the high school graduation year and the year of enrollment in tertiary education are both available in our dataset, we assign a student to the graduation year when estimating the effects on enrollment decisions and assign the student to the enrollment year when estimating completion decisions. In our benchmark model, we count wells within 10 km, but present robustness checks at different buffer ranges. The decision to employ a 10km buffer is also based on the relatively low number of schools with wells within a smaller buffer.

$$y_{st} = \beta Wells^k_{st} + \delta X^k_{st} + \gamma_s + \lambda_{dt} + \epsilon_{st} \tag{1}$$

$$y_{ist} = \beta Wells^k_{ist} + \delta {X^k}_{ist} + \gamma_s + \lambda_{dt} + \epsilon_{ist} \tag{2}$$

The school fixed effects swept out any time-invariant characteristics of the schools in our dataset, while the department-time trend captures all common shocks over time that schools in the same department might face. We use quadratic trends as they fit better with the oil price dynamics during the study period, but our results are robust to different polynomial specifications. An ordinary least squares (OLS) estimation of Equation 2 and Equation 1 has two econometric concerns in the setting of this study: omitted variables and reverse causality.

There are two obvious omitted variables that can affect tertiary education decisions and also be correlated with oil drilling activity. First, an oil company might take public education spending into account when locating oil wells, as the latter could influence the local labor supply and as well as the costs of drilling. The fact that we use schools and individuals as our unit of analysis mitigates this concern as schools do not directly receive any rents derived from oil activities.

Second, violence and conflict have been shown to affect education decisions in several different contexts (Barrera and Ibañez, 2004; Miguel and Roland, 2011; Shemyakina, 2011), including Colombia (Rodriguez and Sánchez, 2012). Using the number of landmine accidents as a control for violence alleviates this concern, as landmines are the best available proxy of violence at the school level. However, studies have also shown that oil activity can generate increases in civil conflict in Colombia (Dube and Vargas, 2013), as terrorist groups try to capture the rents generated by oil exploitation. This may raise concerns over bad controls in our estimation. However, the main mechanism identified by Dube and Vargas (2013) is not binding in our estimation as schools do not directly receive rents derived from oil exploitation. Furthermore, landmines have been used in Colombia by terrorist groups to attack the military or to protect their coca plantations (Ruiz and Pinto, 2017), but not in operations related to oil wells.

To account for reverse causality and other potentially omitted variables, we use an instrumental variable (IV) approach to estimate the two-stage least squares (2SLS) estimator. We begin by instrumenting our oil activity variable with the interaction between international oil prices and the total number of wells drilled around school s within a buffer of k km until year T, prior to 2001. Since we use all the information available on oil well drilling and wells are the best available predictor of production at the local level, our instrument can be interpreted as an oil suitability proxy at the school level. In our benchmark model we use $T = 2000$, but we present robustness checks using $1970, 1980$ and 1990 as thresholds. Equation 3 and Equation 4 present the first stage of the estimations at the school and individual level, respectively.

$$Wells^k_{st} = \beta Price_t \cdot Wells^k_{s;T} + \delta X_{st} + \gamma_s + \lambda_{dt} + \epsilon_{st} \tag{3}$$

$$Wells^k_{ist} = \beta Price_t \cdot Wells^k_{is;T} + \delta X_{ist} + \gamma_s + \lambda_{dt} + \epsilon_{ist} \tag{4}$$

We argue that both the exogeneity and the exclusion restriction of our instrument are fully satisfied. First, Colombia is a price taker in the international oil market. Thus, international oil prices are not correlated with the error term as they are set in the international market. The second part of our instrument reflects geological characteristics that cannot have endogenous responses in the model. Moreover, wells that have already been drilled cannot disappear, and the intensity of the measure provides information on the possible oil endowments of the school's immediate surroundings. Together these facts ensure the exogeneity of our instrument. However, our instrument is subject to concerns relating to path dependence, since oil wells are often drilled repeatedly in the same areas. We show that our findings are robust to using 1970, 1980, and 1990 as thresholds to create our instrument, which alleviates this concern.

Measuring the total number of oil wells in a year prior to the first year of our study period ensures that the exclusion restriction of our instrument is satisfied. Since schools do not directly receive rents from oil exploitation, oil endowments and international prices only affect human capital decisions through their impact on economic activity. The basic intuition behind our instrument is that international oil prices should disproportionately affect the number of wells drilled in schools where oil production is more likely to be successful, namely sites with previous evidence of oil presence.[7]

Though a reduced form of our estimation has been used in related studies to estimate causal effects (*e.g.*, Black et al. (2005); Bonilla (2020); Dube and Vargas (2013); Michaels (2011)), our paper is able to use much more detailed data to capture current spatial and temporal variation in oil activity. Since we are interested in estimating the impact of increases in oil activity on human capital accumulation measures, our instrumental variable approach gives us the precise local average treatment effect (LATE) that we are looking for and satisfies the exclusion restriction.

Finally, our instrument is the best available predictor of oil well drilling at the local level. As discussed in section 3, oil well drilling is very responsive to the international oil price. Moreover, the general uncertainty in the literature and the public debate on the future

[7] Bonilla (2020) uses a similar strategy in some exercises for the case of gold mining.

production of oil stems from poor quality data. The modeling of the natural distribution of oil fits fairly well with past oil production (Laherrère, 2003) and our instrument accounts for granular spatial variation in oil activity by measuring the number of oil wells that have been drilled around the school.

For ease of interpretation, we standardize both our instrument and instrumented variables. To give a more intuitive interpretation of the first stage of our IV, we use the logarithm of the international oil price. Our estimates use the Brent price, which is the benchmark for Colombian oi, though our results remain unchanged when using WTI or a composite crude price. The results of this study can be interpreted as the effect of the number of wells changing by one standard deviation, which is the best proxy available of oil production at the school level.

5 Results

Enrollment Decisions

We begin our analysis by presenting the impact of oil activity on enrollment decisions. Table 6 shows how oil activity affects tertiary enrollment decisions at the school level. Panel A contains the results from the OLS, estimating Equation 1 without instrumenting our wells variable, while Panel B presents the results of the reduced form and Panel C provides the IV estimates. Each column shows the results for the outcomes of interest, which in this case are the enrollment rate and program selection. The first stage of our IV estimates indicates the relevance of our instrument. Following Lee et al. (2020), the Kleibergen-Paap F statistic is well above the 104.7 threshold. Furthermore, all of the estimates go in the same direction, with the IV estimates larger than the OLS results.

Our results suggest that an increase of one standard deviation in the number of well drilled decreases the tertiary enrollment rate by 2.81pp. This magnitude represents more than one eighth of a standard deviation of the enrollment rate in our sample. Likewise, it has a negative effect on the number of students enrolling in professional programs relative to technical programs.

Table 6: Effect of Oil Exploitation on School Level Human Capital Measures

	Enrolment Rate	*Professional Program Intensity*
A. OLS		
Wells	-0.938	-1.603
	(0.62)	(1.55)
Observations	68,701	66,635
B. Reduced Form		
$Price \cdot Wells_{2000}$	-0.351**	-0.859***
	(0.15)	(0.31)
Observations	68,701	66,635
C. IV Estimates		
Wells	-2.813**	-7.004**
	(1.21)	(2.79)
Observations	68,701	66,635
Kleibergen-Paap F	675	703

School fixed effects; Time-Department quadratic trends; Landmines included as control. Oil suitability and Wells are standardized and Price is in logs. Buffer of 10Km. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

For a better sense of the interpretation of these results, Table 7 provides the estimations at the individual level. In addition to presenting the probability of enrollment and program selection, we also measure the impact on the number of years between high school graduation and tertiary education enrollment. Consistent with the school-level estimates, we find that increased oil exploitation lowers tertiary education enrollment and the relative probability of enrolling in a professional degree. Specifically, an increase of one standard deviation in the number of nearby oil wells decreases tertiary enrollment by 1.8 pp and professional degree enrollment by 3.6 pp, while also delaying students' decisions to pursue tertiary education by an average of half a semester.

Table 7: Effect of Oil Exploitation on Individual-Level Human Capital Measures

	Enroled	*Professional Degree*	*Semesters to Enrolment*
A. OLS			
Wells	-0.007**	-0.006	0.185***
	(0.00)	(0.00)	(0.04)
Observations	2,794,699	1,164,185	1,225,191
B. Reduced Form			
$Price \cdot Wells_{2000}$	-0.002***	-0.004***	0.053***
	(0.00)	(0.00)	(0.01)
Observations	2,794,699	1,164,185	1,225,191
C. IV Estimates			
Wells	-0.018***	-0.036***	0.484***
	(0.01)	(0.01)	(0.10)
Observations	2,794,699	1,164,185	1,225,191
Kleibergen-Paap F	44,148	20,216	25,040

School fixed effects; Time-Department quadratic trends; Landmines included as control. Wells are standardized and Price is in logs. Buffer of 10Km. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

We now turn to the specific programs that individuals choose to pursue, examining the probability of enrollment in STEM programs, business, economics, law and related programs, and all other programs (Table 8). These outcomes, are of interest for two reasons. First, STEM programs have a higher wage premium (Saavedra et al., 2017). Second, the literature has found that positive oil shocks generate higher enrollment in business, economics, law and related programs (Ebeke et al., 2015), which might in itself be pervasive since those programs can be rent-seeking behavior, while an oversupply of labor in those subjects might hinder economic growth (Murphy et al., 1991). In line with previous studies, our results suggest that oil activity decreases the probability of enrolling in STEM programs (Bonilla, 2020) and increases the probability of entering programs in the social sciences, business, law and related areas (Ebeke et al., 2015).

Table 8: Effect of Oil Exploitation on Individual-Level Human Capital Measures

	STEM	*Soc. Sci, Business, Law*	*Others*
A. OLS			
Wells	-0.039***	0.034***	0.007**
	(0.00)	(0.00)	(0.00)
Observations	1,293,718	1,293,718	1,293,718
B. Reduced Form			
$Price \cdot Wells_{2000}$	-0.009***	0.008***	0.000
	(0.00)	(0.00)	(0.00)
Observations	1,293,718	1,293,718	1,293,718
C. IV Estimates			
Wells	-0.076***	0.074***	0.001
	(0.01)	(0.01)	(0.01)
Observations	1,293,718	1,293,718	1,293,718
Kleibergen-Paap F	25,807	25,807	25,807

School fixed effects; Time-Department quadratic trends; Landmines included as control. Wells are standardized and Price is in logs. Buffer of 10Km. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Completion Decisions

We now turn to analyze completion decisions among those who decided to enroll in tertiary education. Since a professional program in Colombia takes between 4 and 5 years to complete, we limit our sample to students who enrolled in higher education prior to 2010. Our data includes information on whether the students in the sample completed or deserted the degree program. Table 9 shows the effect of completion and desertion decisions both at the school and the individual level. We do not find any impact of oil activity on these decisions at either level. However, these results are not unsurprising in that it is plausible that students across the country accurately consider the costs of completing their tertiary education programs and that oil activity does not play a role once they are already enrolled.

Table 9: Effect of Oil Exploitation on Individual-Level Human Capital Measures

	Completion		*Desertion*	
	Individual	School	Individual	School
A. OLS				
Wells	0.011	2.293	-0.022*	-3.015
	(0.01)	(2.22)	(0.01)	(2.20)
Observations	536,312	40,011	536,312	40,011
B. Reduced Form				
$Price \cdot Wells_{2000}$	-0.003	-0.367	0.002	0.460
	(0.00)	(0.35)	(0.00)	(0.36)
Observations	536,312	40,011	536,312	40,011
C. IV Estimates				
Wells	-0.038	-3.988	0.018	5.000
	(0.03)	(3.90)	(0.03)	(3.99)
Observations	536,312	40,011	536,312	40,011
Kleibergen-Paap F	8,444	473	8,444	473

School fixed effects; Time-Department quadratic trends; Landmines, age and gender included as control. Wells are standardized and Price is in logs. Shock assigned in year of enrolment in tertiary education. Sample trimmed to 2010. Buffer of 10Km. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Quality and Selection

Since the impact of oil exploitation on educational outcomes could be driven by the general quality of education in schools near oil-producing areas, we test whether increased oil activity has an impact on students' test scores. Table 10 provides the results of this analysis indicating no impact on the percentile of test scores. his finding makes sense as schools do not directly receive any rents from oil exploitation, .

Selection represents a potential barrier to the identification of our results. We consequently test whether there is any impact of oil activity on the number of students in each school. Our results consistently show that this form of selection is not present. Unfortunately, we cannot check whether a migration-type self-selection occurs since we lack information on each student's place of origin. However, as we previously discussed, migration-related self-selection bias naturally attenuates over time. Moreover, as we show in the next subsection, our results are robust to using different thresholds for constructing our instrument, making this is a minor concern.

Table 10: Effect of Oil Exploitation on Individual-Level Human Capital Measures

	Test Scores	*Number of Students*
A. OLS		
Wells	-0.311**	-1.315*
	(0.16)	(0.75)
Observations	2,771,137	68,701
B. Reduced Form		
$Price \cdot Wells_{2000}$	-0.049	-0.323
	(0.03)	(0.24)
Observations	2,771,137	68,701
C. IV Estimates		
Wells	-0.417	-2.585
	(0.30)	(1.89)
Observations	2,771,137	68,701
Kleibergen-Paap F	43,875	675

School fixed effects; Time-Department quadratic trends; Landmines included as control. Oil suitability and Wells are standardized and Price is in logs. Buffer of 10Km. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Another source of selection might stem from schools opening or closing depending on local oil endowments. We performed two exercises to test whether such selection is present our context and if it might be biasing our results. First, we replicated our results using only schools with information for at least the first two years of our study period. We then dropped schools with less than six years (half the length of the study period) of information from our sample. Appendix Table A1, Table A2, Table A3, and Table A4 present the results of these exercises. Both the qualitative and quantitative characteristics of our main estimations remain fairly unchanged, indicating that this kind of selection bias does not affect our results.

Deviations from Benchmark Model

Oil Suitability Threshold

To further support our claims regarding the exogeneity of the instrument, we repeat our analysis using a more restrictive measure of our instrument. For instance, we measure our oil suitability proxy using 1970, 1980, and 1990 as cutoff years. While measuring our instrument starting further back in time weakens potential bias from path dependence, doing so also causes us to lose information as the number of wells naturally increases over time. Appendix Table A5, Table A6, Table A7, Table A8, and Table A9 show that all of our estimations are robust to this modification. Note that, by construction, the OLS estimation is the same as in the benchmark model.

Buffer Size

The definition of the treatment intensity, of our instrument, and of our local violence control depend on the size of the buffer used to count both wells and landmine accidents. We therefore carry out our estimations using varied sized buffers around the school as a robustness check. Appendix Table A10, Table A11, Table A12, Table A13, and Table A14 show the results from replicating our analysis using buffers ranging from 5 to 30 km.[8] For estimations using 20 and 30 km buffers, the quantitative and qualitative results of our benchmark model remain unchanged. For some of the estimations using a 5 km buffer the first stage of our instrument is weaker than the Lee et al. (2020) threshold, which might be due to the small number of schools that have a well within this size buffer (see Table 5).

Oil Well Life Cycle

A well's oil production can decrease over time. In fact, according to the Canadian Association of Petroleum Producers (CAPP), the average lifetime of an oil well is 30 years. Thus, we test whether our results are robust to adjusting our wells measure to considering only 1-, 15-, 30- and 45-year-old wells in the vicinity of schools. Appendix Figure A2, Figure A3, and Figure A4 show the IV estimates for our main results adjusting for the age of the wells. While the qualitative characteristics of the estimators remain unchanged, the magnitude of the estimators drops when using wells that are 15 years old or younger. In narrowing the restriction and using only younger wells we begin to deviate from using oil activity as a whole and capture only the impact of drilling. In fact, when considering only one-year-old wells, we just capture the impact of newly drilled wells. As oil activity comprises much more than well drilling, it is unsurprising that the magnitude of the estimators decreases under these settings.

As a final robustness check, we combined the restriction on the well life cycle and the threshold at which we measure our instrument. We present the results of restricting our instrument to 1970 and using only 30-year-old wells in Appendix Table A15, Table A16, Table A17, Table A18, and Table A19. The tables also present the full results of simply restricting the well age to 30 years old and using the benchmark threshold for our instrument to complement the figures discussed above. Again, the quantitative and qualitative characteristics of our estimations remain unchanged.

6 Mechanisms

Returns to Education

Higher oil activity might have an impact on a region's general wage level. In fact, Feyrer et al. (2017) find that one million dollars of new oil and gas production in the US is associated with an $80,000 increase in wage income. In general, oil exploitation can generate positive spillovers in the the local economy via local labor markets (Black et al., 2005; Jacobsen and Parker, 2016; Weber, 2012). In our setting, oil activity might disincentivize human capital

[8] Our results are also robust to 35 km. Tables available upon request.

accumulation by increasing the economic activity in the vicinity of the schools. We exploit our data on income to explore the validity of this mechanism.

We model the effect of oil activity on income by estimating Equation 5 using individual panel data from 2008 until 2014, where $Wage_{ist}$ is the total annual earnings of student i, who graduated from school s, adjusted by the minimum wage in t. $Enroled_{ist}$ is a dummy variable equal to one for every year t after student i's enrollment in tertiary education, and X_{ist} is a set of controls that include the student's age, gender and experience as measured by the number of years between high school graduation and the current year t. We also include the quadratic form of experience, the number of landmine accidents, test scores, and the inverse mills ratio to control for self-selection in the labor market. Finally, we also include school fixed effects and department-time trends.

$$Wage_{ist} = \beta_1 Wells_{ist} + \beta_2 Enrolled_{ist} + \beta_3 Enrolled_{ist} \times Wells_{ist} + \delta X_{ist} + \gamma_s + \lambda_{dt} + \epsilon_{ist} \quad (5)$$

Table 11 presents the results of our estimation using wages reported to the health care system. While we also have data of income reported to the pension funds, we lack the year 2012 for that variable. For that reason in Appendix Table A20 we present as a robustness check the estimation using wages reported to the pension funds but inputting the values reported ti the health care system for the year 2012. The results and conclusions that can be derived using that data remain unchanged.

We find a large and significant effect of oil exploitation on income. The magnitude of the estimation is economically significant as it represents approximately 13 minimum wages per year. These results are in line with previous findings (*e.g* Feyrer et al., 2017). Since oil production generates higher economic activity, students more closely exposed to oil activity might have access to higher wages. Our results also show that, in general, there is a premium to higher education: students who enroll in higher education gain 1.5 more minimum wages. Nevertheless, students that enroll in higher education and graduate in resource-rich areas do not seem to accrue the higher education premium.

It is important to highlight that oil production mainly generates positive spillovers for economic activities that do not require professionally trained workers, like construction and retail (Marchand, 2012). According to the National Administrative Department of Statistics (DANE) of Colombia almost 49% of employees in Colombia worked in the informal sector in 2019. Since workers without professional training might be more exposed to informal labor markets, these results may actually represent but a lower bound. This result should also be taken with caution as we are not able to control for migration dynamics within our sample, meaning that we cannot discard potential bias from the latter. However, since our observations are consistent with previous evidence of higher economic activity at the local level, we regard this as a minor concern.

Table 11: Formal Sector Wages

	OLS	Reduced Form	IV Estimates
Wells	1.854***	.	13.096***
	(0.30)	.	(1.95)
$Price \cdot Wells_{2000}$	.	0.533***	.
	.	(0.08)	.
Enroled	1.440***	1.439***	1.444***
	(0.04)	(0.04)	(0.04)
Enroled ×Wells	0.099**	.	-0.031
	(0.05)	.	(0.05)
Enroled$\times Price \cdot Wells_{2000}$	.	0.017	.
	.	(0.01)	.
Observations	1,043,662	1,043,662	1,043,662
Kleibergen-Paap F	.	.	1,432

School fixed effects; Time-Department quadratic trends; Landmines included as control. Wages are adjusted for the minimum wage. Wells are standardized and Price is in logs. Buffer of 10Km. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

7 Discussion

This paper leverages detailed spatial data on the locations of oil wells and schools in Colombia to estimate the impact of an increase in oil production on several human capital measures. Oil production at the school level is proxied through the number of wells drilled in the vicinity of the school. The drilling of new wells is driven, among other factors, by international oil prices and the area's suitability. By relying on an instrumental variable approach we are able to estimate causal effects.

We find that oil has a negative impact on several dimensions of human capital accumulation. An increase of one standard deviation in the number of wells drilled around a school leads to a lower rate of enrollment in higher education. Furthermore, we present evidence of a talent allocation effect, with students more likely to decide to enroll in technical programs as well as social sciences, business, law and related programs. In addition, the probability of enrolling in professional programs decreases by 3.6 pp. This result is in line with the general structure of the labor demand in the Colombian oil sector, as well as the findings of Ebeke et al. (2015) based on country-level data. We also find evidence of students delaying their decision to enroll in higher education. The quality of education does not appear to drive our results; we find no effects on student test scores.

One of the main mechanisms discussed in the literature is the so-called political natural resource curse (Ross, 2015). For instance, previous work shows that oil discoveries and oil exploitation lead to higher corruption in producing sites (Brollo et al., 2013; Vicente, 2010), mainly due to excessive public employment or patronage Robinson et al. (2006). By nature, such a mechanism can only operate at an administrative level. Our identification strategy rules this out, as it disregards administrative boundaries and assigns the treatment intensity based on symmetric buffers around individual schools. Since educational institutions do not directly receive rents from higher oil production, students in school areas characterized by higher oil production do not face a greater (or lesser) exposure to corruption and patronage ceteris paribus. This is also consistent with our null results on education quality.

Our identification strategy allows us to isolate the local economic activity effect, which translates mainly through the labor market. Given that our identification strategy relies on the school and individual as the units of analysis, we can only capture the effects of oil exploitation that are transmitted via local markets or spillovers to other economic sectors. Oil-exploitation activities, by nature, require a a workforce comprised mainly of non-professional workers. Indeed, only 3% of the workforce of oil exploration operations in Colombia, and 6% of exploitation workforce, have professional training, respectively (see Table 1). By creating a higher demand for non-professional workers, oil exploitation disincentivizes students from enrolling in professional higher education programs. This also drives the decrease we observe in the enrollment rate. Since the demand for non-qualified workers is also high in the Colombian oil sector, students generally prefer to join the labor force rather than enrolling in higher education programs.

By using individual data on income, we find that both higher education and oil activity have a general positive impact on earnings. However, students in oil-rich areas do not perceive the positive premium of enrolling in tertiary education. This seems to be the driving force behind the decrease in tertiary education enrollment identified in this paper. Our results align with previous literature in pointing out the existence of positive spillovers on local labor markets caused by natural resource exploitation (Black et al., 2005; Jacobsen and Parker, 2016; Weber, 2012), particularly for economic activities that do not require professional workers, such as construction and retail (Marchand, 2012). Furthermore, together with our identification strategy, this mechanism appears to be the most relevant in explaining our results.

Our paper also offers an ideal setting to compare the heterogeneity of the natural resource exploitation dynamic across commodities. Both gold and oil experienced a boom during the same time period, and previous studies show that gold exploitation in Colombia also had some negative effects on human capital accumulation as well (Bonilla, 2020; Santos, 2018). For comparable outcomes, the economic significance of our results seems to be greater than those observed by Bonilla (2020). This is suggests a stronger negative effect in Colombia from oil Ross (2015) than from gold. Since, in contrast to other studies, we find no effects on education quality, our results furthermore imply that oil might have a different impact and operate through other channels than those for gold. Our findings thus expand the general understanding of the stronger effects of oil exploitation.

There are several public policy implications to our results. First, municipalities should consider talent allocation, as such decisions can have long-term impacts on economic development (Murphy et al., 1991). Furthermore, efforts should be made to direct the higher revenues and higher public spending that come from natural resource extraction (Bonet-Morón et al., 2020) towards education for students in resource rich areas. One approach would be to lower the costs of entrance into tertiary education for students coming from oil-rich areas. In the short run, this could be achieved through the creation of scholarships funded by oil extraction rents. As our results show that oil exploitation has no impact on education quality, the mechanism behind such funding could, however, be inefficient if allocated using only test scores as a threshold.

The government can offset some of the negative impact of oil exploitation by facilitating the pass-through of oil activity to other related sectors. In particular, the manufacturing and the agricultural sectors appear to be highly related to extractive activities in Colombia (Balza et al., 2021). An effort should thus be made to take advantage of the positive spillovers of the oil sector into the local economy.

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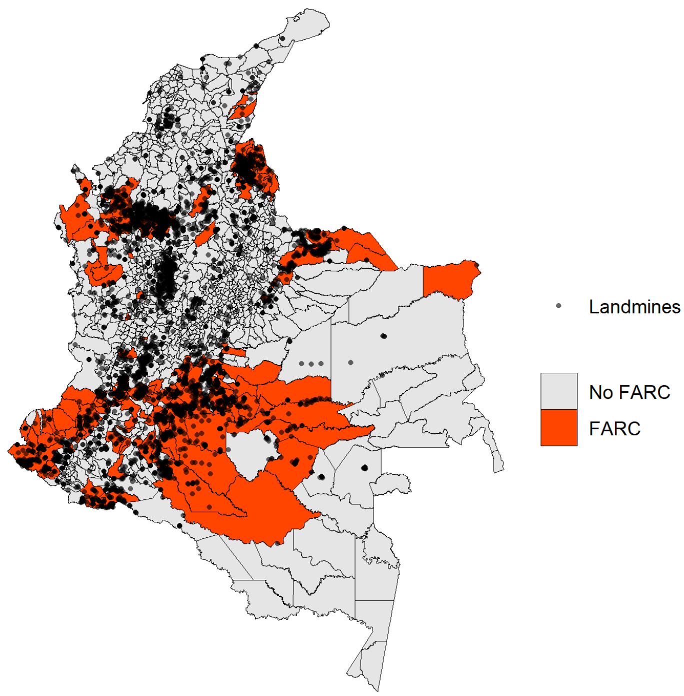
8 Appendix

Figure A1: Landmines and FARC presence



All mines included. Source: FARC presence made available by Prem et al. (2020), and collected and edited by Restrepo et al. (2004) and Universidad del Rosario. Landmine accidents reports were collected by the *Oficina del Alto Comisionado para la Paz (OACP)*

Table A1: Effect of Oil Exploitation on Individual Level Human Capital Measures

	Enrolment Rate		*Professional Program Intensity*	
A. OLS				
Wells	-0.793	-0.708	-0.358	-0.844
	(0.61)	(0.62)	(1.58)	(1.57)
Observations	49,092	63,001	48,176	61,617
B. Reduced Form				
$Price \cdot Wells_{2000}$	-0.425***	-0.326**	-0.755**	-0.886***
	(0.14)	(0.14)	(0.30)	(0.30)
Observations	49,092	63,001	48,176	61,617
C. IV Estimates				
Wells	-3.406***	-2.605**	-6.142**	-7.196***
	(1.20)	(1.18)	(2.79)	(2.77)
Observations	49,092	63,001	48,176	61,617
Kleibergen-Paap F	656	684	688	717
Schools Included	A	B	A	B

This table replicates the main results but using only either schools with date in at least the first two year of the study period (A) or schools with at least 6 years of data (B). School fixed effects; Time-Department quadratic trends; Landmines included as control. Oil suitability and Wells are standardized and Price is in logs. Buffer of 10Km. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table A2: Effect of Oil Exploitation on Individual Level Human Capital Measures

	Enroled		*Professional Degree*		*Semesters to Enrolment*	
A. OLS						
Wells	-0.007**	-0.007**	-0.005	-0.005	0.174***	0.187***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.04)
Observations	2,298,158	2,678,268	978,648	1,126,420	1,036,225	1,188,003
B. Reduced Form						
$Price \cdot Wells_{2000}$	-0.002***	-0.002***	-0.004***	-0.004***	0.051***	0.053***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Observations	2,298,158	2,678,268	978,648	1,126,420	1,036,225	1,188,003
C. IV Estimates						
Wells	-0.020***	-0.019***	-0.035***	-0.036***	0.462***	0.483***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.10)	(0.10)
Observations	2,298,158	2,678,268	978,648	1,126,420	1,036,225	1,188,003
Kleibergen-Paap F	42,917	44,244	19,694	20,279	24,452	25,123
Schools Included	A	B	A	B	A	B

This table replicates the main results but using only either schools with date in at least the first two year of the study period (A) or schools with at least 6 years of data (B). School fixed effects; Time-Department quadratic trends; Landmines included as control. Oil suitability and Wells are standardized and Price is in logs. Buffer of 10Km. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table A3: Effect of Oil Exploitation on Individual Level Human Capital Measures

	STEM		*Soc. Sci, Business, Law*		*Others*	
A. OLS						
Wells	-0.040***	-0.039***	0.034***	0.035***	0.007*	0.007*
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Observations	1,089,794	1,252,396	1,089,794	1,252,396	1,089,794	1,252,396
B. Reduced Form						
$Price \cdot Wells_{2000}$	-0.009***	-0.009***	0.008***	0.008***	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	1,089,794	1,252,396	1,089,794	1,252,396	1,089,794	1,252,396
C. IV Estimates						
Wells	-0.079***	-0.076***	0.075***	0.074***	0.002	0.001
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	1,089,794	1,252,396	1,089,794	1,252,396	1,089,794	1,252,396
Kleibergen-Paap F	25,185	25,893	25185	25,893	25,185	25,893
Schools Included	A	B	A	B	A	B

This table replicates the main results but using only either schools with date in at least the first two year of the study period (A) or schools with at least 6 years of data (B). School fixed effects; Time-Department quadratic trends; Landmines included as control. Oil suitability and Wells are standardized and Price is in logs. Buffer of 10Km. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table A4: Effect of Oil Exploitation on Individual Level Human Capital Measures

	Completion		*Desertion*	
A. OLS				
Wells	0.010	0.009	-0.022	-0.021
	(0.01)	(0.01)	(0.01)	(0.01)
Observations	490,821	532,689	490,821	532,689
B. Reduced Form				
$Price \cdot Wells_{2000}$	-0.003	-0.004	0.001	0.002
	(0.00)	(0.00)	(0.00)	(0.00)
Observations	490,821	532,689	490,821	532,689
C. IV Estimates				
Wells	-0.037	-0.042	0.015	0.022
	(0.03)	(0.03)	(0.03)	(0.03)
Observations	490,821	532,689	490,821	532,689
Kleibergen-Paap F	8311	8319	8311	8319
Schools Included	A	B	A	B

This table replicates the main results but using only either schools with date in at least the first two year of the study period (A) or schools with at least 6 years of data (B). School fixed effects; Time-Department quadratic trends; Landmines included as control. Oil suitability and Wells are standardized and Price is in logs. Buffer of 10Km. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Oil Suitability Robustness Tables

Table A5: Effect of Oil Exploitation on Individual Level Human Capital Measures

	Enrolment Rate			*Professional Program Intensity*		
t	1970	1980	1990	1970	1980	1990
A. OLS						
Wells	-0.938	-0.938	-0.938	-1.603	-1.603	-1.603
	(0.62)	(0.62)	(0.62)	(1.55)	(1.55)	(1.55)
Observations	68,701	68,701	68,701	66,635	66,635	66,635
B. Reduced Form						
$Price \cdot Wells_{2000}$	-0.427***	-0.419***	-0.364**	-0.854***	-0.836***	-0.892***
	(0.14)	(0.15)	(0.15)	(0.31)	(0.31)	(0.31)
Observations	68,701	68,701	68,701	66,635	66,635	66,635
C. IV Estimates						
Wells	-3.749***	-3.626***	-2.978**	-7.578***	-7.313***	-7.403***
	(1.33)	(1.31)	(1.24)	(2.76)	(2.74)	(2.81)
Observations	68,701	68,701	68,701	66,635	66,635	66,635
Kleibergen-Paap F	484	609	753	486	617	781

School fixed effects; Time-Department quadratic trends; Landmines included as control. Oil suitability and Wells are standardized and Price is in logs. Buffer of 10Km. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table A6: Effect of Oil Exploitation on Individual Level Human Capital Measures

	Enroled			*Professional Degree*			*Semesters to Enrolment*		
t	1970	1980	1990	1970	1980	1990	1970	1980	1990
A. OLS									
Wells	-0.007**	-0.007**	-0.007**	-0.006	-0.006	-0.006	0.185***	0.185***	0.185***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.04)	(0.04)
Observations	2,794,699	2,794,699	2,794,699	1,164,185	1,164,185	1,164,185	1,225,191	1,225,191	1,225,191
B. Reduced Form									
$Price \cdot Wells_t$	-0.002***	-0.002***	-0.002***	-0.004***	-0.004***	-0.004***	0.054***	0.052***	0.055***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
Observations	2,794,699	2,794,699	2,794,699	1,164,185	1,164,185	1,164,185	1,225,191	1,225,191	1,225,191
C. IV Estimates									
Wells	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.10)	(0.10)	(0.10)
Observations	2,794,699	2,794,699	2,794,699	1,164,185	1,164,185	1,164,185	1,225,191	1,225,191	1,225,191
Kleibergen-Paap F	39,601	47,438	49,656	15,468	19,478	22,627	19,053	24,080	28,006

School fixed effects; Time-Department quadratic trends; Landmines included as control. Wells are standardized and Price is in logs. Buffer of 10Km. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table A7: Effect of Oil Exploitation on Individual Level Human Capital Measures

	STEM			*Soc. Sci, Business, Law*			*Others*		
t	1970	1980	1990	1970	1980	1990	1970	1980	1990
A. OLS									
Wells	-0.039***	-0.039***	-0.039***	0.034***	0.034***	0.034***	0.007**	0.007**	0.007**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	1,293,718	1,293,718	1,293,718	1,293,718	1,293,718	1,293,718	1,293,718	1,293,718	1,293,718
B. Reduced Form									
$Price \cdot Wells_t$	-0.008***	-0.008***	-0.008***	0.008***	0.008***	0.008***	-0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	1,293,718	1,293,718	1,293,718	1,293,718	1,293,718	1,293,718	1,293,718	1,293,718	1,293,718
C. IV Estimates									
Wells	-0.072***	-0.074***	-0.077***	0.072***	0.073***	0.075***	-0.000	0.000	0.000
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	1,293,718	1,293,718	1,293,718	1,293,718	1,293,718	1,293,718	1,293,718	1,293,718	1,293,718
Kleibergen-Paap F	19,881	25,007	28,860	19,881	25,007	28,860	19,881	25,007	28,860

School fixed effects; Time-Department quadratic trends; Landmines included as control. Wells are standardized and Price is in logs. Buffer of 10Km. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table A8: Effect of Oil Exploitation on Individual Level Human Capital Measures

	Completion						*Desertion*					
	Individual			School			Individual			School		
t	1970	1980	1990	1970	1980	1990	1970	1980	1990	1970	1980	1990
A. OLS												
Wells	0.011	0.011	0.011	2.293	2.293	2.293	-0.022*	-0.022*	-0.022*	-3.015	-3.015	-3.015
	(0.01)	(0.01)	(0.01)	(2.22)	(2.22)	(2.22)	(0.01)	(0.01)	(0.01)	(2.20)	(2.20)	(2.20)
Observations	536,312	536,312	536,312	40,011	40,011	40,011	536,312	536,312	536,312	40,011	40,011	40,011
B. Reduced Form												
$Price \cdot Wells_t$	-0.003	-0.003	-0.003	-0.379	-0.366	-0.394	0.001	0.001	0.002	0.449	0.428	0.477
	(0.00)	(0.00)	(0.00)	(0.35)	(0.35)	(0.35)	(0.00)	(0.00)	(0.00)	(0.36)	(0.36)	(0.36)
Observations	536,312	536,312	536,312	40,011	40,011	40,011	536,312	536,312	536,312	40,011	40,011	40,011
C. IV Estimates												
Wells	-0.032	-0.032	-0.039	-4.334	-4.154	-4.347	0.015	0.014	0.019	5.137	4.863	5.269
	(0.03)	(0.03)	(0.03)	(3.92)	(3.92)	(3.94)	(0.03)	(0.03)	(0.03)	(4.08)	(4.08)	(4.04)
Observations	536,312	536,312	536,312	40,011	40,011	40,011	536,312	536,312	536,312	40,011	40,011	40,011
Kleibergen-Paap F	5,962	7,463	9,331	461	540	530	5,962	7,463	9,331	461	540	530

School fixed effects; Time-Department quadratic trends; Landmines, age and gender included as control. Wells are standardized and Price is in logs. Shock assigned in year of enrolment in tertiary education. Sample trimmed to 2010. Buffer of 10Km. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table A9: Effect of Oil Exploitation on Individual Level Human Capital Measures

	Test Scores			*Number of Students*		
t	1970	1980	1990	1970	1980	1990
A. OLS						
Wells	-0.311**	-0.311**	-0.311**	-1.315*	-1.315*	-1.315*
	(0.16)	(0.16)	(0.16)	(0.75)	(0.75)	(0.75)
Observations	2,771,137	2,771,137	2,771,137	68,701	68,701	68,701
B. Reduced Form						
$Price \cdot Wells_t$	-0.049	-0.040	-0.048	-0.286	-0.316	-0.334
	(0.03)	(0.03)	(0.03)	(0.21)	(0.22)	(0.24)
Observations	2771137	2771137	2771137	68701	68701	68701
C. IV Estimates						
Wells	-0.436	-0.358	-0.416	-2.509	-2.736	-2.727
	(0.31)	(0.31)	(0.30)	(1.85)	(1.85)	(1.94)
Observations	2771137	2771137	2771137	68701	68701	68701
Kleibergen-Paap F	39456	47249	49380	484	609	753

School fixed effects; Time-Department quadratic trends; Landmines included as control. Oil suitability and Wells are standardized and Price is in logs. Buffer of 10Km. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Buffer Robustness Tables

Table A10: Effect of Oil Exploitation on Individual Level Human Capital Measures

	Enrolment Rate			*Professional Program Intensity*		
Km	5	20	30	5	20	30
A. OLS						
Wells	1.181**	-0.747	-0.245	1.266	-0.798	0.143
	(0.59)	(0.69)	(0.65)	(1.81)	(1.55)	(1.45)
Observations	68,701	68,701	68,701	66,635	66,635	66,635
B. Reduced Form						
$Price \cdot Wells_{2000}$	-0.004	-0.341**	-0.313**	-0.556*	-0.637**	-0.602*
	(0.14)	(0.15)	(0.15)	(0.29)	(0.31)	(0.32)
Observations	68,701	68,701	68,701	66,635	66,635	66,635
B. IV Estimates						
Wells	-0.036	-2.312**	-2.147**	-4.665	-4.356**	-4.156*
	(1.19)	(1.02)	(1.04)	(3.53)	(2.20)	(2.25)
Observations	68,701	68,701	68,701	66,635	66,635	66,635
Kleibergen-Paap F	95	1,731	1,503	91	1,727	1,489

School fixed effects; Time-Department quadratic trends; Landmines included as control. Oil suitability and Wells are standardized and Price is in logs. Buffer of 10Km. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table A11: Effect of Oil Exploitation on Individual Level Human Capital Measures

	Enroled			*Professional Degree*			*Semesters to Enrolment*		
Km	5	20	30	5	20	30	5	20	30
A. OLS									
wells_accum	0.013***	-0.003	0.000	0.004	-0.001	0.002	0.062	0.058	-0.013
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.05)	(0.05)	(0.04)
Observations	2,794,699	2,794,699	2,794,699	1,164,185	1,164,185	1,164,185	1,225,191	1,225,191	1,225,191
B. Reduced Form									
$Price \cdot Wells_{2000}$	-0.000	-0.001**	-0.001*	-0.003***	-0.003***	-0.003***	0.069***	0.035***	0.039***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
Observations	2,794,699	2,794,699	2,794,699	1,164,185	1,164,185	1,164,185	1,225,191	1,225,191	1,225,191
C. IV Estimates									
Wells	-0.002	-0.010**	-0.009*	-0.027***	-0.022***	-0.022***	0.615***	0.259***	0.300***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.09)	(0.08)	(0.08)
Observations	2,794,699	2,794,699	2,794,699	1,164,185	1,164,185	1,164,185	1,225,191	1,225,191	1,225,191
Kleibergen-Paap F	2,974	109,046	90,875	1,361	48,916	40,773	1,499	58,860	49,485

School fixed effects; Time-Department quadratic trends; Landmines included as control. Wells are standardized and Price is in logs. Buffer of 10Km. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table A12: Effect of Oil Exploitation on Individual Level Human Capital Measures

	STEM			*Soc. Sci, Business, Law*			*Others*		
Km	5	20	30	5	20	30	5	20	30
A. OLS									
Wells	-0.013***	-0.057***	-0.049***	0.003	0.045***	0.037***	0.011***	0.015***	0.015***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	1,293,718	1,293,718	1,293,718	1,293,718	1,293,718	1,293,718	1,293,718	1,293,718	1,293,718
B. Reduced Form									
v_brent_price	-0.004***	-0.009***	-0.009***	0.003***	0.009***	0.009***	0.001	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	1,293,718	1,293,718	1,293,718	1,293,718	1,293,718	1,293,718	1,293,718	1,293,718	1,293,718
C. IV Estimates									
Wells	-0.038***	-0.068***	-0.070***	0.028***	0.064***	0.066***	0.009	0.003	0.003
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	1,293,718	1,293,718	1,293,718	1,293,718	1,293,718	1,293,718	1,293,718	1,293,718	1,293,718
Kleibergen-Paap F	1,513	61,018	51,202	1,513	61,018	51,202	1,513	61,018	51,202

School fixed effects; Time-Department quadratic trends; Landmines included as control. Wells are standardized and Price is in logs. Buffer of 10Km. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table A13: Effect of Oil Exploitation on Individual Level Human Capital Measures

	Completion						*Desertion*					
	Individual			School			Individual			School		
Km	5	20	30	5	20	30	5	20	30	5	20	30
A. OLS												
Wells	0.012	0.013	0.018	2.065	2.060	2.289	-0.022*	-0.011	-0.015	-3.170	-0.691	-0.784
	(0.01)	(0.01)	(0.01)	(2.22)	(1.84)	(1.98)	(0.01)	(0.01)	(0.01)	(2.22)	(1.89)	(2.03)
Observations	536,312	536,312	536,312	40,011	40,011	40,011	536,312	536,312	536,312	40,011	40,011	40,011
B. Reduced Form												
$Price \cdot Wells_{2000}$	-0.002	-0.003	-0.003	-0.462	-0.299	-0.333	0.001	0.002	0.002	0.522	0.407	0.406
	(0.00)	(0.00)	(0.00)	(0.39)	(0.35)	(0.35)	(0.00)	(0.00)	(0.00)	(0.39)	(0.35)	(0.36)
Observations	536,312	536,312	536,312	40,011	40,011	40,011	536,312	536,312	536,312	40,011	40,011	40,011
C. IV Estimates												
Wells	-0.022	-0.029	-0.033	-3.896	-2.546	-3.082	0.008	0.014	0.015	4.398	3.462	3.754
	(0.03)	(0.02)	(0.02)	(3.37)	(3.02)	(3.34)	(0.02)	(0.02)	(0.02)	(3.39)	(3.09)	(3.39)
Observations	536,312	536,312	536,312	40,011	40,011	40,011	536,312	536,312	536,312	40,011	40,011	40,011
Kleibergen-Paap F	322	19026	18599	37	1240	1269	322	19026	18599	37	1240	1269

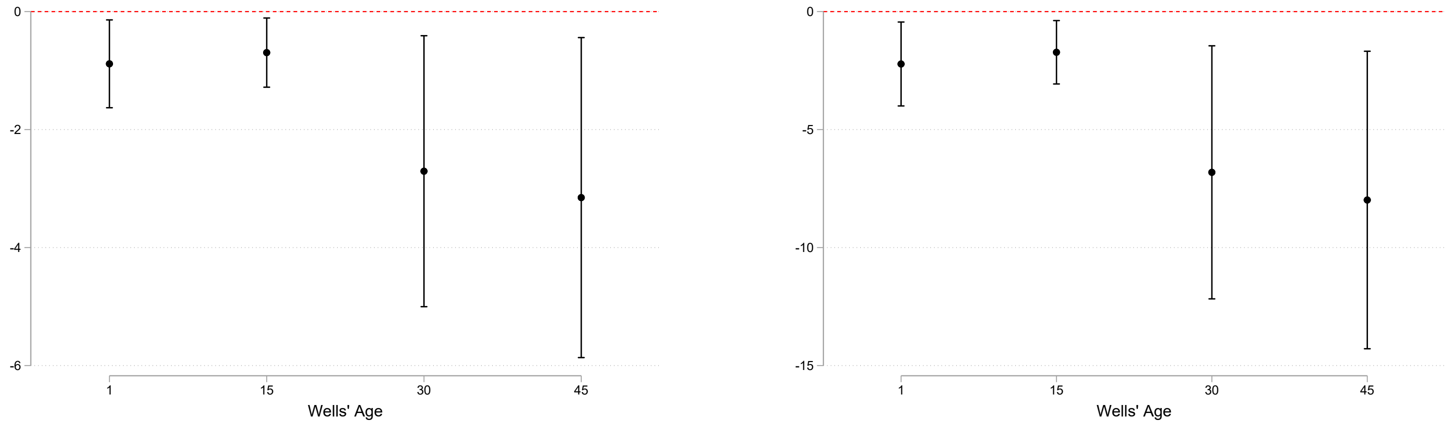
School fixed effects; Time-Department quadratic trends; Landmines, age and gender included as control. Wells are standardized and Price is in logs. Shock assigned in year of enrolment in tertiary education. Sample trimmed to 2010. Buffer of 10Km. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table A14: Effect of Oil Exploitation on Individual Level Human Capital Measures

	Test Scores			*Number of Students*		
Km	5	20	30	5	20	30
A. OLS						
Wells	-0.407***	-0.248	-0.143	0.787**	-2.030**	-1.772*
	(0.14)	(0.17)	(0.16)	(0.38)	(0.97)	(0.91)
Observations	2,771,137	2,771,137	2,771,137	68,701	68,701	68,701
B. Reduced Form						
$Price \cdot Wells_{2000}$	-0.093***	-0.050	-0.062*	0.138	-0.431*	-0.409*
	(0.03)	(0.04)	(0.04)	(0.11)	(0.25)	(0.25)
Observations	2,771,137	2,771,137	2,771,137	68,701	68,701	68,701
C. IV Estimates						
Wells	-0.794***	-0.349	-0.436*	1.105	-2.925*	-2.801*
	(0.23)	(0.25)	(0.25)	(0.89)	(1.69)	(1.70)
Observations	2,771,137	2,771,137	2,771,137	68,701	68,701	68,701
Kleibergen-Paap F	2946	108648	90587	95	1731	1503

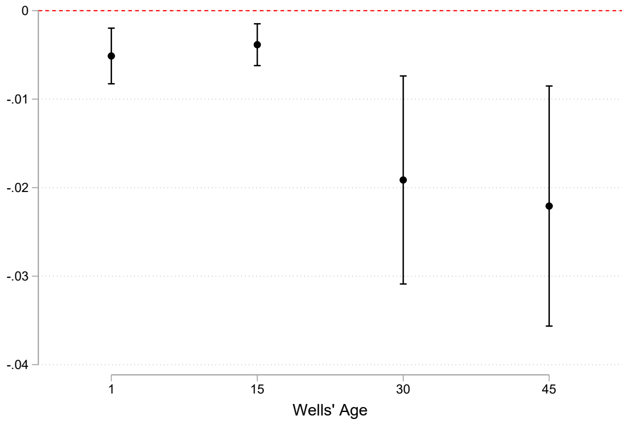
School fixed effects; Time-Department quadratic trends; Landmines included as control. Oil suitability and Wells are standardized and Price is in logs. Buffer of 10Km. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Oil Wells Life Cycle Robustness Figures

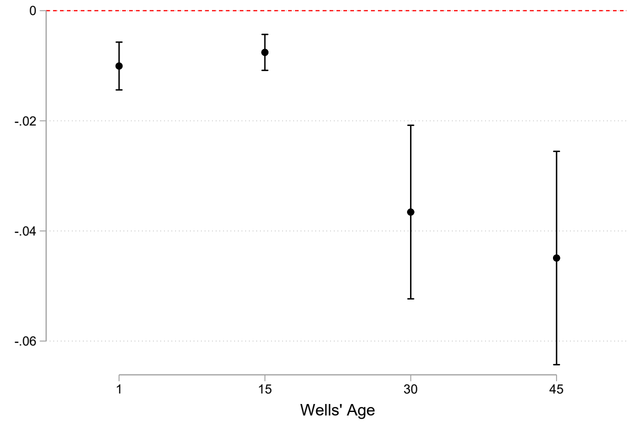


(a) Enrolment Rate (b) Professional Program Intensity

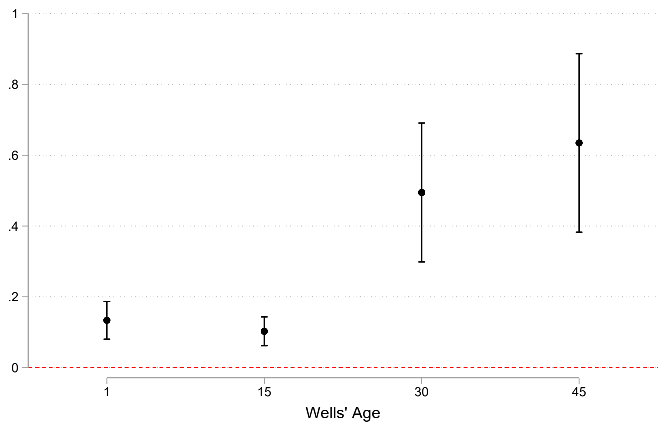
Figure A2: Enrolment at the School Level. COOL LEGEND.



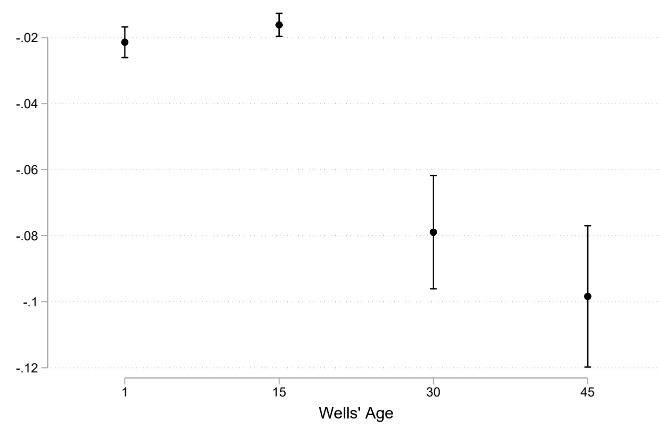
(a) Enrolled



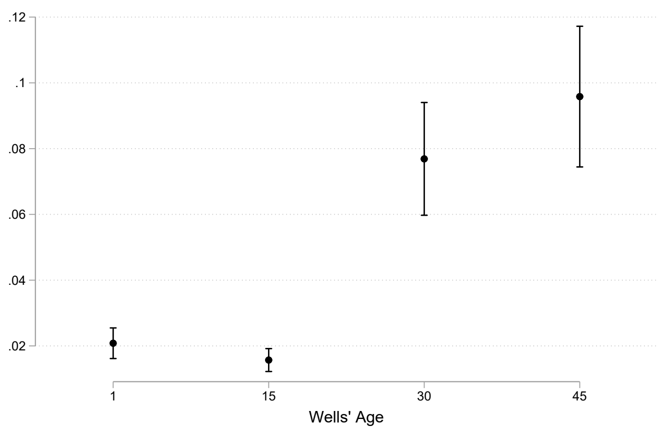
(b) Professional Program



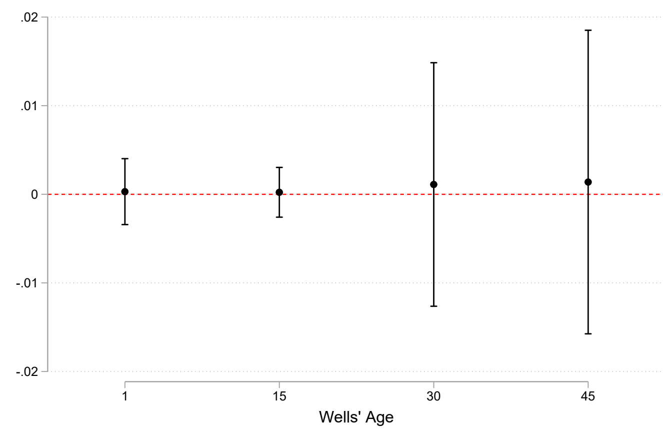
(c) Semesters to Enrollment



(d) STEM

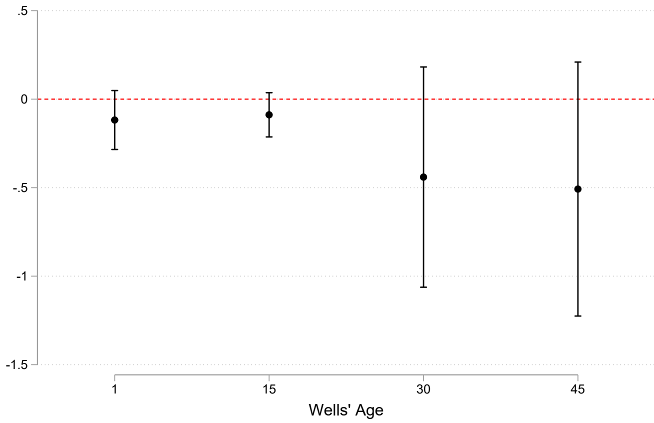


(e) Soc. Science, Business, Law

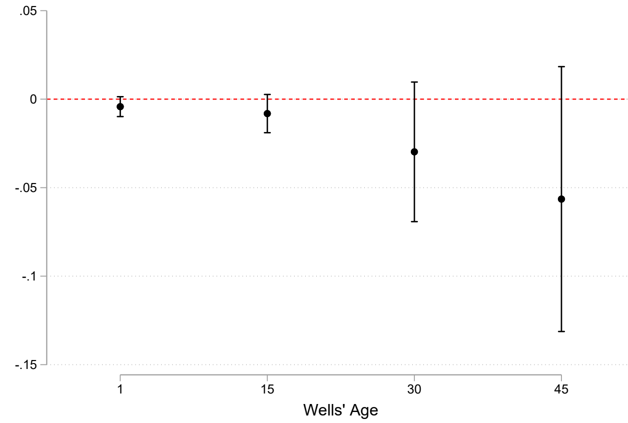


(f) Others

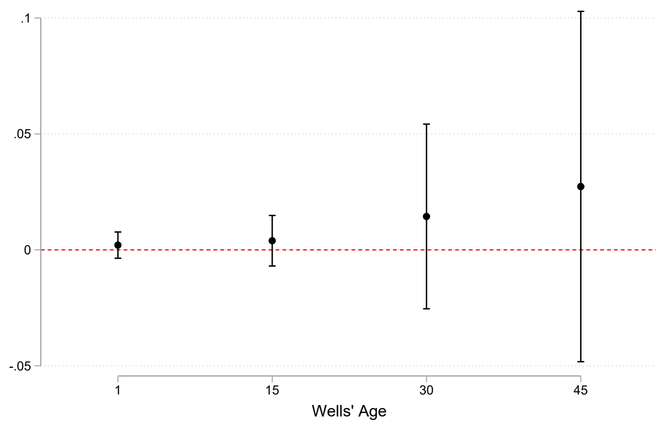
Figure A3: Individual Level Enrollment. Cool Legend



(a) Test Scores



(b) Completion



(c) Deserted

Figure A4: Other cool things. Cool Legend

Instrument Threshold and Oil Wells life Cycle Robustness Tables

Table A15: Effect of Oil Exploitation on Individual Level Human Capital Measures

	Enrolment Rate		*Professional Program Intensity*	
t	1970	2000	1970	2000
A. OLS				
Wells	-0.321	-0.321	-0.804	-0.804
	(0.37)	(0.37)	(1.01)	(1.01)
Observations	68701	68701	66635	66635
B. Reduced Form				
$Price \cdot Wells_t$	-0.427***	-0.351**	-0.854***	-0.859***
	(0.14)	(0.15)	(0.31)	(0.31)
Observations	68701	68701	66635	66635
C. IV Estimates				
Wells	-3.546***	-2.705**	-7.205***	-6.811**
	(1.24)	(1.17)	(2.59)	(2.74)
Observations	68701	68701	66635	66635
Kleibergen-Paap F	396	254	388	255

School fixed effects; Time-Department quadratic trends; Landmines included as control. Oil suitability and Wells are standardized and Price is in logs. Buffer of 10Km. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table A16: Effect of Oil Exploitation on Individual Level Human Capital Measures

	Enroled		*Professional Degree*		*Semesters to Enrolment*	
t	1970	2000	1970	2000	1970	2000
A. OLS						
Wells	-0.002	-0.002	-0.003	-0.003	0.114***	0.114***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.03)
Observations	2,794,699	2,794,699	1,164,185	1,164,185	1,225,191	1,225,191
B. Reduced Form						
$Price \cdot Wells_t$	-0.002***	-0.002***	-0.004***	-0.004***	0.054***	0.053***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Observations	2,794,699	2,794,699	1,164,185	1,164,185	1,225,191	1,225,191
C. IV Estimates						
Wells	-0.020***	-0.019***	-0.037***	-0.037***	0.513***	0.495***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.10)	(0.10)
Observations	2,794,699	2,794,699	1,164,185	1,164,185	1,225,191	1,225,191
Kleibergen-Paap F	23,870	14,556	9,909	6,610	12,587	8,414

School fixed effects; Time-Department quadratic trends; Landmines included as control. Wells are standardized and Price is in logs. Buffer of 10Km. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table A17: Effect of Oil Exploitation on Individual Level Human Capital Measures

	STEM		*Soc. Sci, Business, Law*		*Others*	
t	1970	2000	1970	2000	1970	2000
A. OLS						
Wells	-0.016***	-0.016***	0.013***	0.013***	0.005**	0.005**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	1,293,718	1,293,718	1,293,718	1,293,718	1,293,718	1,293,718
B. Reduced Form						
$Price \cdot Wells_t$	-0.008***	-0.009***	0.008***	0.008***	-0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	1,293,718	1,293,718	1,293,718	1,293,718	1,293,718	1,293,718
C. IV Estimates						
Wells	-0.073***	-0.079***	0.073***	0.077***	-0.000	0.001
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	1,293,718	1,293,718	1,293,718	1,293,718	1,293,718	1,293,718
Kleibergen-Paap F	12,628	8,429	12,628	8,429	12,628	8,429

School fixed effects; Time-Department quadratic trends; Landmines included as control. Wells are standardized and Price is in logs. Buffer of 10Km. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table A18: Effect of Oil Exploitation on Individual Level Human Capital Measures

	Completion				*Desertion*			
	Individual		School		Individual		School	
t	1970	2000	1970	2000	1970	2000	1970	2000
A. OLS								
Wells	0.007	0.007	1.264	1.264	-0.015*	-0.015*	-1.886	-1.886
	(0.01)	(0.01)	(1.44)	(1.44)	(0.01)	(0.01)	(1.41)	(1.41)
Observations	536,312	536,312	40,011	40,011	536,312	536,312	40,011	40,011
B. Reduced Form								
$Price \cdot Wells_t$	-0.003	-0.003	-0.379	-0.367	0.001	0.002	0.449	0.460
	(0.00)	(0.00)	(0.35)	(0.35)	(0.00)	(0.00)	(0.36)	(0.36)
Observations	536,312	536,312	40,011	40,011	536,312	536,312	40,011	40,011
C. IV Estimates								
Wells	-0.025	-0.030	-3.279	-3.027	0.012	0.014	3.887	3.794
	(0.02)	(0.02)	(2.96)	(2.96)	(0.02)	(0.02)	(3.08)	(3.03)
Observations	536,312	536,312	40,011	40,011	536,312	536,312	40,011	40,011
Kleibergen-Paap F	4,890	4,169	363	245	4,890	4,169	363	245

School fixed effects; Time-Department quadratic trends; Landmines, age and gender included as control. Wells are standardized and Price is in logs. Shock assigned in year of enrolment in tertiary education. Sample trimmed to 2010. Buffer of 10Km. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table A19: Effect of Oil Exploitation on Individual Level Human Capital Measures

	Test Scores		*Number of Students*	
t	1970	2000	1970	2000
A. OLS				
Wells	-0.522***	-0.522***	-0.369	-0.369
	(0.10)	(0.10)	(0.41)	(0.41)
Observations	2771137	2771137	68701	68701
B. Reduced Reform				
v_brent_price	-0.049	-0.049	-0.286	-0.323
	(0.03)	(0.03)	(0.21)	(0.24)
Observations	2771137	2771137	68701	68701
C. IV Estimates				
Wells	-0.461	-0.440	-2.373	-2.486
	(0.33)	(0.32)	(1.77)	(1.83)
Observations	2771137	2771137	68701	68701
Kleibergen-Paap F	23728	14421	396	254

School fixed effects; Time-Department quadratic trends; Landmines included as control. Oil suitability and Wells are standardized and Price is in logs. Buffer of 10Km. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table A20: Formal Sector Wages

	OLS	Reduced Form	IV Estimates
Wells	1.767***	.	11.945***
	(0.32)	.	(1.94)
$Price \cdot Wells_{2000}$	.	0.487***	.
	.	(0.08)	.
Enroled	1.646***	1.645***	1.650***
	(0.04)	(0.04)	(0.04)
Enroled $\times$Wells	0.082	.	-0.034
	(0.05)	.	(0.05)
Enroled$\times Price \cdot Wells_{2000}$	.	0.014	.
	.	(0.01)	.
Observations	1,044,133	1,044,133	1,044,133
Kleibergen-Paap F	.	.	1,437

School fixed effects; Time-Department quadratic trends; Landmines included as control. Wages are adjusted for the minimum wage. Wells are standardized and Price is in logs. Buffer of 10Km. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.