INFER WORKING PAPER SERIES

INTERNATIONAL NETWORK FOR ECONOMIC RESEARCH

No. 17 | 2024

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Sustainable development and the extractive industry. An assessment of the Mexican case

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Abstract

This paper investigates the impact of mining on sustainable development in Mexico. Specifically, it examines whether mining affects different dimensions of sustainable development, including consumption patterns, inequalities, education, and environmental quality. Using household data on 2,403 municipalities over a period of 30 years considering four waves of census data (1990, 2000, 2010, 2020), we find that the mining sector has mixed effects on sustainable development. It has a limited positive effect on the income of neighboring households but it also generates negative environmental spillovers. We do not find significant effects on inequalities or education. Overall, our study provides a more nuanced understanding of the impact of mining on various aspects of sustainable development, contributing to ongoing debates on the relationship between natural resource extraction and sustainable development in emerging economies.

JEL: O13, O44, O54, Q01, Q32

Keywords: Sustainable Development, Environment, Extractive industry, Mexico

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1 Introduction

The 2030 Agenda for Sustainable Development, adopted by all United Nations Member States in 2015, introduced 17 sustainable development goals (SDGs).[1] While these SDGs have played a crucial role in the political agenda so far, the 2023 SDG Progress report indicates that these objectives are still far from being accomplished. In fact, some goals have regressed to their 2015 baseline due to recent events such as the COVID-19 pandemic, the war in Ukraine, and climate-related disasters (UN General Assembly, 2023).

An urgent need for action is evident, particularly in addressing climate change. Meeting the climate objectives outlined in the United Nations Climate Change Conference (COP) Agreement and limiting global warming require a significant transformation of our economic activities. This transition involves shifting towards a less energy-intensive economy and embracing a future that is low-carbon or carbon-free.

Notably, the energy transition will inevitably result in a reduction in the demand for fossil fuels, impacting the producers of these resources. However, at the same time, it will also create an unprecedented demand for Energy Transition Metals (ETM). Recognizing this potential, the World Bank emphasizes the significant benefits (notably in the form of windfalls) that increased demand for ETM can bring to developing countries. Latin American economies, in particular, hold substantial deposits of copper, iron ore, silver, lithium, aluminum, nickel, manganese, and zinc, making them well-positioned to play a pivotal role in meeting the emerging demand for ETM (World Bank Group, 2017).

Nevertheless, it is crucial to highlight the potential adverse environmental impact of the mining sector. The mining industry is widely recognized as one of the most ecologically impactful sectors (Lei et al., 2016).

As the world strives to meet the SDGs and combat climate change, the intricate interplay between sustainable development and the energy transition becomes increasingly evident. Many Latin American countries find themselves navigating this intricate balance. Economies work to reduce poverty and inequalities, and in general to improve the social standards of the population while trying to address climate change challenges, notably by reducing their dependency on fossil fuels.

Several Latin American countries have introduced incentives to generate more investment in the mining sector and diversify their economies.

Mexico is one such country that has made significant efforts to promote

[1] The UN defines sustainable development as a development process that meets the needs of the present without compromising the ability of future generations to meet their own needs, and it puts particular attention to the eradication of poverty and reduction of inequalities.

its mining sector. During the 1970s, Mexico was severely impacted by the oil crisis. In response, the government took measures to diversify its economy offering incentives to boost the manufacturing and mining sectors. An important step to promote mining was the implementation of the New Mining Law in 1993, which opened up mining, both exploration and exploitation, to foreign capital. Furthermore, with the entry into force of the North American Free Trade Agreement (NAFTA) with the United States and Canada in January 1994, the new Foreign Investment Law allowed for greater liberalization of the mining industry in Mexico (Saade Hazin, 2013).

As a result, Mexico's economy has experienced significant growth in the extraction of natural resources, particularly in the mining sector, in recent decades. However, this growth has also been accompanied by an increase in socio-environmental conflicts (Tetreault, 2022). Although Mexico's economy has not undergone the same level of "reprimarization" as certain South American countries, it is essential to understand the impact of mining on sustainable development indicators. To this end, this study aims to investigate the contribution of the mining boom to sustainable development in Mexico.

What sets our study apart is our holistic approach to understanding the complex interplay between mining activities and sustainable development. While previous research has often focused on isolated dimensions, we comprehensively analyze three critical aspects: economic performance and inequalities, education, and environmental quality. Notably, our research stands out as it pioneers the use of a staggered difference-in-differences (DID) to address the impact of the mining industry, specifically metals and minerals, on sustainable development. We adopt the estimator proposed by Callaway and Sant'Anna (2020) for our analysis as the conventional two-way fixed-effect estimation may be biased (Goodman-Bacon, 2021; de Chaisemartin and D'Haultfoeuille, 2022; Callaway and Sant'Anna, 2020; Sun and Abraham, 2021). Furthermore, we contribute significantly to the limited literature that uses the discoveries of mineral deposits as exogenous sources of variation, to assess the effects of the mining industry.

For this purpose we construct a unique dataset covering 2403 municipalities from 1990 to 2020. Our study sheds light on the multifaceted impact of mining on these dimensions. The findings reveal the potential for mining to boost local income levels but also highlight the adverse environmental consequences it can bring. We do not find significant effects on education or economic inequalities. Through this in-depth exploration of the Mexican case, we contribute to the global discourse on the effects of the mining sector on sustainable development in developing countries, providing valuable insights for policymakers, researchers, and stakeholders who are addressing the challenges posed by the mining industry in their pursuit of a more sustainable future.

The rest of the paper is divided as follows. Section 2 proposes a literature review on the topic. Section 3 offers a comprehensive overview of the mining sector development in Mexico, and describes the data and methodology used in the paper. Section 4 presents the results of our analysis. In Section 5, we discuss the drivers of our results. Finally, Section 6 presents the conclusions.

2 Literature Review

Given the extensive body of literature examining the effects of natural resource extraction on sustainable development, this paper primarily centers on empirical studies at the subnational level, as the comprehensive analysis of national-level empirical results is beyond the scope of our research. The mining industry plays a crucial role in the economic development of countries by supplying essential inputs for production. However, it is frequently perceived as one of the sectors with the most significant effects on both society and the environment. As a result, the industry actively engages in discussions on sustainable development. While mining companies acknowledge their role in contributing to the energy transition and sustainable development, they often overlook the negative impacts associated with the extraction process (Frederiksen and Banks, 2022).

Taking into account the SDG as a map to measure the possible contributions of the mining sector, Merino-Saum et al. (2018) highlight that minerals are directly involved in achieving affordable and clean energy (SDG7), responsible consumption and production (SDG 12) and climate action (SDG 13). Additionally, mining companies can make direct or indirect contributions to reducing poverty (SDG 1), improving health (SDG 3), enhancing education (SDG 4), empowering women (SDG 5), and reducing inequalities (SDG 10) (Frederiksen and Banks, 2022; Hilson and Maconachie, 2019). However, it is crucial to note that the mining sector is also known for its negative environmental impacts, potentially affecting land (SDG 14) and bodies of water (SDG 6 and 15) among others.

The intrinsic relationship between sustainable development and the exploitation of natural resources has been extensively explored in the literature. One prevailing concept often discussed is the resource curse, which suggests that countries heavily reliant on natural resources tend to experience negative development outcomes. As a consequence, much of the literature has focused on examining the positive or negative effects of resource extraction and overdependency on natural resources on various dimensions of sustainable development.

The literature developed at national level gives mixed results, and is not yet settled (Badeeb et al., 2017; Rosser, 2006). It does however suggest that the quality of institutions may shape the effect of natural resources in the economy. That is, once the quality of institutions is taken into account natural resources do not represent a curse (Aragon et al., 2015; Epo and Nochi Faha, 2019; Mehlum et al., 2006; Sala-i Martin and Subramanian, 2013).

There is growing literature analyzing the effects of the extraction of non-renewable natural resources at the sub-national level. Aragón and Rud (2013) is one of the earliest and key studies to investigate the effect of a mine on consumption in neighboring communities. They find that gold mining increases the level of consumption of the population in the neighboring area.

Similar setups have been used to analyze the effect of natural resource extraction around the globe in different aspects of sustainable development. In the case of Africa, positive effects are generally found in consumption Bazillier and Girard (2020), urbanization (Mamo et al., 2019) or other (Axbard et al., 2021; Benshaul-Tolonen, 2018). Negative spillover effects are found in agricultural productivity (Aragón and Rud, 2015), health (von der Goltz and Barnwal, 2018), inequalities (Aragon et al., 2015) and increase in corruption (Knutsen et al., 2016).

In the case of LAC, the literature also shows mixed results. For instance, gold mining in Peru has positive spillover effects on consumption in the vicinity of the mine (Aragón and Rud, 2013). Nevertheless, the oil activity in Brazil does not show a significant effect on consumption (Caselli and Michaels, 2013). Further Rau et al. (2015) find that waste from a mining site in Chile lead to a decrease in academic performance due to lead concentration in the blood of people in the neighboring area.

Regarding the Mexican case, the literature related to the effects of the mining sector highlights, the negative effects on the vicinity of the mines in Aguascalientes (Mitchell et al., 2016), Zacatecas (SalasMuñoz et al., 2022) and San Luis Potosí (Monzalvo-Santos et al., 2016). The empirical studies are conducted by sampling and analyzing the composition of the flora and fauna affected. As a result, the studies only focus on specific locations.

On a more general note Tetreault (2022) shows that the mining sector has been increasing since the liberation of the sector. However, the increase has been accompanied by a spike in socio-environmental conflicts with neighboring communities.

In conclusion, the literature related to the extraction of natural resources at the sub-national level is growing and gives mixed results. Most of the authors focus on particular aspects of sustainable development, revealing both positive and negative spillover effects. However, research on this topic remains limited, particularly in the context of LAC, and even more so in the case of Mexico. Therefore, our objective is to contribute to the existing literature by offering a comprehensive examination of the effect on the sustainable development of the mining sector in Mexico.

3 Data and Specification

3.1 Mexican Case

Mexico recognizes the importance of fostering the mining sector and has actively promoted its growth. This is not surprising considering the long mining tradition of the country. The mining sector has been part of the Mexican economy since pre-Hispanic civilizations.

Currently, Mexico holds a prominent position as the leading producer of silver worldwide and has considerable deposits of other minerals and metals, including gold, copper, and zinc (Figure A1). The mining sector in Mexico contributes significantly to the industrial GDP, accounting for 8.6% of its total. Mexico's vast territory encompasses an abundance of geological riches, with nearly 70% of the land exhibiting favorable geology for mining operations (Secretaría de Economía de Mexico, 2022).

The sector's notable growth can be partly attributed to the efforts of the government to promote it, which began with the New Mining Law in 1993. This landmark legislation facilitated the entry of foreign capital into the mining sector, enabling both exploration and exploitation to thrive. The mining situation in the country mirrors that of its counterparts in Latin America and the Caribbean (LAC), with the state owning the minerals and the mining companies having to pay fees for exploration and resource extraction.

Following the implementation of the Mining Law, the government opted not to introduce a royalties system for the mining sector. Instead, payments for extraction rights were based on the size of the extraction site. However, due to the sector's growth and the rising commodity prices during the 2000s, the Mexican government decided to introduce additional taxes resembling a royalties scheme. The generated revenues from these taxes are partially allocated to a fund dedicated to mining municipalities involved in the extraction, transportation, and processing of the materials (Morones, 2016). This move aligns the country's system with the widely used royalty scheme (International Monetary Fund, 2012). This fiscal mechanism is also used in other Latin American and Caribbean (LAC) countries such as Brazil, Colombia, and Peru, among others.

Further, the modifications of the mining law in 2022, declared lithium a mineral of national interest, consequently "The exploration, exploitation, benefit, and use of lithium are exclusively in charge of the State". [2] Hence making evident the interest of the country in active participation in the energy transition.

[2] Text translated by the authors from Spanish. The original text says "La exploración, explotación, beneficio y aprovechamiento del litio quedan exclusivamente a cargo del Estado..."

3.2 Data

3.2.1 Sustainable development measures

To assess the impact of the mining sector on sustainable development in Mexico, we focus on income, inequalities, education, and environmental damages. The mining sector accounts for 8.6% of Mexico's industrial GDP; therefore, we can anticipate that it contributes to the economic development of the municipalities where mines are located. Additionally, our analysis delves into the intricate relationship between mining and income inequalities, as these activities can either alleviate poverty or exacerbate disparities within local communities. We also explore the potential effects of the sector on education, considering both possible improvements in access to education and potential detrimental effects. It is worth noting that empirical evidence at the national level suggests that natural resource abundance can be negatively correlated with education (Gylfason, 2001; Ross, 2001; Sachs and Warner, 2001). Furthermore, considering that the mining sector is often viewed for its substantial environmental impact; our research addresses the environmental sustainability aspects of mining, offering an examination of land degradation (proxied by NDVI as a measure of vegetation health) as well as water and air pollution.

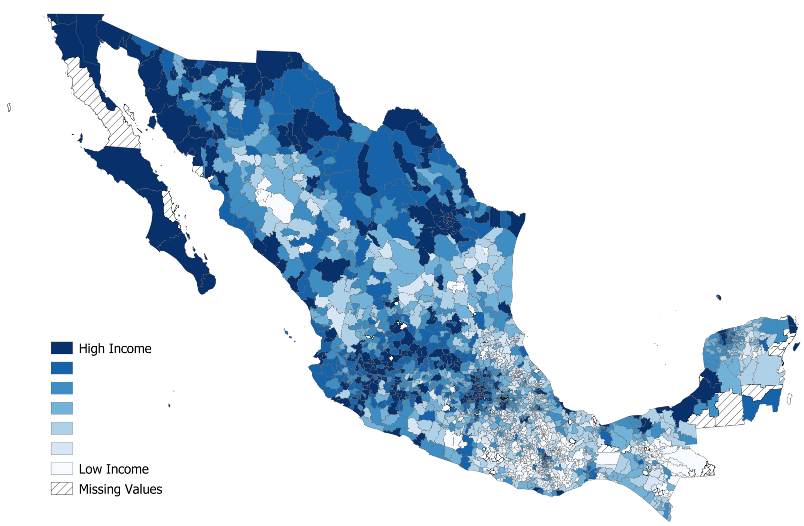
We construct a novel dataset for Mexico covering 2,403 municipalities considering information on key sustainable development indicators and the mining sector.

Our main data source for the characteristics of Mexican municipalities is the extended survey of the census. The main differences between the basic questionnaire and the extended version lie in their coverage and the number of questions they contain. We rely on the extended survey as it has information on the municipality of the households, their characteristics, and their income (other standardized surveys conducted in Mexico as the household survey do not specify the location at the municipality level). We consider data from four rounds of the Census covering 1990-2020.

We employ the information of the households and individuals for different variables of interest and the control variables. For household income, we use the question "Monthly income from work in the household" or equivalent. In total, our dataset has information on 10,931,947 households. Figure 1 maps the average income of municipalities for 2020 as a reference year. We observe that municipalities with higher levels of income are mostly located in the north of the country as well as the near area of the capital, highlighting the well documented disparities between the northern and southern regions (Sánchez-Reaza and Rodríguez-Pose, 2002; Trejo Nieto, 2020).

We use household income to construct two measures of income inequalities, namely the Gini and Theil index. [3] Figure A2 maps the Gini at the municipality level. We drop municipalities that present missing values in any of the four rounds of the census used. As a result, our dataset finally covers 2,403 municipalities. Income inequalities show an overall decrease (Figure A3). Using the information on the education status of individuals in the survey, we build a measure of the secondary schooling rate and average years of schooling. Over time there has been a noticeable improvement in education indicators (Figure A4).

Figure 1: Income Distribution



To assess the environmental impact we use high-definition satellite data from NASA to construct a normalized difference vegetation index (NDVI) at the municipality level. The NDVI is a commonly used remote sensing index that indicates the amount and vigor of vegetation in an area by analyzing the difference in reflectance between near-infrared and red light. It is computed as:

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{1}$$

Where NIR and RED are the amounts of near-infrared and red light, respectively, reflected by the vegetation and captured by the sensor of the satellite. The formula is based on the fact that chlorophyll absorbs RED whereas the

[3] We use the INEQDECO package in Stata for the construction of the Gini and Theil indices based on income data from the census

mesophyll leaf structure scatters NIR. NDVI values thus range from -1 to +1, where negative values correspond to an absence of vegetation (Pettorelli et al., 2005).

The literature highlight the potential and documented negative effects of the mining sector. In the case of Mexico, Several studies have demonstrated a correlation between the mining industry and land degradation resulting from exposure to metal contamination (Mitchell et al., 2016; SalasMuñoz et al., 2022; Monzalvo-Santos et al., 2016). We hypothesize that this land degradation will adversely affect the local flora, leading to a reduction in the quality and quantity of vegetation, which, in turn, would be reflected in decreased NDVI values.

The NDVI is high-frequency data. To harmonize our model we aggregate the data at the municipality-year level. For this reason, we use yearly data from 2000-2020 in our model (in that regard, the frequency of the environmental data is different than other sustainable development outcomes). Figure A5 shows the distribution of the NDVI in Mexico for 2020. As expected high values of the index are located in the south of the country. Further, in the sample, we observe that there is an overall decrease in the mean NDVI in the country with a slight recovery at the end of the studied period.

For robustness purposes we also check whether the environmental impact of the mining sector, affects bodies of water and reflects in air contamination. We use data from the Comisión Nacional del Agua (2023), which provides information on water quality from 2012 to present for selected bodies of water (superficial water, as in rivers, and lakes). In the case of air quality we rely on ODIAC dataset which is a high-spatial resolution global emission data product of CO2 emissions from fossil fuel combustion (Oda and Maksyutov, 2015). Similarly with the case of NDVI data, we aggregate the CO2 emissions data at municipality level for the period 2000-2020.

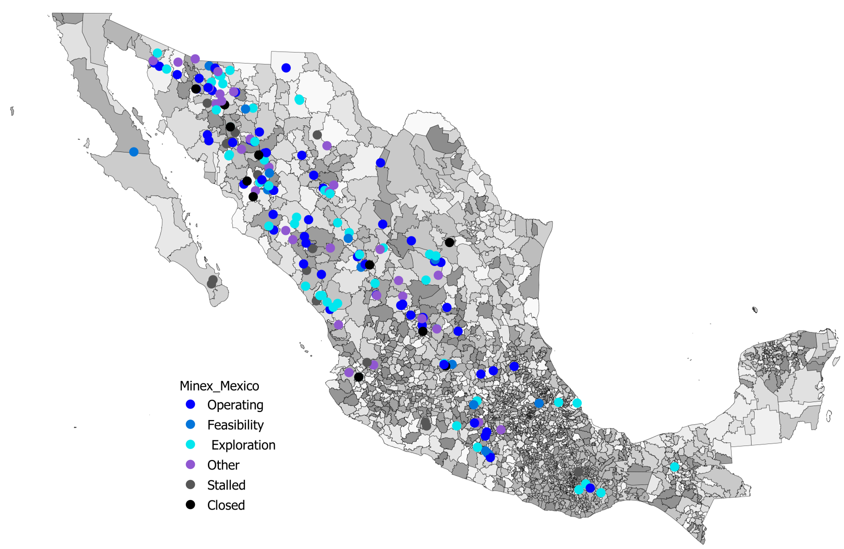
3.2.2 Mining variables

We combine the information from the census with data on mining, taken from Minex. The database provides information about medium-size or larger known mineral commodities, their characteristics, and the geographical location of mines with a global scope. In the case of Mexico, the dataset covers 193 observations. Figure 2 shows the location of the different activities in the territory. The data shows that 33% of the mines are operating, 25% are in exploration, 16% in feasibility and the rest present another status. Furthermore, most of the mining activity is concentrated in northern and central areas of the country.

In this study, we employ data on both the start of mining operations and the discovery of mineral deposits. Our approach is based on the observation that there was a significant surge in the number of mining discoveries and the establishment of new mines after the early 1990s as shown in Figure A6. This growth of the sector corresponds to the liberalization of the mining industry, which occurred after the new mining law and the North American Free Trade Agreement (NAFTA) was implemented. The goal of these policy changes was to encourage foreign investment in the mining sector.

When considering the composition of the materials being extracted, we observe that a large proportion of the mining activities in our sample pertain to precious metals. Approximately 77% of the mining operations in our study involve gold or silver as the primary metal in the deposit. Copper ranks as the third most common metal, accounting for 12% of the sample, followed by Zinc at 4%. Other minerals present in the deposits included in our analysis comprise graphite, iron, lithium, and several others.

Figure 2: Mines location



3.2.3 Control variables

We use census data to control for the demographic characteristics of the population. In particular, we use information on age, sex, indigenous language, and accumulated education of the head of the family as controls. Further, we rely on information from INEGI and geocoded data to construct geographical controls. At the municipality level, we use a percentage of agricultural land, a dummy if the municipality has a coastline if it is the capital of the state, distance to capitals, and to DF.

3.3 Methodology

To evaluate the impact of the mining sector on sustainable development, we start by testing whether municipalities with active mines (the treated group) exhibit higher or lower levels of key development factors compared to non-mining municipalities. To achieve this, we adopt a staggered difference-in-differences (DID) model:

$$Y_{it} = \beta D_{it} + \lambda X_{it} + \alpha_i + \alpha_t + e_{it} \tag{2}$$

where Y_{it} represents the outcomes of interest. We use income to asses economic development; years of schooling and percentage of secondary enrollment for education; Gini index and Theil index for economic inequalities; and we use NDVI for environmental damages. D_{it} is a binary variable equal to 1 if there is a mine operating since year $\tau \leq t$. X_{it} is a vector of time-varying socio-demographic characteristics used as controls in the model. Finally α_i, α_t represent municipality and year fixed effects respectively. e_{it} is the error term.

We define the treatment and control group based on the characteristics of the mining sector. The treatment is composed of those municipalities that present an operating mine ($D_{it} = 1$). The control group is composed of those municipalities that do not have one. As a robustness check, we also test whether the discovery of a deposit has an impact on development. To do this, we generate a binary variable equal to 1 if there is a discovery in a given municipality.

Given the nature of the mining sector, our approach differs from the conventional difference-in-differences (DID) methodology as we have multiple time periods to consider. As shown in Figure A6, the start of mine operations in Mexico is staggered, and we assume that once a municipality begins mining operations, it does not change this status. However, as the implicit assumption of a constant treatment effect over time is unlikely to hold in our case, the standard two-way fixed-effect estimation may be biased (Goodman-Bacon, 2021; de Chaisemartin and D'Haultfoeuille, 2022; Callaway and Sant'Anna, 2020; Sun and Abraham, 2021). To address this issue, we adopt the estimator proposed by Callaway and Sant'Anna (2020) for our analysis. In the sample, 54 municipalities experienced the discovery of a new deposit during the study period (1990-2020). Additionally, 40 municipalities started mining sector operations for the first time within the same period.

We use this estimator to compute the average treatment on the treated (ATT) using various approaches. Specifically, we take advantage of group-specific ATT and event study methodologies to analyze our results. The former enables us to examine the impact of mining on different groups of municipalities based on the year of treatment. In other words, we assess the average treatment effect for municipalities that entered the treatment group in year t. The latter approach involves running Equation (3) to explore the dynamic effects of the treatment. This allows us to observe the treatment's impact and its evolution until time $t = L$, while also accounting for the anticipation of municipalities receiving the treatment.

$$y_{it} = \sum_{e=-K}^{-1} \beta_e^{anticip} D_{it}^e + \sum_{e=0}^{L} \beta_e D_{it}^e + \gamma X_{it} + \alpha_t + \alpha_i + v_{it} \tag{3}$$

Note that there are three versions of equations (2) and (3), depending on the outcome of interest. For inequalities, education, and consumption, the time dimension covers the period of 1990-2020 using four points (1990, 2000, 2010, and 2020). For consumption, we use data at the household level instead of the municipality level. The treatment criteria are chosen at the municipality level, that is, treated households are those in a municipality where there is an operating mine. For NDVI, due to the type of information, we use yearly data over the period 2000-2020 and we only include geographical controls. Our approach to assessing the environmental impact of the mining sector differs from existing literature in a significant way. Unlike methods that directly measure water or soil quality (Mitchell et al., 2016; SalasMuñoz et al., 2022; Monzalvo-Santos et al., 2016), our methodology does not allow for a detailed assessment of contamination from sampling. However, it does enable us to consider larger geographical areas in our study.

4 Main Results

4.1 Baseline

Table 1 presents a summary of our main findings, with detailed result tables available in the appendix. We observe that the start of a mine in a municipality increase the level of income of households. Additionally, we observe a reduction in the NDVI, indicating a decline in vegetation quality. For the analysis of household consumption, we used a repeated cross-sectional regression approach from the Callaway and Sant'Anna (2020) estimator to take advantage of a more comprehensive dataset. Figure A7 presents the event study set-up for the effect of mining on household income. Detailed results are displayed in Table A1. Our results reveal a significant impact of the mining sector on household income. The average treatment effect is positive and statistically significant, and it continues to remain positive even after the initial period of treatment. We also observe a positive effect one period before the start of the mine ($t-1$); however, the average effect prior to the start of the mine is negative. This result can be explained by the various activities that surround the mining sector before the start of mining operations, such as the feasibility and construction of the mine site. Furthermore, due to data constraints we are unable to measure growth rates of household income. Consequently, we interpret our findings as indication a one-time increase in the level of income of those households located in the municipality where a mine starts operation. This increase happens even before the start of the mine.

Table 1: Dynamic effects of mining

Consumption		Environment (NDVI)	
Event - Study			
Average $(t < 0)$	-0.116*** (0.0228)	Average $(t < 0)$	78.84*** (20.51)
Average $(t \geq 0)$	0.137*** (0.0259)	Average $(t \geq 0)$	-377.3** (181.9)
Group Specific Effect			
G. Average	0.124*** (0.0134)	G. Average	-59.96*** (22.69)
N	8300793	N	51282

Note: the table shows staggered DID estimations. The dependent variable for consumption is logarithm of income of the households and in the case of environment the NDVI at municipality level. Average treatment effect on the treated (ATT) of start of a mine for each specification. Event study results show the overall ATT across all groups overtime, while the group-specific results average the ATT of each group. $(t < 0)$ Represent average anticipation of the treatment and $(t \geq 0)$ and G. Average are the ATT of start of the mine depending of the specification. . WildBootstrap (WB) standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The second part of table 1 shows the main findings of the results for environmental impacts using the NDVI. We observe the average effect of mining over the studied period (2000-2022). The results indicate that the mining sector has a significant environmental impact, as expected. The negative effects reflect a reduction of the NDVI, hence, a reduction in the health of the vegetation in the municipality. Table A2 presents short-listed results for the NDVI estimation, Table O1 in online appendix presented detailed results.The event study suggests that the effect of the opening of a mine is not significant in the years following the event but over the years it becomes visible and is captured by the health of the vegetation as displayed in Figure A8. We interpret this lag in the impact as the time it takes for the sector to have significant negative environmental impacts that are observed with satellite imagery. Moreover, we observe that on average the post-treatment effect is negative and significant along different aggregation methods allowed by the Callaway and Sant'Anna (2020) estimator. In this regard, our results are in line with the literature that highlights the negative environmental spillovers of the sector.

Table A3 for the rest of the outcomes. We observe that the start of mine does not significantly impact neither education, measured by secondary enrollment rate or average years of education, nor the distribution of income. We do not find any significance for the average effect post-treatment, neither the effect in ten nor 20 years is significant. We observe a modest reduction of the inequalities before the start of the mine measured by the Gini. However, the result is not fully consistent with the Theil index. In the case of the Theil index, the pre-treatment indicates a reduction of inequalities as the Gini. Nevertheless, the effect after 10 years of the start of the mine indicates an increase in inequalities, this effect of the start of the mine is not observed using the Gini. Consequently, we conclude that the effect of the mining sector on inequalities is not robust.

The baseline results suggest a dual effect of the start of operation of a mine in a municipality: on one hand, there is an increase in the income levels of households. However, this increase is accompanied by an increase in environmental contamination, as evidenced by the reduction of the NDVI. We highlight that the effect on income is perceived earlier than the environmental damage, according to the results. Furthermore, the extractive sector does not appear to have a significant influence on education or economic inequalities within the host municipalities. Therefore, in the following section, we will focus on the robustness of the impact of the mining sector on household income and environmental damage.

4.2 Robustness Checks

To ensure the robustness of our findings, we employ several approaches. Firstly, we modify the treatment and control group by selecting municipalities in closer proximity to the mining sites. Secondly, we account for the possibility that changes in the surrounding areas may occur before the actual start of mining activities due to differences in time between the discovery of deposits and the start of mining. To do this, we re-estimate our baseline equation using the year of discovery as the treatment. Finally, we adopt an alternative estimation method to test the validity of our results.

To ensure the robustness of our findings regarding the effects on income and the environment, we conducted additional tests. Firstly, we examined whether the impact of mining sites spills over to neighboring municipalities. To do this, we created buffers around the mine sites and included municipalities located within these buffers as part of the treated group. We tested different buffer sizes ranging from 5km to 75km from the mines.

In the case of consumption, we found that the results remained consistent and qualitatively similar with the selected buffers (See Table A4, Figure A9). However, the magnitude of the results decreased beyond 10 kilometers. Additionally, while the average effect on the treated is positive, group-specific coefficients are less significant (and even negative in the 75km buffer).

The event study analysis revealed that there was an increase in income levels even before the start of the mine, and this level remained relatively stable in the periods following the mine's start for the closest municipalities (within 5km). However, for farther buffer distances, the income boost observed initially decays over time as shown in figure A11a.

We interpret these results as evidence of the enclave nature of the mining sector. The initial income boost may be attributed to the construction phase of the mine, but once the mine is operational, we observe a slight decline in income levels.

These findings support the idea that the mining sector has only local effects on income, and these effects tend to diminish as distance from the mine increases.

The extensive literature on the environmental effects of mining consistently highlights the negative impacts on nearby areas. Indeed, our findings suggest a similar picture. We observe that the significance of the effects diminishes beyond a distance of 25km, and the results are no longer robust out with a 10 km buffer (Figure A10). Table A5 presents the average effects for different distances, revealing that in the event study setup, the average effect after the start of the mine is significant at 5km, 10km, and 25km. However, when examining group-specific average effects, we find that only the treatment at 5 km and 10 km distances is statistically significant. These results partially align with the literature, which emphasizes the enclave nature of the environmental impacts, suggesting that the effects are more concentrated in closer proximity to the mining sites.

Our findings on consumption patterns suggest that changes in income dynamics start to occur even before the actual start of mining operations. This observation can be attributed to preliminary phases such as exploration, feasibility studies, and construction, which require investments that can impact household incomes. Additionally, once a mineral deposit is discovered in a municipality, expectations and anticipation may start to build up, potentially influencing income levels or the environment for that matter.

To address this issue, we modify our approach by using the year of discovery instead of the year of the mine's start to define the treatment group. This adjustment allows us to capture the effects of the different mining phases and their potential influence on income dynamics, providing a more accurate representation of the treatment effect. By using this approach we add to the literature that uses the discovery of deposits as exogenous sources of variation (Brunnschweiler and Poelhekke, 2021; Cavalcanti et al., 2019; Cotet and Tsui, 2013; Smith, 2015).

We first test whether we find similar results using as a treated group all the municipalities that have a discovery in our sample, this method differs from the baseline as the treated group is bigger due to those locations in which there has been a discovery but a mine is not operating yet. As a result, we do not expect to have the same results with this methodology as the treated group may include municipalities with stalled projects or in feasibility that do not necessarily have a significant impact on the municipality. In the second step, we slice the treated group so that it only includes municipalities with operating mines.

The results obtained for consumption levels show weak effects in our analysis. We observe an increase in consumption levels in the period immediately following the discovery of a mineral deposit. However, the average effect over the post-discovery period is not statistically significant. When examining the group-specific setup, we find mixed results as well. While the average effect is positive, two specific groups (2000 and 2020) exhibit a negative effect on consumption levels. These findings remain consistent even when we exclude municipalities with deposit discoveries that are not currently operating.

We interpret the results as evidence of the limited capacity of the mining sector to permanently increase household wealth through consumption. Despite an initial boost in consumption levels following a deposit discovery, the effects are not sustained over time. This suggests that the mining sector may have limitations in its ability to generate long-term prosperity for households in terms of consumption patterns.

In the case of NDVI we find similar results as the baseline (see Figure A11), the average effect is negative in both set-ups. Further, we observe negative effects sooner compared with using the start of the mine as a source of variation (from two years after the discovery). The results are largely unchanged when we omit those municipalities without operating mines.

In addition to our baseline estimator, we also employ an alternative estimation method for Equation (3). Specifically, we utilize the estimator proposed by de Chaisemartin and D'Haultfoeuille (2022). Unlike the approach presented by Callaway and Sant'Anna (2020), this estimator does not allow for group or cohort-specific Average Treatment Effects (ATT).

The results obtained using this alternative estimator exhibit a similar pattern to our baseline findings. However, the significance levels differ as shown in Table O3 and Figure A12. Specifically, in the case of consumption, we observe a significant effect only in the year of the start of the mine. On the other hand, for the Normalized Difference Vegetation Index (NDVI), we observe a significant effect only after t+13.

Lastly, we validate the results related to environmental damage by employing alternatives measures, specifically we test for contamination in bodies of water and air contamination. For the former, we utilize data from Comisión Nacional del Agua (2023), which provides information on water quality from 2012 to the present for selected bodies of water (superficial water, as in rivers, and lakes).

We conduct tests to determine if the start of a mine increases the presence of heavy metals in the water. [4] For this analysis, we define the treatment group as those observations (rivers, lakes, etc.) located within a 10-kilometer radius from a mine. The results indicate that mining does indeed lead to an increase in the levels of arsenic, mercury, and potentially chromium in the water.

Table A9 displays the results, and we observe that the average effect is both significant and positive in the event study setup. However, in the case of chromium, the group-specific setup no longer yields a positive effect. These findings provide additional evidence for the concerns regarding the environmental impact of mining activities.

We use data from ODIAC dataset, a high-spatial resolution global emission data product that tracks CO2 emissions from fossil fuel combustion (Oda and Maksyutov, 2015). Similar to our approach with the NDVI data, we aggregated the CO2 emissions data at the municipal level for the period from 2000 to 2020, and the results are presented in Table A10. Our analysis reveals that the average effect is not statistically significant, neither post the start of mining activities nor in the group specification. However, we do find weak evidence of an increase in CO2 emissions; notably, the dynamic effect in the year of the start of mining is significant as well as other specific years. Furthermore, in the group specification, six cohorts show an increase in emissions, while only two exhibit a reduction.

In summary, the different proxies we employed provide evidence of the mining sector's adverse impact on the environment. In line with previous studies, our results suggest that the sector contributes to land degradation, as reflected in the reduced health of vegetation. Furthermore, we also observe evidence of heavy metals in bodies of water, but we do not find strong evidence of increased

[4] We test for the presence or increase of arsenic, cadmium, chromium, mercury, nickel, lead, cyanide, copper, and zinc.

pollution at the municipal level, although such effect cannot be ruled out.

5 Discussion

In the previous section, we showed that the mining sector had a significant effect on household income, while also resulting in negative environmental spillovers. In this section, we aim to analyze whether these effects are driven by specific types of mines, such as those involved in the extraction of precious metals, bulk commodities, particularly energy transition metals, or mining sites of a particular size. Additionally, we conduct further tests to examine whether the income shock resulting from mining activities affects different quantiles of the population.

We initially investigate whether the size of a mine influences the impact of the mining sector on a municipality. Our dataset categorizes mines into three sizes: medium, major, and giant deposits. To examine this, we modify the treatment group in our baseline analysis, including only municipalities with specific mine sizes, while excluding other mining municipalities from the sample.

Table A11 presents the ATT based on the characteristics of the mine. In terms of consumption, the results indicate that the effects are primarily driven by giant and major mining sites. Interestingly, we observe a slightly larger effect for giant operations. In municipalities where the mining sector starts with moderate-sized operations, the effect of the mine's start on income is not statistically significant. Additionally, major-sized mines tend to have negative spill-over effects on the environment of the host municipalities.

Furthermore, the behavior of the mining sector is primarily influenced by the extraction of precious metals. This finding aligns with our expectations, considering that nearly 80% of the sample consists of mines where the primary metals extracted are gold or silver. Consequently, we do not find any significant effects of Energy Transition Metals (excluding silver) on household income. The negative environmental effect do not seem to be exclusive to a particular type of commodity, although the effect in our sample is not robust among specifications. [5]

To analyze the distributional effects of the mining boom on households within the municipalities, we divide our sample into quantiles and estimate the outcomes for each cohort. Table A12 presents the results. The findings indicate that the lowest quantile, as well as the 3rd and 4th quantiles, benefit from the mining sector. Interestingly, although the lowest quantile experiences

[5] The results of precious metals present qualitatively the same behavior of the baseline, although, in the case of event study specification, the average post treatment effect is not significant

the largest effect, this impact is not persistent over time in the dynamic setting. On the other hand, higher quantiles continue to experience positive effects from the mining boom.

The results suggest that the discovery and further extraction of natural resources do not necessarily guarantee an increase in household consumption in the neighboring areas. Rather, the implications are similar to opening Pandora's box, as positive spillovers on consumption if there are any, may be accompanied by negative environmental effects. This interaction explains the increase of unrest and conflicts in communities with mining projects. As the positive and negative effects of the mining sector will largely depend on the characteristics of the mine.

6 Conclusion

In this study, we have analyzed the role of the mining sector in the sustainable development of Mexican municipalities. For this purpose, we use a novel dataset constructed with Satellite data, Mining information, and the Mexican Census. We exploit the variability that occurred in the country due to the introduction of the new mining law and the NAFTA that liberalized the mining sector. Consequently, we analyze whether the start of a mine in a municipality improves or deteriorates sustainable development.

Our findings reveal that the discovery and start of mining activities contribute to an increase in the income levels of municipalities. However, the persistence of this effect over time varies depending on the characteristics of the mine. Furthermore, it is important to note that the benefits are not evenly distributed among households within the municipalities. Additionally, some spillover effects can be observed in neighboring areas, albeit to a lesser extent.

Simultaneously, the mining sector has negative environmental spillovers, particularly in the host municipality. However, these effects may not be immediately evident in the short term. Our analysis does not uncover significant effects on education or monetary inequalities. It is the combination of these outcomes that helps explain the rise in conflicts between communities and mining projects.

Overall, our study sheds light on the complex dynamics of the mining sector, highlighting both the economic benefits and environmental challenges associated with it. The unequal distribution of benefits and potential negative consequences contribute to the increased unrest observed between communities and mining projects.

The energy transition required to mitigate climate change is intensive in the use of minerals and metals. Consequently, an increase in extraction within the mining sector is expected to meet the demand for addressing climate change. Hence, mitigation policies aimed at achieving carbon neutrality may function as a double-edged sword. On one hand, they reduce carbon emissions, but on the other, there are mixed effects on sustainable development for mining communities, with increases of levels of income accompanied by an increase in environmental damage due to material extraction.

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7 Appendix

Figure A1: Global supply participation

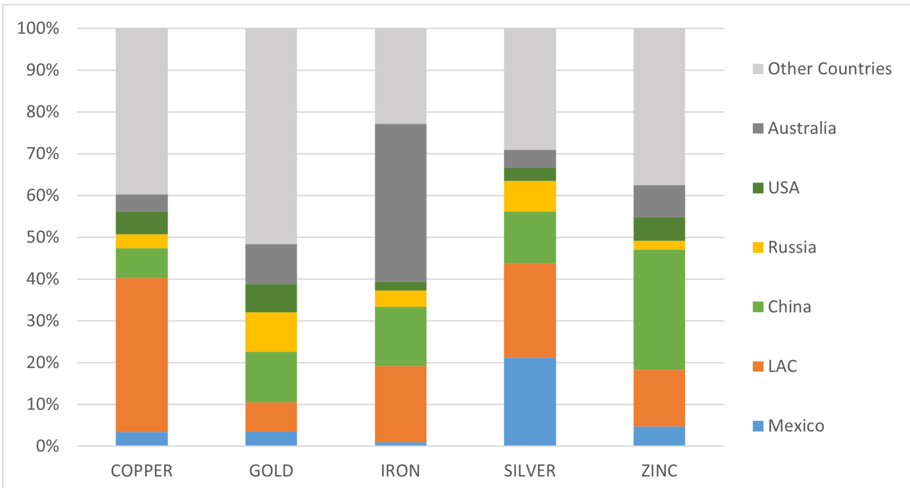


Figure A2: Gini Index

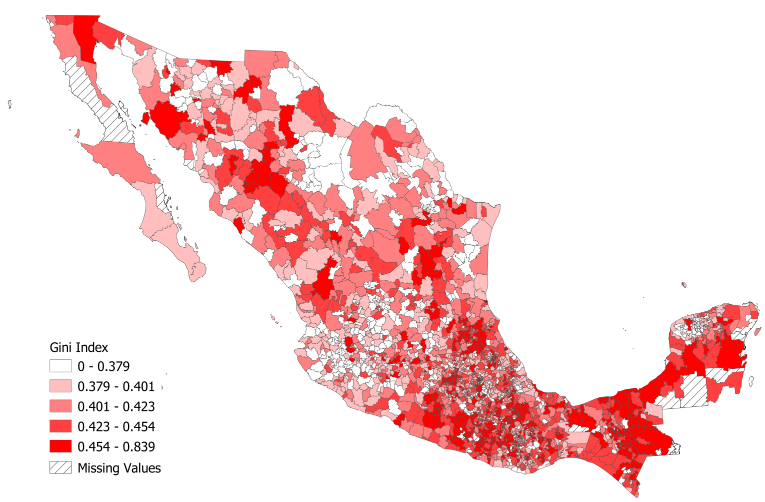
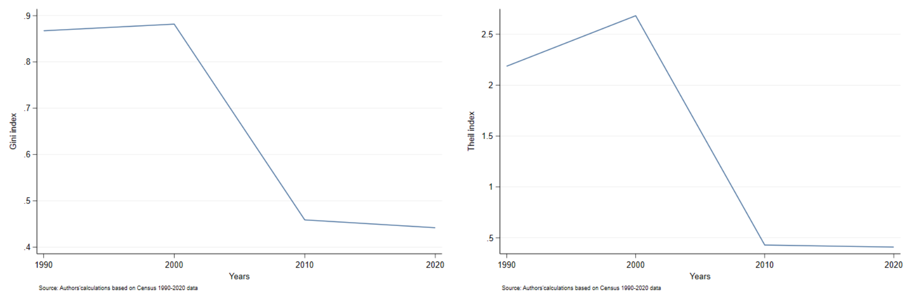
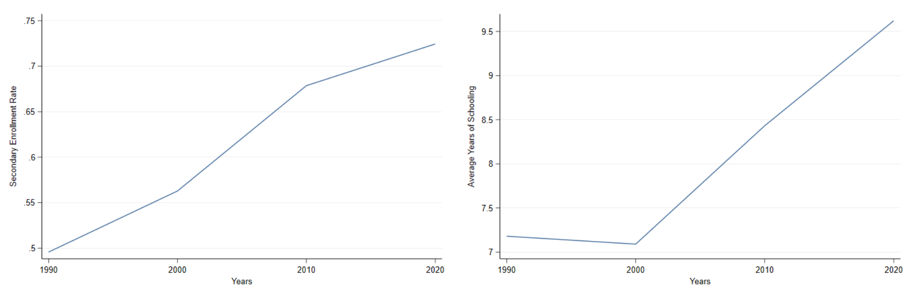


Figure A3: Evolution of inequalities indicators



(a) Gini index (b) Theil index

Figure A4: Evolution of education indicators



(a) Secondary enrollment rate (b) Average years of schooling

Figure A5: NDVI Maps

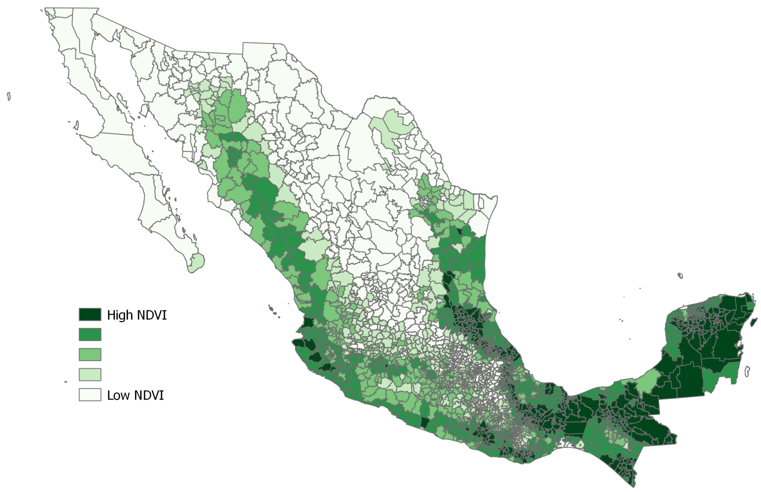
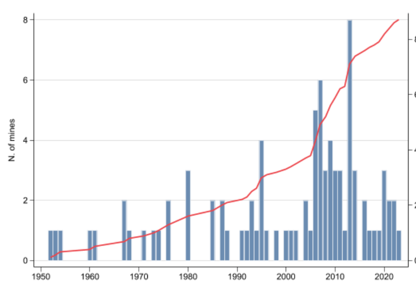
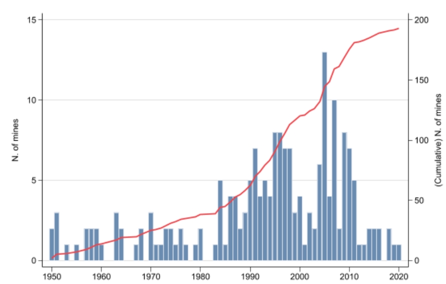


Figure A6: Evolution of the mining sector

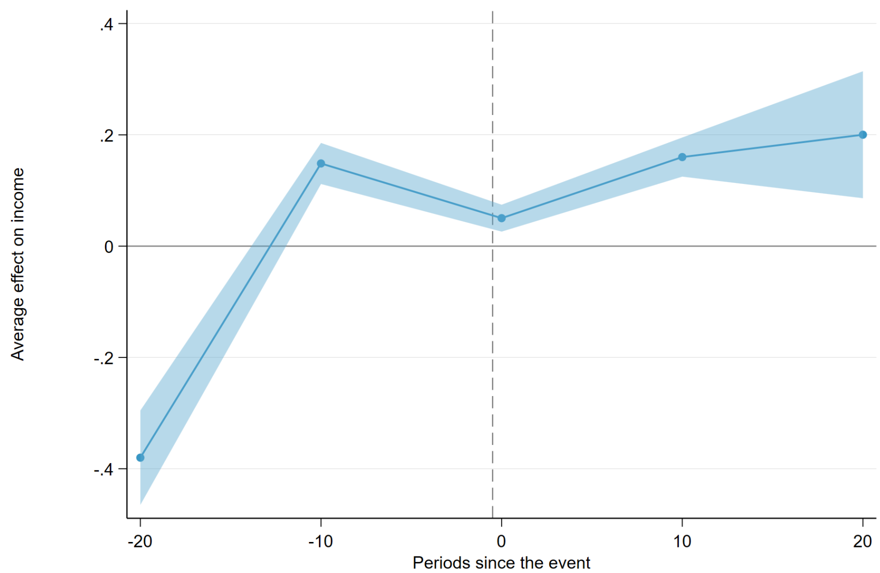


(a) Year of Start of mines



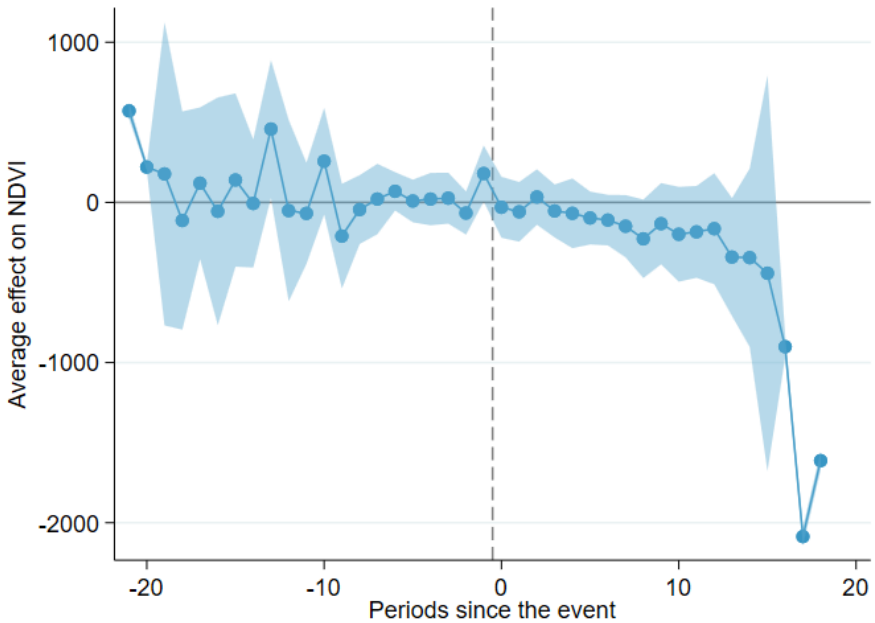
(b) Year of Discovery of Deposit

Figure A7: Effect of mining on Income



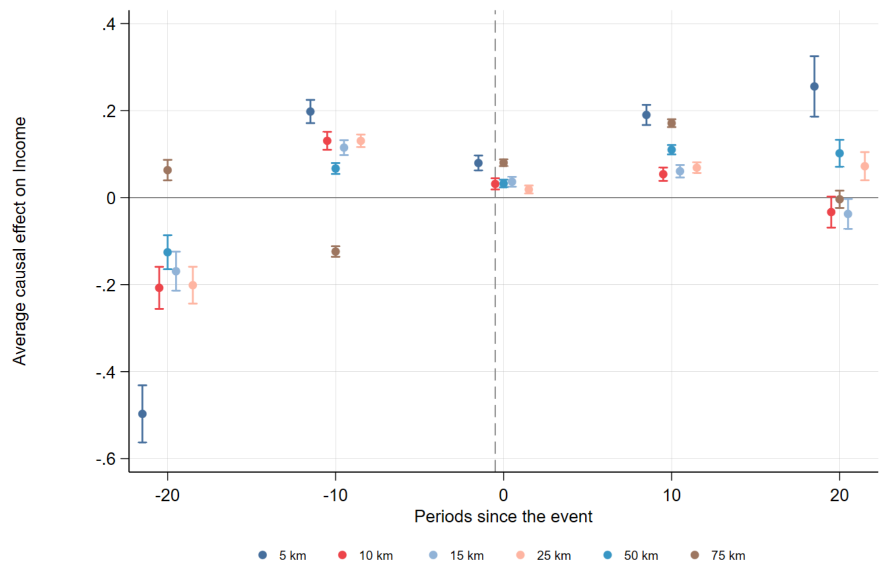
Event Study based on Callaway and Sant'Anna (2020) estimator. The treatment is defined by the start of the operation of a mine in the municipality. We use WB for the standard errors.

Figure A8: Effect of mining on Environment (NDVI)



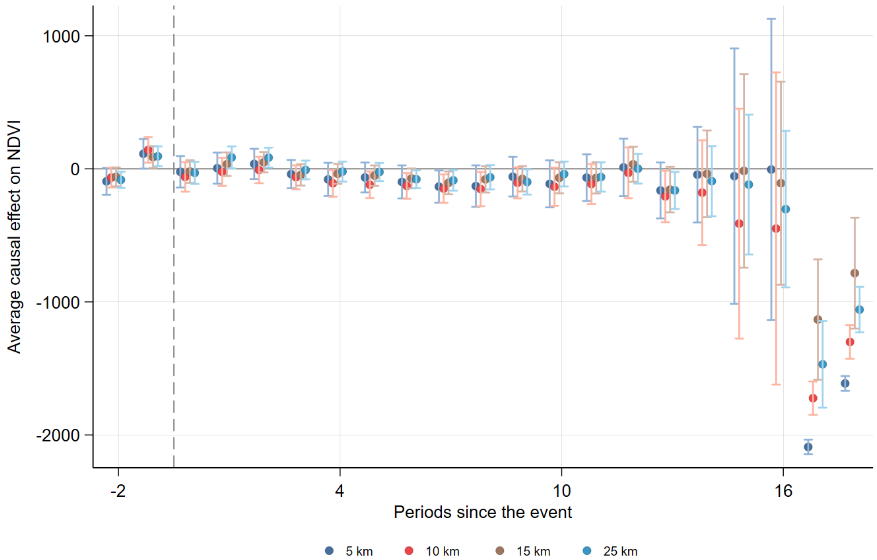
Event Study based on Callaway and Sant'Anna (2020) estimator. The treatment is defined by the start of operation of a mine in the municipality. We use WB for the standard errors.

Figure A9: Robustness test: Effect of mining on Income



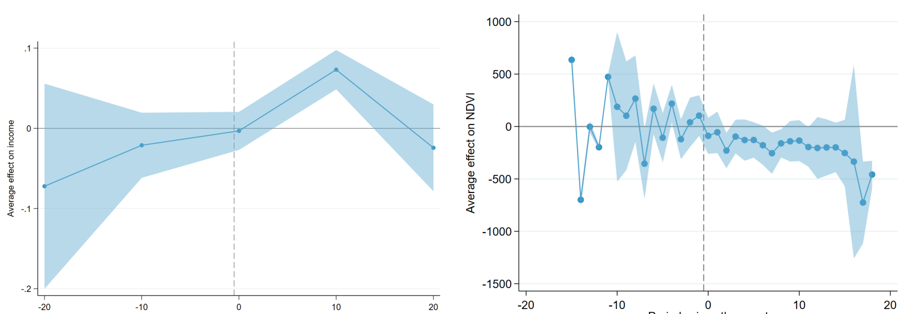
Event Study based on Callaway and Sant'Anna (2020) estimator. The treatment is defined by the start of operation of a mine, the treated municipalities are chosen based on distance from the mine. We use WB for the standard errors.

Figure A10: Robustness test: Effect of mining on Environment (NDVI)



Event Study based on Callaway and Sant'Anna (2020) estimator. The treatment is defined by the start of operation of a mine, the treated municipalities are chosen based on distance from the mine. We use WB for the standard errors.

Figure A11: Robustness test: Discovery year

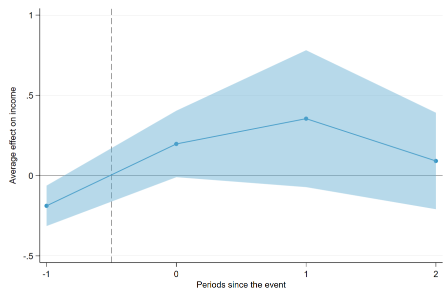


(a) Effect on Income

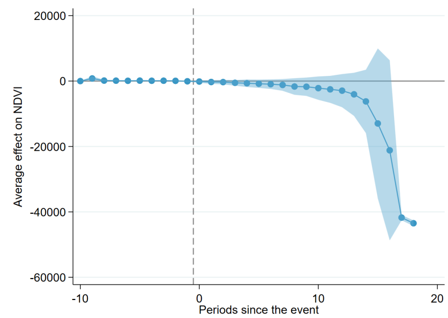
(b) Effect on Environment (NDVI)

Event Study based on Callaway and Sant'Anna (2020) estimator. The treatment is defined by the year of discovery of the deposit. We use WB for the standard errors.

Figure A12: Robustness test: Alternative estimator



(a) Effect on Income



(b) Effect on Environment (NDVI)

Event Study based on de Chaisemartin and D'Haultfoeuille (2022) estimator. The treatment is defined by the year of the start of the operation of the mine. We use WB for the standard errors.

Table A1: Dynamic effects of mining on consumption

(Event Study)		(Group-Specific Effect)	
Average	-0.116***	G. Average	0.124***
($t < 0$)	(0.0228)		(0.0134)
Average	0.137***	$g = 2000$	0.0987**
($t \geq 0$)	(0.0259)		(0.0465)
$t = -20$	-0.380***	$g = 2010$	0.117***
	(0.0432)		(0.0177)
$t = -10$	0.149***	$g = 2020$	0.159***
	(0.0188)		(0.0154)
$t = 0$	0.0503***		
	(0.0123)		
$t = 10$	0.160***		
	(0.0179)		
$t = 20$	0.200***		
	(0.0582)		
N	8300793	N	8300793

Note: the table shows staggered DID estimations. The dependent variable for consumption is logarithm of income of the households. Average treatment effect on the treated (ATT) of start of a mine for each specification. Event study results show the overall ATT across all groups overtime, while the group-specific results average the ATT of each group. ($t < 0$) Represent average anticipation of the treatment and ($t \geq 0$) and G. Average are the ATT of start of the mine depending of the specification. ($t = n$) represents the ATT of n years since/before the event (being 0 the year of the start of the mine).$g = k$ represents the ATT across time of the group of municipalities that received the treatment in the year k. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. WildBootstrap (WB) standard errors in parentheses.

Table A2: Dynamic effects of mining on NDVI

(Event Study)		(Group-Specific Effect)	
Average ($t < 0$)	78.84*** (20.51)	G. Average	-59.96*** (22.69)
Average ($t \geq 0$)	-377.3** (181.9)	g =2002	-2092.9*** (26.74)
$t = 0$	-30.45 (97.02)	g =2005	384.9*** (5.548)
t =8	-227.3* (125.1)	g = 2009	-261.2*** (19.36)
t =13	-341.4* (187.8)	g = 2011	-49.15*** (13.35)
t =16	-901.0*** (32.09)	g = 2014	169.9*** (11.50)
t =17	-2086.4*** (28.65)	g = 2019	-193.7*** (6.330)
t =18	-1612.2*** (29.89)	g = 2020	181.4*** (6.477)
N	51282	N	51282

Note: the table shows staggered DID estimations. Complete table of results available in online appendix. The dependent variable for environment is the NDVI at municipality level. Average treatment effect on the treated (ATT) of start of a mine for each specification. Event study results show the overall ATT across all groups overtime, while the group-specific results average the ATT of each group. ($t < 0$) Represent average anticipation of the treatment and ($t \geq 0$) and G. Average are the ATT of start of the mine depending of the specification. ($t = n$) represents the ATT of n years since/before the event (being 0 the year of the start of the mine).$g = k$ represents the ATT across time of the group of municipalities that received the treatment in the year k. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. WildBootstrap (WB) standard errors in parentheses.

Table A3: Dynamic effects of mining on Education and Economic Inequalities

	(Event Study)					(Group-Specific Effect)			
	Enrollrate	Esco	Gini	Theil		Enrollrate	Esco	Gini	Theil
Average	-0.0329*	0.00894	-0.0551***	-0.206***	G. Average	-0.00125	-0.0595	-0.0105	0.109*
$(t < 0)$	(0.0193)	(0.0986)	(0.0141)	(0.0786)		(0.0153)	(0.0851)	(0.00971)	(0.0617)
Average	-0.0177	-0.0461	-0.0188	0.101	$g = 2000$	-0.0439	0.0132	-0.0238	0.0828
$(t \geq 0)$	(0.0207)	(0.125)	(0.0150)	(0.0962)		(0.0346)	(0.217)	(0.0255)	(0.163)
$t = -20$	-0.0195	0.0225	-0.0740***	-0.293*	$g = 2010$	0.00750	-0.0778	-0.0127	0.150**
	(0.0386)	(0.214)	(0.0206)	(0.172)		(0.0223)	(0.125)	(0.00982)	(0.0755)
$t = -10$	-0.0463**	-0.00457	-0.0361***	-0.119	$g = 2020$	0.0255	-0.100	0.00503	0.0743
	(0.0229)	(0.107)	(0.0115)	(0.0829)		(0.0180)	(0.106)	(0.0113)	(0.0618)
$t = 0$	0.00777	0.00729	-0.00955	0.105					
	(0.0177)	(0.0903)	(0.0117)	(0.0716)					
$t = 10$	-0.0313	-0.124	-0.0154	0.137*					
	(0.0214)	(0.113)	(0.0114)	(0.0772)					
$t = 20$	-0.0294	-0.0220	-0.0314	0.0604					
	(0.0357)	(0.234)	(0.0263)	(0.148)					
N	9522	9522	9519	9519		9522	9522	9519	9519

Note: the table shows staggered DID estimations.The dependent variable 'Enrollrate' represents the secondary school enrollment rate, while 'Esco' denotes average years of schooling. 'Gini' and 'Theil' correspond to respective economic inequality indexes. The table displays the Average Treatment Effect on the Treated (ATT) for each specification. Event study results show the overall ATT across all groups overtime, while the group-specific results average the ATT of each group. $(t < 0)$ Represent average anticipation of the treatment and $(t \geq 0)$ and G. Average are the ATT of start of the mine depending of the specification. $(t = n)$ represents the ATT of n years since/before the event (being 0 the year of the start of the mine).$g = k$ represents the ATT across time of the group of municipalities that received the treatment in the year k. WildBootstrap (WB) standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Robustness Test: Treatment Groups by Distance on Income

	(Event Study)	(Group-Specific Effect)
5 km	0.175***	0.145***
	(0.0163)	(0.00919)
10 km	0.0174*	0.0444***
	(0.00910)	(0.00619)
15 km	0.0199**	0.0511***
	(0.00882)	(0.00552)
25 km	0.0533***	0.0532***
	(0.00771)	(0.00464)
50 km	0.0815***	0.0750***
	(0.00773)	(0.00459)
75 km	0.0825***	0.110***
	(0.00534)	(0.00372)

Note: the table shows staggered DID estimations. The dependent variable is logarithm of income of the households. Average treatment effect on the treated (ATT) of start of a mine for each specification. Event study results show the overall ATT across all groups overtime, while the group-specific results average the ATT of each group. First column refers to the criteria to choose treated municipalities based on distance to the mine. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. WB standard errors in parentheses.

Table A5: Robustness Test: Treatment Groups by Distance on Environment

	(Event Study)	(Group-Specific Effect)
5 km	-248.5**	-39.40*
	(116.0)	(21.17)
10 km	-287.8***	-66.12***
	(103.8)	(19.33)
15 km	-111.7	-20.31
	(102.9)	(16.53)
25 km	-186.5**	6.157
	(76.04)	(14.98)
50 km	-109.9	-31.70
	(101.7)	(21.15)
75 km	-38.11	-50.02***
	(88.29)	(16.89)

Note: the table shows staggered DID estimations. The dependent variable is the NDVI at municipality level. Average treatment effect on the treated (ATT) of start of a mine for each specification. Event study results show the overall ATT across all groups overtime, while the group-specific results average the ATT of each group. First column refers to the criteria to choose treated municipalities based on distance to the mine. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. WB standard errors in parentheses.

Table A6: Robustness Test: Treatment based on Discovery date for Income

(Event Study)		(Group-Specific Effect)	
Average	-0.0467	G. Average	0.0315***
$(t < 0)$	(0.0332)		(0.0116)
Average	0.0152	$g = 2000$	-0.0474**
$(t \geq 0)$	(0.0140)		(0.0237)
$t = -20$	-0.0722	$g = 2010$	0.105***
	(0.0653)		(0.0151)
$t = -10$	-0.0211	$g = 2020$	-0.0851***
	(0.0207)		(0.0227)
$t = 0$	-0.00325		
	(0.0121)		
$t = 10$	0.0731***		
	(0.0125)		
$t = 20$	-0.0243		
	(0.0276)		
N	8175666	N	8175666

Note: the table shows staggered DID estimations. The dependent variable for consumption is logarithm of income of the households. Average treatment effect on the treated (ATT) of discovery of a deposit for each specification. Event study results show the overall ATT across all groups overtime, while the group-specific results average the ATT of each group. $(t < 0)$ Represent average anticipation of the treatment and $(t \geq 0)$ and G. Average are the ATT of discovery of a deposit depending of the specification. $(t = n)$ represents the ATT of n years since/before the event (being 0 the year of the start of the mine).$g = k$ represents the ATT across time of the group of municipalities that received the treatment in the year k. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. WildBootstrap (WB) standard errors in parentheses.

Table A7: Robustness Test: Treatment based on Discovery date for Environment

(Event Study)		(Group-Specific Effect)	
Average	47.69	G. Average	-147.0***
($t < 0$)	(38.07)		(52.76)
Average	-219.4*	$g = 2002$	-413.9***
($t \geq 0$)	(132.7)		(63.09)
$t = 0$	-88.96	$g = 2003$	-1482.2***
	(87.78)		(13.93)
t =6	-178.6*	$g = 2004$	-5.229
	(95.42)		(13.08)
t =7	-254.7**	$g = 2006$	-154.5***
	(100.4)		(12.43)
t =8	-160.9**	$g = 2008$	133.1***
	(68.55)		(6.102)
t =11	-195.9**	$g = 2011$	-208.8***
	(95.78)		(59.00)
t =17	-725.5***	$g = 2016$	-16.49
	(198.7)		(14.91)
t =18	-458.3***		
	(67.05)		
N	50316		50316

Note: the table shows staggered DID estimations. Complete table of results in online appendix. The dependent variable for environment is the NDVI at municipality level. Average treatment effect on the treated (ATT) of discovery of a deposit for each specification. Event study results show the overall ATT across all groups overtime, while the group-specific results average the ATT of each group. ($t < 0$) Represent average anticipation of the treatment and ($t \geq 0$) and G. Average are the ATT of discovery of a deposit depending of the specification. ($t = n$) represents the ATT of n years since/before the event (being 0 the year of the start of the mine).$g = k$ represents the ATT across time of the group of municipalities that received the treatment in the year k. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. WildBootstrap (WB) standard errors in parentheses.

Table A8: Robustness Test: Treatment based on Discovery date for Environment

NDVI		Income	
Average ($t \geq 0$)	-130.7 (133.5)	Average ($t \geq 0$)	0.2599* (0.1426)
$t = 0$	-30.1 (126.5)	$t = 0$	0.1972* (0.1056)
t =13	-341.4* (203.2)	t =1	0.3546 (0.2175)
t =17	-2085.9*** (27.7)	t =2	0.0911 (0.1533)
t =18	-1612.2*** (27.6)	$t = -1$	-0.1883*** (0.0642)

Note: the table shows staggered DID estimations. Complete table of results in online appendix. The dependent variable for consumption is logarithm of income of the households and in the case of environment the NDVI at municipality level. Average treatment effect on the treated (ATT) of start of a mine. $t \geq 0$) is the ATT of start of a mine. ($t = n$) represents the ATT of n years since/before the event (being 0 the year of the year of start of operation of a mine).WildBootstrap (WB) standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A9: Robustness Test: Effect of mining on bodies of water

	(Event Study)	(Group-Specific Effect)
Arsenic	0.00320***	0.00413***
	(0.000605)	(0.000406)
Mercury	0.000187***	0.000150***
	(0.0000538)	(0.0000184)
Chromium	0.00661**	0.00171
	(0.00325)	(0.00442)

Note: the table shows staggered DID estimations. The dependent variable measures of concentration of heavy metals in bodies of water. Average treatment effect on the treated (ATT) of start of a mine for each specification. Event study results show the overall ATT across all groups overtime, while the group-specific results average the ATT of each group. All measures of heavy metals are coded in mg/L. WB standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A10: Robustness Test: Effect of mining on CO2 emissions

Event Study		Group Specific	
Average	0.00801	G. Average	-0.0422
($t < 0$)	(0.00864)		(0.0486)
Average	-0.0209	$g = 2004$	0.133***
($t \geq 0$)	(0.0834)		(0.0160)
$t = 0$	0.0321**	$g = 2010$	0.251***
	(0.0147)		(0.0422)
t =15	0.137*	$g = 2013$	0.103***
	(0.0775)		(0.0303)
t =18	0.530***	$g = 2020$	-0.0549***
	(0.134)		(0.00965)
N	51177		51177

Note: the table shows staggered DID estimations. The dependent variable is average CO2 emissions at municipality level. Average treatment effect on the treated (ATT) of start of a mine for each specification. Event study results show the overall ATT across all groups overtime, while the group-specific results average the ATT of each group. ($t < 0$) Represent average anticipation of the treatment and ($t \geq 0$) and G. Average are the ATT of start of the mine depending of the specification. ($t = n$) represents the ATT of n years since/before the event (being 0 the year of the start of the mine).$g = k$ represents the ATT across time of the group of municipalities that received the treatment in the year k. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Wild-Bootstrap (WB) standard errors in parentheses.

Table A11: Discussion: Treatment based on characteristics of the mine

	Income		NDVI	
	(Event Study)	(Group-Specific)	(Event Study)	(Group-Specific)
		By Size		
Giant	0.296***	0.293***	170.4***	144.2***
	(0.0451)	(0.0424)	(13.60)	(3.316)
Major	0.236***	0.232***	-498.9***	-128.3***
	(0.0469)	(0.0225)	(216.1)	(22.16)
Moderate	-0.000	-0.006	-100.0	-23.16
	(0.0528)	(0.020)	(0.0451)	(47.01)
		By Type		
Precious	0.218***	0.213***	-378.9	-50.05*
	(0.0311)	(0.0177)	(246.2)	(27.26)
ETM	0.021	-0.045	-168.7*	-92.12
	(0.0738)	(0.0316)	(101.4)	(57.90)

Note: the table shows staggered DID estimations. The dependent variable is logarithm of income of the households in the case of Income and in the case of environment the NDVI at municipality level. Average treatment effect on the treated (ATT) of start of a mine for each specification. Event study results show the overall ATT across all groups overtime, while the group-specific results average the ATT of each group. First column refers to the criteria to choose treated municipalities based on the characteristics of the mine, treated municipalities that do not meet the criteria are excluded from the sample. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. WB standard errors in parentheses.

Table A12: Discussion: Treatment based on income distribution of the population

	(Event Study)	(Group-Specific Effect)
Bottom 20%	0.565***	0.511***
	(0.185)	(0.0897)
20% - 40%	0.218***	0.148***
	(0.034)	(0.0191)
40% - 60%	0.356	0.229***
	(0.0088)	(0.017)
60% - 80%	0.235***	0.208***
	(0.013)	(0.011)
Top 20%	0.0514	0.0686***
	(0.042)	(0.0263)

Note: the table shows staggered DID estimations. The dependent variable is logarithm of income of the households. Average treatment effect on the treated (ATT) of start of a mine for each specification. Event study results show the overall ATT across all groups overtime, while the group-specific results average the ATT of each group. First column refers to the quantile of the population used. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. WB standard errors in parentheses.

O1 Online Appendix

Table O1: Dynamic effects of mining on NDVI

(Event Study)		(Group-Specific Effect)	
Average	78.84***	G. Average	-59.96***
($t < 0$)	(20.51)		(22.69)
Average	-377.3**	g =2002	-2092.9***
($t \geq 0$)	(181.9)		(26.74)
$t = -21$	571.5***	g =2004	42.05***
	(26.16)		(6.115)
$t = -20$	220.6***	g =2005	384.9***
	(12.17)		(5.548)
$t = -19$	177.8	$g = 2006$	-284.4***
	(482.7)		(94.96)
$t = -18$	-113.1	$g = 2007$	53.15
	(347.6)		(43.89)
$t = -17$	120.1	$g = 2008$	64.21
	(241.5)		(51.07)
$t = -16$	-55.63	$g = 2009$	-261.2***
	(362.8)		(19.36)
$t = -15$	140.0	$g = 2010$	-54.60***
	(276.0)		(5.234)
$t = -14$	-6.584	$g = 2011$	-49.15***
	(204.1)		(13.35)
$t = -13$	458.1**	$g = 2013$	197.6**
	(219.2)		(81.17)
$t = -12$	-51.24	$g = 2014$	169.9***
	(288.6)		(11.50)
$t = -11$	-68.34	$g = 2018$	19.59***
	(161.2)		(5.587)
$t = -10$	257.2	$g = 2019$	-193.7***

(Event Study)		(Group-Specific Effect)	
	(169.5)		(6.330)
$t = -9$	-210.6	$g = 2020$	181.4***
	(166.6)		(6.477)
$t = -8$	-44.62		
	(109.6)		
$t = -7$	20.97		
	(112.1)		
$t = -6$	69.24		
	(61.02)		
$t = -5$	8.615		
	(67.88)		
$t = -4$	20.76		
	(83.39)		
$t = -3$	26.60		
	(81.21)		
$t = -2$	-66.35		
	(68.82)		
$t = -1$	180.4**		
	(89.20)		
$t = 0$	-30.45		
	(97.02)		
$t = 1$	-58.71		
	(95.05)		
$t = 2$	33.78		
	(88.36)		
$t = 3$	-53.42		
	(84.30)		
$t = 4$	-68.06		
	(111.0)		
$t = 5$	-97.20		

	(Event Study)		(Group-Specific Effect)
	(84.16)		
t =6	-110.3		
	(80.46)		
t =7	-148.7		
	(99.28)		
t =8	-227.3*		
	(125.1)		
t =9	-132.8		
	(129.3)		
t = 10	-198.8		
	(151.1)		
t =11	-183.8		
	(146.2)		
t =12	-164.2		
	(177.1)		
t =13	-341.4*		
	(187.8)		
t =14	-345.0		
	(284.3)		
t =15	-442.3		
	(629.8)		
t =16	-901.0***		
	(32.09)		
t =17	-2086.4***		
	(28.65)		
t =18	-1612.2***		
	(29.89)		
N	51282	N	51282

Note: the table shows staggered DID estimations. The dependent variable for environment is the NDVI at municipality level. Average treatment effect on the treated (ATT) of start of a mine for each specification. Event study results show the overall ATT across all groups overtime, while the group-specific results average the ATT of each group. ($t < 0$) Represent average anticipation of the treatment and ($t \geq 0$) and G Average are the ATT of start of the mine depending of the specification. ($t = n$) represents the ATT of n years since/before the event (being 0 the year of the start of the mine).$g = k$ represents the ATT across time of the group of municipalities that received the treatment in the year k. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. WildBootstrap (WB) standard errors in parentheses.

Table O2: Robustness Test: Treatment based on Discovery date for Environment

(Event Study)		(Group-Specific Effect)	
Average ($t < 0$)	47.69 (38.07)	G. Average	-147.0*** (52.76)
Average ($t \geq 0$)	-219.4* (132.7)	$g = 2002$	-413.9*** (63.09)
$t = -5$	-106.9 (119.8)	G2003	-1482.2*** (13.93)
$t = -4$	218.3** (91.74)	$g = 2004$	-5.229 (13.08)
$t = -3$	-121.8 (96.86)	$g = 2005$	6.809 (61.63)
$t = -2$	40.33 (120.0)	$g = 2006$	-154.5*** (12.43)
$t = -1$	103.9 (99.07)	$g = 2007$	-47.23 (33.53)
$t = 0$	-88.96 (87.78)	$g = 2008$	133.1*** (6.102)
t =1	-54.87 (100.9)	$g = 2009$	-201.5** (82.03)
t =2	-229.1*** (86.15)	$g = 2010$	-62.35 (74.09)
t =3	-96.17 (82.26)	$g = 2011$	-208.8*** (59.00)
t =4	-129.2 (100.3)	$g = 2016$	-16.49 (14.91)
t =5	-128.6 (86.25)		
t =6	-178.6* (95.42)		

	(Event Study)	(Group-Specific Effect)
t =7	-254.7**	
	(100.4)	
t =8	-160.9**	
	(68.55)	
t =9	-141.0	
	(98.46)	
$t = 10$	-134.5	
	(99.66)	
t =11	-195.9**	
	(95.78)	
t =12	-204.8	
	(150.4)	
t =13	-199.8	
	(136.7)	
t =14	-199.3*	
	(120.4)	
t =15	-253.0	
	(161.5)	
t =16	-335.5	
	(470.8)	
t =17	-725.5***	
	(198.7)	
t =18	-458.3***	
	(67.05)	
N	50316	

Note: the table shows staggered DID estimations. The dependent variable for environment is the NDVI at municipality level. Average treatment effect on the treated (ATT) of discovery of a deposit for each specification. Event study results show the overall ATT across all groups overtime, while the group-specific results average the ATT of each group. ($t < 0$) Represent average anticipation of the treatment and ($t \geq 0$) and G. Average are the ATT of discovery of a deposit depending of the specification. ($t = n$) represents the ATT of n years since/before the event (being 0 the year of the start of the mine).$g = k$ represents the ATT across time of the group of municipalities that received the treatment in the year k. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. WildBootstrap (WB) standard errors in parentheses.

Table O3: Robustness Test: **?** estimator

(NDVI)		(Income)	
Average	-130.7	Average	0.2599*
($t \geq 0$)	(133.5)	($t \geq 0$)	(0.1426)
$t = 0$	-30.1	$t = 0$	0.1972*
	(126.5)		(0.1056)
$t = 1$	-58.6	$t = 1$	0.3546
	(123.8)		(0.2175)
$t = 2$	33.9	$t = 2$	0.0911
	(99.8)		(0.1533)
$t = 3$	-53.2	$t = -1$	-0.1883***
	(100.3)		(0.0642)
$t = 4$	-67.6		
	(124.2)		
$t = 5$	-96.6		
	(105.8)		
$t = 6$	-109.9		
	(98.9)		
$t = 7$	-148.2		
	(117.8)		
$t = 8$	-226.7		
	(149.3)		
$t = 9$	-132.4		
	(149.2)		
$t = 10$	-198.3		
	(175.6)		
$t = 11$	-183.5		
	(169.4)		
$t = 12$	-164.0		
	(184.2)		
$t = 13$	-341.4*		

	(NDVI)	(Income)
	(203.2)	
t =14	-344.4	
	(203.2)	
t =15	-442.3	
	(900.7)	
t =16	-900.6	
	(1016.6)	
t =17	-2085.9***	
	(27.7)	
t =18	-1612.2***	
	(27.6)	
$t = -1$	-172.8	
	(110.2)	
$t = -2$	4.9	
	(55.9)	
$t = -3$	5.4	
	(82.2)	
$t = -4$	-22.1	
	(84.8)	
$t = -5$	-33.3	
	(104.4)	

Note: the table shows staggered DID estimations. The dependent variable for consumption is logarithm of income of the households and in the case of environment the NDVI at municipality level. Average treatment effect on the treated (ATT) of start of a mine. $t \geq 0$) is the ATT of start of a mine. ($t = n$) represents the ATT of n years since/before the event (being 0 the year of the year of start of operation of a mine).WildBootstrap (WB) standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$