Unearthing Inequality: The Impact of Mining Operations on Politically Marginalized Communities

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1 Introduction

Existing literature has documented that mining can have positive effects on local wealth [von der Goltz and Barnwal, 2018], poverty [Aragon and Rud, 2013], employment Kotsadam and Benshaul-Tolonen [2016], infrastructure [Dietler et al., 2021] and education [Mejia, 2020] in developing countries. However, there is still no thorough understanding of which types of communities reap the benefits of mining activity. Importantly, ethnic favoritism and political patronage have been documented in a variety of settings in developing countries, including local labor markets, the provision of public goods and infrastructure, as well as the awarding of business concessions. Mines and the burgeoning local economies that they spur introduce a new context through which this ethnic and political favoritism could emerge. In particular, politically powerful or favored ethnic groups could influence decisions on where mines should open and thus the communities that might benefit. At the same time, within communities with different ethnic groups, favored groups might benefit more from the presence of a mine nearby, for example through the preferential awarding of contracts.

This paper seeks to answer three research questions. First, are the positive wealth effects generated by mines heterogeneous across ethnic groups facing differing levels of political exclusion risk? Second, do mine openings disproportionately affect the movement of these politically excluded ethnic groups? Lastly, does political representation affect the likelihood of a mine opening?

To answer these questions, this paper combines data on the precise geo-location of mine centroids from S&P Global Market Intelligence, with data on ethnicity and wealth levels from the Demographic Health Surveys (DHS), as well as information on political exclusion risk and political transitions from the Ethnic Power Relations dataset (EPR). When investigating whether wealth effects differ by political exclusion risk, this paper adopts the difference-in-difference (DID) model used by the existing literature that compares wealth levels for households near mines to households slightly further away, before and after a mine opening. This DID is modified by including a triple-interaction with a dummy for whether the household includes a member at risk of political exclusion. This paper finds that while mine openings lead to economically and statistically significant increases in the wealth levels of households near mines, these wealth increases are smaller for households belonging to ethnic groups that face political exclusion risk.

To understand the types of individuals that are induced to move into mining areas, this paper leverages a different DID-style design comparing individuals that moved close to mining areas after a mine opened to those that moved close to mining areas before a mine opened, relative to those that moved to areas slightly further away. This paper documents that individuals belonging to politically excluded ethnic groups are more likely to sort into mining areas after a mine opens. Finally, to investigate whether political representation can influence where a mine opens, this paper uses a two-way fixed effects model that compares areas with a large share of the population belonging to ethnic groups that would benefit from increased political representation, to areas with a smaller share, before and after political transitions that empowered these groups. The findings suggest that political transitions which give a voice to previously excluded ethnic groups lead to the establishment of mines in areas where these groups reside.

This paper contributes to two important strands of the literature. The first is a recent body of research discussing whether natural resources are a blessing or a curse for development. Chuhan-Pole et al. [2017] et al. provide a comprehensive summary of the research about whether mining benefits local communities. They outline three main channels - market, fiscal and environmental - through which local communities may be affected by mining activity. This paper builds upon the framework of Chuhan-Pole et al. [2017] by elucidating the role that political and ethnic favoritism play in both the market and fiscal channels. Secondly, this paper speaks to the literature on the economic consequences of ethnic favoritism and political patronage in developing countries. Existing work has documented politically motivated siting of transportation infrastructure [Burgess et al., 2015], as well as schools and hospitals [Franck and Rainer, 2012]. In the mining context, this paper shows that political representation can also influence the siting of industries that are associated with local economic booms. Furthermore, this paper uses the existing literature documenting the role of co-ethnic leaders in the preferential awarding of opportunities and private goods (Amodio and Chiovelli [2016], Marx and Suri [2019]) to explain why politically excluded ethnic groups benefit less from mines.

2 Data

This paper constructs three key datasets to answer the three research questions. The datasets are created by combining the precise geo-locations of mine centroids from S&P Global Market Intelligence with the GPS coordinates of survey clusters from the Demographic Health Surveys (DHS). As an overview, the wealth effects analysis uses data at the household-year level, the sorting analysis uses data at the household member-year level and the political inclusion analysis uses data at the grid cell-year level. The construction of these three datasets, along with the reasons behind why different units of observation are used for each type of channel, are described in more detail below.

2.1 Mines

Existing research has used the S&P data to examine the effects of mining on local labor markets [Kotsadam and Benshaul-Tolonen, 2016], corruption [Knutsen et al., 2016], women and child health (von der Goltz and Barnwal [2018]; Benshaul-Tolonen [2018]), conflict [Berman et al., 2017], ethnic identity salience [Berman et al., 2023], crime [Axbard et al., 2021], deforestation [Xie et al., 2022], water and sanitation infrastructure [Dietler et al., 2021], air pollution [Korb, 2024] and other outcomes. The S&P dataset is proprietary and considered to be the most comprehensive source of information on the mining sector, covering mines across the world. However, this dataset covers mostly large-scale mines operated by multinationals or government. Though artisanal and small-scale mines (ASM) or mines that are illegally operated often open on the fringes of these large-scale mining operations, these smaller mines are not included in the S&P data. The OECD (2013) defined ASM as "formal or informal mining operations with predominantly simplified forms of exploration, extraction, processing and transportation, which is normally low capital intensive and uses high labour intensive technology." Gamu et al. [2015] review how large-scale mining and ASM may have differential effects on local populations. Unfortunately, given data limitations, disentangling the effects from these two types of mining is beyond the scope of this study.

The S&P data provides the geo-location of the centroid of each mine's operations. In line with previous work, this paper defines the treated area of each mine, that is, the area most strongly exposed to mining activity, as the area inside the circle with a radius of 10 kilometers around the mine's centroid. Conversely, the control area for each mine is defined as the area within circle of radius 50 kilometers around the mine centroid but outside the circle of radius 10km. The existing literature suggests that the effects of mining are concentrated in communities within 5–20 kilometers of the mine (Aragon and Rud [2013]; Aragon and Rud [2015]; von der Goltz and Barnwal [2018]; Kotsadam and Benshaul-Tolonen [2016]). This paper chooses a buffer of 10 kilometers over the smaller 5 kilometer buffer used by von der Goltz and Barnwal [2018] to account for the jittering of DHS cluster coordinates.[1] Robustness of the main results is examined by increasing the radius of the buffer used to define the treatment group up to 30 km.

Each mine in the analysis is linked to the year that mining activity began, the primary mineral extracted, the primary extraction method and the primary processing method. In line with the definition provided by

[1] In DHS household surveys the GPS coordinate displacement process is carried out as follows: urban clusters are displaced a distance up to two kilometers (0-2 km) and rural clusters are displaced a distance up to five kilometers (0-5 km), with a further, randomly-selected 1% (every 100th) of rural clusters displaced a distance up to 10 kilometers (0-10 km).

S&P, this paper defines the start of mining activity, also referred to as the opening of a mine, as the year that "the mine/plant has been commissioned or has produced its first metal, concentrates, or bulk commodity at a commercial rate." Other papers have defined mining activity based on years where a mine had non-zero output (von der Goltz and Barnwal [2018], Benshaul-Tolonen [2018]). Although the S&P data provides yearly production data for some mines, this information is missing or incomplete for many mines, meaning activity would need to be imputed. As the S&P data on the start year of commercial production is more complete, this paper opts to define mining activity based on this year instead.

2.2 Demographic Health Surveys (DHS)

The Demographic Health Surveys (DHS) collect information on household demographics, health and fertility for developing countries across the world. This paper uses the IPUMS DHS data, which harmonizes DHS files across countries and time. Repeated cross-sectional DHS datasets for the following 25 countries are used: eight survey rounds for Senegal, 5 survey rounds each for Mali, Nigeria, Ghana, and Ethiopia, four survey rounds each for Zimbabwe, Uganda, Nepal, Malawi, Jordan, Guinea, Cameroon, Benin and Burkina Faso, 3 survey rounds each for Zambia, Tanzania, Namibia, Niger, Kenya and Cote d'Ivoire, and 2 survey rounds each for Togo, Pakistan, Liberia, Democratic Republic of the Congo and Burundi.

GPS coordinates are available for most clusters in the DHS, where multiple households are linked to each cluster. The sample used in this paper corresponds to all DHS clusters with non-missing GPS data that could be matched to an S&P mine. For the sorting and wealth effects analysis, this is further refined to only include the set of clusters located within 50km of a mine. The underlying DHS data used in this sample consists of women aged 15-49 and their partners, from randomly selected households chosen according to the DHS sampling strategy. For each individual in the sample, their age, ethnicity, the wealth quintile of the household they belong to, the DHS wealth index of the household they belong to, the age of the household head in the household they belong to and the number of years they have lived in their current place of residence is extracted. Finally, each individual is linked to a mine by calculating the distance in kilometers between the DHS cluster that they reside in and the mine that cluster is closest to.

2.3 Grid cell

For the political inclusion analysis, this paper aggregates data on ethnic population distribution and wealth from the DHS to grid cells of size 0.5 x 0.5, each of which is roughly equivalent to 56 x 56 kilometers at the equator. The grid-cell level analysis is used to maintain consistent geographic units for comparison across different DHS survey rounds, which may shift in terms of cluster locations and interviewed households. In particular, this paper generates a proportion of the population that is subject to high levels of political exclusion risk for each cell-year, so that the degree of risk of political exclusion varies across cells and time. The analysis focuses on five countries, Guinea, Kenya, Nepal, Niger, and Pakistan. These countries were selected based on observable political transitions that affected ethnic populations, resulting in shifts in the risk of political exclusion of specific ethnic groups over time. Specifically, these political transitions allowed certain ethnic groups to participate more in the decision-making process, reducing their risk of political exclusion.

2.4 Geology

While the Food and Agriculture Organization (FAO) and other sources have generated global, high resolution crop suitability data, there is still no established global dataset of mining suitability. Girard et al. [2023] define a simple method using geological data to identify areas that are suitable for mining. In their method, an area must satisfy two criteria in order to be considered suitable for mining. First, the geological age of a given sediment or rock layer in an area must align with the age when a mineral was expected to have formed (geological age criteria). Second, the area must belong to a lithology known to be suitable for hosting a mineral. In other words, the observable physical characteristics of a given sediment or rock layer must be suitable for that mineral. Girard et al. [2023] apply these two criteria to geological data on the contours, age and physical composition of African geological bedrocks from Thieblemont and BRGM (2016) to identify areas in Africa that would be suitable for gold mining.

Unfortunately, as the data from Thieblemont and BRGM (2016) is proprietary and the method ofGirard et al. [2023] is specific to gold, this paper is unable to implement the same method to identify suitable areas for mining in our context. As an alternative, this analysis uses data on African surficial lithology from the Standardized Terrestrial Ecosystems of Africa, produced by the United States Geological Survey (USGS) and other collaborators in 2013. This database compiles existing data on geology and rock type from global (Geologic Data Systems, 2008), regional (FAO et al., 2009) and national (FAO, 2003; DuPuy and Moat, 1998) scales. The Africa surficial lithology map is available as a raster at 90 meter resolution. Each cell is classified into one of nine bedrock types (carbonate, karst, non-carbonate sedimentary, metasedimentary, alkaline intrusive volcanic, acidic intrusive volcanic, metamorphic intrusive, ultramafic, extrusive volcanic) or one of ten unconsolidated surficial materials (colluvium, hydric organics, aeolian sediments, alluvial fan, fluvial sediments, alluvial beach or dune, alluvial saline, alluvial gypsum, other alluvial, and volcanic ash, tuffs, and mudflows).

To identify lithologies that are suitable for mining, this paper overlays the geo-locations of S&P mines on top of the lithology raster to extract the lithology associated with each African mine in the S&P dataset. For each mineral, lithologies which have been linked to at least 3 mines of that mineral type are considered suitable for mining that mineral. Each 90-m cell in the Africa lithology data is then classified as suitable for mining if it belongs to a lithology deemed suitable. Unlike Girard et al. [2023], who use geological literature to identify lithologies that are suitable for gold mining, our method should be considered a data-driven approach. While it might be preferable to use geological literature over the data-driven approach, as our analysis uses over 15 different mineral types, the literature-based method is not feasible. Another limitation of our method is that we are unable to incorporate the geological age criteria to determine suitability, given lack of the appropriate data.

This paper aggregates suitability data at the 90 m resolution to each 50 km x 50 km grid cell by calculating the share of lithology raster cells within each grid cell that are suitable for mining. Thus, the mining suitable share of each grid cell can take values from 0 to 1.

The method described above is specifically used to define suitability at the grid cell level in Africa. As the siting analysis uses two countries outside of Africa, Pakistan and Nepal, this paper implements a similar method to the one outlined above using a digital geological map of South Asia from Wandrey (1998). This map is available as a shapefile, which is rasterized to define the suitable share for cells in South Asia in the same way as the cells in Africa.[2]

The final output of the procedure above is a dataset covering Guinea, Kenya, Nepal, Niger, and Pakistan, where each observation is a 50 km x 50 km grid cell containing the share of the cell that is suitable for mining, based on the lithology criteria alone.

2.5 Political Exclusion Risk

The assessment of political exclusion risk is anchored in the extent to which ethnic groups have access to executive power within a nation, as recorded by the Ethnic Power Relations (EPR) dataset (Vogt et al., 2015; Cederman et al., 2010), which tracks politically significant groups. Following the approach of Ebadi and Damania [2024], this identification is used to determine ethnic groups that may be at risk of political exclusion, including all ethnicities, irrespective of their political weight.

The determination of which ethnic groups are at risk of political exclusion does not change over time. If an ethnic group has never been marginalized from the decision-making process, it is considered to be at low risk of political exclusion. All other groups are presumed to be high risk. Each individual in the DHS data is classified as politically excluded if they are a member of an ethnic group facing a high risk of political

[2]The bedrock classifications are inconsistent between the Africa and South Asia data.

exclusion, based on ethnicities listed in the EPR. Similarly, each household is classified as politically excluded if it has at least one household member that is classified as politically excluded.

In the wealth effect and sorting analysis, this paper investigates if the effects of opening a mine are heterogeneous by political exclusion risk. However, in the political inclusion analysis, this paper also considers how changes in political exclusion risk for ethnic groups initially deemed high risk might affect where mines are sited. Information on the years when changes in political exclusion occurred is derived from the EPR dataset for the 5 countries used in the political inclusion analysis: Guinea, Kenya, Nepal, Niger, and Pakistan.

2.6 Summary

For the estimation of local wealth effects of mines, each observation is a household in a given DHS survey round. Each household is linked to the mine nearest to the cluster that the household lives in, along with information on the year the household was surveyed, the wealth index of the household, whether any member of the household belongs to a politically excluded group and whether any individual in the household has always lived at the household's place of residence at the time the interview was conducted. This analysis uses 52,069 households across 21 countries, with this sample size decreasing to 17,772 households across 12 countries when incorporating data on political exclusion risk. The loss in observations is due to missing data on ethnicity needed to determine political exclusion risk.

Next, for the sorting analysis each observation is an individual in a given DHS survey round. Each individual is linked to the mine nearest to the cluster they live in, along with information on the year they were surveyed, their age, the wealth index of the household they belong to, whether they are a member of a politically excluded group and the number of years they have lived in their current place of residence. This sample covers 46,631 individuals across 12 countries.

Lastly, the paper uses an unbalanced panel for the political inclusion analysis, where each observation is a cell-year linked to a dummy variable for whether a mine was open in that cell-year, the share of the cell that is suitable for mining and the share of individuals in that cell that belong to ethnic groups at high risk of political exclusion.

The table below provides summary statistics of key variables used in our analysis at the household level, grouped by whether the household is politically excluded and including only households located within 50km of a mine.

		Politically Excluded		
Household Characteristic	**N**	**0**, N = 25,712[1]	**1**, N = 34,092[1]	**p-value**[2]
Wealth Index	59,804	0.89 (3.53)	0.73 (1.75)	<0.001
Wealth Quintile	59,804			<0.001
1		2,718 / 25,712 (11%)	3,324 / 34,092 (9.8%)	
2		3,960 / 25,712 (15%)	3,758 / 34,092 (11%)	
3		4,507 / 25,712 (18%)	4,481 / 34,092 (13%)	
4		5,928 / 25,712 (23%)	6,957 / 34,092 (20%)	
5		8,599 / 25,712 (33%)	15,572 / 34,092 (46%)	
Age of head of household	59,804	45 (15)	43 (14)	<0.001
Distance to Nearest Mine (km)	59,804	26 (13)	28 (13)	<0.001
Distance to Neighboring Mine (km)	59,804	35 (61)	43 (95)	<0.001
Urban	59,804	15,166 / 25,712 (59%)	21,681 / 34,092 (64%)	<0.001

[1] Mean (SD); n / N (%)

[2] Welch Two Sample t-test; Pearson's Chi-squared test

3 Results

3.1 Wealth Effects

Existing literature has documented that mining increases wealth levels and income in communities near mines relative to ones further away (von der Goltz and Barnwal [2018], Aragon and Rud [2013]). This paper investigates whether these positive wealth effects may differ by political exclusion risk by estimating the following difference-in-differences model identical to ones used in the existing literature, but with a triple interaction to examine heterogeneity:

$$
\begin{aligned}
\text{Household Wealth}_{hjmct} = \alpha_m + \lambda_{ct} + \beta_1 Near_{jm} + \beta_2 Post_{mt} + \beta_3 Near_{jm} \times Post_{mt} + \\
\beta_4 \text{Politically Excluded}_{hjmct} + \beta_4 Near_{jm} \times \text{Politically Excluded}_{hjmct} + \\
\beta_5 Post_{mt} \times \text{Politically Excluded}_{hjmct} + \\
\beta_6 Near_{jm} \times Post_{mt} \times \text{Politically Excluded}_{hjmct} + X_{hjmct}\Gamma + \epsilon_{hjmct}
\end{aligned} \tag{1}
$$

where h indexes a household, j indexes the DHS cluster that h resides in, m indexes the mine nearest to cluster j, c indexes the country and t indexes the year of the DHS survey. The household wealth measure is the DHS wealth index, with units expressed in standard deviations. As a robustness check, we consider an alternative dependent variable that is whether the household falls in the top two wealth quintiles. The variable $Near_{jm}$ is a dummy variable equal to 1 if the cluster j that household h resides in falls within 10km of mine m and 0 otherwise. The variable $Post_{mt}$ is a dummy variable equal to 1 if mine m linked to household h was open in year t, 0 otherwise. The variable Politically Excluded$_{hjmct}$ is a dummy variable equal to 1 if household h contains at least one member that belongs to a politically excluded ethnic group. The regressions include mine-level indicators as area fixed effects, as well as country-year indicators as time fixed effects. Standard errors are clustered at the mine level and the regression includes controls for whether the household is located in an urban area, as well as linear and quadratic terms in head of household age. This specification is identical to that of von der Goltz and Barnwal [2018], with the exception of including a triple interaction with the dummy for political exclusion risk. Several papers have used a similar near vs. far DID design to investigate the effect of mining on different outcomes (von der Goltz and Barnwal [2018], Benshaul-Tolonen [2018], Kotsadam and Benshaul-Tolonen [2016], Aragon and Rud [2013], Aragon and Rud [2015], Knutsen et al. [2016]). The identifying assumption of this design is that conditional on observables, local wealth levels would have evolved in a parallel fashion between areas very close to mines and areas slightly further away in the absence of a mine opening.

The regression sample consists of only households living in DHS clusters within 50 kilometers of a mine, meaning that the "treated" group, the near group, is defined as households living within 10 km of a mine while the "control" group is defined as households living 10-50 km away from a mine. To ensure that the effect estimated is a direct wealth effect of mining activity on local communities, rather than the sorting of wealthier individuals into mining areas, the sample is restricted to only households who have at least one member that has never moved.[3]. Robustness to increasing the radius of the near group from 10 km away from a mine up to 30 kilometers away is also examined.

[3] An individual is classified as never having moved if they report always living in the current location in the DHS.

The coefficient β_3 captures the extent to which households with no members that belong to a politically excluded group that live near mines become wealthier after a mine opening. The key coefficient of interest is β_6, which measures the difference in the wealth effects of mine openings between households with at least one member that belongs to a politically excluded group and households with no members that belong to a politically excluded group.

Table 2: Effects of Mining on Wealth Levels of Households Near A Mine, non-movers only, heterogeneity by political exclusion

	Within 10km	Within 20km	Within 30km
Near	0.0261	-0.112**	-0.122
	(0.0683)	(0.0498)	(0.109)
Post mine opening	-0.0392	-0.0626	-0.122
	(0.0559)	(0.0514)	(0.0798)
Near x Post	0.218**	0.135*	0.163
	(0.0872)	(0.0796)	(0.112)
Near x Post x Politically Excluded	-0.116	-0.0182	-0.0749
	(0.148)	(0.0825)	(0.0952)
Observations	17770	17770	17770
Number of DHS Clusters	2437	2437	2437

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

First, this paper finds that households near mines are considerably wealthier than households slightly further away. The magnitude of the wealth effect for households not at risk of political exclusion is 0.218 standard deviations, which is very similar to the findings of von der Goltz and Barnwal [2018]. However, this paper fails to find a statistically significant difference in the wealth effects by political exclusion risk. Taken together with the main effect estimate of 0.218, the negative coefficient on the triple interaction of -0.116 provides suggestive evidence that while mine openings increase wealth for politically excluded households, these households benefit less than those that are not at risk of political exclusion.[4] Work by Aragon and Rud [2013] and Kotsadam and Benshaul-Tolonen [2016] suggests that the positive effects on local wealth and employment are generated through backward linkages, with the development of local businesses and services to support the mine. If mine operators and local chiefs tend to belong to groups that are not at risk of political exclusion, then the literature suggests that one might expect to see favoritism towards co-ethnics that work in local businesses and services, for example, by preferential awarding of small contracts. Unfortunately, absent ethnicity data on mine employees and local chiefs, testing for ethnic favoritism in backward linkages is beyond the scope of this paper. However, Ravetti et al. [2019] describe how the mining

[4]The DID estimate for politically excluded groups is 0.218 - 0.116 = 0.102 standard deviations.

industry in South Africa "often recruited workers on the basis of particular skill sets attributed to certain ethnic groups." Furthermore, they report that within South African mining houses, faction fights broke out due to unequal treatment of workers, such as differential contract length, pay or access to jobs based on ethnicity. Given this evidence from within mining industry, it could be plausible that even outside the mining industry, workers belonging to politically excluded ethnic groups may be allocated to slightly lower paying jobs, resulting in weaker wealth effects.

Appendix Table 5 reports the results of estimating Equation 1 using a dummy variable for whether the household falls in the top two wealth quintiles as the outcome of interest. While the estimated effects tells the same story as Table 2, they are not statistically significant. The continuous DHS wealth index is the preferred outcome as it is more granular, while the dummy definition only captures bigger movements from low wealth quintiles to high wealth quintiles. That is, with the dummy outcome, wealth increases for households who become wealthier relative to their past state but remain at the same point in the overall wealth distribution are missed.

Additional robustness checks include estimating Equation 1 using the set of households near spatially isolated mines, defined as those with no other mine located within 50 km (Appendix Table 6), to address concerns about overlapping treatment and control groups with neighboring mines. In addition, this paper examines spatial decay in wealth effects (Appendix Table 10). Figure 1 shows the results of estimating a similar model to Equation 1, where the Near dummy is replaced by dummies for the following distance bins: 0-10km, 10-20km and 20-30km. The omitted category is the distance bin for 30-50km, so the coefficients show the effect of a mine opening for each of the closer distance bins, relative to the 30-50km bin. This spatial lag model is estimated separately over the samples of politically excluded and non-excluded households. Figure 1 reinforces that local wealth effects are concentrated within 10 km of a mine, with larger effects for households not at risk of political exclusion. Appendix Figure 2 shows the results of estimating the spatial lag model by pooling both excluded and non-excluded households.

Furthermore, Appendix Tables 8 and 9 examine whether local wealth effects are heterogeneous by measures of ethnic fractionalization and polarization by estimating Equation 1 separately over the set of clusters that belong to administrative units above median levels of ethnic fractionalization or polarization and the set of clusters below the median levels. This median is calculated within country.

The findings suggest that areas with lower fractionalization and polarization, which are indicative of less ethnic diversity and conflict, exhibit greater wealth benefits. This implies that such regions may offer better conditions for coordination, leading to an environment that is more favorable for business expansion (Alesina and La Ferrara, 2005; Montalvo and Reynal-Querol, 2005). The positive impact on local wealth and employment, facilitated by backward linkages, seems to be more pronounced in homogeneous areas. This

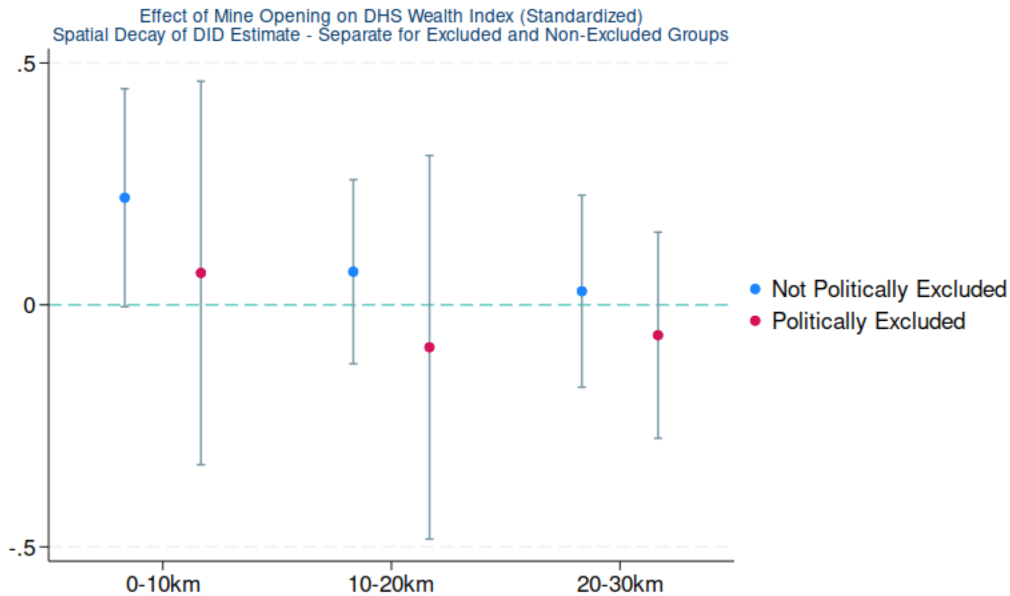

Figure 1: Spatial Decay of Local Wealth Effects of Mining

pattern is particularly noticeable in Africa, where high levels of ethnic fractionalization and polarization have been cited as factors impeding economic advancement in the region (Easterly and Levine, 1997).

3.2 Moving to opportunities

The sorting question asks whether and what types of individuals move in response to mining activity. Although this question would ideally be answered using data on migration flows or stocks, this data is not available at the spatial and temporal granularity needed for our analysis. As an alternative, this paper estimates a difference-in-difference model that compares the difference in characteristics between individuals who moved before a mine opened to those who moved after a mine opened, between areas near and slightly further away from a mine. Intuitively, this paper is interested in whether the characteristics of individuals that move close to mines change after a mine opens. For example, do we observe that people who move after a mine opening are more likely to belong to politically excluded groups? To be clear, while sorting can refer to out-migration or displacement of communities, this paper focuses on in-migration, where people move close to mines to take advantage of local economic opportunities afforded by the mine. The empirical strategy is specified according to the following regression:

$$\begin{aligned}\text{Demographic Characteristic}_{ijmct} = \alpha_m + \lambda_{ct} + \beta_1 Near_{jm} + \beta_2 \text{Moved After Mine Opening}_{imt} + \\ \beta_3 Near_{jm} \times \text{Moved After Mine Opening}_{imt} + X'_{ijmct}\Gamma + \epsilon_{ijmct}\end{aligned} \tag{2}$$

where i indexes the individual, j indexes the DHS cluster that the individual lives in, m indexes the nearest mine to individual i, t indexes the year of the DHS survey and c indexes the country. The main demographic characteristic examined is whether the individual is a member of a politically excluded group. Other outcome variables considered include whether the individual belongs to a household in the top 40% of the wealth distribution and the continuous wealth index of the household that the individual belongs to. The variable $Near_{jm}$ is a dummy variable equal to 1 if the cluster j that individual i resides in falls within 10km of mine m and 0 otherwise. *Moved After Mine Opening*$_{imt}$ is a dummy variable equal to 1 if individual i moved after mine m opened and 0 otherwise. As with the estimation of direct wealth effects, these regressions include mine and country-year fixed effects. Standard errors are clustered at the mine level. Likewise, those who moved near mines consist of movers living within 10 kilometers while the far group is composed of movers living 10-50 kilometers away from the mine.

The key coefficient of interest is β_3, which gives the difference in demographic characteristics between individual who moved near mines after a mine opened and individuals who moved near mines before a mine opened, relative to individuals that moved to areas slightly further away. The identifying assumption of this model relies on individuals that moved to areas slightly further away from mines being a good control group for individuals that moved to areas close to mines. That is, conditional on observables, we need the decision of whether and when an individual moves to an area close to or slightly further away from a mine to be uncorrelated with unobservables that relate to our demographic characteristics of interest. This paper addresses concerns about the identifying assumption in the following ways. First, selection bias based on unobservables that might influence certain types of individuals to move is addressed by focusing only on individuals that moved. Second, the control group is tightly bounded to be those that moved 10-50 kilometers away from mines. Appendix Table 20 presents additional robustness checks that define this control group even more narrowly to be those that moved 10-30 kilometers away from mines. This identifying assumption would be strengthened with data on the origin and destination for each individual that moved. Unfortunately, due to the lack of data on the origins and destinations of individuals who have relocated, our sample does not allow us to distinguish between in and out-migration from mining areas.

Table 3 shows that even after controlling for wealth, individuals that moved close to mines after a mine opened are 8-10 % more likely to belong to a politically excluded group than those that moved close to

Table 3: Sorting Into Mining Areas Based On Political Exclusion - both

	Within 10km	Within 20km	Within 30km
Near	-0.0417*	-0.0617**	-0.0591***
	(0.0232)	(0.0256)	(0.0189)
Moved After Mine Opening	-0.0368**	-0.0586***	-0.0694***
	(0.0165)	(0.0184)	(0.0213)
Near x Moved After Mine Opening	0.0845***	0.107***	0.0862***
	(0.0205)	(0.0197)	(0.0201)
Wealth Factor Score	0.00419	0.00358	0.00363
	(0.00827)	(0.00800)	(0.00791)
Mine FE	Yes	Yes	Yes
Country x Year FE	Yes	Yes	Yes
Observations	46631	46631	46631

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

mines before a mine opened, relative to those than moved further away from mines. The effects seem to be concentrated to the area within 20 kilometers of a mine and decay with distance beyond this. These findings suggest that politically excluded groups may be moving closer to mines to try to take advantage of perceived economic opportunities afforded by the mine or neighboring amenities developed to support the mine. Why would politically excluded groups tend to migrate closer to mines after a mine opening? One potential explanation is that these groups may face discrimination in the labor market so are more likely to be unemployed or have a difficult time keeping a steady job [Amodio and Chiovelli, 2016]. As mine openings provide new employment opportunities, politically excluded groups may move towards the mine at higher propensities since their non-mining employment prospects are low. Another possible explanation is that if mines open in the homelands of politically excluded ethnic groups, these groups may move back towards their homelands to take advantage of co-ethnic connections in obtaining better employment. Collier (2017) reports that the start of mining operations can raise aspirations related to resource rents and economic development. In addition, Berman et al. [2023] outline the link between mining activity and salience of ethnic identity.

Appendix Tables 14, 15 and 16 suggest that individuals who moved close to mines after a mine opened are wealthier than those who moved close to mines before a mine opened, relative to those that moved slightly further away. These estimates are not statistically significant or robust to varying the distance used to define the near group. In addition, Appendix Table 17 suggests that individuals belonging to politically excluded groups that move close to mines tend to be wealthier, though these estimates are not statistically significant. This aligns with literature showing that poorer individuals are less able to migrate due to prohibitive costs

[Murrugarra et al., 2011].

Furthermore, Appendix Table 20 defines the treatment group as individuals living within 10km of a mine and the control group more narrowly as those living within 10-30km of a mine. This specification still recovers a statistically significant estimate showing that individuals who moved close to mines after a mine opened are more likely to belong to a politically excluded group than those that moved before a mine opened, relative to those that moved slightly further away, though the magnitude of the effect is smaller. Appendix Table 21 replicates the specification of Equation 2 using only clusters near spatially isolated mines. The magnitude of the main coefficient of interest remain the same, although statistical significance is lost due to decreased power as the sample of mines in the analysis shrinks.

Finally, Appendix Tables 11 and 12 suggest that the sorting effects are not heterogeneous by gender. The results suggest that both men and women belonging to politically excluded groups tend to move near mines after a mine opening. One might expect that men would be more likely to migrate into mining areas. However, Jenkins [2014] highlights that women are heavily involved in the mining sector, mostly in artisanal and small scale mining, where they account for 30 - 75% of those employed. Furthermore, Kotsadam and Benshaul-Tolonen [2016] find that mine openings cause women to shift out of agriculture and into the services sector, suggesting that women might be starting new small businesses that serve the mine and the growing neighboring community.

3.3 Creating opportunities

In our analysis, we find that mining increases local wealth levels. This beneficial impact of mining on nearby communities is echoed by other work by von der Goltz and Barnwal [2018], Aragon and Rud [2013], Kotsadam and Benshaul-Tolonen [2016] and Benshaul-Tolonen [2018], all of whom find that mining improves a variety of outcomes, including local wealth, infant mortality and employment. As a result, local communities may want mines to open near them. While mining companies likely take many factors into account when deciding where to open a mine, such as mineral potential or mining costs, existing literature on political favoritism and the siting of local infrastructure suggests that mine siting decisions may be influenced by political agents. This body of research documents evidence of politically or ethnically motivated provision of roads Burgess et al. [2015], schools and hospitals [Franck and Rainer, 2012], housing [Marx and Suri, 2019] and employment opportunities [Amodio and Chiovelli, 2016]. Furthermore, in the context of mining, Ayee et al. [2011] describe how mining concessions in Ghana are awarded as a result of negotiations between the government, mining companies, chiefs and their communities, highlighting the importance of local communities having a representative in political power who can advocate on their behalf during this informal and non-transparent bargaining process.

To empirically test for the influence of political representation in the establishment of mines and their resulting economic hubs, this paper investigates whether political transitions that strengthen the voices of politically excluded groups increase the likelihood of a mine opening in areas where these groups tend to reside. The empirical strategy compares the probability of a mine opening between cells where over 50% of the population belong to ethnic groups that would gain a voice from being politically included, to those with less than 50% of the population satisfying this criteria, before and after a political transition that strengthened the voices of these excluded groups. That is, this strategy compares areas that are more likely to benefit from a political transition that strengthens the voice of excluded groups to those that are less likely to benefit, before and after such a transition. This analysis focuses on the 5 countries in the DHS sample that had undergone the political change in their executive power to include ethnic communities at risk of political exclusion: Guinea, Kenya, Nepal, Niger, and Pakistan.

The empirical strategy is specified according to the following regression:

$$MineOpened_{gt} = \beta \text{Majority Excluded}_g \times \text{Post-transition}_{ct} + \text{Post-transition}_{ct} + \alpha_g + \lambda_t + \epsilon_{gct} \tag{3}$$

where g indexes a grid cell, c indexes a country and t indexes a year. Note that a cell g is classified as belonging to country c if the centroid of g falls within c. The dependent variable is whether a mine is open in grid cell g in year t. The variable Post-transition$_{ct}$ is a dummy variable equal to 1 for the years t after a political transition that reduced the risk of political exclusion for marginalized communities occurred in country c, 0 otherwise. Majority Excluded$_g$ is a dummy variable equal to 1 if the share of the population at risk of political exclusion in cell g who has been successful in having a representative in the executive power of a country is greater than 50%. Majority Excluded$_g$ is based on the share of the population for each ethnic group before the opening a mine. Grid cell and DHS survey year fixed effects are included in the regressions. Standard errors are clustered at the first administrative unit and year levels.

Grid cells that have more than 50% of their population belonging to ethnic communities that gained a voice in the decision-making process are treated grid cells that would benefit from political inclusion. These grid cells would see a reduction in their risk of political exclusion because the majority of the population living in these grid cells would have a representative from their ethnic community in positions of political power.

Following a political transition toward the inclusion of marginalized ethnic communities, mines were established in 22 distinct grid cells across the four nations, predominantly in Guinea.[5] Out of 1,492 grid cells reviewed, only 5 had existing mines prior to the political change. This underscores the importance of political influence in mining site selection, as evidenced by the initiation of mining in 17 grid cells subsequent to the political transition. Grid cells with pre-existing mines prior to the political shift were omitted from the analysis.

Table 4: Siting Based on Political Inclusion

	Suitability70	Suitability75	Suitability80
Treatment	0.076*	0.078*	0.085*
	(0.045)	(0.047)	(0.050)
Constant	0.009	0.010	0.005
	(0.007)	(0.008)	(0.008)
Grid and year FEs	YES	YES	YES
Observations	603	563	523
R^2	0.606	0.607	0.480

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4 shows that after including marginalized communities in decision-making policies, mines are more likely to open in areas where these newly-included ethnic groups predominantly reside. This table also shows how these effects may vary depending on an area's suitability for mining by estimating Equation 3 separately over subsets of grid cells that meet specific criteria for suitability. In Table 4, Column 1 reports results from estimating Equation 3 over set of cells where over 70% of the area within a cell is suitable for mining. Columns 2 and 3 report the results from estimating the model using subsets meeting the 75% and 80% cutoff. As expected, the magnitude of the coefficient is largest for areas that are most geologically suitable for mining, emphasizing the importance of mineral potential in the decision of where to site mines.

In addition, this paper examines robustness of the main results to different cutoffs used to define which cells would benefit from a political transition. While the baseline model defines treated cells as those with greater than 50% of their population belonging to ethnic groups that became politically included due to a political transition, this paper tests cutoffs from 10-90%, with results shown in Appendix Figure 5.3. These regressions are run only over the subset of cells with over 75% of the cell area deemed suitable for mining [6]. Appendix Table 5.3 highlights that the estimated coefficients are statistically significant only for

[5] With the exception of Nepal, each of the other four countries undergoing political transition also initiated the operation of at least one mine within their territories. 5% of all grid cells in Guinea, 1% in Kenya, and less than 1% in Niger and Pakistan initiated the mining operation after the political transition. In four distinct grid cells, a pair of mines commenced operations following the political transition. For the purposes of our analysis, which aims to observe the initiation of mining activities post-transition, each of these grid cells is considered to have a single mining operation, irrespective of the actual number of mines.

[6] A 75% threshold was selected because it includes all four countries that have experienced political transitions in our study. If we raise the threshold to 80%, Kenya is no longer part of the analysis, and increasing it to 90% also excludes Niger.

specifications using the 30 to 50 percent cutoff for the cell population belonging to the ethnic group of those who are appointed in the executive power.

This paper also explores whether the effects of increased political inclusion on the probability of a mine opening vary based on wealth. A cell-level wealth index is computed by averaging the DHS wealth index across all DHS clusters that fall within that cell. Each grid cell is then classified into wealth quartiles based on the cell-level wealth index. Appendix Table 22 examines if the preference for opening mines in regions with populations that benefited more from increased political inclusion was stronger for poorer areas by separately estimating Equation 3 by wealth quartile. The negative coefficient in Column 1 of Appendix Table 22 indicates that after certain ethnic groups were politically included, the probability of opening a mine decreased by 4% in cells belonging to the lowest wealth quartile. In contrast, the coefficients are positive for wealthier areas. Assuming that local communities advocate for the opening of mines to benefit from increased economic activity, these findings suggest that political transitions that empower previously excluded communities tend to benefit politically excluded communities that are relatively wealthier. To further investigate this, the analysis in Appendix Table 23 examines the relationship between wealth levels and the risk of political exclusion. It finds that the interaction between wealth and political exclusion is statistically significant, primarily in the poorest regions. This indicates that, unlike regions dominated by ethnic groups who have a voice in governance, poor areas with a substantial proportion of these ethnic groups do not have an increased likelihood of mine establishment. In other words, the political inclusion of ethnic groups that have been historically excluded only seems to boost the chances of initiating mining operations in wealthier areas.

Note that the effects estimated above are specific to politically excluded ethnic groups that were successful in having a representative in the executive power. Other ethnic groups that face political exclusion but lack political representation are not captured as beneficiaries of political transitions that promote inclusion of these ethnic groups in the model above. This caveat is important to note when relating our findings to those of Berman et al. [2023], who find that feelings of pessimism and reports of economic deprivation increase significantly in mining areas. They argue that these reactions might arise when the start of mining raises expectations about local economic development but these expectations fail to align with reality. Furthermore, the authors find that these negative feelings are stronger and statistically significant in ethnic groups that are politically excluded, but a small and statistically insignificant effect for politically powerful ethnic groups. This paper's finding of political transitions increasing the likelihood of a mine opening is specific to ethnic groups that gained a voice during the transition, that is, groups that become more politically powerful. If a mining area is home to multiple ethnic groups, it is possible that groups that did not have a political representative would benefit less from the opening of a mine than groups that did, contributing to feelings of pessimism and deprivation stemming from comparison.

Finally, as a robustness check we estimate the direct wealth effect and sorting models using the subset of countries used in the political transition analysis. While the political transition analysis uses data on five countries, Guinea, Niger, Pakistan, Kenya and Nepal, the direct wealth and sorting effects are identified using variation from only Guinea and Kenya. These two countries have clusters within 50 kilometers of a mine observed before and after a mine opening, as well as contain information in the DHS needed to classify individuals as movers and non-movers. The findings that mine openings increase local wealth and encourage movement of politically excluded groups towards the mine are recovered, although statistical significance is reduced or lost, due to smaller sample size. However, these estimates should still be interpreted cautiously as they are identified using only two countries.

4 Conclusion

While existing evidence suggests that mining can economically benefit local communities, we know little about how these positive economic effects are influenced by and interlinked with political representation and ethnic favoritism. To shed light on this complicated dynamic, this paper first documents economically and statistically significant positive wealth effects of mine openings on households near mines. These effects are smaller for households belonging to ethnic groups at risk of political exclusion, though the difference in effects is not statistically significant. One can cautiously interpret this as weak evidence of potential ethnic favoritism in local economic opportunities generated by the mine. Next, this paper highlights that mine openings increase the probability that individuals moving close to mines belong to a politically excluded ethnic group. One potential explanation to motivate this finding is that a mine opening may generate expectations of potential employment or business opportunities for politically excluded groups that face discrimination in their current place of residence, encouraging movement of these groups towards perceived "greener pastures." Finally, this paper emphasizes the importance of political influence in the decision of where to open a mine by documenting that mines are more likely to open in areas with a higher population of ethnic groups that were previously excluded but benefited from a political transition that increased their representation. While some might interpret these findings as suggesting that mining is a net positive for previously excluded ethnic groups, the reality is likely much more complex. Berman et al. [2023] find that mining activity increases the salience of ethnic identity, suggesting that that while mining may open doors for previously excluded groups, it may also intensify ethnic favoritism in non-mining sectors and encourage negative attitudes towards these groups. Further research is needed to better understand the feedback loops between ethnic identity, mining, migration and local employment.

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5 Appendix

5.1 Wealth Effects

Table 5: Effects of Mining on Wealth Levels of Households Near A Mine, non-movers only, Quintiles 4 and 5, heterogeneity by political exclusion

	Within 10km	Within 20km	Within 30km
Near	0.0478	-0.0109	-0.00630
	(0.0332)	(0.0216)	(0.0240)
Post mine opening	-0.0129	-0.0191	-0.00642
	(0.0249)	(0.0234)	(0.0302)
Near x Post	0.0422	0.0393	-0.00553
	(0.0455)	(0.0353)	(0.0373)
Near x Post x Politically Excluded	-0.0776	-0.0155	0.0211
	(0.0536)	(0.0367)	(0.0385)
Mine FE	Yes	Yes	Yes
Country x Year FE	Yes	Yes	Yes
Observations	17770	17770	17770
Number of DHS Clusters	2437	2437	2437

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Effects of Mining on Wealth Levels of Households Near A Mine, non-movers only, standardized, heterogeneity by political exclusion, no other mine within 50km

	Within 10km	Within 20km	Within 30km
Near	0.0188	-0.124**	-0.0508
	(0.127)	(0.0475)	(0.0623)
Post mine opening	-0.0567	-0.0854	-0.0354
	(0.108)	(0.0993)	(0.111)
Near x Post	0.133	0.0266	-0.135
	(0.205)	(0.0656)	(0.111)
Near x Post x Politically Excluded	-0.175	-0.0451	0.0301
	(0.280)	(0.148)	(0.145)
Observations	4906	4906	4906
Number of DHS Clusters	560	560	560

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Effects of Mining on Wealth Levels of Households Near A Mine, non-movers, siting subset

	Within 10km	Within 20km	Within 30km
Near	0.106	0.123	0.00765
	(0.0843)	(0.106)	(0.109)
Post mine opening	-0.223**	-0.183*	-0.230
	(0.101)	(0.0967)	(0.134)
Near x Post	0.0475	-0.0882	0.0153
	(0.137)	(0.138)	(0.148)
Observations	2068	2068	2068
Number of DHS Clusters	6934	6934	6934

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Effects of Mining on Wealth Levels of Households Near A Mine, non-movers only, Quintiles 4 and 5, heterogeneity by political exclusion, by fractionalization index

	Within 10km	Within 20km	Within 30km
Panel 1: Above Median Fractionalization			
Near	0.0571	-0.0755	-0.0876
	(0.0688)	(0.0535)	(0.119)
Post mine opening	0.00273	-0.0243	-0.0669
	(0.0729)	(0.0666)	(0.113)
Near x Post	0.0843	0.0663	0.0844
	(0.0813)	(0.0846)	(0.124)
Near x Post x Politically Excluded	-0.0565	-0.0291	-0.0371
	(0.133)	(0.0826)	(0.0926)
Panel 2: Below Median Fractionalization			
Near	-0.111	-0.149***	-0.154
	(0.0788)	(0.0389)	(0.0940)
Post mine opening	-0.139	-0.181**	-0.195**
	(0.0935)	(0.0897)	(0.0974)
Near x Post	0.388***	0.193***	0.155
	(0.143)	(0.0603)	(0.105)
Near x Post x Politically Excluded	-0.284	-0.0790	-0.0959
	(0.211)	(0.125)	(0.121)
Mine FE	Yes	Yes	Yes
Country x Year FE	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Effects of Mining on Wealth Levels of Households Near A Mine, non-movers only, Quintiles 4 and 5, heterogeneity by political exclusion, by polarization index

	Within 10km	Within 20km	Within 30km
Panel 1: Above Median Polarization			
Near	-0.140	-0.171**	-0.0441
	(0.121)	(0.0737)	(0.101)
Post mine opening	-0.153**	-0.187***	-0.164*
	(0.0706)	(0.0707)	(0.0886)
Near x Post	0.281**	0.159*	0.0616
	(0.131)	(0.0930)	(0.101)
Near x Post x Politically Excluded	-0.0962	0.00461	0.0434
	(0.222)	(0.115)	(0.115)
Panel 2: Below Median Polarization			
Near	0.0926	-0.0605	-0.138
	(0.0627)	(0.0467)	(0.109)
Post mine opening	0.00185	-0.0461	-0.147
	(0.0642)	(0.0613)	(0.110)
Near x Post	0.204**	0.182***	0.205*
	(0.0792)	(0.0619)	(0.111)
Near x Post x Politically Excluded	-0.142	-0.0913	-0.101
	(0.109)	(0.0770)	(0.0913)
Mine FE	Yes	Yes	Yes
Country x Year FE	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Effects of Mining on Wealth Levels of Households Near A Mine, non-movers only, standardized, heterogeneity by political exclusion, control group = 30-50km

	0-10km	10-20km	20-30km
Near	-0.0844	-0.152*	-0.0961
	(0.101)	(0.0799)	(0.0856)
Post mine opening	-0.0683	-0.0816	-0.0961
	(0.0574)	(0.0588)	(0.0629)
Near x Post	0.282**	0.174*	0.129
	(0.112)	(0.0931)	(0.0886)
Near x Post x Politically Excluded	-0.201	-0.0917	-0.0590
	(0.126)	(0.0832)	(0.0750)
Observations	10275	12883	17770

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

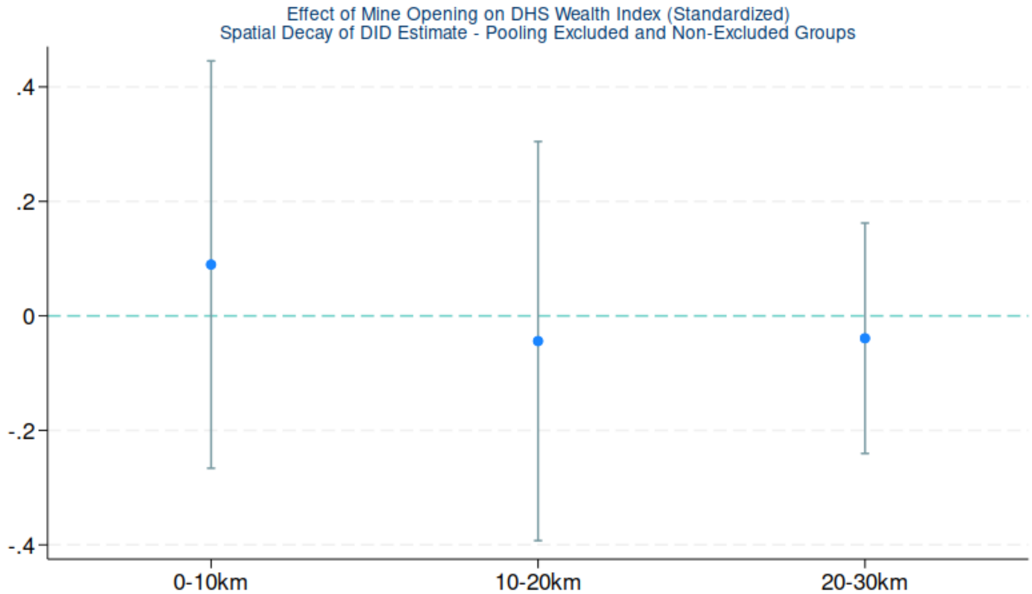

Figure 2: Spatial Decay of Wealth Effects: Pooling Excluded and Non Excluded Groups

Table 11: Sorting Into Mining Areas Based On Political Exclusion - both, Heterogeneity by Gender

	Within 10km	Within 20km	Within 30km
Near	-0.0444	-0.0427	-0.0248
	(0.0278)	(0.0302)	(0.0326)
Moved After Mine Opening	-0.0471*	-0.0604***	-0.0602**
	(0.0246)	(0.0216)	(0.0243)
Near x Moved After Mine Opening	0.0770***	0.0780***	0.0513
	(0.0267)	(0.0274)	(0.0346)
Near x Moved After Mine Opening x Female	0.0138	0.0484	0.0536
	(0.0341)	(0.0309)	(0.0413)
Wealth Factor Score	0.00399	0.00332	0.00334
	(0.00821)	(0.00794)	(0.00781)
Mine FE	Yes	Yes	Yes
Country x Year FE	Yes	Yes	Yes
Observations	46631	46631	46631

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Sorting Into Mining Areas Based On Political Exclusion - both, Heterogeneity by Gender, Head of Household Only

	Within 10km	Within 20km	Within 30km
Near	-0.0408*	-0.0584*	-0.0322
	(0.0243)	(0.0302)	(0.0267)
Moved After Mine Opening	-0.0601***	-0.0869***	-0.0918***
	(0.0209)	(0.0212)	(0.0240)
Near x Moved After Mine Opening	0.0898***	0.114***	0.0865***
	(0.0253)	(0.0277)	(0.0285)
Near x Moved After Mine Opening x Female	-0.0336	0.0217	0.0484
	(0.0407)	(0.0460)	(0.0491)
Wealth Factor Score	0.00509	0.00514	0.00498
	(0.00771)	(0.00746)	(0.00763)
Mine FE	Yes	Yes	Yes
Country x Year FE	Yes	Yes	Yes
Observations	14991	14991	14991

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Sorting Into Mining Areas Based On Political Exclusion - Siting Subset - both

	Within 10km	Within 20km	Within 30km
Near	0.0329	-0.0217	-0.00753
	(0.0876)	(0.0677)	(0.0806)
Moved After Mine Opening	-0.00603	-0.0162	-0.00742
	(0.0235)	(0.0270)	(0.0291)
Near x Moved After Mine Opening	0.104*	0.0780*	0.0312
	(0.0554)	(0.0439)	(0.0547)
Wealth Factor Score	0.0468*	0.0472*	0.0473
	(0.0254)	(0.0266)	(0.0277)
Mine FE	Yes	Yes	Yes
Country x Year FE	Yes	Yes	Yes
Observations	3339	3339	3339

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Sorting Into Mining Areas Based On Wealth Levels, Quintile 4 and 5 - both

	Within 10km	Within 20km	30km
Near	0.131***	0.0737***	0.0568***
	(0.0272)	(0.0200)	(0.0185)
Moved After Mine Opening	0.0399***	0.0210**	0.0299**
	(0.00942)	(0.0103)	(0.0133)
Near x Moved After Mine Opening	0.0283	0.0713***	0.0281
	(0.0285)	(0.0247)	(0.0247)
Mine FE	Yes	Yes	Yes
Country x Year FE	Yes	Yes	Yes
Observations	151192	151192	151192

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: Sorting Into Mining Areas Based On Wealth Levels, Wealth Score, Standardized - both

	Within 10km	Within 20km	30km
Near	0.249***	0.160***	0.150***
	(0.0654)	(0.0504)	(0.0479)
Moved After Mine Opening	0.00858	-0.0479	-0.0484
	(0.0300)	(0.0553)	(0.0777)
Near x Moved After Mine Opening	0.142	0.237	0.148
	(0.133)	(0.152)	(0.137)
Mine FE	Yes	Yes	Yes
Country x Year FE	Yes	Yes	Yes
Observations	151192	151192	151192

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16: Sorting Into Mining Areas Based On Wealth Levels, Quintile 1 - both

	Within 10km	Within 20km	30km
Near	-0.118***	-0.0754***	-0.0479***
	(0.0200)	(0.0153)	(0.0134)
Moved After Mine Opening	-0.0425***	-0.0317***	-0.0283***
	(0.00747)	(0.00845)	(0.0108)
Near x Moved After Mine Opening	-0.00701	-0.0368*	-0.0298
	(0.0197)	(0.0191)	(0.0185)
Mine FE	Yes	Yes	Yes
Country x Year FE	Yes	Yes	Yes
Observations	151192	151192	151192

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Sorting Into Mining Areas Based On Political Exclusion, Heterogeneity by Wealth: Continuous Wealth Score Standardized - both

	Within 10km	Within 20km	30km
Near	-0.0501*	-0.0822***	-0.0570***
	(0.0265)	(0.0266)	(0.0208)
Moved After Mine Opening	-0.0336*	-0.0587***	-0.0673***
	(0.0189)	(0.0204)	(0.0238)
Near x Moved After Mine Opening	0.0598**	0.105***	0.0752***
	(0.0270)	(0.0239)	(0.0231)
Near x Moved After Mine Opening x Wealth Index	0.0344	-0.00178	0.0202
	(0.0261)	(0.0232)	(0.0217)
Mine FE	Yes	Yes	Yes
Country x Year FE	Yes	Yes	Yes
Observations	46631	46631	46631

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 18: Sorting Into Mining Areas Based On Political Exclusion, by Fractionalization Index

	Within 10km	Within 20km	Within 30km
Panel 1: Above Median Fractionalization			
Near	-0.0533	-0.0768**	-0.0654**
	(0.0321)	(0.0354)	(0.0258)
Moved After Mine Opening	-0.000244	-0.0174	-0.0138
	(0.0130)	(0.0147)	(0.0197)
Near x Moved After Mine Opening	0.0844***	0.0979***	0.0497***
	(0.0275)	(0.0255)	(0.0183)
Wealth Factor Score	0.00793	0.00712	0.00782
	(0.0105)	(0.0102)	(0.0100)
Panel 2: Below Median Fractionalization			
Near	-0.00286	-0.0227	-0.0214
	(0.0179)	(0.0179)	(0.0160)
Moved After Mine Opening	-0.0266**	-0.0361***	-0.0393***
	(0.0108)	(0.0111)	(0.0132)
Near x Moved After Mine Opening	0.0184	0.0338***	0.0316**
	(0.0131)	(0.0122)	(0.0134)
Wealth Factor Score	-0.000638	-0.0000705	-0.000609
	(0.00627)	(0.00610)	(0.00592)
Mine FE	Yes	Yes	Yes
Country x Year FE	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 19: Sorting Into Mining Areas Based On Political Exclusion, Above Median Polarization Index - both

	Within 10km	Within 20km	Within 30km
Panel 1: Above Median Polarization			
Near	-0.000453	-0.0191	-0.0400**
	(0.0245)	(0.0313)	(0.0159)
Moved After Mine Opening	-0.0138	-0.0260	-0.0388**
	(0.0159)	(0.0175)	(0.0189)
Near x Moved After Mine Opening	0.0718**	0.0783***	0.0804***
	(0.0272)	(0.0284)	(0.0170)
Wealth Factor Score	0.00982	0.00983	0.00956
	(0.0119)	(0.0120)	(0.0120)
Panel 2: Below Median Polarization			
Near	-0.0115	-0.0406**	-0.0196
	(0.0189)	(0.0167)	(0.0191)
Moved After Mine Opening	-0.0148	-0.0319***	-0.0196
	(0.0102)	(0.0101)	(0.0156)
Near x Moved After Mine Opening	0.0406*	0.0637***	0.0230
	(0.0214)	(0.0188)	(0.0181)
Wealth Factor Score	-0.00197	-0.00161	-0.00128
	(0.00925)	(0.00866)	(0.00892)
Mine FE	Yes	Yes	Yes
Country x Year FE	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 20: Sorting Into Mining Areas Based On Political Exclusion - both

	Within 10km
Near	0.00921
	(0.0169)
Moved After Mine Opening	-0.0141
	(0.0175)
Near x Moved After Mine Opening	0.0386*
	(0.0215)
Wealth Factor Score	0.00711
	(0.0114)
Mine FE	Yes
Country x Year FE	Yes
Observations	28062

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 21: Sorting Into Mining Areas Based On Political Exclusion - both, no other mines within 50km

	Within 10km	Within 20km	Within 30km
Near	0.0116	-0.0310	-0.0141
	(0.0722)	(0.0365)	(0.0299)
Moved After Mine Opening	-0.0247	-0.0354**	-0.0277
	(0.0148)	(0.0158)	(0.0235)
Near x Moved After Mine Opening	0.0817	0.0873*	0.0199
	(0.106)	(0.0492)	(0.0409)
Wealth Factor Score	0.0147	0.0134	0.0141
	(0.0177)	(0.0170)	(0.0177)
Mine FE	Yes	Yes	Yes
Country x Year FE	Yes	Yes	Yes
Observations	10238	10238	10238

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.1.1 Wealth Effect Heterogeneity by Ethnic Fractionalization and Polarization

5.1.2 Spatial Decay of Wealth Effects

5.2 Sorting

5.2.1 Gender Heterogeneity in Sorting

5.2.2 Sorting Effects in Political Inclusion country analysis

5.2.3 Sorting based on Wealth

5.2.4 Sorting Heterogeneity by Ethnic Fractionalization and Polarization

5.2.5 Sorting Additional Robustness Checks

5.3 Siting

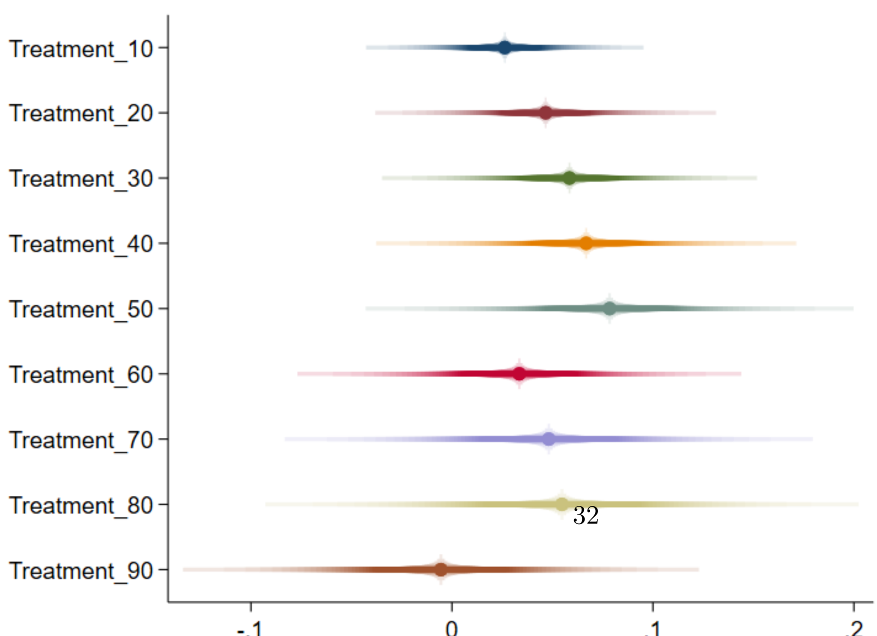

Table 22: Siting Based on wealth

	$Wealth_{Q1}$	$Wealth_{Q2}$	$Wealth_{Q3}$	$Wealth_{Q4}$
Treatment	-0.049**	0.032	0.009	0.005
	(0.023)	(0.032)	(0.026)	(0.037)
Constant	0.026***	0.018***	0.020***	0.021***
	(0.006)	(0.006)	(0.006)	(0.005)
Grid and year FEs	YES	YES	YES	YES
Observations	563	563	563	563
R^2	0.601	0.599	0.597	0.597

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 23: Siting Based on wealth and political exclusion risk

	(1)	(2)	(3)	(4)
Treatment	0.107*	0.039	0.100*	0.063
	(0.061)	(0.049)	(0.053)	(0.045)
Wealth Q1	-0.018			
	(0.013)			
Wealth Q2		-0.012		
		(0.011)		
Wealth Q3			0.035	
			(0.027)	
Wealth Q4				-0.010
				(0.013)
Interaction	-0.107*	0.103	-0.083	0.154
	(0.057)	(0.086)	(0.081)	(0.184)
Constant	0.010	0.013	0.004	0.011
	(0.009)	(0.008)	(0.008)	(0.008)
Grid and year FEs	YES	YES	YES	YES
Observations	563	563	563	563
R^2	0.616	0.612	0.610	0.612

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$