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RESOURCE RENTS, URBANISATION, AND STRUCTURAL TRANSFORMATION

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Abstract

This paper examines whether resource rents drive the urbanization-without-industrialization phenomenon observed in many developing countries today. We combine several spatially granular global data sets and estimate how mineral price booms affect the population and industrial composition of local cities. We find that increases in the prices of minerals extracted from nearby mines lead to increases in city population and employment reallocation away from agriculture and primarily into low-skilled services. The mechanism is consistent with an income effect, which creates jobs primarily in the urban non-tradable sector. Cities in Sub-Saharan Africa exhibit exceptionally strong responses to mining booms.

Key Words: resource rents, mineral price, urbanization, structural transformation

JEL code: O14, O18, Q32, R11

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1 Introduction

Historically, urbanization in the European and Neo-European countries has accompanied industrialization (Michaels et al., 2012; Jedwab and Vollrath, 2015). In the past few decades, however, urbanization in many developing countries has deviated from this pattern. Many countries today—especially those in Sub-Saharan Africa (SSA)—have high rates of urbanization at low levels of per capita income and have limited manufacturing employment shares at the same time (Glaeser, 2014; Rodrik, 2016; Gollin et al., 2016; Henderson and Kriticos, 2018; Diao et al., 2019, 2021; McMillan and Zeufack, 2022). The manufacturing sector matters for economic growth for at least three reasons: First, manufacturing activities tend to generate productivity spillovers on nearby firms (e.g., Ellison et al., 2010; Greenstone et al., 2010; Kline and Moretti, 2014). A small or shrinking manufacturing sector implies the loss of potential learning-by-doing opportunities. Second, relatedly, manufacturing is a technologically dynamic sector, which exhibits unconditional convergence in labor productivity (Rodrik, 2013). Third, as a tradable sector, the expansion of manufacturing is not constrained by the size of a home market. Yet, despite the presence and importance of urbanization without industrialization, the key forces behind this phenomenon still remain unknown.

One influential explanation for this phenomenon is the consumption city hypothesis, which highlights the important role played by resource rents (Gollin et al., 2016). They notice that the deviation between urbanization and industrialization mainly occurs in resource-dependent countries. High resource rents generate relatively higher incomes, which, in turn, create disproportionate demand for urban non-tradable services, leading to urbanization and labor reallocation from agriculture to services but not to manufacturing. This explanation, more broadly, is in line with theories that emphasize the income effect as a driver of structural transformation (Kongsamut et al., 2001; Boppart, 2014; Comin et al., 2021; Fan et al., 2023). However, it is difficult to test the consumption city hypothesis using cross-country data because proxies for resource rents are confounded with many other unobserved country characteristics that could also affect urbanization and industrialization levels.

In this paper, we rigorously examine the role of resource rents in causing urbanization and structural transformation. Specifically, we estimate how urban populations and local industrial structures change in response to the global price shocks of minerals extracted from nearby mining sites. The idea is that increases in mineral prices imply more active local mining activities and higher resource revenues, given that the impacts of natural resource booms are highly local.[1] If the consumption city hypothesis holds, we should observe an increase in the local city population, as well as a shift in sectoral employment shares away from agriculture and toward services in nearby cities or districts. Moreover, if the Dutch disease exists, we should also observe a decline in the local manufacturing employment share.

To conduct our empirical analysis, we combine several spatially granular data sets, including a collection of all urban settlements across the world with populations above a certain threshold, a global high-resolution population data layer, global property-level mining data containing the coordinates of each mining site and their primary commodities produced, and population census microdata from 76 countries in Integrated Public Use Microdata Series (IPUMS). The scale and spatial granularity of these data sets enable us to evaluate the relationship between mineral price changes, urban population growth, and changes in industrial structure in a comparable way across time and space.

In our regressions, each observation is a city with a population size above a certain threshold in 2018. The primary outcomes of interest are changes in population (density) within 10 km of each city's centroid and changes in sectoral employment shares within 60 km of each city's centroid. The key explanatory variable is the average log price change of minerals extracted from mines located within 60 km (or 120 km) of each city's centroid.[2] We drop minerals that are mined in fewer than 10 countries. Our study period is from circa 1975 to circa 2015. The identification assumption is that from the perspective of each city, a handful of mining sites nearby a city are unable to affect the international prices of the minerals extracted from those mines. Therefore, the volatile and highly unpredictable world mineral price changes can be viewed as exogenous shocks to each mining site.

This research yields three sets of findings. First, using the full global sample, we show that mining booms within 60 km of the city centroids (which we call buffer zones hereafter) lead to significant population growth within 10 km of the city centroids. According to our estimates, on average, global mining booms between 1975 and 2015 accounted for roughly 5.5% of urban population growth within the 10-km buffer zones of cities. We also estimate the heterogeneous effects by region,[3] finding that the effect is significantly positive only among African cities but not among other cities. Mineral price changes in our study period

[1]For evidence from SSA, see Mamo et al. (2019); for evidence from Peru, see Aragón and Rud (2013).

[2]The reasons behind these choices of radius are discussed in Sections 2 in this paper.

[3]We define seven global regions according to the classification of the World Bank: Sub-Saharan Africa, Middle East and North Africa, Latin America and the Caribbean, South Asia, East Asia and Pacific, Europe and Central Asia, and North America. This grouping is based on the definition by the World Bank. See https://datahelpdesk.worldbank.org. We merge Europe and Central Asia into one group because the Central Asia sample contains a relatively small number of cities.

contributed to approximately 9.7% and 14.0% of urban population growth in SSA and North Africa, respectively.

Second, on a global scale, we find that mineral price spikes in nearby mining sites lead to structural transformation away from agriculture in the 60-km city buffer zones. We show that a 10% increase in local mineral prices decreases the employment share in agriculture by 0.24 percentage points and decreases the employment share in not-recorded industries by 0.10 percentage points.[4] We find that the labor force is primarily reallocated to the service sector, particularly to the low-skilled service sector. A 10% increase in relevant mineral prices leads to a 0.28-percentage-point increase in the employment share in low-skilled services. Again, African cities exhibit special patterns: the labor reallocation out of the agricultural sector is particularly fast in SSA compared to the rest of the world. According to our estimates, mining booms between 1975 and 2015 contributed to 23.2% and 136% of the increases in the low-skilled services employment share on a global average and in SSA, respectively. On the other hand, globally we find a significantly positive or insignificant effect of mineral price shocks on the share of manufacturing employment, depending on different buffer zone definitions, i.e., there is no Dutch disease for the global cities in our sample. The positive impact on manufacturing is driven by cities in Asian countries. Consistent with the "consumption city hypothesis", resource-led booms have no impact on manufacturing growth in African countries.

We interpret the findings on city population growth and structural transformation as a result of the income effect generated by resource rents. The literature has provided rich evidence for the existence of an income effect associated with mining booms.[5] While income data are missing for many countries in our IPUMS sample, by using the census samples for which we have income data (11 out of 76 countries), we show that an increase in local mineral prices is associated with a significant increase in local average income. Taking our results and the literature's results together, there is suggestive evidence that in our full global city sample, there is a positive local income effect of mining booms. We also find the income effect is significant in the city core areas, consistent with the notion that a significant portion

[4] People may report a not-recorded industry in IPUMS because many of them are farmers and work in other sectors as well (Henderson et al., 2021). The decline in employment share in these industries may also indicate a structural transformation out of agriculture.

[5] Focusing on particular countries or regions, the existing literature has shown that the discovery of natural resources and the expansion of mining activities lead to increases in local non-agricultural GDP for Brazil (Cavalcanti et al., 2019), increases in local households' wealth index and nightlight intensity for SSA (Mamo et al., 2019), and increases in households' real incomes in Peru (Aragón and Rud, 2013) and the United States (Allcott and Keniston, 2018).

of resource rents are spent in cities. Further evidence suggests that mineral resource rents near a city induce the migration of workers into the city (who are relatively younger and less educated), which raises the share of prime-age individuals in the population and decreases the average years of schooling of the employees in urban non-agricultural sectors.

Third, we explore the potential mechanisms behind the fact that African cities respond differently to mineral price shocks. To do so, we interact mineral prices with an African region dummy and with country characteristics simultaneously. We consider six categories of country characteristics: (1) resource reliance, (2) agricultural productivity, (3) GDP per capita, (4) average years of schooling, (5) governance performance, and (6) conflict risks. Among all these six categories of country characteristics, we find that agricultural productivity plays a significant role in explaining the distinct responsiveness of African cities to mineral price shocks. A plausible explanation for this finding is that farmers face lower opportunity costs moving from rural areas if their local agricultural productivity is lower, and African countries on average have significantly lower agricultural productivity compared to other countries (Henderson and Turner, 2020; Lin et al., 2023).

Taken together, the results in our paper provide evidence for the important role played by resource rents in driving urbanization and structural transformation. The findings are consistent with the consumption city hypothesis proposed by Gollin et al. (2016). These results have implications for studies on structural transformation: while previous papers have placed a heavy weight on relative productivity growth between sectors as a driver of structural transformation in both theoretical models (Baumol, 1967; Gollin et al., 2002; Ngai and Pissarides, 2007; Herrendorf et al., 2014; Storesletten et al., 2019; Huneeus and Rogerson, 2023) and empirical work (Foster and Rosenzweig, 2004; Hornbeck and Keskin, 2015; Bustos et al., 2016; Emerick, 2018; Carillo, 2021; Asher et al., 2022), our research indicates that another driving force of structural transformation—namely, the non-homothetic preferences for services—is also empirically relevant, which has been highlighted by the theories of Kongsamut et al. (2001); Fan et al. (2023). While we are not the first to establish the empirical relevance of the consumption city hypothesis—see, for example, Cavalcanti et al. (2019) for Brazil—we are the first to causally identify the effect of mineral price changes on local city population and industrial structure on a global scale, which greatly extends the external validity of the hypothesis test. In terms of empirical approach, our work complements a growing body of literature that uses microdata to study macro-development questions, for example, the research of Asher and Novosad (2020); Bustos et al. (2020); Budí-Ors and Pijoan-Mas (2022); Eckert and Peters (2022); Fried and Lagakos (2021); Fajgelbaum and Redding (2022); Fiszbein (2022); Gollin et al. (2021); Hjort and Poulsen (2019); Nath (2022).[6]

Furthermore, by using comparable measures and specifications to estimate the same effects across different regions in the world, we uncover important regional heterogeneity: we find SSA exhibits exceptionally high responsiveness to mineral price shocks. On the one hand, this finding echoes the growing literature that notes the uniqueness of Africa in terms of both its manufacturing sector (Henderson and Kriticos, 2018; Henderson and Turner, 2020; Diao et al., 2021; McMillan and Zeufack, 2022) and its distinct responsiveness to mineral price shocks (Berman et al., 2017; Mamo et al., 2019). On the other hand, our estimates also suggest that there is still a large gap in our understanding regarding why African cities behave so differently in terms of urbanization and structural transformation compared to the rest of the world.

The results concerning the effect of mineral prices on the local manufacturing share connect to a large body of work on the Dutch disease and the natural resource curse (see Van der Ploeg, 2011, for a review). The most closely related research is the growing literature that exploits within-country variations to identify the effects of resource booms on firms (De Haas and Poelhekke, 2019) and on local industrial structure (for example, see the works of Black et al. (2005); Michaels (2011); Glaeser et al. (2015); Allcott and Keniston (2018) for the US, Fernihough and O'Rourke (2021) for Europe, and Cavalcanti et al. (2019) for Brazil). We show that the Dutch disease does not exist in a global city sample. This result implies that among the four commonly raised reasons why a resource curse might exist: The Dutch disease, rent-seeking, overconfidence, and neglect of education (Gylfason, 2001), the other three channels might be more important.

The remainder of the paper is structured as follows. Section 2 describes our data sources and provides summary statistics. Section 3 introduces our empirical strategy. Section 4 presents the results on the impact of mineral price shocks on urban population growth and the change in local industrial structure. Section 5 explores the potential mechanisms. Section 6 concludes.

[6]For a good review, see Lagakos and Shu (2021).

2 Data and Summary Statistics

2.1 Data Description

We are interested in whether mineral price booms result in urbanization and structural transformation, and examine this question at the city level instead of at the country level (see Gollin et al. 2016; Henderson and Kriticos 2018, for example). To construct the variables from various data sources, we proceed using the following steps. First, we select the universe of global cities with a population above a certain threshold and obtain their latitudes and longitudes. These cities represent all the human settlements above a certain population size. Second, based on the centroids of this list of cities, we draw circles to encompass the mines surrounding each city. We then examine the impact of price changes of the minerals extracted in nearby mines on two major city outcomes: city population, and local industrial composition. We describe the data construction process, as well as each data source, in detail below.

Urban Agglomerates and Population Data First, we locate the centroids of a collection of urban settlements covering the whole world using data provided by World Urbanization Prospects: The 2018 Revision (WUP 2018) and Africapolis. WUP 2018 presents estimates and projections of urban populations based mainly on official statistics. It identifies 1,860 urban agglomerates with at least 300,000 inhabitants in 2018, accounting for approximately 55% of the world's population residing in urban areas in that year.[7] Africapolis defines urban units in Africa using two criteria: a continuously built-up area detected via satellite and aerial imagery; and more than 10,000 inhabitants since 1960, calculated by official demographic data. We select the urban agglomerates in Africapolis that reached a population of at least 200,000 at some point since 1960, yielding a sample of 181 African cities.[8] By combining the data on non-African cities in WUP 2018 and the data on Africa-only cities in Africapolis, we obtain the coordinates of the centroids for a list of 2,041 cities

[7]The criteria of WUP 2018 for distinguishing between urban and rural areas involve administrative designations, demographic characteristics, economic characteristics, and other assessments like the existence of paved streets, water-supply systems, sewerage systems, or electric lighting. More information about WUP 2018 can be found on the official site of WUP: https://www.un.org/development/desa/pd/content/world-urbanization-prospects-2018-revision.

[8]We adopt a different threshold for defining African cities because African cities are, on average, much smaller than metropolises in the rest of the world. Using a smaller threshold allows us to keep a larger number of African cities in our sample. See more information about African cities on the official website of Africapolis: https://africapolis.org/en.

worldwide.[9]

After determining the centroids of the cities, our second step is to define consistent geographical boundaries across cities and time. This step is challenging because the geographic sizes of the cities are different and vary over time. To ensure comparability, we draw a circle of fixed radius around each city's centroid–which we call buffer zones hereafter–to define the "local" population (as well as, later, the "local" industrial structure) for each city. In the baseline, we use 10-km buffer zones to define local population and 60-km buffer zones to define local industrial structures. We adopt different radiuses because the population data and the industrial structure data are available at different spatial granularities.[10] We also consider buffer zones of 30-60 km for robustness checks. Circles of fixed size allow us to examine the effect within a fixed-sized area over time and across city agglomerations.[11] In addition to considering the city "core" areas—defined by these circles—we also consider the "ring" areas of each city centroid, which are defined by the areas between r and R kilometers away from the city centroids shown in Figure A2.

To calculate population changes within the equally sized buffer zones across the world, we use the Global Human Settlement Population Layer (GHSL) released by the European Commission in 2019 (Florczyk et al., 2019). GHSL provides an estimated gridded population of the world at the 250-m resolution for the years 1975, 1990, 2000, and 2015. These high-resolution population data are estimated based on administrative unit-level population data from the censuses, as well as on the 30-m resolution Landsat data produced by the EU circa 2015 (Corbane et al., 2018, 2019).[12] We spatially merge the GHSL 250-m gridded population data with the buffer zones of the cities, and then we obtain the average population density within each buffer zone for each city in each sample year (1975, 1990, 2000, and 2015).

[9]In this study, we also experiment with different city samples: cities only from WUP 2018, as well as non-African cities from WUP 2018 combined with African cities from Africapolis that have reached a population of at least 100,000 residents at some point since 1960. We test the robustness of our results using these alternative city samples in the Appendix.

[10]The average size of the IPUMS geographic (GEOLEV2) units is 5120.15 square kilometers, and the median size of the IPUMS GEOLEV2 units is 1388.07 square kilometers, which implies a radius of, respectively, 40 km and 21 km if the corresponding geographic unit is a circle.

[11]Figure A1 in the Appendix illustrates the 30-km city buffer zones of several countries.

[12]The GHSL data map the population data from the census units into these 250-m grid squares according to the spatial distribution and density of the footprint of built cover within each area. The built cover information is made available via the Landsat data. More information about the GHSL data can be found in Florczyk et al. (2019). Another population raster data is Gridded Population of the World version 4 (GPWv4). GPWv4 visualizes the world in grid cells of approximately 1 km and assumes that a population is evenly distributed across a polygon-shaped enumeration area. The GHSL uses the census unit population data in the same as GPWv4, but it allocates the population to the grid cells differently.

Mining Data We then link the information on these cities to the information on mining sites near each city. The original data set on mining sites contains information on the location and characteristics of 33,262 mining sites around the world, as collected by SNL Financial from company annual reports, technical reports, news articles, etc. For each mine, we know the current and historical operating status, the primary commodities extracted, mine characteristics, and work history.[13] We calculate the distance between each mine and each city center and keep only those mines that are within 60 km or 120 km of the centroid of each city. It is worth mentioning that the thresholds for the distances between city centroids and the mining sites (*mine buffer zones*) are different from the distance thresholds for defining the local population and local industrial structure (*city buffer zones*). We illustrate this distinction in Figure A2. We conduct robustness checks on both thresholds in the later analysis.

We retrieve information on global mineral prices from the World Bank Commodity Price Data (The Pink Sheet), supplemented by the US Geological Survey (USGS). We obtain annual price data for 10 minerals from the World Bank and another 13 minerals from USGS spanning over the study period. Table A2 in the Appendix summarizes the price data sources and the number of mining sites for each mineral in our sample. We find that 38.5% of the mines produce gold as their primary commodity. Other primary commodities include coal, copper, iron ore, nickel, silver, zinc, and others.

We construct the average price change of the *relevant* minerals experienced by each city during each period, which we use as the main independent variable throughout the study. We first calculate the price changes (log difference) of the main commodity during each period for every mine in the dataset.[14] For each city, there could be multiple mines surrounding it, and thus, we take the simple average of the log price changes of all mines surrounding a given city. This measure captures the intensity of the mineral price shocks experienced by each city.

Industrial Structure Data Besides linking mineral price changes to local population changes, we also connect mineral price changes to local industrial structure. To measure industrial structure, we draw on population census microdata from IPUMS to calculate employment shares by sector within the buffer zone of each city. Since the administrative

[13]However, annual production data and the year when production started are not available for most of the properties. We thus exploit the information on the mining sites' coordinates and the primary mineral extracted.

[14]The periods are the same as the sample periods in which the outcome variables are observed.

boundaries defined in IPUMS are inconsistent with our defined city buffer zones (60 km is used as the baseline), we spatially join these two data sources by taking the weighted average of the variable contained within each city buffer zone. Panel B of Figure A2 in the appendix illustrates the spatial join.[15] In our IPUMS sample, we select 261 rounds of population censuses from 76 countries spanning the years 1970 to 2017.[16] We describe the construction of other supplemental data in the appendix.

2.2 Summary Statistics

In this section, we present the summary statistics and plot the spatial patterns of the key explanatory variables and outcome variables using the data discussed above.

Change in Local Population. Figure A3 in the appendix maps the location of the cities, or the 10-km city buffer zones, across the world, as well as their population growth rates between 1975 and 2015. Most of the cities experienced positive population growth in this period. There is also substantial heterogeneity in the log change in population between 1975 and 2015 across the space, ranging from -3.060 (Nay Pyi Taw of Myanmar) to 8.231 (Luanda of Angola). On average, city populations grew fastest in Africa between 1975 and 2015, followed by South Asia and Latin America and the Caribbean. Cities in Europe and North America saw much smaller population increases during this same period.

Change in Local Employment Shares By Sector. Table 1 documents how the industrial structure of the cities (within 60 km of their centroids) changed in our study period. Panel A summarizes the changes between the 1970s and the 2010s in employment shares by sector and region. During the whole sample period, the cities in our sample experienced an outflow of labor from agriculture overall, but the sectors into which these agricultural workers moved differed across regions. For cities in Latin America and the Caribbean, Europe and Central Asia, and North America, the labor force left both the agricultural and manufacturing sectors and entered the services sectors. Cities in Sub-Saharan Africa and in the Middle East and North Africa saw a reallocation of labor from agriculture to low-skilled

[15]Specifically, we first intersect the city buffer zones with the global shapefile and calculate the area of the overlapping parts between each administrative unit and the city buffer zone using Quantum Geographic Information System (QGIS). Then, for each overlapping part, we estimate its number of employees by the number of employees in the corresponding, greater administrative unit in IPUMS, multiplied by the area share of this overlapping part in the total area of the corresponding administrative unit. We then sum the number of employees of each overlapping part contained within each buffer zone to obtain the buffer-zone-level estimate of the number of employees. Based on these sector-specific employee estimates, we can derive the employment shares at the city buffer zone level.

[16]The sample selection criteria and details of variable construction are described in the appendix.

services but saw few changes in the employment shares in the manufacturing and high-skilled services sectors. In East Asia and South Asia, the labor force moved out of agriculture and into the manufacturing and other services sectors.

Table 1: Change in Employment Shares by Sectors and Regions, 1970s-2010s

	East Asia and Pacific	South Asia	Latin America and the Caribbean	Sub-Saharan Africa	Middle East and North Africa	Europe and Central Asia	North America
Panel A. Change in employment shares from the 1970s to the 2010s							
Agriculture	-0.130	-0.086	-0.124	-0.044	-0.063	-0.037	-0.015
Mining	-0.007	-0.001	-0.005	-0.000	-0.000	-0.005	0.001
Manufacturing	0.023	-0.002	-0.024	0.004	0.004	-0.053	-0.045
High-skilled services	0.018	0.013	0.028	-0.004	0.012	0.024	0.057
Low-skilled services	0.093	0.078	0.104	0.040	0.057	0.074	0.009
Not recorded	0.002	-0.002	0.021	0.003	-0.009	-0.003	-0.007
Number of cities	506	215	208	140	96	215	161
Panel B. Level of employment shares in the 2000s							
Agriculture	0.535	0.481	0.113	0.424	0.279	0.151	0.012
Mining	0.011	0.007	0.006	0.020	0.002	0.003	0.004
Manufacturing	0.154	0.131	0.135	0.081	0.100	0.158	0.157
High-skilled services	0.024	0.021	0.060	0.030	0.028	0.100	0.163
Low-skilled services	0.271	0.360	0.604	0.378	0.583	0.577	0.663
Not recorded	0.005	0.000	0.083	0.067	0.007	0.011	0.000
Number of cities	506	196	202	104	57	125	161

Notes: The table reports the changes and levels in employment shares of the cities within a 60-km radius of the city centers. Data source: IPUMS.

Panel B of Table 1 presents the levels of the cities' employment shares in the 2000s.[17] We observe that there is a significant share of agricultural employment in all cities. This is consistent with our definition of a "city," which includes not only the urban core but also areas peripheral to the city, such as suburban areas. Comparing the different continents, cities in Asia and Africa had the highest employment shares in agriculture than other regions. African cities had the lowest employment share in manufacturing, but they had a relatively high

[17] We focus on the 2000s because older population census data in many developing countries are not publicly available, making the level of employment shares at the beginning of the sample period less comparable across countries. Table A4 in the Appendix provides more details about the IPUMS sample.

employment share in low-skilled services. Combined with the information shown in Figure A3, this pattern reflects "urbanization without industrialization" in Africa, a phenomenon that is also documented by Gollin et al. (2016).

Mines and Cities. We link the global sample of cities to the global sample of mining sites by spatial proximity. Table 2 provides the descriptive statistics of the mining sites. Several features are worth noting from Panel A. First, within a certain buffer zone of the cities, not all the cities have mines in their surrounding areas. For example, only 14.3% of the cities have a mine within 10 km of their centroids. The fraction of cities having at least one mine nearby gradually increases as the buffer zones expand, up to 77.7% as the radius of the buffer zones increases to 120 km. The average number of mines ranges from 0.17 (in the 5-km buffer zones) to 11.98 (in the 120-km buffer zones). Second, the mining sites tend to be spatially clustered. Conditional on observing at least one mine located within 5 km-120 km of a city center, the average number of mines ranges from 1.77 to 15.43. Furthermore, mines close to one another tend to yield the same kind of mineral commodity. The average number of primary commodities produced by these mines is only 1.86 within the 60-km buffer zone, and it is only 2.87 within the 120-km buffer zone. This pattern suggests that in the presence of price shocks on over twenty minerals, a single urban agglomerate is usually affected by only one or just a few mineral prices.[18]

To provide a more complete picture of the geographic extent of mining sites used in our analysis, we rely on recently developed mining area delineation data. Maus et al. (2020) provides a global georeferenced dataset on mining land use based on visual interpretations of satellite images. Their definition of mining areas includes different mining-related infrastructures such as open cuts, tailing dams, water ponds, processing plants, etc; thus, their mining delineation is broad. We present the relevant summary statistics in Panel B of Table 2. The full dataset from Maus et al. (2020) features both large-scale and small-scale mining operations. The longest side of their full sample global mining polygons is around 0.7 km on average. Among the polygons identified by Maus et al. (2020) that also intersect with the SNL data, the mean of the longest side of these mining polygons is around 1.2 km and the 90th percentile is around 2.5 km. Therefore, even the largest mining sites are geographically contained within a 3-km buffer zone. This fact has implications for the interpretation of our empirical results: given the limited geographic scope of the mining sites, the observed population and employment changes within 10 km or 60 km of city centroids are unlikely to

[18] We provide the number of mines nearby the cities by different continents in Table A3 in the appendix. We find relatively small differences in mine density across the different global regions.

Table 2: Descriptive Statistics of the Mines and Mining Areas

Panel A: Mines and Cities						
Mines' furthest distance to city center	5 km	10 km	30 km	60 km	90 km	120 km
A.1 For all cities ($N = 2{,}041$)						
Whether mines located nearby	0.097	0.143	0.301	0.523	0.672	0.777
Average number of mines	0.171	0.312	1.171	3.584	7.216	11.977
A.2 For cities with surrounding mines						
Average number of mines	1.766	2.182	3.887	6.849	10.735	15.427
Average number of primary commodities	1.188	1.220	1.481	1.855	2.371	2.873

Panel B: Global Mining Land Use			
Mining area	Mean (km)	Median (km)	90th percentile (km)
Longest side of mining polygons	0.7	0.5	1.5
Shortest side of mining polygons	0.1	0.1	0.3
Longest side, intersected with SNL data	1.2	0.8	2.5
Shortest side, intersected with SNL data	0.2	0.1	0.4

Notes: Panel A is calculated by the authors according to the coordinates of the city centroids and mining sites. Panel B is calculated based on data from Maus et al. (2020).

be solely driven by growth in mining activities within the mining areas.

Change in Mineral Prices. We calculate the city-level mineral price changes by taking the average of the log price changes of all mines surrounding a city. One potential concern in this long-difference framework is that mineral price changes over the course of 5, 10, or more years would ignore hidden price volatility. However, in our case, this might not be a big problem. Figure A6 in the appendix shows the trends of mineral prices by mineral type. For most minerals, we observe two commodity supercycles in world prices: the prices first increased in the 1980s, they were roughly constant in the 1990s, and then they escalated again in the 2000s. The price volatility over the whole period is very low. It is also interesting to note that the three price cycle phases roughly correspond to the periods we use to measure mineral price changes, which are 1975-1990, 1990-2000, and 2000-2015. On the other hand, these cycles are aperiodic. The upward trends in specific mineral commodity prices during the 1980s' peak are typically attributed to the post-World War II reconstruction of Western Europe and Japan and the cartelization of the crude oil market (Cuddington and Jerrett, 2008; Erten and Ocampo, 2013). The escalation in commodity prices in the 2000s is often attributed to rising global demand, driven by rapid growth and the search for natural resources in emerging markets (Humphreys, 2010; Carter et al., 2011; Canuto et al., 2014; Reinhart et al., 2016). In the long term, the timing of these cycles is highly unpredictable.

Figure A4 in the appendix plots the city-level mineral price changes on a map of the world. We see that the mineral price changes are dispersed, with some cities experiencing rapid price increases while others going through much slower mining booms or even mining busts. Moreover, there is no obvious evidence that mining booms were concentrated on only a few continents.

3 Empirical Strategy

To estimate the impact of mineral price changes on urbanization and structural change, we estimate the following long-difference econometric specification:

$$\Delta Y_{i,t} = \beta_0 + \beta_1 \Delta \log Price^R_{i,t} + \alpha Y_{i,t0} + \gamma \log NumMines^R_i + \delta_m + \lambda_c + \eta_{gt} + \epsilon_{i,t}, \qquad (1)$$

where $\Delta Y_{i,t}$ is the outcome variable of interest, i.e., log changes in population[19] or changes in the employment share by sector in city i during period t. In the main analysis, we calculate the outcome variables within the 10-km buffer zone of the city i for the population changes and use the 60-km buffer zone for calculating the employment share changes. We choose a larger buffer zone to calculate the employment shares because the geographic units from IPUMS are less granular than those from the GHSL population data. As a robustness check, we also analyze different radiuses to define the buffer zones and consider the ring zones. We calculate changes in population (density) in three periods for each city (within its buffer zone or ring zone): 1975-1990, 1990-2000, and 2000-2015. For employment, the periods in which employment share data are available depend on the census years, which vary across countries. Therefore, we measure changes in the employment share over different periods for cities in different countries.[20]

The key independent variable, $\Delta \log Price^R_{i,t}$, is the average log price change of the minerals extracted from mines located within R km of city i during the same period t as the dependent variable, $\Delta Y_{i,t}$. In the baseline specification, we use the 60-km buffer zone to calculate the average log mineral price change when the city buffer zone is 10 km (for population), and we use the 120-km buffer zone to calculate mineral price change when the city buffer zone is 60 km (for employment shares). We use larger buffer zones to encompass the

[19]This is equivalent to population density because we fix the geographic boundaries of cities.

[20]The corresponding period fixed effects include four groups: 1971-1990, 1991-1999, 2000-2009, and 2010-2017.

mines surrounding the cities because mines are typically located in remote areas. Again, we experiment with different mine buffer zone radiuses to test the robustness of our results. β_1 is the coefficient of interest, which captures the sensitivity of the outcome variable changes in response to the changes in the prices of the minerals extracted from the nearby mines.[21]

We include a set of fixed effects. The continent (one of the seven country groups) $\times$ period fixed effects, η_{gt}, control for continent-specific time trends in the outcome variables. The country (commodity) fixed effects, λ_c (δ_m), absorb the effect of any time-invariant country (commodity) characteristics that could be correlated with changes in urban population and industrial structure. In addition, we control for the initial value of the outcome variable, $Y_{i,t0}$, because the pace of population growth or structural change may depend on the stage that development city i is at.[22] Finally, we control for the log number of mining sites, $\log NumMines_i^R$, located in the corresponding buffer zone, which captures the idea that resource abundance in the local area might have an effect on the outcome variables. We cluster the standard errors at the city level to allow for city-specific serial correlations. As a robustness check, we also estimate the standard errors using the spatial heteroskedasticity- and autocorrelation-consistent (HAC) correction methods by Conley (1999) and Colella et al. (2019). We demonstrate that our results are robust to these two approaches.

The identification assumption for estimating equation (1) is that after controlling for these fixed effects and control variables, the world prices of minerals are exogenous to city-level outcomes. Given that we exclude minerals that are produced in fewer than 10 countries, most mines account for a tiny fraction of worldwide production. Therefore, each mine can be viewed as a price taker, which alleviates the concern that mining booms nearby a given city are driven by local population growth or industrial structure change.[23]

[21] Recall that to calculate employment shares, the period length varies by country/census. Since we always calculate the outcome variables and the independent variables during the same time windows, the coefficient β_1 is still comparable across countries/censuses; the implicit assumption is that the sensitivity of the outcome to mineral prices is similar during different time windows. We think this is a reasonable assumption because the gap between two census years in the IPUMS sample varies between 5 and 15 years and is highly concentrated in 5 or 10 years. Therefore, the coefficient β_1 can be roughly interpreted as "a one-log-point increase in mineral prices over the 10 years translates into a $\beta_1 \times 100$ percentage-point increase in the employment share of sector A over the sample years."

[22] For example, when Y_{it} is the employment share, $Y_{i,t0}$ refers to the initial employment shares in the agricultural, manufacturing, and mining sectors in t_0.

[23] As shown in Table 2, a non-negligible fraction of the cities have no mining sites in their surrounding areas, which is a particularly high figure (roughly 70%) if we consider only the mines within 30 km of the city centers. In the main analysis, we restrict the regression sample to cities that have at least one mine in the corresponding buffer zones. By making this restriction, we are comparing "resource cities" that experienced fast mineral price changes with "resource cities" that experienced slow or no mineral price changes, as well as comparing the same city across different time periods. An alternative approach, such as one suggested by

4 Results

In this section, we present our main empirical results. First, we report the estimated effect of mineral price changes on the urban population. After establishing a positive relationship between mineral price changes and urban population growth, we turn to investigate how mining booms surrounding a city affect the industrial structure of that city. In both parts of the analysis, we estimate the global average effect and then the heterogeneous effects by region.

4.1 Local Population

Table 3: The Effect of Price Shocks on Local Populations: Global Analysis

	(1)	(2)	(3)	(4)	(5)	(6)
	Outcome: Δ log Population in the City					
City Zone	Buffer, 10 km		Ring, 10-120 km	Buffer, 30 km		Ring, 30-120 km
Mine Buffer Zone	60 km	120 km	120 km	60 km	120 km	120 km
$\Delta \log \mathit{Price}$	0.031**	0.024*	0.023**	0.028**	0.016	0.022**
	(0.014)	(0.014)	(0.010)	(0.013)	(0.013)	(0.010)
log Initial Population	-0.092***	-0.095***	-0.036***	-0.046***	-0.051***	-0.031***
	(0.015)	(0.012)	(0.006)	(0.010)	(0.008)	(0.006)
FE	Country–group×period, Country, Commodity					
N	3,195	4,737	4,740	3,195	4,740	4,740
Adj. R^2	0.579	0.570	0.549	0.567	0.550	0.539

Notes: This table reports the regression coefficients of equation 1. The dependent variables are changes in log population (density) in the corresponding city zones. The independent variable (changes in log price) and the control variable (log number of mines) draw on all mines within the mine buffer zone. The buffer zone used to calculate the log initial population is consistent with the city zone of the dependent variable. Countries are categorized into seven groups: Sub-Saharan Africa, Middle East and North Africa, Latin America and the Caribbean, South Asia, East Asia, Europe and Central Asia, and North America. Standard errors in parentheses are clustered at the city level. ***, **, * denote statistical significance at the 1%, 5%, 10% levels, respectively.

Table 3 reports the effect of mineral price changes on population growth using the global city sample. In Columns (1) and (4), we consider the average price change of minerals extracted from mines within 60 km of the city centers. In Columns (2)(3)(5)(6), we consider the average price change of minerals extracted from mines within 120 km of the city centers. Columns (1)(2) define the outcome in the 10 km city buffer zones (the core areas), Column

Berman et al. (2017), would be to assume the price change to be zero for cities that have no mines in nearby areas. In the robustness checks, we show that our results are similar using this alternative (full) sample of cities.

(3) defines the outcome in the 10-120 km ring zones (the periphery areas), Columns (4)(5) focus on the 30-km city buffer zone (the core areas), and Column (6) examines the 30-120 km ring zones (the periphery areas). Across different city buffer/ring zones and mine buffer zones, we find that mining booms are significantly positively associated with city population growth (except Column (5)—30-km city buffer zone, 120-km mine buffer zone). Taking Column (1) for instance, the estimated effect suggests a 100% increase in mineral prices from mines within 60 km of a city center leads to a 3.1% increase in population within 10 km of the city center. When comparing the estimated results in Column (2)(core) with Column (3) (periphery) and comparing Column (5) (core) with Column (6) (periphery), the coefficients show similar magnitudes, suggesting the price changes of minerals extracted from mines within a certain distance of the city centroids have a similar impact on city core areas and the periphery areas. The significant impact of mineral price changes on the city core population is surprising given that most of these mines are located far away from the city centers. We will explore the mechanisms behind this result in Section 5.

During the sample period, the average annual price change is about 3.3% among cities with at least one mine within their 60-km radius. According to the estimate in Column (1) of Panel A, this translates into a $0.033 \times 3.1 = 0.102\%$ annual increase in urban population density within the 10-km city buffer zones. On the other hand, the annual population growth in the same areas during the 1975-2015 period is 1.9%. Therefore, our estimates suggest that mineral price shocks contribute to roughly $0.102/1.9 = 5.5\%$ of the population growth within 10 km of the centroids of the sample cities between 1975 and 2015.

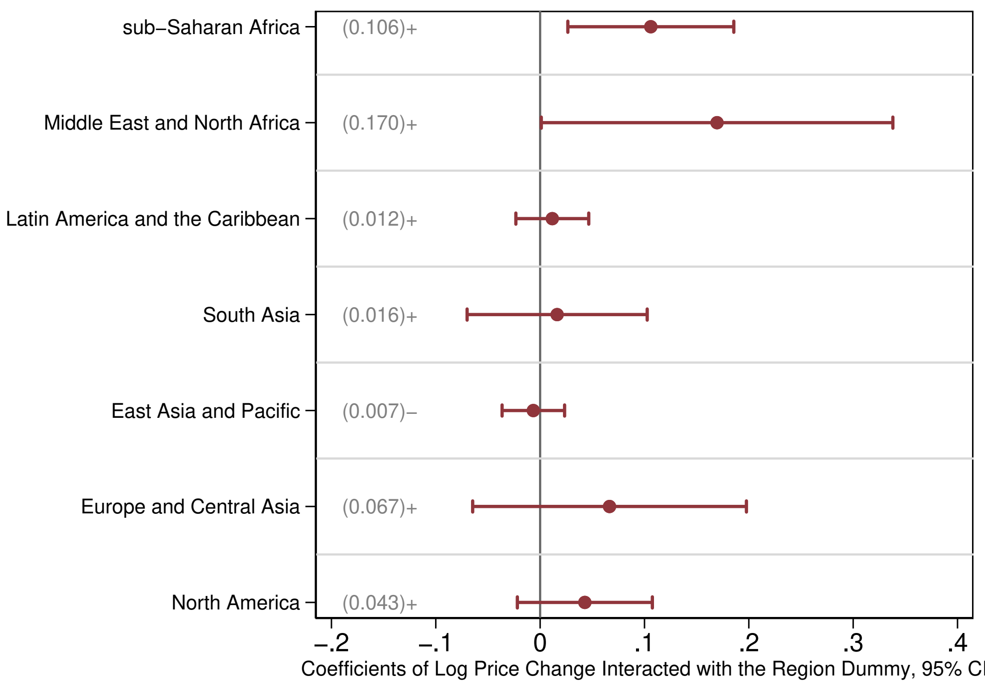
Thus far in the paper, we show that mining booms lead to significant urban population growth on a global scale. As depicted in Figure A3 in Section 2.2, cities across the world have followed different paths of urbanization. A natural question to ask next is whether urban populations in different regions exhibit different sensitivities to mineral price shocks. The global coverage of our assembled data set offers a rare opportunity to examine this heterogeneity.

We use the following equation to estimate the region-specific impact of mineral price shocks on urban population growth

$$\begin{aligned}\Delta Y_{i,t} = \beta_0 + \sum_g \beta_{1g} \Delta \log Price_{it}^R \times \mathbb{1}(Country_{i,c} \in Group_g) + \alpha Y_{i,t0} \\ + \gamma \log NumMines_i^R + \delta_m + \lambda_c + \eta_{gt} + \epsilon_{i,t},\end{aligned} \tag{2}$$

Similar to equation 1, $\Delta Y_{i,t}$ and $\Delta \log Price_{it}^R$ are, respectively, the changes in the outcome variable and the changes in mineral prices experienced by the city. Additionally, $\mathbb{1}(Country_{i,c} \in Group_g)$ are dummy variables that equal 1 if city i of country c belongs to country group g; otherwise, 0. The coefficient of interest is β_{1g}, which captures the average effect of mineral price shocks on population growth for cities in country group g.

Figure 1: The Effect of Price Shocks on Local Populations: Regional Heterogeneity



Notes: This figure plots the estimated coefficients of log changes in mineral prices interacted with the region dummy, based on equation 2. The dependent variable is log changes in population density within a radius of 10 km of a city center. The independent variable is the average of log changes in mineral prices across mines within the 60-km buffer zone. All the regressions control for the initial log population density of the 10-km city buffer zone, log number of mines within the radius of 60 km of a city, country–group×period fixed effects, country fixed effects, and commodity fixed effects. Standard errors are clustered at the city level.

Figure 1 plots the estimated coefficients on the interaction terms between mineral price shocks and country group dummies. We focus on the 10-km city buffer zone to measure the change in urban population and the 60-km mine buffer zone to locate mining sites near a city (corresponding to Column (1) of Table 3). Here, we have two significant findings. First, the effect of mineral price shocks on urban population growth is significant only in North African and SSA cities, which also have the largest magnitudes. We find that a 100% increase in the global prices of minerals extracted from nearby mines leads to a 10.6% increase in city population for SSA cities and a 17% increase in city population for North African cities.

On the other hand, from 1975 to 2015, the city populations in the North African and SSA sub-samples increased annually by 3.9% and 3.4%, respectively, and the annual mineral price changes of minerals extracted from nearby mines are 3.16% and 3.17%, respectively. These numbers suggest that mineral price shocks account for roughly 9.7% of the increases in the population of the sample cities (i.e., cities that have at least one mine within 60 km of their centroids) in SSA, and 14.0% in North Africa.

Second, we find almost no impact from mining booms on urban population growth in the other continents, including Latin America and the Caribbean, South Asia, East Asia, Europe and Central Asia, and North America. We find similar results when adopting a larger city buffer zone—specifically, 30 km—to calculate the urban population, as shown in Figure A7. To summarize, the results in this subsection suggest that mineral price shocks of nearby mines result in significant increases in the population of nearby cities, and such an effect is particularly large for African cities. In Section 5, we will investigate why African cities exhibit such different patterns.

4.2 Local Employment Shares by Sector

Thus far, we have found that mineral price spikes contribute to urban population increases. So, is this type of urban population growth accompanied by a synonymous process of industrialization, as the classical economic models of structural transformation assume? In this subsection, we explore how industrial composition within the cities and their greater areas changes in response to nearby mineral price shocks. Similar to the last subsection, we begin by estimating the global average effect, and then we estimate the heterogeneous effects across the regions.

Table 4 presents the estimated global average effect of mineral price shocks on changes in employment shares by sector. In Columns (1) and (4), we consider the average price change of minerals extracted from mines within 60 km of the city centers. In Columns (2)(3)(5)(6), we consider the average price change of minerals extracted from mines within 120 km of the city centers. Columns (1)(2) define the outcome in the 30-km city buffer zones, Column (3) defines the outcome in the 30-120-km ring zones, Columns (4)(5) focus on the 60-km city buffer zone, and Column (6) examines the 60-120-km ring zones. Panel A uses the log change in total employment (measured in IPUMS) as the outcome variable. Panel B uses the log change in population (measured in GHSL) as the outcome variable while keeping the city sample the same as Panel A. Panels C-H consider changes in employment share by sector as the outcome variable (also measured in IPUMS).

We highlight the following results. First, from Panel A and Panel B, we see that across the buffer zones and ring zones, a positive local mineral price change is associated with an increase in local total employment and population. The effect on employment is always larger than the effect on the population in the respective zone, and many of these effects are statistically significant. Comparing Column (2) with Column (3), and Column (5) with Column (6), we find that the effects in the city core areas and periphery areas have similar magnitudes. This set of results indicates that local mining booms boost local economic activity, and such an impact occurs both in the city cores and their periphery areas.

Second, across all the buffer zones and ring zones, the local agricultural employment share decreases in response to increases in mineral prices. In other words, mining booms in the local area lead to structural transformation out of agriculture in the local area. Again, such a process takes place both in the city cores and in the peripheries. Taking the estimate in Column (5) of Panel C as an example, a 100% increase in mineral prices within the 120 km buffer zones leads to a reduction in the agricultural employment share within the 60 km buffer zones by approximately 2.4 percentage points. Another non-negligible source of structural transformation is the change that takes place in the share of not-recorded industries, a large fraction of which represents people working in both farming and non-farming sectors (Henderson et al., 2021). According to Column (5) of Panel H, a 100% increase in mineral prices also results in a 1-percentage-point decrease in the employment share in the not-recorded industries. These two effects combined together imply very substantial reductions in the agricultural employment share due to mining booms.

Third, Panels F and G suggest that agricultural workers primarily reallocate to the low-skilled services sector but not to the high-skilled services sector. According to Column (5) of Panel G, A 100% increase in mineral prices leads to an increase in the employment share in low-skilled services by approximately 2.8 percentage points. Mining price shocks also significantly increase the employment share of high-skilled services but with much smaller magnitudes (Panel F). Comparing Column (2) with Column (3), and Column (5) with Column (6), we see that the effect on the low-skill service employment share is much stronger in the city core areas than in the periphery areas, which is consistent with the consumption city hypothesis in the sense that resource rents could be disproportionately spent in the central cities rather than in the rural areas.

Fourth, we see a significantly positive effect from mineral price shocks on manufacturing employment shares in the city core areas (Columns 1, 2, 5, Panel E), and an almost zero effect on manufacturing employment shares in the periphery areas (Columns 3, 6, Panel E).

This result connects to the findings of a number of studies on the Dutch disease (Black et al., 2005; Michaels, 2011; Glaeser et al., 2015; Allcott and Keniston, 2018; Cavalcanti et al., 2019). A great advantage of our estimates is the global coverage of our city sample, which covers 1,398 cities in 88 countries on seven continents, whereas most previous studies that exploit within-country, cross-city variations focus on only one country or one region. The finding of a non-negative effect on manufacturing employment share suggests that the Dutch disease does not exist in our global sample. The significantly positive effect on manufacturing employment share in the city core areas somewhat contrasts with Gollin et al. (2016), as their theory would predict no effect on manufacturing employment share. One possible reason is that manufacturing goods are not perfectly tradable as assumed in their model, so an increase in local demand would translate into an increase in local employment.

Fifth, we find a close-to-zero and insignificant effect of mineral price shocks on mining employment share in the city core areas (Columns 1, 2, 4, 5, Panel D) but a significantly positive effect on mining employment share in the periphery areas (Columns 3, 6, Panel D). In addition, we show in Table A5 in the appendix that mining booms also significantly raise the overall local employment in the mining sector in the periphery areas but not in the city cores. The reason why we do not find a significantly positive effect on mining employment share in the city cores is likely because there are not many mining activities in close proximity to the city centers. Also, note from Row 2 of Panel B of Table 1 that mining activity accounts for a tiny share of local economic activity (between 0.2% and 2.0% in terms of total employment in the 2000s across the continents). Meanwhile, from Panel A of Table 4, there is an economically large effect of mineral price booms on total employment. Therefore, these results indicate that mining booms likely affect the local economy not primarily through the mining sector itself but through its impacts on the other sectors.

Table 4: The Effect of Price Shocks on Local Employment: Global Analysis

	(1)	(2)	(3)	(4)	(5)	(6)
City Zone	Buffer, 30 km		Ring, 30 -120 km	Buffer, 60 km		Ring, 60 -120 km
Mine Buffer Zone	60 km	120 km	120 km	60 km	120 km	120 km
Panel A. $\Delta \log$ Total Employment Level						
$\Delta \log Price$	0.054	0.063*	0.053	0.086	0.136**	0.149***
	(0.042)	(0.037)	(0.035)	(0.056)	(0.056)	(0.051)
N	1,767	2,705	2,567	1,850	2,839	2,685
Adj. R^2	0.128	0.145	0.136	0.288	0.259	0.169
Panel B. $\Delta \log$ Population in the City, Same City Sample As Panel A						
$\Delta \log Price$	0.023*	0.033**	0.023**	0.014	0.030**	0.023***
	(0.013)	(0.013)	(0.009)	(0.012)	(0.012)	(0.009)
N	2,367	3,441	3,441	2,367	3,441	3,441
Adj. R^2	0.659	0.591	0.518	0.641	0.581	0.507
Panel C. Δ Agriculture Emp. Share						
$\Delta \log Price$	-0.021***	-0.023***	-0.017***	-0.015***	-0.024***	-0.021***
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)
N	1,767	2,705	2,567	1,850	2,839	2,685
Adj. R^2	0.203	0.218	0.288	0.247	0.226	0.284
Panel D. Δ Mining Emp. Share						
$\Delta \log Price$	0.000	0.001	0.002***	0.000	0.000	0.002**
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
N	1,767	2,705	2,567	1,850	2,839	2,685
Adj. R^2	0.421	0.397	0.400	0.426	0.400	0.352
Panel E. Δ Manufacture Emp. Share						
$\Delta \log Price$	0.004*	0.005**	-0.001	0.003	0.004*	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
N	1,767	2,705	2,567	1,850	2,839	2,685
Adj. R^2	0.196	0.209	0.232	0.208	0.210	0.214
Panel F. Δ High-skilled Services Emp. Share						
$\Delta \log Price$	0.001	0.000	0.003***	0.002	0.002**	0.002***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
N	1,767	2,705	2,567	1,850	2,839	2,685
Adj. R^2	0.402	0.387	0.506	0.338	0.332	0.424
Panel G. Δ Low-skilled Services Emp. Share						
$\Delta \log Price$	0.026***	0.029***	0.009**	0.022***	0.028***	0.010***
	(0.005)	(0.004)	(0.004)	(0.005)	(0.003)	(0.004)
N	1,767	2,705	2,567	1,850	2,839	2,685
Adj. R^2	0.306	0.302	0.330	0.297	0.273	0.276
Panel H. Δ Not-recorded Emp. Share						
$\Delta \log Price$	-0.010**	-0.011***	0.004	-0.012***	-0.010***	0.005**
	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
N	1,767	2,705	2,567	1,850	2,839	2,685
Adj. R^2	0.340	0.314	0.294	0.268	0.243	0.227

Notes: This table reports the coefficients of equation 1. The dependent variables are total employment/population or changes in employment shares by sector in the corresponding city zones. The independent variable (log price change) and the control variable (log number of mines) draw on all mines within the mine buffer zone. All the regressions control for the country-group*period, country, and commodity fixed effects. Panel A additionally controls for initial total employment, Panel B additionally controls for initial population, and Panels C-H additionally control for the initial employment shares of agriculture, manufacturing, and mining within the corresponding city zones. Standard errors in parentheses are clustered at the city level. ***, **, * denote statistical significance at the 1%, 5%, 10% levels, respectively.

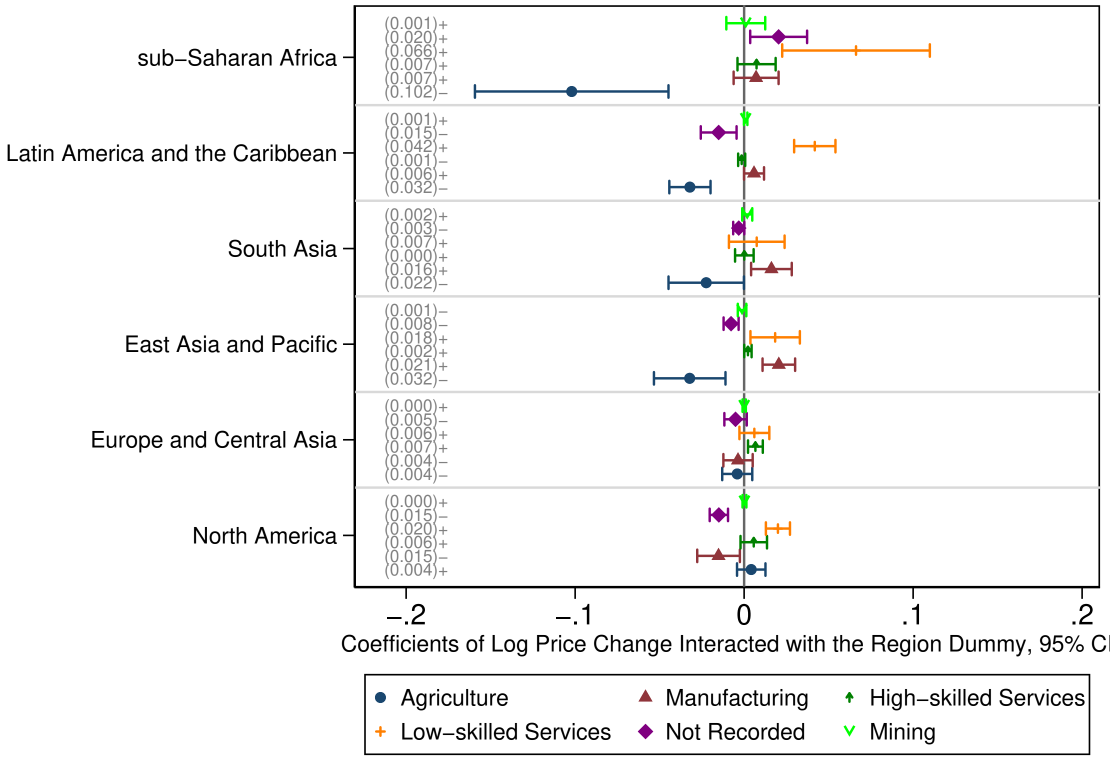
Next, we investigate the heterogeneous impacts of mineral price shocks on structural transformation across different continents. The empirical specification follows equation (2), where the outcome variable is the changes in employment share by sector. We exclude North Africa due to its small sample size. For the other continents, we plot the coefficient estimates by region and by sector in Figure 2, where we use the 60-km city buffer zone and 120-km mine buffer zone. Similar effects are found when we use the 30-km city buffer zone and the 120-km mine buffer zone, as shown in Figure A8 in the appendix.

From this work, we have three findings. First, in response to the same degree of mineral price shocks, the SSA cities exhibit the most rapid changes in employment shares across sectors. In line with average patterns globally, price spikes in SSA induce the labor force to move out of agriculture and primarily into the low-skilled services sector. The magnitudes of the coefficients for SSA are at least four times larger compared to those in the rest of the world—a pattern we discuss further in the next section. Specifically, the average annual price change of minerals is about 3.1% among mines within 120 km of city centroids worldwide and about 5.2% among mines within 120 km of SSA cities (based on the IPUMS sample). Meanwhile, the average annual change in the employment share of low-skilled services within 60 km of city centroids is 0.37 percentage points globally and 0.25 percentage points in SSA. After conducting a simple back-of-the-envelope calculation, we find that the contribution of mineral price shocks to the increases in the low-skilled services employment share is approximately 23.2% on a global average and 136% for SSA cities.

Second, in regions besides SSA, the most common labor-reallocation pattern induced by rising mineral prices is from agriculture to low-skilled services as well, although it occurs at a much slower pace than in SSA. This finding is consistent with the consumption city hypothesis, which suggests that resource rents will be spent disproportionately on urban non-tradable goods and services, initiating a labor demand in related sectors.

Third, for most parts of the world, there is little evidence for the Dutch disease: the effect of mineral price shocks on the manufacturing employment share is statistically indistinguishable from zero or is significantly positive (except in North America). In East Asia and South Asia, the manufacturing sector expanded in the presence of mining booms, suggesting that East Asian and South Asian cities seem to have been able to harness the resource rents and promote the manufacturing sector. On the other hand, cities in North America have experienced declines in the manufacturing employment share in response to mining booms. This result contrasts with the work of Allcott and Keniston (2018), who find no evidence of Dutch disease as a consequence of large oil and gas price booms. However, our finding is consistent

Figure 2: The Effect of Price Shocks on Local Employment Shares by Sector: Regional Heterogeneity



Notes: This figure plots the estimated coefficients of log changes in mineral prices interacted with the region dummy, based on equation 2. The dependent variables are changes in employment shares by sector within a radius of 60 km of a city. The price change is the average log change of the price of minerals extracted from mines located within a radius of 120 km of a city. All the regressions control for initial employment shares of agriculture, manufacturing, and mining within the radius of 60 km of a city, log number of mines within the radius of 120 km of a city, country–group×period fixed effects, country fixed effects, and commodity fixed effects. We exclude the Middle East and North Africa region due to a lack of observations. Standard errors are clustered at the city level.

with Glaeser et al. (2015), who provide evidence that, from the 1970s onward, proximity to historical mines is associated with reduced urban entrepreneurship in industries unrelated to mining. The distinct findings could be the result of the different types of natural resources considered by each study.

Finally, we conduct additional checks to test the robustness of our results. We examine: (1) whether mining booms and busts differentially impact the city populations and local industrial structure; (2) whether the effects differ between capital cities and non-capital cities; (3) whether the results are affected by the measure error in mines' open/close status in our data; (4) whether the results are robust to alternative sample restriction rules, control variables, and weighting methods. In summary, we find our core results are still similar under various robustness checks. The details of the discussion and the related results are provided in the appendix.

5 Mechanisms

In this section, we discuss the mechanisms through which mineral price shocks affect the local population and industrial structure. First, in Section 5.1, we investigate why workers reallocate out of agriculture and move primarily into the low-skilled services sector. We also investigate whether population increases are driven by migration or by demographic changes. Then, in Section 5.2, we explore why SSA exhibits such different patterns in terms of city population change and structural change in response to mineral price shocks compared to the rest of the world.

5.1 Mechanisms Behind Labor Reallocation Between Sectors

In Section 4.2, we find that positive mineral price shocks induce structural transformation out of agriculture and primarily into low-skilled services. According to the theoretical model proposed by Gollin et al. (2016), the key mechanism is that mining booms generate an income effect, and such incomes will be spent disproportionately on local non-tradable goods and services. Therefore, we investigate whether there is an income effect in our study context.

First, before using our data to conduct this exercise, we review the related literature. By focusing on single countries or individual regions, existing studies provide rich evidence that the discoveries of natural resources and the expansion of mining activities lead to increases in local income (or proxies for income). Cavalcanti et al. (2019) exploit a quasi-experiment of oil discoveries from 1940 to 2000 in Brazil and find that municipalities where oil was discovered experienced significant increases in local non-agricultural GDP relative to the municipalities with drilling but no oil discovery. Mamo et al. (2019) examine the effects of mining and find positive effects on local households' wealth index and nightlight intensity using district-level data from 42 SSA countries for the period 1992-2012. Further, using more direct measures of incomes, Aragón and Rud (2013) document that households' real incomes increased significantly following an expansion in the production of a large gold mine in Peru, while Allcott and Keniston (2018) show that local wages were 1.6%-3% higher in

US counties with one standard deviation more oil and gas endowment during the mining boom of 2007-2014.

To verify whether the income effect of mining booms exists in our context, we also use the IPUMS microdata. While income data are missing for many countries in the IPUMS sample, we can use the censuses for which income data are available (11 out of 76 countries) for this analysis. To control for the observational changes in individual characteristics that may also affect average income, we first estimate a Miner regression for each individual's income.[24] We then use the regional average residual income as the outcome variable, which reflects the income of an "observationally representative" individual in that region. Table 5 presents the results. Column (1) pools workers from all sectors, and Columns (2)-(6) report the results for workers in each sector separately. Panels A and C report the results using the global sample, while Panels B and D report the results using the South African sample (which is the only country in SSA that has available income data). Panels A and B examine the income changes within the city cores (<60 km of city centroids), while Panels C and D examine the outcome within the periphery areas (60-120 km of city centroids).

The estimates in Column (1) in Panel A suggest that a 100% increase in mineral prices leads to a 13.3% significant increase in the average total income of local workers living in the city core areas. Finding a positive income effect in the city core areas is important because it supports one important assumption of the consumption city hypothesis that a large portion of resource rents will be spent in cities. From Columns (2)-(6) in Panel A, we find that income increases significantly in all sectors. Combined with the fact that overall employment increases significantly following a mining boom (Panel A, Table 4), this set of results indicates that mining booms not only lead to expansions and income growth in the mining sector itself but also raise the incomes and employment in other sectors. Comparing Panel A (core) with Panel C (periphery), we find that the coefficients in the periphery areas are larger, which suggests that the income effect is larger in the periphery areas than in the core areas. A possible reason is that a larger number of mining sites are located on the periphery of the cities, and mining booms have a more direct effect on the local areas. In Panels B and D, we analyze the income effect for South Africa in the core and the periphery areas, respectively. Here, we find a positive effect on income in the aggregate sector (Column 1), a significantly positive effect on the income of mining workers (Column 3), which is expected, and a significantly positive effect on the income of low-skilled service

[24] Specifically, we use the variable "INCTOT" in IPUMS. We regress log individual income on an individual's age, age squared, years of schooling, and gender, as well as the country fixed effects and year fixed effects.

workers (Column 6).

Table 5: The Effect of Price Shocks on Personal Income

	(1)	(2)	(3)	(4)	(5)	(6)
	Outcome: $\Delta \log$ *Residue Income*					
	All Workers	Agr.	Mining	Manu.	HS Serv.	LS Serv.
Panel A. Global Sample, City Buffer Zone = 60 km						
$\Delta \log Price$	0.133***	0.117***	0.061*	0.114***	0.126***	0.129***
	(0.034)	(0.037)	(0.034)	(0.033)	(0.035)	(0.032)
N	511	511	498	511	507	511
Adj. R^2	0.752	0.628	0.654	0.739	0.711	0.779
Panel B. South Africa, City Buffer Zone = 60 km						
$\Delta \log Price$	0.089	0.055	0.300***	0.036	-0.066	0.124**
	(0.061)	(0.102)	(0.090)	(0.051)	(0.099)	(0.044)
N	25	25	25	25	25	25
Adj. R^2	0.655	0.885	0.961	0.629	0.327	0.691
Panel C. Global Sample, City Ring Zone = 60 - 120 km						
$\Delta \log Price$	0.246***	0.207***	0.160***	0.222***	0.233***	0.236***
	(0.026)	(0.028)	(0.031)	(0.026)	(0.024)	(0.027)
N	462	462	461	462	461	462
Adj. R^2	0.826	0.747	0.732	0.820	0.790	0.838
Panel D. South Africa, City Ring Zone = 60 - 120 km						
$\Delta \log Price$	0.079**	-0.005	0.316***	-0.009	0.017	0.111***
	(0.033)	(0.079)	(0.045)	(0.030)	(0.044)	(0.029)
N	25	25	25	25	25	25
Adj. R^2	0.807	0.898	0.937	0.879	0.517	0.797

Notes: In Panels A and B, the dependent variables are calculated within the 60-km city buffer zone. In Panels C and D, the dependent variables are calculated within the city ring zone of 60-120 km. Log price change is calculated using mines within the 120-km mine buffer zone. All regressions control for the log number of mines, log initial income, the country-group*period, country, and commodity fixed effects. The income data come from the variable "INCTOT" in IPUMS, which is defined as total personal income from all sources in the previous month or year. "HS Serv" and "LS Serv" indicate high-skilled and low-skilled services, respectively. Standard errors in parentheses are clustered at the city level. ***, **, * denote statistical significance at the 1%, 5%, 10% levels, respectively.

To further investigate the forces behind the population, employment share, and income changes, we examine how the characteristics of the workers change in response to mining booms. In particular, we focus on two important labor-productivity-related personal characteristics: the average years of schooling of the labor force, and the age composition of the population. Since the data we use are city-level averages instead of panel data that track individuals over time, the observed changes in the average years of schooling at the city level are due to a combination of two effects: compositional change, in the sense that the inflow and outflow of people with different skills will change the average skill level; and human capital accumulation, in the sense that higher resource rents could allow parents to invest more in their children's education and/or could allow local governments to build more schools and provide more educational services. Conversely, parents may invest less in schooling when the income opportunity costs are higher during mining booms. The first effect tends to decrease the average skill level in cities because workers in the agricultural sector are typically less educated than workers in the other sectors,[25] and therefore, their migration into cities tends to bring down the average skill level in cities. The second effect could affect the average skill level of the population in both directions.

Table 6 reports the results of this analysis. In the global-city core sample (Panel A), we obtain a close-to-zero effect of mineral price shocks on the average years of schooling of the cities' labor forces overall. From Columns (2)-(6), where we estimate the effect on education by sector, we find that the effect is consistently negative across the different sectors, and most of these estimates are significant. This simultaneous decline in education in almost every sector but almost no change in the overall education level can be explained by reallocation of labor across sectors: since agricultural workers feature significantly fewer years of schooling, the left of relatively better-educated farmers and the move of these workers into sectors that have higher average years of schooling (higher than the education of the migrants) could bring down the average years of schooling in every sector. Comparing the global-periphery sample (Panel C) with the global-core sample (Panel A), we find a more negative effect on education in the global-periphery sample. This result can potentially be explained by the stronger negative sorting process that takes place in the periphery areas in our city sample.

[25] See Table A11 in the appendix for summary statistics on the education of employees in different sectors in our data.

Table 6: The Effect of Price Shocks on Education

	(1)	(2)	(3)	(4)	(5)	(6)
	Outcome: Δ Years of Schooling					
	All Workers	Agr.	Mining	Manu.	HS Serv.	LS Serv.
Panel A. Global Sample, City Buffer Zone = 60 km						
$\Delta \log Price$	0.003	-0.113**	-0.149*	-0.067	-0.082*	-0.093**
	(0.043)	(0.047)	(0.078)	(0.044)	(0.048)	(0.040)
Sample Mean of the Outcome	0.849	0.688	0.756	0.730	0.469	0.661
N	2,610	2,610	2,610	2,610	2,610	2,610
Adj. R^2	0.410	0.352	0.365	0.318	0.555	0.389
Panel B. SSA Sample, City Buffer Zone = 60 km						
$\Delta \log Price$	-0.952	-1.096**	-1.321**	-0.786*	-1.173***	-1.303***
	(0.597)	(0.502)	(0.573)	(0.469)	(0.320)	(0.276)
Sample Mean of the Outcome	0.711	0.830	0.314	0.570	0.174	0.537
N	108	108	108	108	108	108
Adj. R^2	0.435	0.574	0.586	0.511	0.678	0.749
Panel C. Global Sample, City Ring Zone = 60 - 120 km						
$\Delta \log Price$	-0.034	-0.162***	-0.148*	-0.130***	-0.139**	-0.133***
	(0.050)	(0.046)	(0.082)	(0.048)	(0.054)	(0.046)
Sample Mean of the Outcome	0.839	0.667	0.740	0.716	0.480	0.649
N	2,531	2,531	2,527	2,531	2,521	2,531
Adj. R^2	0.436	0.416	0.336	0.340	0.574	0.428
Panel D. SSA Sample, City Ring Zone = 60 - 120 km						
$\Delta \log Price$	-1.434***	-1.168**	-1.380***	-1.421***	-1.538***	-1.599***
	(0.518)	(0.461)	(0.502)	(0.387)	(0.461)	(0.330)
Sample Mean of the Outcome	0.707	0.788	0.386	0.599	0.308	0.558
N	108	108	108	108	108	108
Adj. R^2	0.591	0.690	0.560	0.612	0.576	0.722

Notes: In Panels A and B, the dependent variables are calculated within the 60-km city buffer zone. In Panels C and D, the dependent variables are calculated within the city ring zone of 60 - 120 km. Log price change is calculated using mines within the 120-km mine buffer zone. All regressions control for the log number of mines, the initial average years of schooling in the corresponding sector, the country-group*period, country, and commodity fixed effects. "HS Serv" and "LS Serv" indicate high-skilled and low-skilled services, respectively. Standard errors in parentheses are clustered at the city level. ***, **, * denote statistical significance at the 1%, 5%, 10% levels, respectively.

In Panel B and D of Table 6, using the SSA sample only, we also find that mining booms are associated with a negative impact on the average years of schooling overall as well as by sector. Moreover, the effects on SSA cities are much more significant and more negative within each sector and at the aggregate level. This result is surprising given that the average years of schooling are lower in SSA, which implies an even larger proportional decrease in education for SSA cities. This fact is consistent with a scenario where migrants in African countries are much more responsive to mineral price changes across regions within a country compared to migrants in other countries, and it can also be explained by the possibility that parents invest less in children's education when the opportunity costs of education become higher due to positive income shocks (Atkin, 2016; Shah and Steinberg, 2017; Xu, 2021). While we cannot directly test the second channel, we exploit the migration history information in IPUMS and estimate a gravity equation of migration flows country by country to test the first channel. The details of the econometric specification and the results are provided in Appendix A.3 (Tabels A1). In summary, we find evidence that individuals in African countries are responsive to mineral price shocks in their migration decisions. These results can also help explain the heterogeneity results in Figure 1.

Table 7: The Effect of Price Shocks on the Age Composition of the Populations

	(1)	(2)	(3)	(4)
	Outcome: Δ Share of Population			
	Age 0-14	Age 15-44	Age 45-59	Age 60+
Panel A. Global Sample, City Buffer Zone = 60 km				
$\Delta \log Price$	-0.008***	0.006***	0.002***	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
N	3,497	3,497	3,497	3,497
Adj. R^2	0.406	0.537	0.537	0.350
Panel B. SSA Sample, City Buffer Zone = 60 km				
$\Delta \log Price$	-0.004	0.010***	-0.001	-0.005***
	(0.004)	(0.003)	(0.002)	(0.001)
N	350	350	350	350
Adj. R^2	0.237	0.316	0.293	0.423
Panel C. Global Sample, City Ring Zone = 60 - 120 km				
$\Delta \log Price$	-0.008***	0.005***	0.003***	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
N	3,409	3,409	3,409	3,409
Adj. R^2	0.434	0.551	0.568	0.414
Panel D. SSA Sample, City Ring Zone = 60 - 120 km				
$\Delta \log Price$	-0.003	0.004*	0.000	-0.002***
	(0.004)	(0.003)	(0.002)	(0.001)
N	350	350	350	350
Adj. R^2	0.226	0.286	0.294	0.340

Notes: In Panels A and B, the dependent variables are calculated within the 60-km city buffer zone. In Panels C and D, the dependent variables are calculated within the city ring zone of 60 - 120 km. Log price change is calculated using mines within the 120-km mine buffer zone. All regressions control for the log number of mines, the initial share of the population in the corresponding age group, the country-group*period, country, and commodity fixed effects. Standard errors in parentheses are clustered at the city level. ***, **, * denote statistical significance at the 1%, 5%, 10% levels, respectively.

In addition to average years of schooling, we also examine the impact of mineral price shocks on another important outcome related to labor productivity: the age composition of the local areas. For each geographic unit, we calculate the share of individuals aged 0-14, 15-44, 45-59, and 60+ among the total population. We use the baseline specification with changes in the population shares of the different age groups as the outcome variables. We report the estimation results in Table 7. In Panels A and C, we focus on the global city-core sample and the global city-periphery sample, respectively, where we find that an increase in prices of minerals mined nearby leads to significant increases in the share of prime-age individuals (i.e., ages 15-44 and 45-59, shown in Columns (2) and (3), respectively) and significant decreases in the share of young children (age 0-14) in the local area's population. This change in the population pyramid could be due to the migration of prime-age individuals, or due to changes in the fertility and mortality rates in the cities, or both. The patterns in SSA countries are slightly different, as shown in Panels B and D (core and periphery, respectively). Here, in both panels, we see a positive and significant effect of mining booms on the share of the population aged 15-44, a negative and significant effect of mining booms on the share of the population aged 60+, and an insignificant effect on the other two age groups. Given that it is usually the prime-age individuals who are most likely to migrate, the fact that the share of prime-aged individuals increases in all four panels suggests that the migrant share could also significantly increase in the local areas.

To summarize, mineral price booms lead to increases in local residual income (accounting for observed changes in individual characteristics), and such increases occur for workers in almost every sector and even for workers living in the city core areas. These facts suggest that the structural transformation process observed in Section 4.2 is likely to be driven by the income effect. We also find a reduction in the education of the employees in almost every sector, no change in the average education of the overall employment, and an increase in the share of prime-age individuals in the population, which suggests a migration process of agricultural workers to urban nonagricultural sectors.

5.2 The Uniqueness of Africa

Previously in this study, we find that in nearly every key outcome we examine, African countries exhibit significantly different patterns in response to mineral price shocks. In this subsection, we begin by documenting the summary statistics of key economic variables of the countries across the seven regions in our data sample. Then, after noting some distinct characteristics of SSA countries, we use regressions to empirically estimate which of these country characteristics plays the largest role in explaining the heterogeneous responses to mineral price shocks across the seven regions.

We select a set of country characteristics that are potentially relevant to our question about Africa's uniqueness. Table A12 presents the descriptive statistics. First, in years past, the Middle East and North Africa, Latin America and the Caribbean, and SSA had the highest ratios of natural resource exports to GDP (over 3%) compared to the rest of the world. Second, agricultural productivity was significantly lower in Africa than in other regions. In the early 1990s, for example, cereal yields per hectare in SSA were only half of those in Latin America and South Asia and less than one-third of those in Europe and North America. Third, SSA countries had fewer years of schooling among their respective populations aged 25 and above. In SSA, the average years of schooling were only 3.49 years, ranking the lowest among the continents. Fourth, SSA and North Africa showed weaker governance performance, measured by the rule of law, control of corruption, and democracy indices. Lastly, conflict risks in SSA and North Africa have been higher than those of other continents. Conflicts per million persons from 1960 to 2000 were 1.44 in SSA and 2.62 in North Africa, figures that can be compared to 0.004 in North America. We include this measure because mining activity is found to have causal effects on the incidence of local conflicts (Dube and Vargas, 2013; Bazzi and Blattman, 2014; Berman et al., 2017), so the frequency of conflicts is another potential factor that could affect a country's responsiveness to mineral price shocks. In summary, we find that African countries have differed significantly in various development indicators from the rest of the world, ranging from agricultural productivity, human capital, governance, conflict risks, and democracy.

We next examine whether and which of these country characteristics might help explain Africa's unique patterns of urbanization and structural transformation in reaction to mineral price shocks. Our empirical strategy is the following:

$$\begin{aligned}\Delta Y_{i,t} = \beta_0 + \beta_1 \Delta \log Price^R_{it} + \beta_2 \Delta \log Price^R_{it} \times \mathbb{1}(Cnty_{i,c} \in Africa) + \beta_3 \Delta \log Price^R_{it} \times X_{i,c} \\ + \alpha Y_{i,t0} + \gamma \log NumMines^R_i + \delta_m + \lambda_c + \eta_{gt} + \epsilon_{i,t},\end{aligned} \tag{3}$$

where $\mathbb{1}(Cnty_{i,c} \in Africa)$ denotes dummy variables that equal 1 if city i of country c belongs to the country group of SSA or North Africa; otherwise, 0. $X_{i,c}$ indicates the above-mentioned country characteristics, mostly measured in the 1990s. The coefficient β_1 captures the average effect of mineral price shocks for non-African cities. The coefficient β_2 is the difference in the estimated price effects between (Sub-Saharan and North) African cities and non-African cities. β_3 captures the effects of various country characteristics on price elasticity. Ultimately, we are interested in whether the inclusion of the interaction term $\Delta \log Price_{it}^{R} \times X_{i,c}$ affects the coefficient on the interaction term $\Delta \log Price_{it}^{R} \times \mathbb{1}(Cnty_{i,c} \in Africa)$.

Table 8 reports the estimation results. Country characteristics are omitted in the regressions in Column (1). They are then added one by one from Column (2) to Column (9). Panel A and Panel B report the effects on the changes in city population and share of agricultural employment, respectively. The effects on the employment share in the other sectors are reported in Table A13 in the appendix. Column (1) in Table 8 confirms our previous findings: urban population and agricultural employment shares in African cities are significantly more responsive to changes in mineral prices than those in the rest of the world. We can take the estimates on the population as an example (see Column (1) of Panel A). The coefficient on $\Delta \log Price$ is 0.008, which suggests that mineral price shocks have little effect on urbanization in non-African cities. However, the coefficients on $\Delta \log Price \times NorthAfrica$ and $\Delta \log Price \times SSA$ are 0.161 and 0.096, respectively—both statistically significant—suggesting that North African cities and SSA cities experience, respectively, 16.1% and 9.6% higher increases in city population in response to a doubling in local mineral prices.

Then, from Columns (2)-(9) in Table 8, we focus on whether the inclusion of the country characteristic*mineral price interaction term might explain the unique patterns of African cities. In Panel A, we focus on the city population as the outcome. Three results stand out: First, across all eight country characteristics, only the share of natural resource exports in GDP and agricultural productivity interact significantly with mineral prices. The coefficient on $\Delta \log Price \times natural\ resource\ exports$ is positive, suggesting that city populations in countries that rely more heavily on resource exports are more responsive to mineral price shocks. This finding is consistent with the consumption city hypothesis, which predicts that with a higher reliance on resource exports, resource rents could lead to faster structural transformation through a stronger income effect. The coefficient on $\Delta \log Price \times agricultural\ yield$ is negative, which indicates that the cities in countries that have lower agricultural productivity are more responsive to mineral price shocks. Intuitively, farmers living in low-agricultural-productivity countries face lower opportunity costs to transition out of agriculture (Henderson and Turner, 2020; Lin et al., 2023). Second, controlling for agricultural productivity has the largest power to explain SSA cities' exceptional responsiveness to mineral price shocks: the coefficient on $\Delta \log Price \times SSA$ drops from 0.096 (Row 2, Column 1) to 0.050 (Row 2, Column 3), which is about a 48% decrease. This finding confirms one of the conjectures put forward by Henderson and Turner (2020). Third, controlling for the share of natural resource exports in GDP has the largest power to explain North

African cities' exceptional responsiveness: the coefficient on $\Delta \log Price \times North\ Africa$ drops from 0.161 (Row 1, Column 1) to 0.054 (Row 1, Column 2), which is about a 66% decrease. In comparison, controlling for the other country characteristics has a much smaller effect on the coefficient of $\Delta \log Price \times SSA$ and that of $\Delta \log Price \times North\ Africa$.

In Panel B of Table 8, we focus on the employment share in agriculture as the outcome. Here, we highlight two findings. First, in Row 3 of Panel B, years of schooling (Column 4), GDP per capita (Column 5), and measures of institutional quality—rule of law (Column 6), control of corruption (Column 7), and democracy (Column 9) all interact positively and significantly with mineral prices, suggesting that in the presence of mineral price booms, cities in countries that have higher average level of education, income, or institutional quality experience a smaller decrease in their agricultural employment share. Second, resource export share of GDP, agricultural productivity, education, GDP per capita, rule of law, control of corruption, and democracy all have some power to explain SSA cities' exceptional responsiveness in terms of industrial structure. However, the magnitude of the coefficient on $\Delta \log Price \times SSA$ does not drop much. The biggest drop is in Column (5) (GDP per capita) and (6) (rule of law), both dropping from 0.081 (Column 1) to 0.058. One interpretation of the above results could still be the opportunity cost story: In countries with higher incomes or higher institutional quality, individuals probably have better economic opportunities, so they are less responsive to the new economic opportunities created by mining booms. However, none of the above country characteristics can explain a large portion of SSA's exceptional responsiveness in terms of agricultural employment share changes.

Table 8: The Uniqueness of Africa: The Role of Country Characteristics

	(1) Baseline	(2) Natural Resource Exports % of GDP	(3) Agriculture Yield (in log)	(4) Years of Schooling	(5) GDP Per Capita (in log)	(6) Rule of Law	(7) Control of Corruption	(8) Conflict	(9) Democracy
Panel A. Outcome: $\Delta \log$ Population									
$\Delta \log Price$ × North Africa	0.161*	0.054	0.157*	0.190**	0.157*	0.163*	0.163*	0.176*	0.161*
	(0.086)	(0.037)	(0.087)	(0.084)	(0.087)	(0.086)	(0.086)	(0.093)	(0.086)
$\Delta \log Price$ × Sub-Saharan Africa	0.096**	0.080	0.050	0.091*	0.086*	0.076*	0.074*	0.099**	0.095**
	(0.043)	(0.057)	(0.041)	(0.049)	(0.045)	(0.040)	(0.040)	(0.043)	(0.043)
$\Delta \log Price$	0.008	0.007	0.313***	-0.007	0.016	0.010	0.010	0.008	0.008
	(0.012)	(0.012)	(0.105)	(0.017)	(0.042)	(0.012)	(0.012)	(0.012)	(0.012)
$\Delta \log Price$ × Country Characteristic		0.005***	-0.038***	0.003	-0.001	-0.003	-0.007	-0.004	0.000
		(0.001)	(0.013)	(0.002)	(0.005)	(0.006)	(0.006)	(0.007)	(0.001)
N	3,195	2,715	3,168	3,000	3,114	3,153	3,153	3,195	3,186
Adj. R^2	0.581	0.579	0.581	0.597	0.581	0.580	0.580	0.581	0.581
Panel B. Outcome: Δ Agricultural Emp. Share									
$\Delta \log Price$ × Sub-Saharan Africa	-0.081***	-0.062	-0.065**	-0.070**	-0.058**	-0.058*	-0.061**	-0.084***	-0.071**
	(0.029)	(0.050)	(0.031)	(0.029)	(0.029)	(0.030)	(0.030)	(0.030)	(0.029)
$\Delta \log Price$	-0.021***	-0.018***	-0.144*	-0.048***	-0.113***	-0.025***	-0.024***	-0.022***	-0.036***
	(0.003)	(0.004)	(0.079)	(0.009)	(0.024)	(0.004)	(0.004)	(0.003)	(0.006)
$\Delta \log Price$ × Country Characteristic		-0.002	0.015	0.004***	0.010***	0.019***	0.014***	0.008	0.003***
		(0.003)	(0.010)	(0.001)	(0.002)	(0.003)	(0.003)	(0.010)	(0.001)
N	2,755	2,674	2,755	2,748	2,668	2,741	2,741	2,755	2,752
Adj. R^2	0.229	0.226	0.229	0.231	0.231	0.232	0.229	0.229	0.233

Notes: In Panel A, the dependent variables are changes in log population density in the 10-km city buffer zone, and the price change is the average log price change of minerals extracted from mines located within a radius of 60 km of a city. In Panel B, the dependent variables are changes in the agricultural employment share in the 60-km city buffer zone, and the price change is the average log price change of minerals extracted from mines located within a radius of 120 km of a city. All regressions control for the log number of mines within the mine buffer zone same as the price change, country–group×period FEs, country FEs, and commodity FEs. Panel A controls for initial log population density, and Panel B controls for the initial employment share of agriculture, manufacturing, and mining within the corresponding city buffer zone. Countries are categorized into seven groups: Sub-Saharan Africa, Middle East and North Africa, Latin America and the Caribbean, South Asia, East Asia, Europe and Central Asia, and North America. In Panel B, the Middle East and North Africa region is excluded due to a lack of observations. Standard errors in parentheses are clustered at the city level. ***, **, * denote statistical significance at the 1%, 5%, 10% levels, respectively.

6 Conclusion

Both urbanization and structural transformation are important topics in economic development and growth. While, historically, urbanization has been accompanied by industrialization in developed nations, many developing countries have recently experienced rapid urbanization at minimum levels of industrialization. This paper investigates the role of mineral resource rents in driving this diverging pattern of urbanization and structural transformation, exploiting exogenous variations in global mineral prices for identification. We provide the first global, city-level estimate of how mining booms affect local city populations and industrial compositions by combining several spatially granular data sets.

Overall, this study has three main findings. First, we find a positive and significant effect of mineral price booms on local city population growth in Africa but no such effect for other regions. Between 1975 and 2015, mineral price changes during our study period contributed to around 9.7% and 14.0% of city population growth inside the 10-km buffer zones of SSA and North African cities, respectively. Second, we show that mining booms in nearby areas promote structural transformation out of agriculture and into low-skilled services in the cities. Similar to our results concerning urbanization, the effect is more pronounced in SSA cities. Using cities' 60-km buffer zones, the mining booms between 1975 and 2015 contributed to 23.2% of the increase in the low-skilled services employment share on a global average and 136% of the increase in the low-skilled services employment share in SSA cities alone. Third, as mineral prices increase, there is no evidence of manufacturing crowd-out, i.e., there is no Dutch disease in our global city sample. Further evidence indicates that in the presence of mining booms, the average income level increases significantly, the average skill level does not change significantly, and the share of the prime-age population increases significantly in the local areas. The patterns of changes in average education level across sectors suggest that low-skilled agricultural workers relocate from the rural, agricultural sector toward the urban, nonagricultural sectors.

Our findings have two policy implications. First, as the global search for critical minerals continues, it offers potential economic opportunities for mineral-rich countries. Our results indicate that mining booms lead to positive changes in urban population and employment growth, as well as labor reallocation from agriculture to the service sector in the cities surrounded by mines. All these facts are signs of local economic growth. Moreover, we show that such a process does not necessarily crowd out manufacturing activity. While the negative impacts of mining booms should be taken into serious consideration, such as those on conflicts (Dube and Vargas, 2013; Bazzi and Blattman, 2014; Berman et al., 2017), worker safety (Charles et al., 2022) and environmental outcomes (Goldblatt et al., 2022), policies that facilitate sustainable natural resource development in developing countries should be encouraged. Second, while globally, we find mining booms are associated with a significant increase in manufacturing in the city core areas, this effect is mainly driven by manufacturing growth in Asian cities. For most parts of the world, especially in SSA, resource booms lead to "consumption cities" without significantly encouraging industrial development in the local areas. To the extent that manufacturing employment growth is linked to the creation of good jobs, productivity gain, and poverty reduction (McMillan and Zeufack, 2022), our results suggest that policymakers may need to balance the development of primary resource sectors while implementing additional industrial policies and trade policies to encourage manufacturing.[26]

Our results also lead to three further questions. First, despite being qualitatively consistent with the consumption hypothesis, the estimated effects of mineral prices on local city population and industrial composition in our study are not large enough to explain all the differences in the pace of urbanization and structural transformation between resource-booming cities and cities with natural resources but without booms. The limited size of the effect indicates that there are other factors that are also important in explaining the distinct urbanization and industrialization patterns in today's developing countries (Henderson and Kriticos, 2018; Henderson and Turner, 2020). Second, our results indicate that SSA countries exhibit distinct patterns in urbanization and structural transformation in response to mining booms, and their low agricultural productivity plays a significant role. However, our estimates suggest that there is still a large gap that remains unexplained by agricultural productivity. Third, we document that on a global average, there is no crowding-out in manufacturing activities associated with mining booms. However, the exact mechanisms behind the lack of crowding-out still remain unclear; this calls for studies that use more detailed microdata to uncover the underlying reasons. We view all these aspects as fruitful avenues for future research.

[26]One example is the African Continental Free Trade Act recently effective in 2021.

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Appendix on Resource Rents, Urbanization, and Structural Transformation

A Additional Tables and Figures

A.1 IPUMS Sample Selection and Other Data

We select all available samples provided by IPUMS according to three criteria, namely that: (1) the geo-referenced information of subnational administrative units is available for the country; (2) the sector information in which a person worked is not missing; and (3) there are at least two rounds of censuses between 1975 and 2015 for the country, allowing us to calculate the changes in employment shares. Ultimately, we obtain 260 rounds of population censuses from 76 countries spanning the years 1970 to 2017. Table A3 in the appendix lists all the samples of population censuses or individual survey data we use in this study. In calculating the employment shares, we restrict our full sample to workers between the ages of 16 and 55. We group the industry codes into five industry categories: agriculture, manufacturing, high-skilled services, other services (or alternatively, low-skilled services), and not recorded. "High-skilled services" include financial services and insurance, business services, and real estate. "Other services" include electricity, gas, water, and waste management; construction; wholesale and retail trade; hotels and restaurants; transportation; storage; communications; public administration and defense; education; health and social work; other services; and private household services.

We also employ other country-level indices for this study, including cereal yields, the ratio of exports of natural resources (ores and metals) to GDP, and GDP per capita from the World Development Indicators (WDI). Additionally, the variable mean years of schooling comes from the Global Data Lab.[27] The countries are categorized into seven groups: Sub-Saharan Africa, Middle East and North Africa, Latin America and the Caribbean, South Asia, East Asia and Pacific, Europe and Central Asia, and North America. We use standard measures of governance and political institutions. We use standard measures of governance and political institutions. Our measures of governance include the "rule of law" and "control of corruption" from the Worldwide Governance Indicators (WGI), ranging from -2.5 (weak) to 2.5 (strong) governance performance. Our measure of political institution quality is a rescaled Polity2 score from Teorell et al. (2023), ranging from -10 (most autocratic) to 10

[27] The Global Data Lab's website is found at https://globaldatalab.org/shdi/download/msch/.

(most democratic). Additionally, we calculate the number of state-based armed conflicts per million residents at the country-year level using the UCDP/PRIO Armed Conflict Dataset.

A.2 Robustness Checks

We next conduct additional checks to test the robustness of our results. First, our primary analysis focuses on the linear effects of mineral price changes, which assumes that the effects from positive mineral price changes have the same magnitudes as the effects from negative mineral price changes. However, this assumption does not necessarily hold, especially given that there is evidence showing city populations change differentially in response to positive or negative economic shocks (Glaeser and Gyourko, 2005). Therefore, we test whether mining booms (positive price changes) and busts (negative price changes) differentially impact the city populations and local industrial structure. To do so, we interact the log price change with two dummy variables: one indicating whether cities experienced a positive price change, and the other indicating a negative change. We report the estimation results in Table A6.

The different panels report different outcomes, and Columns (1) and (2) correspond to the mine buffer zones of 60 km and 120 km, respectively. Comparing the coefficients of the two interaction terms $\Delta \log Price \times (Positive = 1)$ and $\Delta \log Price \times (Negative = 1)$, we find that most of the coefficients on the positive price change term are statistically significant and exhibit consistent signs with the baseline coefficients. Conversely, most of the coefficients on the negative price change term are insignificant and occasionally exhibit the opposite signs to those on the positive price change term (for example, Column (1) of Panel B, and Columns (1) and (2) of Panels A and E). One possible interpretation of these results is that there is an asymmetric effect of mining booms and busts on the city population and industrial structure. However, because there are many more observations with positive mineral price changes than those with negative changes in the data,[28] these asymmetric effects are imprecisely estimated due to the small sample size. Therefore, we do not use this asymmetric-effect specification as the baseline one.

Second, we test whether mining booms in a country play a special role in its capital city versus non-capital cities. We interact the log price change with two dummy variables: one indicating whether the city is the capital, and the other indicating whether the city is not the capital of any country. As shown in Table A7, the coefficients of the two interactions between price change and dummies on capital cities are very close, suggesting that mineral

[28]For example, in Column (2) of Table A6, 3,209 / 4,740 = 67.7% of city-years in Panel A (regressions on population) have positive price changes.

price shocks have very similar effects on both the capital and non-capital cities.

Third, we address the measure error problem in our empirical analysis. One limitation of the mining data from SNL Financial is that they lack information on mines' open or closed status. While all the mines in our sample were active in 2014–the year when we acquired the data set–we do not know whether they were active throughout the 1975-2015 study period. Therefore, the assumption that the mines were active throughout this period inevitably introduces measurement errors. To overcome this problem, we conduct two exercises. First, we exploit the textual information in the data that describes when each mine was mentioned by any public source.[29] While 31.5% of the mines do not have such information, 22,642 out of 33,078 (68.5%) of the mines do; from this, we plot the distribution of the "opening" years, as shown in Figure A9.[30] We see that for over 40% of the mines having public information, the "opening" year was prior to 1990, which is actually a conservative estimate because the media coverage time could have occurred years after the actual opening year. Second, related to the first exercise, we restrict our analysis to later years, i.e., 1990-2015, when the mines in our sample were more likely to be active. We find similar mineral price shock effects as the baseline results that use the 1975-2015 data (see Figure A10 in the Appendix). Thus, we continue to use the 1975-2015 sample as the baseline because it covers a much longer period and because mining sites, in general, are usually highly persistent.[31]

Finally, we perform a series of checks to test whether the baseline results hold under alternative sample restriction rules, control variables, and weighting methods. The results are reported in Tables A8, A9 and A10 in the Appendix. First, we use four alternative city samples: (1) cities with and without mines in nearby areas; (2) both African and non-African cities with populations over 300,000 residents; (3) non-African cities with populations over 300,000 residents plus African cities with populations over 100,000 residents; and (4) the omission of cities from countries that have no available fine-level geographic units in the IPUMS dataset (GEOLEV1) (see Panels A-C in Table A8; Panels A-E in Tables A9 and A10). Second, we show that our results are robust to country-specific time trends by adding country×period fixed effects (Panel E in Table A8; Panel G in Tables A9 and A10). Third, we consider spatial correlations between cities and estimate standard errors following the approach proposed by Conley (1999) (Panel D in Table A8; Panel F in Tables A9 and A10). Fourth, because the lengths of the census periods vary, we weight each city-period unit by

[29] These sources include media, news, company annual reports, and other textual sources, etc.

[30] We define the "opening" year as the year when each mine was first mentioned.

[31] For example, using mining site data on SSA, Table 1 of Mamo et al. (2019) shows that a mine discovery is a rare event compared to mines in operation (0.001 versus 0.039).

period length (Panel F in Table A8; Panel H in Tables A9 and A10). This weighting method gives greater weights to city-period units with longer periods because these observations allow both the independent and dependent variables to change over a longer period. In short, we find similar results under all of these robustness checks.

A.3 Migration Response to Mineral Price Shocks

As shown in Table 3, price booms in minerals mined from nearby areas have induced increases in city populations. We investigate whether these increases are driven by migration inflows. To answer this question, we first exploit the migration information in IPUMS. However, a caveat is that among all the 265 census samples (country-year), only 16 of them record individuals' migration history 1 year prior to the census, and 47 of them record individuals' migration history 5 years prior to the census.[32] Nevertheless, we use this sample and estimate a gravity equation to examine how internal migration decisions are affected by mineral price shocks in the origins and destinations. The variation we exploit is intra-country cross-districts. We estimate the following gravity equation country by country:

$$\log Flow_{o,d,t} = \beta_0 + \beta_1 \Delta \log Price_{o,t} + \beta_2 \Delta \log Price_{d,t} + \lambda_{o,d} + \eta_t + \epsilon_{o,d,t}, \quad \text{(A1)}$$

where the dependent variable is the logarithm of migration flow from origin o to destination d from $t-1$ to t. The time span can be either 1 year or 5 years, depending on data availability. Origin o is the subnational geographic unit of residence at $t-1$, and destination d is the subnational geographic unit of residence in survey year t. Additionally, $\Delta \log Price_{o,t}$ is the average log price change of minerals extracted from mines located at origin o from $t-1$ to t, while $\Delta \log Price_{d,t}$ is the average log price change of minerals extracted from mines located at destination d from $t-1$ to t. For controls, we include origin-by-destination fixed effects and survey year fixed effects.

[32] Countries for which 1-year migration information is available include Botswana (4 years), Kenya (2 years), Mozambique (2 years), Tanzania (1 year), Trinidad and Tobago (1 year), US (3 years), and Zambia (3 years). Countries for which 5-year migration information is available include Botswana (1 year), Costa Rica (4 years), Dominican Republic (2 years), Ecuador (3 years), Fiji (4 years), Guatemala (4 years), Haiti (2 years), Honduras (3 years), Indonesia (8 years), Malaysia (2 years), Mauritius (3 years), Mozambique (2 years), South Africa (1 year), Trinidad and Tobago (1 year), US (4 years), and Vietnam (3 years).

Table A1: The Effect of Price Shocks on Migration Flows: Gravity Equation

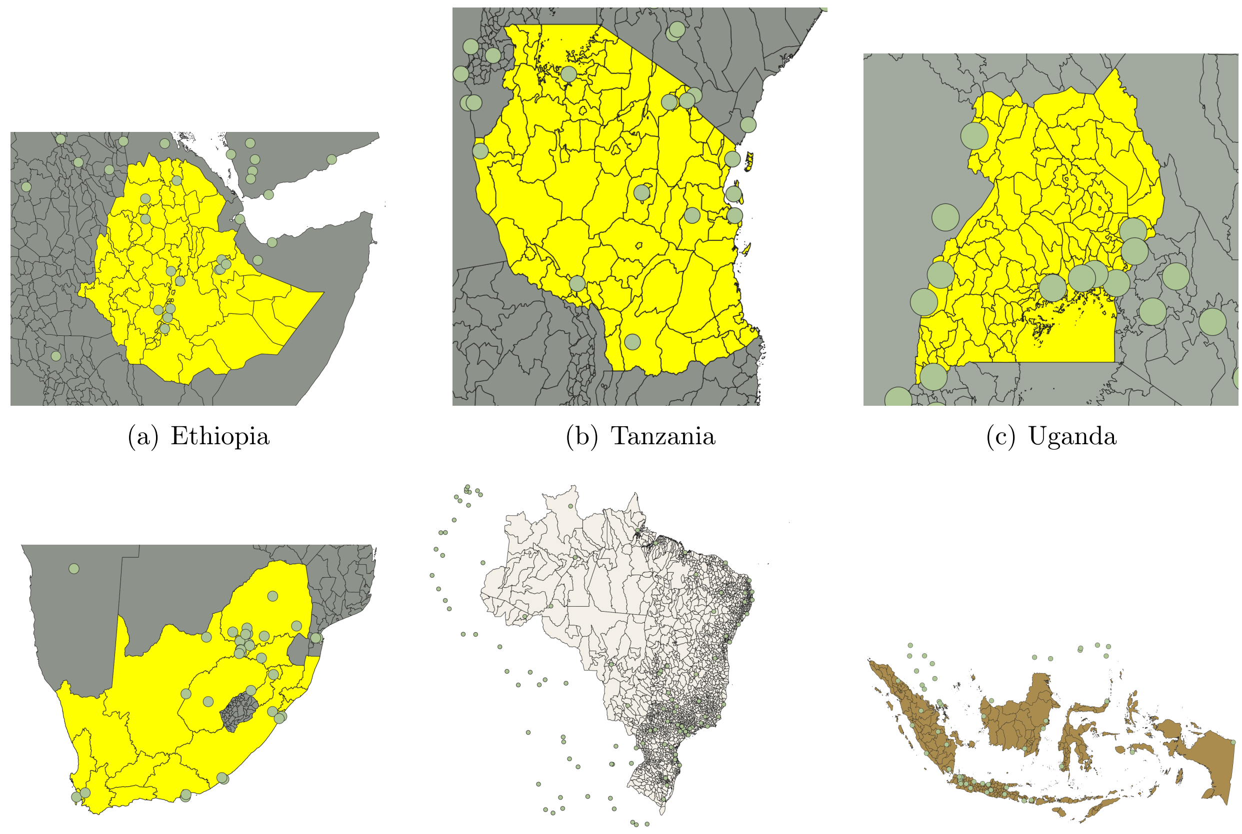
	(1)	(2)	(3)
	Outcome: log Migration Flow from O to D in the Previous Year		
	Botswana	Kenya	Mozambique
$\Delta \log Price$ in Origin	0.149	-0.317*	-0.199
	(0.258)	(0.146)	(0.266)
$\Delta \log Price$ in Destination	0.394*	0.540**	0.365
	(0.219)	(0.170)	(0.566)
FE	Year, O*D	Year, O*D	Year, O*D
N	1,021	50	162
Adj. R^2	0.955	0.990	0.988

Notes: This table reports the regression coefficients of equation A1. Standard errors in parentheses are two-way clustered at the origin and destination levels. ***, **, * denote statistical significance at the 1%, 5%, 10% levels, respectively.

Table A1 reports the estimated results by country in different columns. In three SSA countries–Botswana, Kenya, and Mozambique–we find that positive price shocks in the origin tend to keep individuals in that area in Kenya and Mozambique, but we find an insignificant effect in Botswana. Meanwhile, positive price shocks in the destination induce migration inflows into that area in all three SSA countries. These patterns are consistent with results in Table 7, where migration contribute to the increase in prime-aged individuals in resource cities.

A.4 Supplemental Tables and Figures

Figure A1: Illustration of City Buffer Zones (30 Km) and Administrative Boundaries

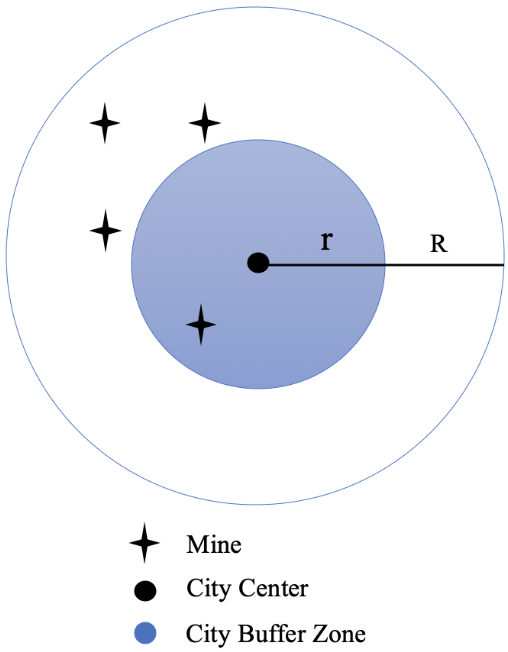


(a) Ethiopia (b) Tanzania (c) Uganda

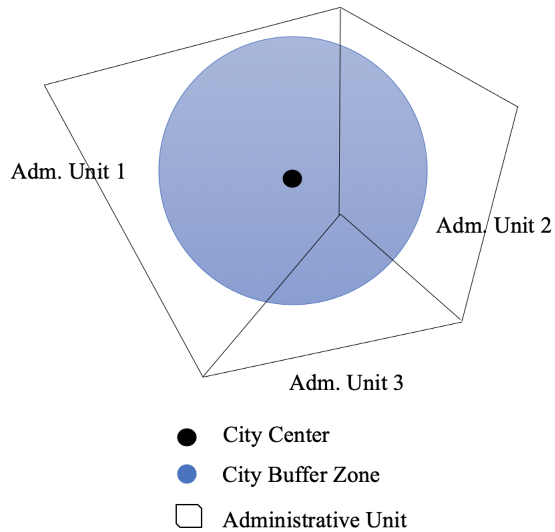
(d) South Africa (e) Brazil (f) Indonesia

Notes: Each dot represents a 30-km city buffer zone in our sample.

Figure A2: Illustration of Data Matching Process



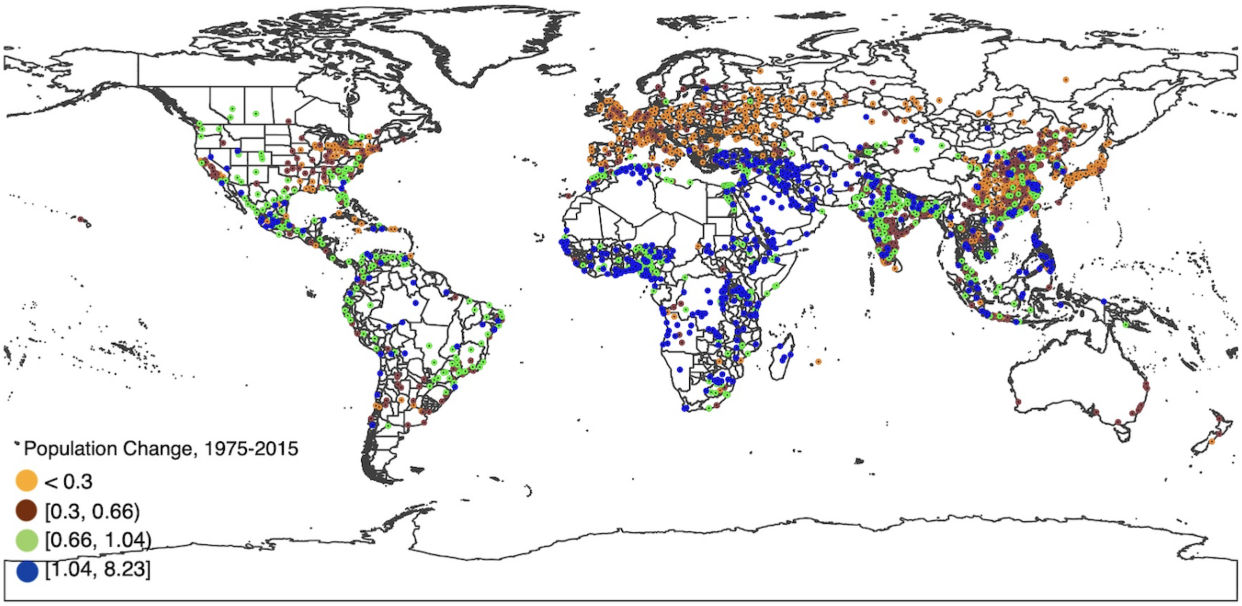
(a) Match Mines with Cities



(b) Match IPUMS with Cities

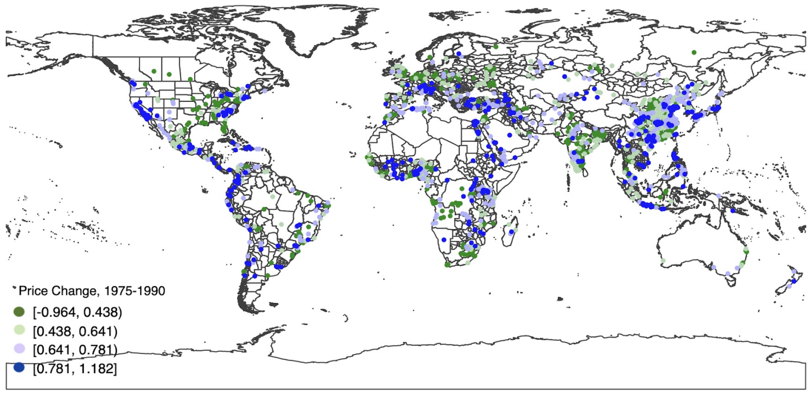
Notes: Panel A shows how to map mining sites with cities. Panel B shows how to calculate employment by industry within city buffer zones.

Figure A3: Spatial Distribution of Cities and Their Population Changes, 1975-2015

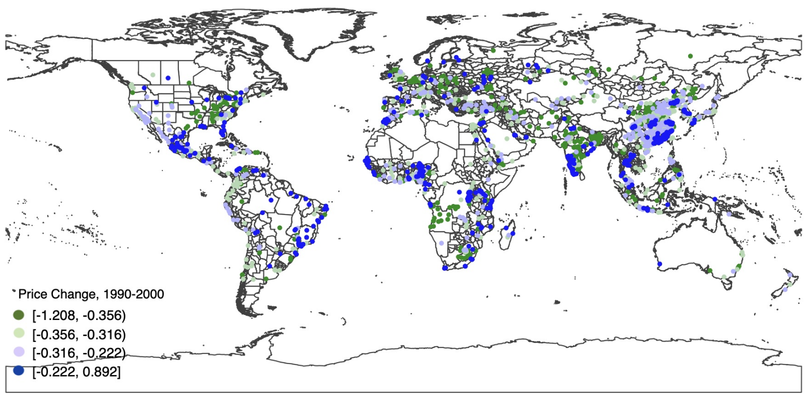


Notes: Figure A3 plots the location of cities globally (N = 2,041), and their respective population changes from 1975 to 2015. Population change is calculated by the difference in log population density within a radius of 10 km from a city centroid. Data source: GHSL population raster and WUP 2018.

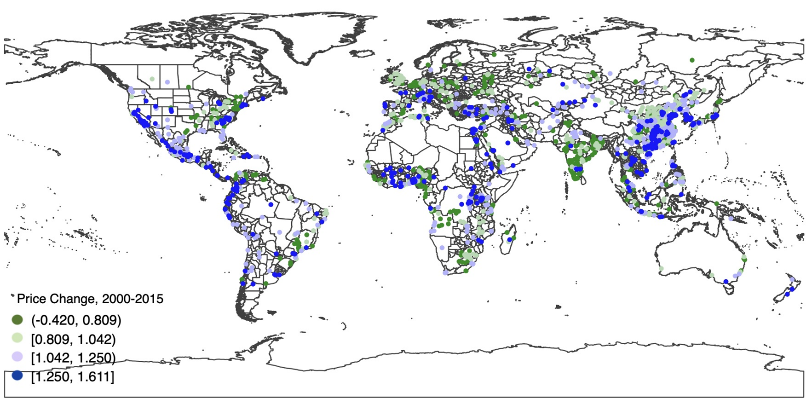
Figure A4: Spatial Distribution of Mineral Price Changes at the City Level



(a) Spatial Distribution of Mineral Price Changes, 1975-1990



(b) Spatial Distribution of Mineral Price Changes, 1990-2000



(c) Spatial Distribution of Mineral Price Changes, 2000-2015

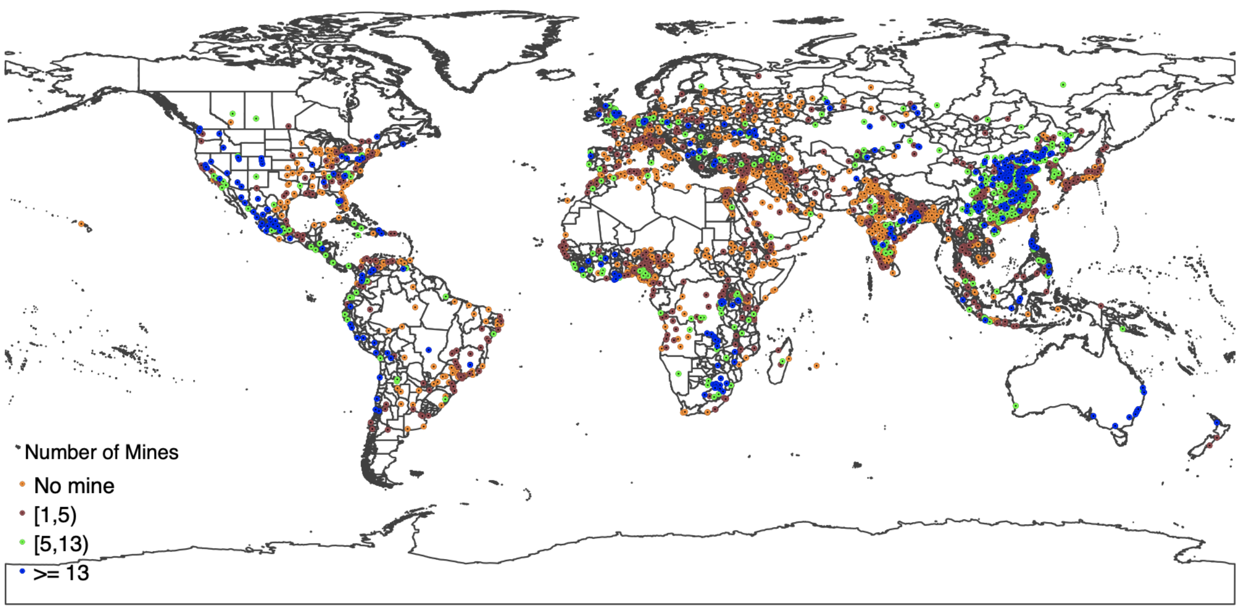
Notes: This figure plots the spatial distribution of mineral price changes experienced by cities globally (N = 2,041). Mineral price change is computed by taking the simple average of the log price changes of the primary minerals extracted from mines located within a radius of 120 km of a city centroid.

Table A2: Data Source of Price Series and Number of Mining Sites By Mineral

	Commodity	Price Series Range		Number of Mines	Source
		First Year	Last Year		
1	Antimony	1970	2015	50	USGS
2	Coal	1970	2015	5,163	World Bank
3	Cobalt	1970	2015	36	USGS
4	Copper	1970	2015	4,249	World Bank
5	Diamonds	1970	2015	1,437	USGS
6	Gold	1970	2015	12,835	World Bank
7	Ilmenite	1970	2015	141	USGS
8	IronOre	1970	2015	1,853	World Bank
9	Lead	1970	2015	250	World Bank
10	Lithium	1970	2015	192	USGS
11	Manganese	1970	2015	197	USGS
12	Molybdenum	1970	2015	301	USGS
13	Nickel	1970	2015	1,172	World Bank
14	Phosphate	1970	2015	267	USGS
15	Platinum	1970	2015	326	World Bank
16	Potash	1970	2015	190	USGS
17	Silver	1970	2015	1,066	World Bank
18	Tantalum	1970	2015	71	USGS
19	Tin	1970	2015	216	World Bank
20	Titanium	1970	2015	26	USGS
21	Tungsten	1970	2015	130	USGS
22	Vanadium	1970	2015	47	USGS
23	Zinc	1970	2015	965	World Bank

Notes: Calculated by authors.

Figure A5: Spatial Distribution of Cities and Mines



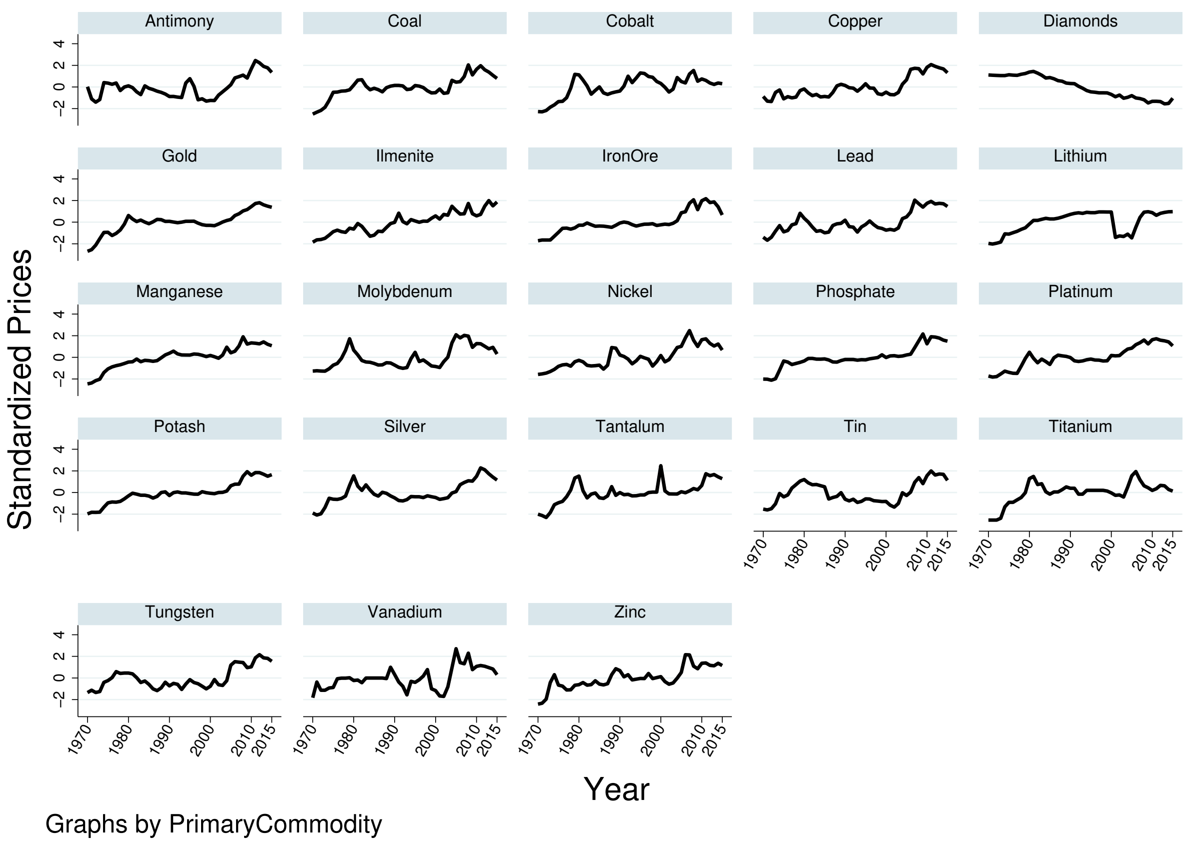
Notes: Figure A5 plots the distribution of cities globally (N = 2,041), and the number of mines located within a 90-km radius of the city centers.

Table A3: Number of Mining Sites Nearby the Cities, By Region

	Mines' largest distance to city center							
	30 km		60 km		90 km		120 km	
	#Cities	#Mines	#Cities	#Mines	#Cities	#Mines	#Cities	#Mines
Sub-Saharan Africa	291	4.732	489	9.215	636	13.962	723	19.942
Middle East and North Africa	63	1.286	126	1.762	225	2.16	333	2.793
Latin America and the Caribbean	234	3.385	363	7.017	450	11.56	528	16.301
South Asia	93	4.742	165	7.782	261	9.644	363	11.132
East Asia and Pacific	828	3.768	1,422	6.325	1,701	10.612	1,803	16.624
Europe and Central Asia	255	4.4	426	6.887	546	10.038	651	13.028
North America	81	2.778	210	6.7	294	11.796	357	18.832
All	1,845	3.88	3,201	6.840	4,113	10.718	4,758	15.379

Notes: Calculated by authors. #Cities is the number of cities that have at least one mining site in a corresponding nearby area. #Mines is the average number of mining sites for cities that have at least one mining site in a corresponding nearby area.

Figure A6: Standardized Price Series for 23 Minerals, 1970-2015



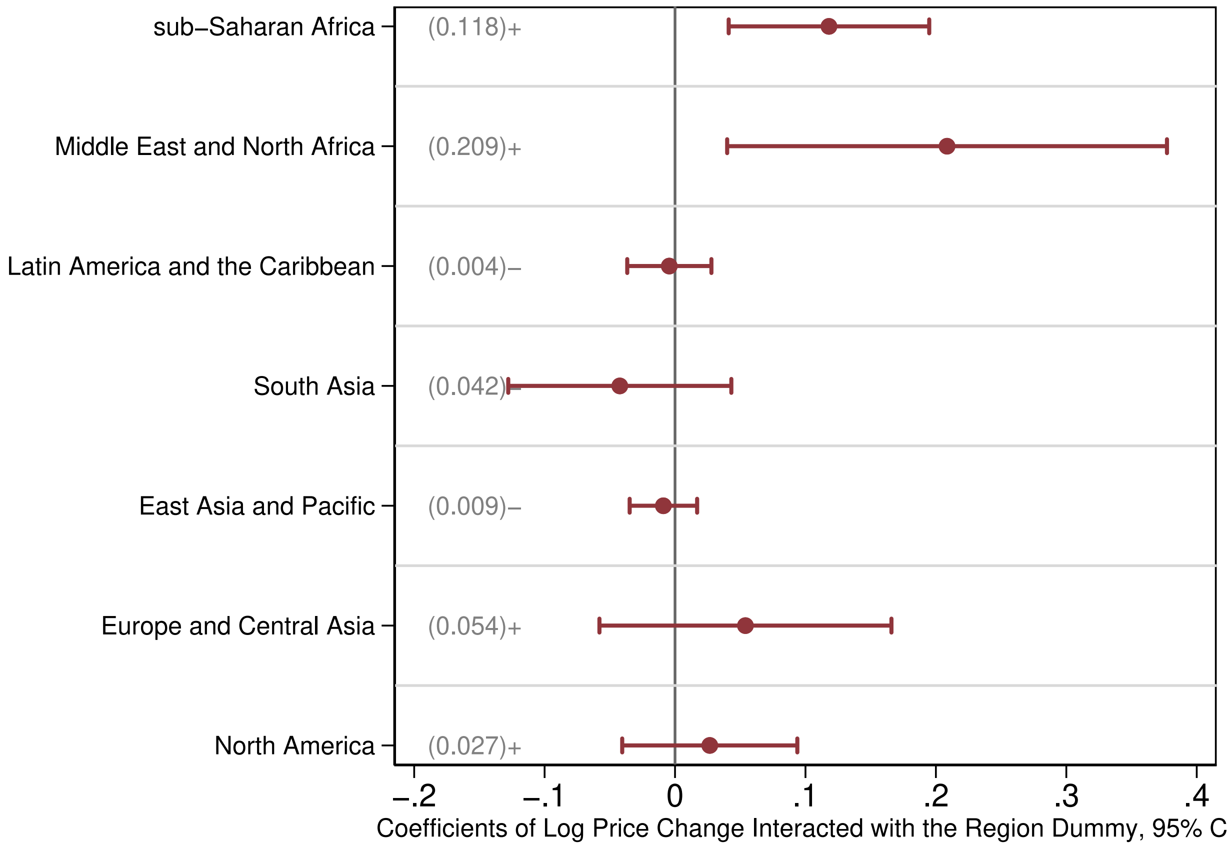
Notes: All prices are in logarithm, and are standardized to have a mean of 0 and a standard deviation of 1.

Table A4: Samples from IPUMS

Country	Year	Country	Year
Argentina	1970, 1980, 1991,2001	Kyrgyz Republic	1999, 2009
Armenia	2001, 2011	Liberia	1974, 2008
Austria	1971, 1981, 1991, 2001, 2011	Malawi	1998, 2008
		Malaysia	1970, 1980, 1991, 2000
Belarus	2002, 2009	Mali	1987, 1998, 2009
		Mauritius	1990, 2000, 2011
Benin	1979, 1992, 2002, 2013	Mexico	1970, 1990, 1995, 2000, 2005, 2010, 2015
Bolivia	1976, 1992, 2001, 2012	Mozambique	1997, 2007
Botswana	1981, 1991, 2001, 2011	Nepal	2001, 2011
Brazil	1970, 1980, 1991, 2000, 2010	Nicaragua	1971, 1995, 2005
Cambodia	1998, 2004, 2008, 2013	Palestine	1997, 2007, 2017
Canada	1971, 1981, 1991, 2001, 2011	Panama	1970, 1980, 1990, 2000, 2010
Chile	1982, 1992, 2002, 2017	Papua New Guinea	1980, 2000
China	1982, 1990, 2000	Paraguay	1972, 1982, 1992, 2002
Colombia	1973, 1993, 2005	Peru	1993, 2007
Costa Rica	1973, 1984, 2000, 2011	Philippines	1990, 1995, 2000, 2010
Cuba	2002, 2012	Portugal	1981, 1991, 2001, 2011
Dominican Republic	1970, 1981, 2010	Puerto Rico	1980, 1990, 2000, 2005, 2010
Ecuador	1982, 1990, 2001, 2010	Romania	1977, 1992, 2002, 2011
Egypt	1996, 2006	Russia	2002, 2010
El Salvador	1992, 2007	Rwanda	2002, 2012
Ethiopia	1994, 2007	Senegal	1988, 2013
Fiji	1976, 1986, 1996, 2007, 2014	Slovak Republic	1991, 2001, 2011
France	1975, 1982, 1990, 1999, 2006, 2011	South Africa	2001, 2007
Germany	1970, 1971, 1981, 1987	Spain	1981, 1991, 2001, 2011
Ghana	1984, 2000, 2010	Suriname	2004, 2012
Greece	1971, 1981, 1991, 2001, 2011	Switzerland	1970, 1980, 1990, 2000
Guatemala	1973, 1981, 1994, 2002	Tanzania	2002, 2012
Guinea	1983, 2014	Thailand	1970, 1980, 1990, 2000
Haiti	1982, 2003	Togo	1970, 2010
Honduras	1974, 1988, 2001	Trinidad and Tobago	1980, 1990, 2000
India	1987, 1999, 2004, 2009	Turkey	1985, 1990, 2000
Indonesia	1971, 1976, 1980, 1985, 1990, 1995, 2000, 2005, 2010	United Kingdom	1991, 2001
Iran	2006, 2011	Uruguay	1963, 1985, 1996, 2006
Ireland	1971, 1981, 1986, 1991, 1996, 2002, 2006, 2011, 2016	United States	1970, 1980, 1990, 2000, 2005, 2010, 2015
Italy	2001, 2011	Venezuela	1981, 1990, 2001
Jamaica	1982, 1991, 2001	Vietnam	1989, 1999, 2009
Kenya	1979, 1989, 1999, 2009	Zambia	1990, 2000, 2010

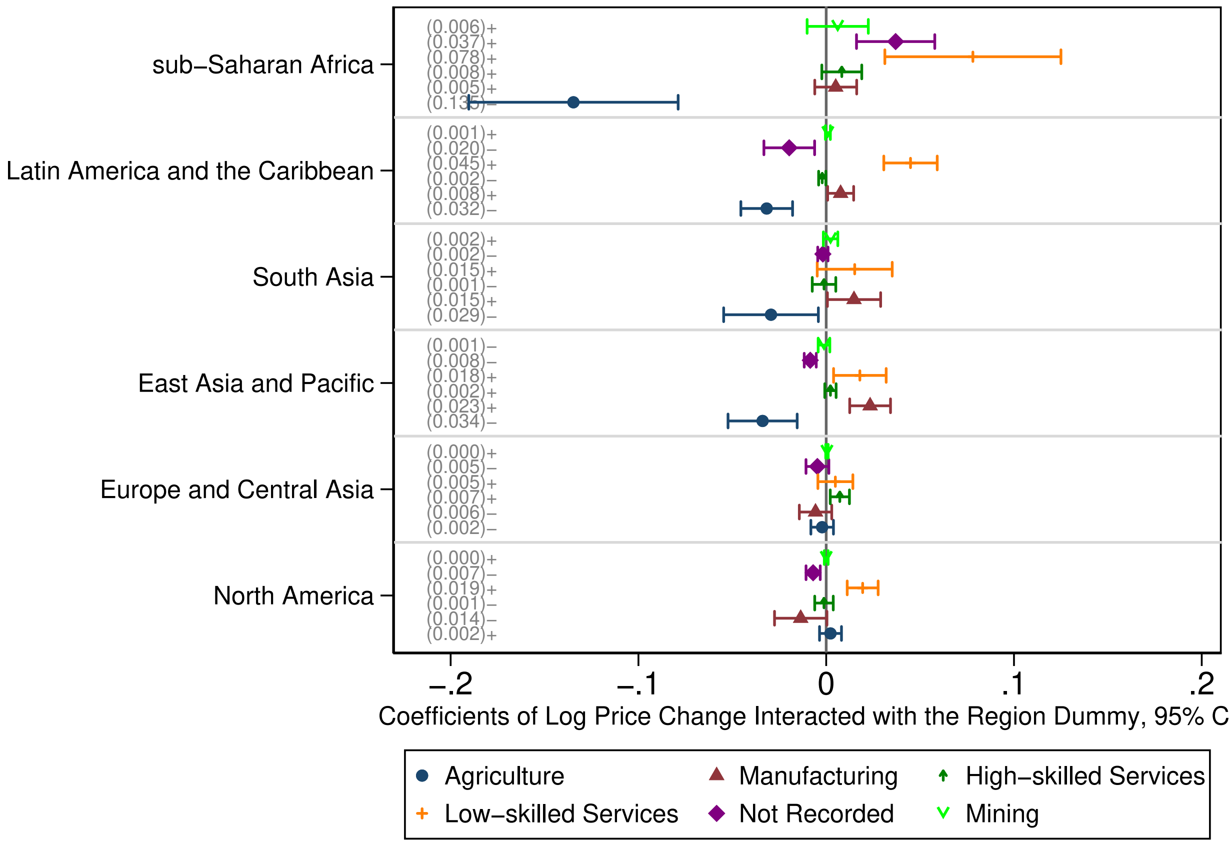
Notes: India samples come from India 0.09% socio-economic survey data, provided by IPUMS.

Figure A7: The Effect of Price Shocks on Local Populations: Regional Heterogeneity



Notes: This figure plots the estimated coefficients of log changes in mineral prices interacted with the region dummy, based on equation 2. The dependent variable is log changes in population density within a radius of 30 km of a city center. The independent variable is the average of log changes in mineral prices across mines within the 60-km buffer zone. All the regressions control for the initial log population density of the 30-km city buffer zone, log number of mines within the radius of 60 km of a city, country–group×period fixed effects, country fixed effects, and commodity fixed effects. Standard errors are clustered at the city level.

Figure A8: The Effect of Price Shocks on Local Employment Shares by Sector: Regional Heterogeneity



Notes: This figure plots the estimated coefficients of log changes in mineral prices interacted with the region dummy, based on equation 2. The dependent variables are changes in employment shares by sector within a radius of 30 km of a city. The price change is the average log change of the price of minerals extracted from mines located within a radius of 120 km of a city. All the regressions control for initial employment share of agriculture, manufacturing, and mining within the radius of 30 km of a city, log number of mines within the radius of 120 km of a city, country–group×period fixed effects, country fixed effects, and commodity fixed effects. We exclude the Middle East and North Africa region due to a lack of observations. Standard errors are clustered at the city level.

Table A5: The Effect of Price Shocks on the Employment Levels: The Mining Sector

	(1)	(2)	(3)	(4)	(5)	(6)
	Outcome: $\Delta \log$ Mining Employment Level					
City Zone	Buffer, 30 km		Ring, 30 -120 km	Buffer, 60 km		Ring, 60 -120 km
Mine Buffer Zone	60 km	120 km	120 km	60 km	120 km	120 km
$\Delta \log Price$	0.051	0.014	0.109*	0.049	0.058	0.189***
	(0.070)	(0.057)	(0.059)	(0.085)	(0.075)	(0.069)
log Initial Mining Employment Level	-0.401***	-0.389***	-0.335***	-0.565***	-0.528***	-0.439***
	(0.041)	(0.030)	(0.045)	(0.069)	(0.052)	(0.053)
FE	Country–group×period, Country, Commodity					
N	1,702	2,526	2,526	1,780	2,693	2,612
Adj. R^2	0.245	0.244	0.309	0.351	0.331	0.310

Notes: This table reports the regression coefficients of equation 1. The dependent variable is log change in mining employment. The independent variable (log price change) and the control variable (log number of mines) draw on all mines within the mine buffer zone. The initial employment level is calculated according to the corresponding city zones. Countries are categorized into seven groups: Sub-Saharan Africa, Middle East and North Africa, Latin America and the Caribbean, South Asia, East Asia, Europe and Central Asia, and North America. Standard errors in parentheses are clustered at the city level. ***, **, * denote statistical significance at the 1%, 5%, 10% levels, respectively.

Table A6: The Asymmetric Effects of Mining Booms and Busts

	(1)	(2)	(3)	(4)
City Zone	Buffer, 10 km in Panel A; Buffer, 60 km in Panels B-F			
Mine Buffer Zone	60 km	120 km	60 km	120 km
	Panel A. $\Delta \log$ Population		**Panel B. Δ Emp. Share of Agriculture**	
$\Delta \log Price \times$(Positive=1)	0.060***	0.022	-0.031***	-0.030***
	(0.018)	(0.019)	(0.008)	(0.006)
$\Delta \log Price \times$(Negative=1)	-0.026	0.017	0.004	-0.021
	(0.035)	(0.043)	(0.017)	(0.020)
N	3,195	4,737	1,850	2,839
Adj. R^2	0.580	0.570	0.249	0.226
	Panel C. Δ Emp. Share of Manufacture		**Panel D. Δ Emp. Share of High-skilled Services**	
$\Delta \log Price \times$(Positive=1)	0.011***	0.007**	0.001	0.003*
	(0.003)	(0.003)	(0.002)	(0.002)
$\Delta \log Price \times$(Negative=1)	0.015*	0.026**	0.008*	0.002
	(0.008)	(0.011)	(0.004)	(0.004)
N	1,850	2,839	1,850	2,839
Adj. R^2	0.214	0.213	0.338	0.331
	Panel E. Δ Emp. Share of Low-skilled Services		**Panel F Δ Emp. Share of Not-Recorded**	
$\Delta \log Price \times$(Positive=1)	0.039***	0.041***	-0.020***	-0.022***
	(0.009)	(0.006)	(0.005)	(0.004)
$\Delta \log Price \times$(Negative=1)	-0.008	-0.021	-0.021	0.013
	(0.014)	(0.014)	(0.014)	(0.012)
N	1,850	2,839	1,850	2,839
Adj. R^2	0.301	0.277	0.270	0.248

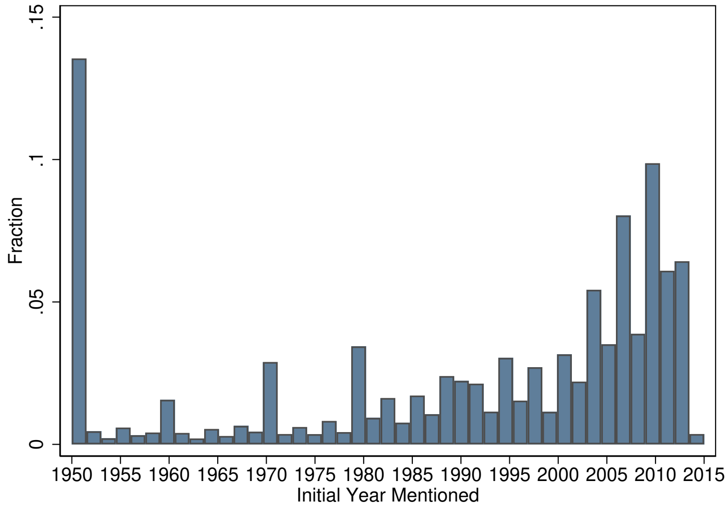
Notes: This table reports the coefficients of equation 1. The dependent variables are changes in log population in the 10-km city buffer zone or employment shares by sector in the 60-km city buffer zone. (Positive=1) is the dummy variable equal 1 if $\Delta \log Price$ is positive; otherwise, 0. (Negative=1) is the dummy variable equal 1 if $\Delta \log Price$ is negative; otherwise, 0. Both dummy variables (Positive = 1) and (Negative = 1) are included. All regressions control for the log number of mines within the mine buffer zone, country–group×period FEs, country FEs, and commodity FEs. Panel A controls for initial log population density, and Panels B-F control for the initial employment share of agriculture, manufacturing, and mining within the corresponding city buffer zone. Countries are categorized into seven groups: Sub-Saharan Africa, Middle East and North Africa, Latin America and the Caribbean, South Asia, East Asia, Europe and Central Asia, and North America. Standard errors in parentheses are clustered at the city level. ***, **, * denote statistical significance at the 1%, 5%, 10% levels, respectively.

Table A7: The Effect of Price Shocks on Capital Cities and Non-Capital Cities

	(1)	(2)	(3)	(4)
City Zone	Buffer, 10 km in Panel A; Buffer, 60 km in Panels B-F			
Mine Buffer Zone	60 km	120 km	60 km	120 km
	Panel A. $\Delta \log$ Population		**Panel B. Δ Emp. Share of Agriculture**	
$\Delta \log Price \times$(Capital=1)	0.041*	0.036*	-0.027**	-0.025*
	(0.022)	(0.019)	(0.013)	(0.013)
$\Delta \log Price \times$(Capital=0)	0.030**	0.023*	-0.014***	-0.024***
	(0.014)	(0.014)	(0.005)	(0.004)
Capital=1	0.088***	0.098***	-0.040**	-0.023*
	(0.033)	(0.026)	(0.016)	(0.013)
N	3,195	4,737	1,850	2,839
Adj. R^2	0.582	0.574	0.251	0.227
	Panel C. Δ Emp. Share of Manufacture		**Panel D. Δ Emp. Share of High-skilled Services**	
$\Delta \log Price \times$(Capital=1)	0.002	-0.003	0.009*	0.006
	(0.004)	(0.006)	(0.005)	(0.004)
$\Delta \log Price \times$(Capital=0)	0.003	0.004**	0.001	0.002
	(0.002)	(0.002)	(0.001)	(0.001)
Capital=1	0.002	0.000	0.002	0.001
	(0.004)	(0.004)	(0.004)	(0.003)
N	1,850	2,839	1,850	2,839
Adj. R^2	0.207	0.210	0.342	0.333
	Panel E. Δ Emp. Share of Low-skilled Services		**Panel F Δ Emp. Share of Not-Recorded**	
$\Delta \log Price \times$(Capital=1)	0.017	0.019*	-0.000	0.003
	(0.012)	(0.011)	(0.009)	(0.008)
$\Delta \log Price \times$(Capital=0)	0.023***	0.029***	-0.013***	-0.012***
	(0.005)	(0.003)	(0.004)	(0.002)
Capital=1	0.038***	0.024***	0.001	-0.001
	(0.012)	(0.009)	(0.007)	(0.005)
N	1,850	2,839	1,850	2,839
Adj. R^2	0.300	0.274	0.268	0.244

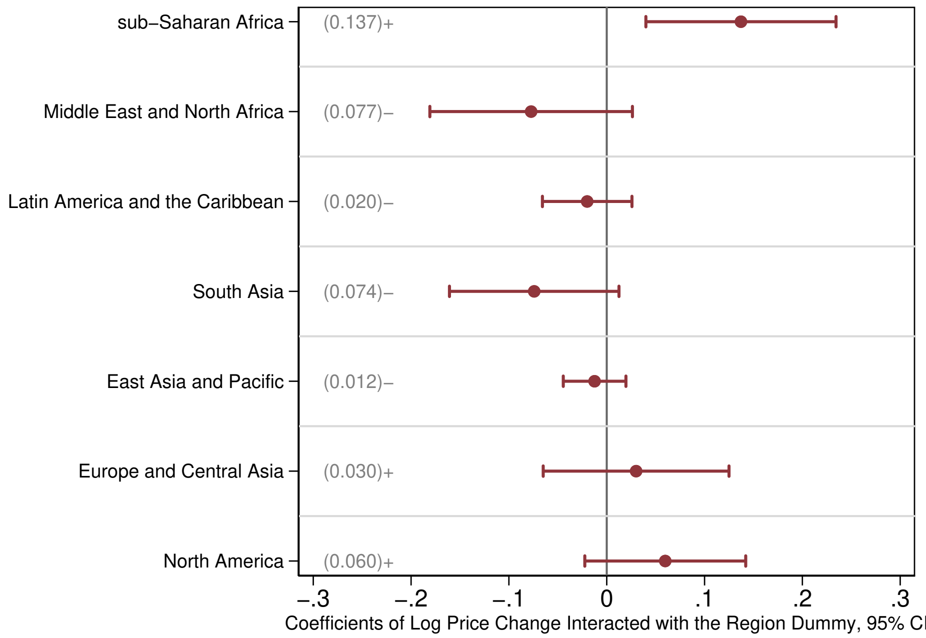
Notes: This table reports the coefficients of equation 1. The dependent variables are changes in log population in the 10-km city buffer zone or employment shares by sector in the 60-km city buffer zone. (Capital = 1) is the dummy variable equal 1 if the city is the capital of any country; otherwise, 0. (Capital = 0) is the dummy variable equal 1 if the city is not the capital of any country; otherwise, 0. Both dummy variables (Capital = 1) and (Capital = 0) are included. All regressions control for the log number of mines within the mine buffer zone, country–group×period FEs, country FEs, and commodity FEs. Panel A controls for initial log population density, and Panels B-F control for the initial employment share of agriculture, manufacturing, and mining within the corresponding city buffer zone. Countries are categorized into seven groups: Sub-Saharan Africa, Middle East and North Africa, Latin America and the Caribbean, South Asia, East Asia, Europe and Central Asia, and North America. Standard errors in parentheses are clustered at the city level. ***, **, * denote statistical significance at the 1%, 5%, 10% levels, respectively.

Figure A9: The Distribution of *Opening Years* of Mines

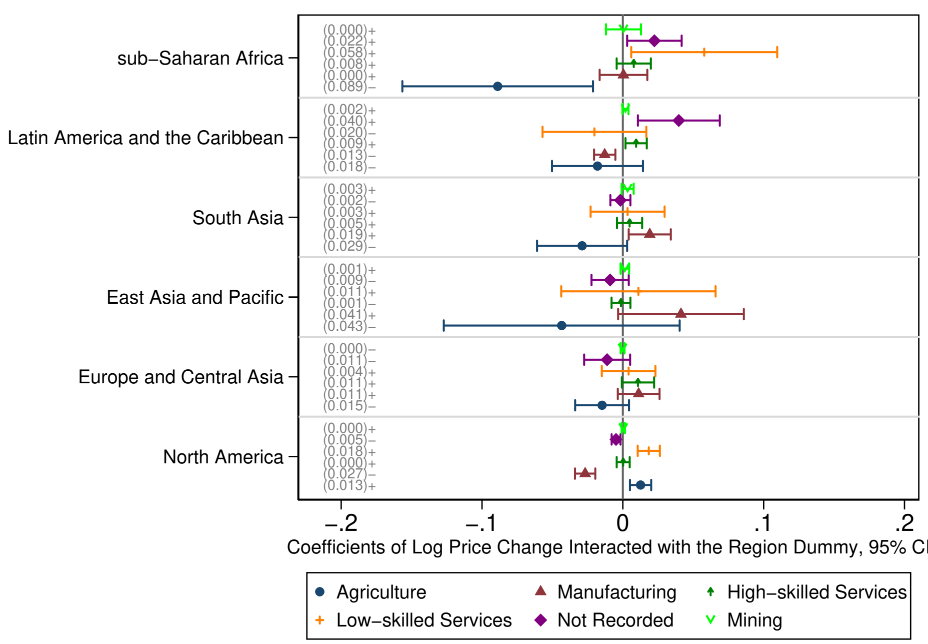


Notes: This figure plots the distribution of the "opening" years for mines with available work history data. Years before 1950 are truncated to 1950. The "opening" year is defined as the year when a mine was first mentioned in any public source and is a conservative estimate of the actual opening year.

Figure A10: The Effect of Price Shocks Since 1990



(a) Urban Population



(b) Employment Shares

Notes: This figure plots the estimated coefficients of price change interacted with the region dummy by equation 2. All regressions take the same specifications as Figures 1 and 2. However, we restrict our analysis to later years, i.e., 1990-2015.

Table A8: The Effect of Price Shocks on Local Populations: Global Analysis

	(1)	(2)	(3)	(4)
		$\Delta \log \textit{Population}$ in the City		
City Zone	Buffer, 10 km		Ring, 10 -120 km	Ring, 30 -120 km
Mine Buffer Zone	60 km	120 km	120 km	120 km
Panel A. Cities With and Without Mines				
$\Delta \log \textit{Price}$	0.014***	0.012*	0.006	0.007
	(0.005)	(0.007)	(0.005)	(0.005)
N	6,120	6,120	6,123	6,123
Panel B. Only Cities from WHP 2018				
$\Delta \log \textit{Price}$	0.038**	0.024*	0.028***	0.026**
	(0.015)	(0.014)	(0.010)	(0.011)
N	2,970	4,356	4,359	4,359
Panel C. WHP 2018+African Cities With Pop. Threshold Above 100,000				
$\Delta \log \textit{Price}$	0.032**	0.032**	0.028***	0.030***
	(0.013)	(0.012)	(0.010)	(0.010)
N	3,753	5,612	5,616	5,616
Panel D. Spatial Correlation				
$\Delta \log \textit{Price}$	0.031*	0.024	0.023	0.022
	(0.018)	(0.021)	(0.017)	(0.017)
N	3,195	4,737	4,740	4,740
Panel E. Country×Period FE				
$\Delta \log \textit{Price}$	0.022*	0.008	0.006	0.005
	(0.013)	(0.015)	(0.011)	(0.011)
N	3,066	4,602	4,605	4,605
Panel F. Varying Period Length				
$\Delta \log \textit{Price}$	0.033**	0.020	0.023**	0.022**
	(0.014)	(0.015)	(0.010)	(0.011)
N	3,195	4,737	4,740	4,740

Notes: This table reports the regression coefficients of equation 1. The dependent variables are log changes in population density in the corresponding city zones. The independent variable (changes in log price) and the control variable (log number of mines) draw on all mines within the mine buffer zone. All the regressions control for the log number of mines (buffer zone same as it is for price shocks) and initial log population, country–group×period fixed effects, country fixed effects, and commodity fixed effects, except in Panel E, which controls for country×period fixed effects and commodity fixed effects. Standard errors in parentheses are clustered at the city level, except in Panel D, which is Conley(1999) standard errors in parentheses allowing for spatial correlation within a 200-km radius and for infinite serial correlation. In Panel F, we run a regression by weighting each city-period unit with the length of each period. ***, **, * denote statistical significance at the 1%, 5%, 10% levels, respectively.

Table A9: The Effect of Price Shocks on Local Employment Shares by Sector: City Buffer Zone

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Outcome: Δ Employment Share of											
	Agriculture		Mining		Manufacturing		High-skilled Services		Low-skilled Services		Not Recorded	
City Zone	Buffer, 60 km											
Mine Buffer Zone	60 km	120 km	60 km	120 km	60 km	120 km	60 km	120 km	60 km	120 km	60 km	120 km
Panel A. Cities With and Without Mines												
$\Delta \log Price$	-0.017***	-0.021***	-0.000	0.000	0.006***	0.004**	0.002*	0.002**	0.020***	0.026***	-0.010***	-0.012***
	(0.004)	(0.003)	(0.000)	(0.000)	(0.002)	(0.002)	(0.001)	(0.001)	(0.004)	(0.003)	(0.003)	(0.002)
N	3,569	3,569	3,569	3,569	3,569	3,569	3,569	3,569	3,569	3,569	3,569	3,569
Panel B. Only Cities from WHP 2018												
$\Delta \log Price$	-0.014***	-0.022***	0.000	0.000	0.003	0.004*	0.002	0.002*	0.022***	0.027***	-0.012***	-0.011***
	(0.004)	(0.004)	(0.000)	(0.000)	(0.002)	(0.002)	(0.001)	(0.001)	(0.005)	(0.003)	(0.004)	(0.002)
N	1,808	2,746	1,808	2,746	1,808	2,746	1,808	2,746	1,808	2,746	1,808	2,746
Panel C. Cities from WHP 2018 and African Cities With Population Threshold Above 100,000												
$\Delta \log Price$	-0.019***	-0.027***	0.001	0.001	0.003	0.004**	0.002*	0.002**	0.023***	0.030***	-0.011***	-0.009***
	(0.005)	(0.004)	(0.000)	(0.000)	(0.002)	(0.002)	(0.001)	(0.001)	(0.005)	(0.003)	(0.003)	(0.002)
N	1,997	3,040	1,997	3,040	1,997	3,040	1,997	3,040	1,997	3,040	1,997	3,040
Panel D. Exclude Canada												
$\Delta \log Price$	-0.016***	-0.025***	0.001	0.000	0.004*	0.004*	-0.001	0.000	0.024***	0.029***	-0.011***	-0.009***
	(0.005)	(0.004)	(0.000)	(0.000)	(0.002)	(0.002)	(0.001)	(0.001)	(0.005)	(0.004)	(0.004)	(0.003)
N	1,800	2,776	1,800	2,776	1,800	2,776	1,800	2,776	1,800	2,776	1,800	2,776
Panel E. Exclude Censuses with Only GEOLEV1 Available												
$\Delta \log Price$	-0.017***	-0.027***	0.001	0.000	0.003	0.004*	-0.001	-0.001	0.025***	0.032***	-0.012***	-0.009***
	(0.005)	(0.004)	(0.000)	(0.000)	(0.002)	(0.002)	(0.001)	(0.001)	(0.005)	(0.004)	(0.004)	(0.003)
N	1,730	2,628	1,730	2,628	1,730	2,628	1,730	2,628	1,730	2,628	1,730	2,628
Panel F. Spatial Correlation												
$\Delta \log Price$	-0.015**	-0.024***	0.000	0.000	0.003	0.004	0.002	0.002	0.022***	0.028***	-0.012***	-0.010***
	(0.007)	(0.006)	(0.000)	(0.001)	(0.003)	(0.003)	(0.002)	(0.001)	(0.007)	(0.005)	(0.005)	(0.004)
N	1,858	2,848	1,858	2,848	1,858	2,848	1,858	2,848	1,858	2,848	1,858	2,848
Panel G. Country×Period FE												
$\Delta \log Price$	-0.013**	-0.021***	-0.000	0.000	0.002	0.002	0.002	0.002*	0.016***	0.025***	-0.007**	-0.008***
	(0.006)	(0.005)	(0.000)	(0.000)	(0.003)	(0.003)	(0.002)	(0.001)	(0.005)	(0.004)	(0.003)	(0.003)
N	1,803	2,787	1,803	2,787	1,803	2,787	1,803	2,787	1,803	2,787	1,803	2,787
Panel H. Varying Period Length												
$\Delta \log Price$	-0.019***	-0.028***	0.000	0.000	0.005**	0.010***	0.000	-0.000	0.032***	0.035***	-0.018***	-0.017***
	(0.004)	(0.003)	(0.000)	(0.000)	(0.002)	(0.002)	(0.001)	(0.001)	(0.005)	(0.004)	(0.005)	(0.003)
N	1,850	2,839	1,850	2,839	1,850	2,839	1,850	2,839	1,850	2,839	1,850	2,839

Notes: This table reports the coefficients of equation 1. The dependent variables are changes in employment shares by sector within a city's 60-km radius. The independent variable (price change) and the control variable (log number of mines) draw on all mines within the mine buffer zone. All the regressions control for the initial employment shares of agriculture, manufacturing, and mining within a radius of 60 km of a city, and include country–group×period fixed effects, country fixed effects, and commodity fixed effects, except in Panel G, which controls for country×period fixed effects and commodity fixed effects. Standard errors in parentheses are clustered at the city level, except in Panel F, which is Conley(1999) standard errors in parentheses, allowing for spatial correlation within a 200 km radius and for infinite serial correlation. In Panel H, we run a regression by weighting each city-period unit with the length of each period. ***, **, * denote statistical significance at the 1%, 5%, 10% levels, respectively.

Table A10: The Effect of Price Shocks on Local Employment Shares by Sector: City Ring Zone

	(1)	(2)	(3)	(4)	(5)	(6)
			Outcome: Δ Employment Share of			
	Agriculture	Mining	Manufacturing	High-skilled Serv.	Low-skilled Serv.	Not Recorded
City Zone			Ring, 60-120 km			
Mine Buffer Zone			120 km			
Panel A. Cities With and Without Mines						
Δ log *Price*	-0.020***	0.002**	0.001	0.003***	0.012***	0.003
	(0.005)	(0.001)	(0.002)	(0.001)	(0.003)	(0.002)
N	3,389	3,389	3,389	3,389	3,389	3,389
Panel B. Only Cities from WHP 2018						
Δ log *Price*	-0.020***	0.002**	0.000	0.002***	0.010***	0.005*
	(0.005)	(0.001)	(0.002)	(0.001)	(0.004)	(0.003)
N	2,592	2,592	2,592	2,592	2,592	2,592
Panel C. Cities from WHP 2018 and African Cities With Population Threshold Above 100,000						
Δ log *Price*	-0.024***	0.002***	0.001	0.003***	0.013***	0.005**
	(0.005)	(0.001)	(0.002)	(0.001)	(0.004)	(0.002)
N	2,884	2,884	2,884	2,884	2,884	2,884
Panel D. Exclude Canada						
Δ log *Price*	-0.021***	0.002***	0.001	0.002***	0.011***	0.005**
	(0.005)	(0.001)	(0.002)	(0.001)	(0.004)	(0.003)
N	2,655	2,655	2,655	2,655	2,655	2,655
Panel E. Exclude Censuses with Only GEOLEV1 Available						
Δ log *Price*	-0.021***	0.002**	0.000	0.002***	0.012***	0.006**
	(0.005)	(0.001)	(0.002)	(0.001)	(0.004)	(0.003)
N	2,566	2,566	2,566	2,566	2,566	2,566
Panel F. Spatial Correlation						
Δ log *Price*	-0.021***	0.002**	0.001	0.002**	0.010*	0.005
	(0.008)	(0.001)	(0.003)	(0.001)	(0.006)	(0.003)
N	2,693	2,693	2,693	2,693	2,693	2,693
Panel G. Country×Period FE						
Δ log *Price*	-0.019***	0.001	0.001	0.001	0.011**	0.005
	(0.007)	(0.001)	(0.003)	(0.001)	(0.005)	(0.003)
N	2,634	2,634	2,634	2,634	2,634	2,634
Panel H. Varying Period Length						
Δ log *Price*	-0.022***	0.002***	0.005**	0.002***	0.008*	0.004
	(0.005)	(0.001)	(0.002)	(0.001)	(0.004)	(0.003)
N	2,685	2,685	2,685	2,685	2,685	2,685

Notes: This table reports the coefficients of equation 1. The dependent variables are changes in employment shares by sector within a city's 60-120 km ring. The independent variable (price change) and the control variable (log number of mines) draw on all mines within the mine buffer zone. All the regressions control for the initial employment shares of agriculture, manufacturing, and mining within a city's 60-120 km ring, and include country–group×period fixed effects, country fixed effects, and commodity fixed effects, except in Panel G, which controls for country×period fixed effects and commodity fixed effects. Standard errors in parentheses are clustered at the city level, except in Panel F, which is Conley(1999) standard errors in parentheses, allowing for spatial correlation within a 200 km radius and for infinite serial correlation. In Panel H, we run a regression by weighting each city-period unit with the length of each period. ***, **, * denote statistical significance at the 1%, 5%, 10% levels, respectively.

Table A11: Average Years of Schooling by Sector and by Region, 2000-2009

	(1) East Asia and Pacific	(2) South Asia	(3) Latin America and the Caribbean	(4) Sub-Saharan Africa	(5) Middle East and North Africa	(6) Europe and Central Asia	(7) North America
All population	7.85	5.96	8.25	6.20	8.11	10.35	12.76
Agriculture workers	6.33	4.30	4.96	4.39	5.07	8.40	10.86
Mining workers	8.52	5.75	7.83	6.15	9.52	9.58	12.27
Manufacturing workers	9.11	6.60	7.96	6.96	7.87	10.18	12.48
High-skilled services workers	10.88	13.11	10.96	9.65	12.36	12.69	13.51
Low-skilled services workers	9.84	7.83	8.71	7.37	9.35	11.18	12.73
Not-recorded industries workers	10.39	6.22	8.30	6.93	9.47	9.49	11.24

Notes: Calculated by authors. Data source: IPUMS.

Table A12: The Comparison of Country Characteristics Between Continents

	(1) East Asia and Pacific	(2) South Asia	(3) Latin America and the Caribbean	(4) Sub-Saharan Africa	(5) Middle East and North Africa	(6) Europe and Central Asia	(7) North America
Natural resource exports, % of GDP, 1990-1995	0.68	0.19	3.27	2.99	4.63	1.18	0.95
Cereal yield, kg per hectare, 1990-1995	2,815	1,830	2,272	1,108	2,489	3,391	3,728
Years of schooling, population 25+, 1990-1995	6.87	3.55	6.23	3.49	5.15	8.99	12.14
GDP per capita, constant 2015 US$, 1990-1995	9,491	1,472	7,269	1,495	12,660	18,302	63,128
Rule of law, 1996	0.35	-0.36	-0.06	-0.68	-0.18	0.45	1.45
Control of corruption, 1996	0.22	-0.49	0.05	-0.52	-0.24	0.43	1.64
# Conflicts, per million pop., 1960-2000	1.01	0.71	0.79	1.44	2.62	0.23	0.004
Democracy, 1990-2000	2.05	2.17	6.1	-.88	-5.93	5.85	10

Notes: Calculated by authors. Natural resource exports includes ores and metals exports. Cereal yield, natural resource exports, GDP, and GDP per capita are from the World Development Indicators. The category " Years of Schooling" is from the Global Data Lab. The categories "Rule of law" and "Control of corruption" are the estimates of governance in standard normal units from the Worldwide Governance Indicators (WGI), ranging from -2.5 (weak) to 2.5 (strong) governance performance. # Conflicts are from UCDP/PRIO Armed Conflict Dataset and count the number of conflicts in each country whose government(s) has a primary claim to the incompatibility; no conflict happened is coded as 0. Democracy is a rescaled Polity2 score, ranging from -10 (most autocratic) to 10 (most democratic), from Teorell et al. (2023).

Table A13: The Uniqueness of Africa: The Role of Country Characteristics–Complementary

	(1) Baseline	(2) Natural Resource Exports % of GDP	(3) Agriculture Yield (in log)	(4) Years of Schooling	(5) GDP Per Capita (in log)	(6) Rule of Law	(7) Control of Corruption	(8) Conflict	(9) Democracy
Panel A. Outcome: Δ Manufacturing Emp. Share									
$\Delta \log Price \times$ Sub-Saharan Africa	0.003	0.006	0.001	-0.005	-0.015*	-0.002	-0.002	0.007	-0.005
	(0.007)	(0.013)	(0.009)	(0.007)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)
$\Delta \log Price$	0.004*	0.003	0.016	0.023***	0.076***	0.006***	0.006***	0.005**	0.016***
	(0.002)	(0.002)	(0.046)	(0.005)	(0.014)	(0.002)	(0.002)	(0.002)	(0.003)
$\Delta \log Price \times$ Country Characteristic		0.000	-0.002	-0.003***	-0.008***	-0.011***	-0.009***	-0.011**	-0.002***
		(0.001)	(0.006)	(0.001)	(0.002)	(0.002)	(0.002)	(0.005)	(0.000)
N	2,755	2,674	2,755	2,748	2,668	2,741	2,741	2,755	2,752
Adj. R^2	0.212	0.207	0.211	0.217	0.219	0.220	0.218	0.213	0.223
Panel B. Outcome: Δ High-skilled Services Emp. Share									
$\Delta \log Price \times$ Sub-Saharan Africa	0.006	-0.028**	-0.001	0.006	0.004	0.006	0.006	0.008	0.006
	(0.006)	(0.011)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.005)	(0.006)
$\Delta \log Price$	0.002*	-0.001	0.055**	0.002	0.017***	0.001	0.001	0.003**	0.001
	(0.001)	(0.001)	(0.021)	(0.002)	(0.006)	(0.001)	(0.001)	(0.001)	(0.001)
$\Delta \log Price \times$ Country Characteristic		0.004***	-0.007**	0.000	-0.002***	0.002*	0.003*	-0.006**	0.000
		(0.001)	(0.003)	(0.000)	(0.001)	(0.001)	(0.001)	(0.003)	(0.000)
N	2,755	2,674	2,755	2,748	2,668	2,741	2,741	2,755	2,752
Adj. R^2	0.336	0.362	0.338	0.340	0.370	0.346	0.346	0.338	0.340
Panel C. Outcome: Δ Low-skilled Services Emp. Share									
$\Delta \log Price \times$ Sub-Saharan Africa	0.040*	0.091***	0.034	0.038*	0.042*	0.029	0.033	0.043*	0.032
	(0.022)	(0.034)	(0.024)	(0.022)	(0.022)	(0.024)	(0.024)	(0.023)	(0.022)
$\Delta \log Price$	0.026***	0.030***	0.076	0.032***	0.015	0.031***	0.029***	0.027***	0.038***
	(0.003)	(0.003)	(0.066)	(0.007)	(0.019)	(0.004)	(0.004)	(0.003)	(0.005)
$\Delta \log Price \times$ Country Characteristic		-0.005**	-0.006	-0.001	0.001	-0.017***	-0.009***	-0.008	-0.002***
		(0.002)	(0.008)	(0.001)	(0.002)	(0.003)	(0.003)	(0.012)	(0.001)
N	2,755	2,674	2,755	2,748	2,668	2,741	2,741	2,755	2,752
Adj. R^2	0.269	0.270	0.269	0.268	0.274	0.274	0.270	0.269	0.272

Notes: The dependent variables are changes in employment shares by sector in the 60-km city buffer zone, and the price change is the average log price change of minerals extracted from mines located within a radius of 120 km of a city. All regressions control for the log number of mines within the mine buffer zone same as it is for the price change, country–group×period FEs, country FEs, commodity FEs, and the initial employment share of agriculture, manufacturing, and mining within the corresponding city buffer zone. Countries are categorized into seven groups: Sub-Saharan Africa, Middle East and North Africa, Latin America and the Caribbean, South Asia, East Asia, Europe and Central Asia, and North America. The Middle East and North Africa region is excluded due to a lack of observations. Standard errors in parentheses are clustered at the city level. ***, **, * denote statistical significance at the 1%, 5%, 10% levels, respectively.