Do Resource Rents Drive Urbanization and Structural Transformation? A Global Analysis*

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February 12, 2024

Abstract

This paper provides the first causal estimate of the impact of mineral price changes on population and industrial structure in a global sample of cities. We find that increases in the prices of minerals extracted from nearby mines lead to employment reallocation away from agriculture and primarily toward low-skilled services, without crowding out manufacturing activities. While city population experiences growth, there is limited evidence for mining booms driving large-scale urbanization. Cities in Sub-Saharan Africa exhibit exceptionally strong responses to mining booms. These results suggest that resource-led structural transformation could present a new development path for resource-rich developing countries.

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

JEL code: O13, O14, O18, Q33, R11, L16

*We thank our discussants Kristina Manysheva and Anna Vitali, as well as Stephie Fried, Thomas Fujiwara, Douglas Gollin, Gordon Hanson, Seema Jayachandran, David Lagakos, Kris Mitchener, Tommaso Porzio, Xiaobo Zhang, and Bo Zhao for detailed comments on this project. We have also benefited from conversations with seminar participants at Princeton University, San Francisco Federal Reserve, Peking University, and UC San Diego, as well as with those at the Third Structural Transformation and Economic Growth (STEG) Annual Conference, the Development Finance Research Workshop at Princeton, the All California Labor Economics Conference (ACLEC), and the 12th European Meeting of the Urban Economics Association. Qing Huang thanks the Center on Contemporary China at Princeton University for financial support. Wei You acknowledges the financial support of the National Natural Science Foundation of China, Young Scientists Fund (No.72103002). Any errors are solely the responsibility of the authors.

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1 Introduction

Both structural transformation and urbanization are key processes that accompany economic growth (Gollin and Kaboski, 2023). In the histories of European and North American countries, economic growth involved a transition from agriculture to manufacturing, and then ultimately from manufacturing to services. Urbanization went hand in hand with industrialization. These patterns are summarized in the pioneering work of Kuznets (1973) and provided solid evidence recently by Herrendorf et al. (2014). In contrast, many developing countries today—such as Sub-Saharan Africa (SSA) and some oil-rich countries—deviate from these patterns: they are transitioning or have transitioned from agriculture to services without experiencing a substantial take-off of manufacturing (Rodrik, 2016). Moreover, these countries have high rates of urbanization but limited shares of manufacturing activities in cities (Gollin et al., 2016; Jedwab and Vollrath, 2015; Jedwab et al., 2022). The forces behind such a deviation remain largely unknown, and this phenomenon is sometimes labeled as the "urbanization without industrialization" puzzle.

In this paper, we provide the first causal evidence to show that resource rents play a crucial role in driving the above patterns. Previous studies rely on cross-country variation, where identification is plagued by unobserved country characteristics and yields conflicting conclusions.[1] In addition, cross-country studies of causes of urbanization have been made difficult due to issues with the comparability of the urbanization rate measure across countries. Our study differs from previous work by using spatially granular microdata with global coverage to achieve identification and comparability of key variables. Specifically, we focus exclusively on global cities (settlements) above a population threshold and create concentric circle areas. These spatial units are consistently defined and allow us to examine how urban populations and local industrial structures respond to economic shocks of interest—mineral price shocks in our case. This constitutes a novel approach to studying macro-development questions related to urbanization and structural transformation.[2] Our analysis reveals that

[1] For example, Gollin et al. (2016) shows that there is a strong and positive association between resource reliance and urbanization rate in Africa and the Middle East, but there is no correlation between these two variables for other countries, which lends support to their hypothesis that resource rents are the key to understand the unique urbanization patterns of Africa and the Middle East. But Henderson and Kriticos (2018) cast doubt on their results by showing that in cross-country regressions where industrialization is added as a control, the above patterns disappear. This contrast in the results on the role of resource rents illustrates the identification difficulty.

[2] In this sense, our approach adds to a growing body of literature that uses microdata to study macro-development questions. For example, 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.

mineral price spikes significantly drive structural transformation out of agriculture and primarily into low-skilled services. The impact of mineral price shocks on population and structural change is particularly pronounced in SSA cities. If the prices of natural resources continue to boom in the future, our results imply that resource-rich developing countries may undergo distinct paths of structural transformation compared to developed countries throughout history.

To conduct our empirical analysis, we combine several spatially granular data sets, including a collection of all urban settlements across the world, 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 73 countries in Integrated Public Use Microdata Series (IPUMS) (Minnesota Population Center, 2020). 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. The primary outcomes of interest are changes in population (density) and sectoral employment shares within a certain distance of each city's centroid. The key explanatory variable is the average log price change of minerals extracted from mines located within a certain distance of each city's centroid.[3] The data cover the period from circa 1975 to circa 2015. We adopt a long difference specification where each period is approximately 10 years, which captures the medium-long run effect of mineral price changes. Our identification assumption is that from the perspective of each city, a handful of mining sites nearby a city do not affect the international prices of the minerals extracted from those mines. The highly unpredictable nature of world mineral price changes can be viewed as exogenous shocks to each mining site.

There are three sets of main findings. First, mining booms drive structural transformation away from agriculture and towards the low-skilled service sector. We show that a 100% increase in mineral prices within 120 km of the city centroids leads to a decrease in the employment share in agriculture by 2.3 percentage points and an increase in the employment share in low-skilled services by 1.3 percentage points, both within 60 km of the city centroids (which we call city buffer zones hereafter). We interpret this finding as a result of the in-

(2021); Nath (2022); Benguria et al. (2023); Porzio et al. (2022); Jedwab et al. (2023). See Lagakos and Shu (2021); Buera et al. (2023); Gollin and Kaboski (2023) for good reviews.

[3] We allow for various thresholds for defining cities in later analysis. We also vary the distance thresholds to define city population, industrial structure, and "nearby" mineral price shocks.

come effect generated by resource rents.[4] We also uncover important regional heterogeneity: African cities exhibit distinct patterns—the labor reallocation out of the agricultural sector is notably pronounced in SSA compared to the rest of the world. According to our estimates, mining booms between 1975 and 2015 contributed to 10.6% and 75.6% of the increases in the low-skilled services employment share on a global average and in SSA, respectively.

Second, there is no evidence that mining booms crowd out manufacturing. Globally, we find a close-to-zero and insignificant effect of mineral price shocks on the share of manufacturing employment within the 60 km city buffer zones. The effect on manufacturing share is of particular interest because this sector is shown to generate productivity spillovers on nearby firms (Ellison et al., 2010; Greenstone et al., 2010; Kline and Moretti, 2014) and is a technologically dynamic sector (Rodrik, 2013; Autor et al., 2020). A large literature on the Dutch Disease probes whether rich natural resources cause slower economic growth by crowding out local manufacturing activities (see Van der Ploeg, 2011 for a review, and Michaels, 2011; Glaeser et al., 2015; Allcott and Keniston, 2018; Cavalcanti et al., 2019; Fernihough and O'Rourke, 2021 for more recent work). Our result indicates that the Dutch Disease does not exist in our global sample. This implies that among the four commonly cited reasons for the existence of a resource curse: The Dutch disease, rent-seeking, overconfidence, and neglect of education (Gylfason, 2001), the other three channels may be more important. In addition, our study reveals significant regional heterogeneity: mineral price increases *fostered* manufacturing growth in Asian and SSA cities but *diminished* manufacturing activities in North America—a novel finding to the literature.

Third, there is only limited evidence for mining booms driving urbanization. In the global sample, we find that mining booms within the 60 km buffer zones lead to significant population growth within the 10 km buffer zones. However, the magnitude of the effect is economically modest. 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.[5] Estimating the heterogeneous effects by region, we find that the effect is notably positive solely among African cities, with no significant impact observed among

[4]Using the census samples for which we have income data (11 out of 73 countries), we show that an increase in local mineral prices is associated with a significant increase in local average income.

[5]In addition, we find that the effect of mineral price changes on population change within the 10-60km ring areas of the city centroids is similar to the effect on population change within the 10 km circle areas. This comparison indicates that mining booms either induce migration inflows to the entire local areas—including the urban cores and the rural peripheries—or induce natural increases in population at similar rates in the entire areas. Furthermore, using the bilateral migration flow data for countries with available information in IPUMS, we find only limited evidence that individuals move in response to mineral price changes.

other cities. Mineral price changes during our study period contributed to approximately 9.7% and 14.0% of urban population growth in SSA and North Africa, respectively.

We demonstrate that all the results above are robust to an extensive set of sensitivity analysis. These include robustness checks using different definitions of the buffer zones, different thresholds of city sizes, sample selection rules, correction for spatial correlation in standard errors, and different control variables and fixed effects. We observe consistent results across all of these robustness analyses.

Our paper provides the first direct empirical test of the consumption city hypothesis raised by Gollin et al. (2016); Jedwab et al. (2022), which, in turn, build on Glaeser et al. (2001). Our identification strategy follows Axbard et al. (2021); Asher and Novosad (2019); Berman et al. (2017); Charles et al. (2022); Dube and Vargas (2013); Goldblatt et al. (2022), who exploit global commodity price shocks to examine various outcomes. We adopt a similar identification approach to answer the macro-development question of whether resource rents cause urbanization and structural transformation. On one hand, we provide causal evidence that resource rents as proxied by mineral price spikes lead to increases in local income and structural transformation primarily into low-skilled services, which supports the income-effect mechanism proposed in Gollin et al. (2016). On the other hand, we also show that resource rents do not necessarily cause significant urbanization. As such, our evidence is consistent with a scenario where within-region labor reallocation plays a major role (Emerick, 2018; Eckert and Peters, 2022). This result also indicates that there are other more fundamental causes driving the observed urbanization in today's developing countries.

More broadly, our paper contrasts with previous literature that focuses on relative productivity growth between sectors as a driver of structural transformation.[6] While non-homothetic preferences play an equally important role in theoretical models (Kongsamut et al., 2001; Gollin et al., 2016), empirical tests of this channel are scarce, probably due to the rarity of exogenous income shocks. Focusing on one country or one region, Black et al. (2005), Aragón and Rud (2013), Cavalcanti et al. (2019) examine the impact of resource booms or discovery on the local employment structure and income levels in the context of the U.S., Peru, and Brazil, respectively. All three papers show that mining booms have positive spillovers on the local non-tradable service sector and increase local incomes. We extend the external validity of these studies by providing the first cross-country, local-level evidence for

[6] See Baumol (1967); Gollin et al. (2002); Ngai and Pissarides (2007); Herrendorf et al. (2014); Storesletten et al. (2019); Huneeus and Rogerson (2023) for theoretical models and Foster and Rosenzweig (2004); Buera and Kaboski (2009); Alvarez-Cuadrado and Poschke (2011); Hornbeck and Keskin (2015); Bustos et al. (2016); Emerick (2018); Carillo (2021); Asher et al. (2022) for empirical tests.

income-effect-driven structural transformation. Our work also complements the work by Fan et al. (2023) who focus on India to study the role of service industries in economic growth.

Our results connect to the debate on the "desirable" path of structural transformation. Early development economists, including (Kuznets, 1973; Chenery, 1960; Syrquin and Chenery, 1989; Rostow, 1990; Reynolds, 1983), emphasize the crucial role of industrialization for successful economic development. The ability of mining booms to drive labor reallocation towards services, coupled with the resource-rich status of many developing countries, suggests that resource-led or service-led structural transformation can present a new path for today's developing countries (Fan et al., 2023; Buera and Kaboski, 2012). However, whether such a path is superior or inferior to the traditional path is still unclear (Jedwab et al., 2022; Gollin and Kaboski, 2023). This raises a further question: does resource-led structure transformation forego learning-by-doing opportunities? This is an open question for future research. A tentative and simple answer is: since we do not find mining booms crowd out manufacturing, resource-led structural transformation could be a path involving efficiency losses smaller than previously thought.

Last but not least, African cities exhibit especially high sensitivity in response to mineral price shocks. In the final section of our analysis, we explore the potential mechanisms. We find that low agricultural productivity and high resource reliance play the most significant roles in explaining the distinct responsiveness of African cities. This finding resonates with the expanding literature that highlights the distinctiveness of Africa, both in terms of its manufacturing sector (Henderson and Kriticos, 2018; Henderson and Turner, 2020; Diao et al., 2021; McMillan and Zeufack, 2022) and its unique responsiveness to mineral price shocks (Berman et al., 2017; Mamo et al., 2019). Our global analysis contributes to this literature by quantitatively assessing which factor(s) are most important to explain Africa's uniqueness in the context of mining booms and labor reallocation.

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. Sections 4 and 5 present the results on the impact of mineral price shocks on the changes in local industrial structure and urban population growth, respectively. Section 6 explores the potential mechanisms behind Africa's distinct responses. Section 7 concludes.

2 Data and Summary Statistics

2.1 Data Description

We aim to determine whether mineral price booms lead to urbanization and structural transformation, focusing our analysis at the city level rather than the country level (see Gollin et al. 2016; Henderson and Kriticos 2018, for example). To construct our data from various sources, we proceed in 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 level. Second, based on the centroids of this list of cities, we draw circles which encompass the mines surrounding each city. We then examine the impact of price changes of the minerals extracted in nearby mines for two main city-level outcomes: city population, and local industrial composition. We detail the process of constructing our dataset and provide in-depth descriptions of each data source 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.[7] 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.[8] Africapolis

[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]Information on cities that had not reached the 300K threshold in 2018 is not available in the WUP 2018 data. The WUP 2018 data also miss cities that had a population of over 300K before 2018 and declined to less than 300K later. We are thus studying the intensive margin of the growth of cities with a population size above a certain threshold in 2018. This raises the concern that this sample of cities is selected based on an outcome and may over-represent the fast-growing cities in the world. To alleviate this concern, we impose some additional restrictions, requiring the city population to be over 50K/100K/200K in 1970, respectively. Table A1 presents the summary statistics of different city samples. By gradually raising the 1970 population threshold, the non-African city sample size shrinks from 1,860 to 794, but the total population growth rate between 1970 and 2015 decreases from 396%(=2470/624) to 252%, which goes below the average urban population growth rate in the world (294%=3981/1354). We test the robustness of our results using different samples defined in Table A1. We also experiment with different African city samples: instead of using 200,000 residents as the threshold, we also select cities from Africapolis that have reached a population of at least 100,000 residents at some point since 1960.

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.[9] 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 worldwide.

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 city 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

[9] 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.

[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

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).

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

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.

[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.

each city.

Industrial Structure Data In addition to linking mineral price changes to local population changes, we also associate mineral price changes to changes in 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 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 249 rounds of population censuses from 73 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

[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.

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 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	-0.131	-0.080	-0.121	-0.042	-0.062	-0.031	-0.010
Mining	-0.007	-0.002	-0.005	0.000	-0.001	-0.005	0.002
Manufacturing	0.022	-0.004	-0.021	0.003	-0.003	-0.049	-0.044
High-skilled services	0.018	0.012	0.027	-0.005	0.006	0.024	0.053
Low-skilled services	0.094	0.077	0.099	0.037	0.040	0.063	-0.001
Not recorded	0.004	-0.003	0.022	0.007	0.018	-0.002	0.000
Number of cities	498	208	208	121	83	205	144
Panel B. Level of employment shares in the 2000s							
Agriculture	0.535	0.482	0.105	0.362	0.292	0.136	0.011
Mining	0.011	0.007	0.006	0.017	0.002	0.002	0.003
Manufacturing	0.153	0.134	0.139	0.090	0.105	0.160	0.156
High-skilled services	0.024	0.021	0.059	0.035	0.026	0.104	0.167
Low-skilled services	0.272	0.356	0.605	0.420	0.568	0.583	0.662
Not recorded	0.005	0.000	0.084	0.075	0.008	0.013	0.000
Number of cities	498	181	202	86	51	110	144

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]

[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

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 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]

We also present summary statistics of the geographic extent of mining sites used in our analysis in Panel B of Table 2, which is based on the data constructed by Maus et al. (2020) and spatially joined to our SNL data. Among the polygons joined between these two data sets, the mean of the longest side of these mining polygons is around 1.2 km and the 90th percentile is around 2.5 km. These statistics suggest the geographic scope of the mining sites is typically limited, and the observed population and employment changes within 10 km or 60 km of city centroids are unlikely to 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

across countries. Table A4 in the Appendix provides more details about the IPUMS sample.

[18]We provide the number of mines near 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).

the average of the log price changes of all mines surrounding a city. Figure A6 in the appendix shows annual 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 surged again in the 2000s. 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 boom 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). Overall, the timing of these commodity price shocks 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 certain cities witnessing rapid increases while others experience more gradual rises or even declines in mining prices. Moreover, there is no evidence suggesting that mining booms were confined to only a few continents. Summary statistics for the main variables used in this paper are presented in Table A5 in the Appendix.

3 Empirical Strategy

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

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

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. 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, $\Delta \log Price^R_{i,t}$, represents a "weighted-average" price change, reflecting the relative significance of various minerals within the surroundings of each city. We first calculate the price change (log difference) of the main mineral extracted from each mine. Then we average the log price change of the minerals extracted from mines located within R km of city i during the same period t, which serves as the dependent variable, $\Delta Y_{i,t}$. In other words, the relative importance (or the weight) of every mineral is proxied by the number of mines producing it.[21] In the baseline specification, we employ the 60-km buffer zone (mine buffer zone) to calculate the average log mineral price change within a 10-km city buffer zone for population, and a 120-km mine buffer zone for a 60-km city buffer zone for employment shares. We opt for larger buffer zones to encompass mines surrounding the cities, as they are typically situated in remote areas. We demonstrate the robustness of our results across various mine buffer zone radii. 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 nearby mines.[22]

[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. In our 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.

[21] We do so because we lack information on the reserves of each mine.

[22] 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

We include a set of fixed effects. The continent (one of the seven country groups) × 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 development stage of a city.[23] 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 affect 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 only a small fraction of worldwide production. Therefore, each mine can be viewed as a price taker, which alleviates the concern that mining booms near a given city are driven by local population growth or industrial structure change.[24]

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."

[23]For example, when Y_{it} is the employment share, $Y_{i,t0}$ refers to the initial employment shares in the agricultural, manufacturing, mining, high-skilled services, and low-skilled services in t_0.

[24]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 periods. An alternative approach, such as one suggested by 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.

4 The Effect of Mineral Price Changes on Local Employment Shares by Sector

In this section, we present our estimation results on structural transformation. First, in Subsection 4.1, we report the estimated global effect of mineral price shocks on changes in local employment share by sector. After documenting a set of important findings, in Subsection 4.2, we turn to estimate heterogeneous effects by country group. In Subsection 4.3, we investigate the mechanisms behind the observed changes in industrial structure.

4.1 Global Effect

Table 3 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)(4)(5) define the outcome in the 60-km city buffer zones, and Column (3)(6) defines the outcome in 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 most estimates 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. Together, Panel A and Panel B indicate that local mining booms increase local employment and population, 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 (2) 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 2.3 percentage points.

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

	(1)	(2)	(3)	(4)	(5)	(6)
City Zone	Buffer, 60 km		Ring, 60 -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			**Panel B. $\Delta \log$ Population in the City**		
$\Delta \log Price$	0.065***	0.072***	0.048***	0.004	0.024**	0.017*
	(0.010)	(0.008)	(0.007)	(0.012)	(0.012)	(0.009)
FE	Country-group×period, Country, Commodity					
N	1,663	2,531	2,499	2,184	3,240	3,240
Adj. R^2	0.505	0.483	0.523	0.637	0.582	0.522
	Panel C. Δ Agriculture Emp. Share			**Panel D. Δ Mining Emp. Share**		
$\Delta \log Price$	-0.021***	-0.023***	-0.024***	0.000	0.001	0.001***
	(0.004)	(0.003)	(0.003)	(0.000)	(0.000)	(0.000)
FE	Country-group×period, Country, Commodity					
N	1,663	2,531	2,499	1,663	2,531	2,499
Adj. R^2	0.243	0.259	0.355	0.432	0.410	0.380
	Panel E. Δ Manufacturing Emp. Share			**Panel F. Δ High-skilled Serv. Emp. Share**		
$\Delta \log Price$	0.002	0.002	0.004**	0.000	0.000	0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.000)
FE	Country-group×period, Country, Commodity					
N	1,663	2,531	2,499	1,663	2,531	2,499
Adj. R^2	0.237	0.246	0.273	0.594	0.562	0.633
	Panel G. Δ Low-skilled Serv. Emp. Share			**Panel H. Δ Not-Recorded Emp. Share**		
$\Delta \log Price$	0.012***	0.013***	0.007***	0.006**	0.007***	0.011***
	(0.004)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
FE	Country-group×period, Country, Commodity					
N	1,663	2,531	2,499	1,663	2,531	2,499
Adj. R^2	0.550	0.548	0.647	0.763	0.763	0.791

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. Panel A additionally controls for initial total employment, Panel B uses the same city sample as Panel A and additionally controls for initial population, and Panels C-H additionally control for the initial employment shares of agriculture, manufacturing, mining, high-skilled services, and low-skilled services 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.

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 (2) of Panel G, A doubling in mineral prices leads to an increase in the employment share in low-skilled services by approximately 1.3 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 nonfarming sectors (Henderson et al., 2021). According to Column (5) of Panel H, a 100% increase in mineral prices also results in a 0.7-percentage-point increase in the employment share in the not-recorded industries. Instead, mining price shocks have no significant effect on the change in the employment share of high-skilled services with almost zero magnitudes (Panel F). In addition, comparing Column (2) with Column (3) in Panel G, we see that the effect on the low-skill service employment share is 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 periphery areas (Column 3, Panel E), and an almost zero effect on manufacturing employment shares in the core areas (Columns 1 and 2, Panel E). This result connects to the findings of many studies on the Dutch disease (Black et al., 2005; Michaels, 2011; Glaeser et al., 2015; Allcott and Keniston, 2018; Cavalcanti et al., 2019). One advantage of our estimates lies in the extensive global coverage, encompassing 1,167 cities across 64 countries, which represents a notable advancement relative to previous literature that explores within-country, cross-city variations within a single country or region. The finding of a non-negative effect on manufacturing employment share suggests that there is no evidence for the Dutch disease due to mineral price booms in our global sample.

The lack of a crowding-out effect in the manufacturing sector is perhaps unexpected, partly because the traditional hypothesis is that mining booms would raise the demand for local inputs (labor) and raise the prices of the inputs (wages). This increase in costs would, in theory, weaken the competitiveness of the tradable or the manufacturing sector.[25] However, there are multiple potential explanations for the lack of a crowding-out effect. First, there can be strong linkages and complementarities between manufacturing and natural resource industries, so mining booms can foster the growth of local industries with upstream or downstream input-output linkages to natural resources (Allcott and Keniston, 2018). Second, if a region primarily adopts capital-intensive extraction techniques rather than labor-intensive ones, the prosperity of the mining industry does not necessarily exert upward pressure on manufacturing wages, and the manufacturing sector may even expand during the mining boom (Pelzl and Poelhekke, 2021). Third, a booming mining sector raises local incomes, which could stimulate investments in human capital, infrastructure, and extraction

[25] Sachs and Warner (2001) argue that Dutch Disease isthe channel behind their empirical finding of slower economic growth in resource-rich countries. Harding and Venables (2016) Harding and Venables (2013) and Ismail (2010) provide cross-country evidence that natural resource exports crowd out manufacturing exports.

technologies, all of which might benefit the manufacturing sector indirectly (Van der Ploeg, 2011).

Fifth, we find a close-to-zero and insignificant effect of mineral price shocks on mining employment share in the city core areas (Columns 4 and 5, Panel D) but a significantly positive effect on mining employment share in the periphery areas (Column 6, Panel D). Additionally, we show in Table A7 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 limited positive impact on mining employment share within urban cores is likely attributable to the sparse presence of mining activities in close proximity to city centers. We also note from Row 2 of Panel B of Table 1 that mining activity accounts for a very small share of local economic activities (between 0.2% and 1.7% in terms of total employment in the 2000s across the continents). Therefore, the large effect of mining booms on total employment which we observe in Panel A is likely not directly attributed to the mining sector itself but rather through indirect effects on other sectors in the economy.

4.2 Heterogeneous Effects by Country Group

So far we have shown that mining booms lead to significant structural transformation on a global scale. As shown in Table 1 in Section 2.2, cities across the world have followed different paths of structural transformation. A natural question to ask next is whether industrial structures in different regions exhibit different sensitivities to mineral price shocks. We use the following equation to estimate the region-specific impact of mineral price shocks on local employment shares by sector:

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

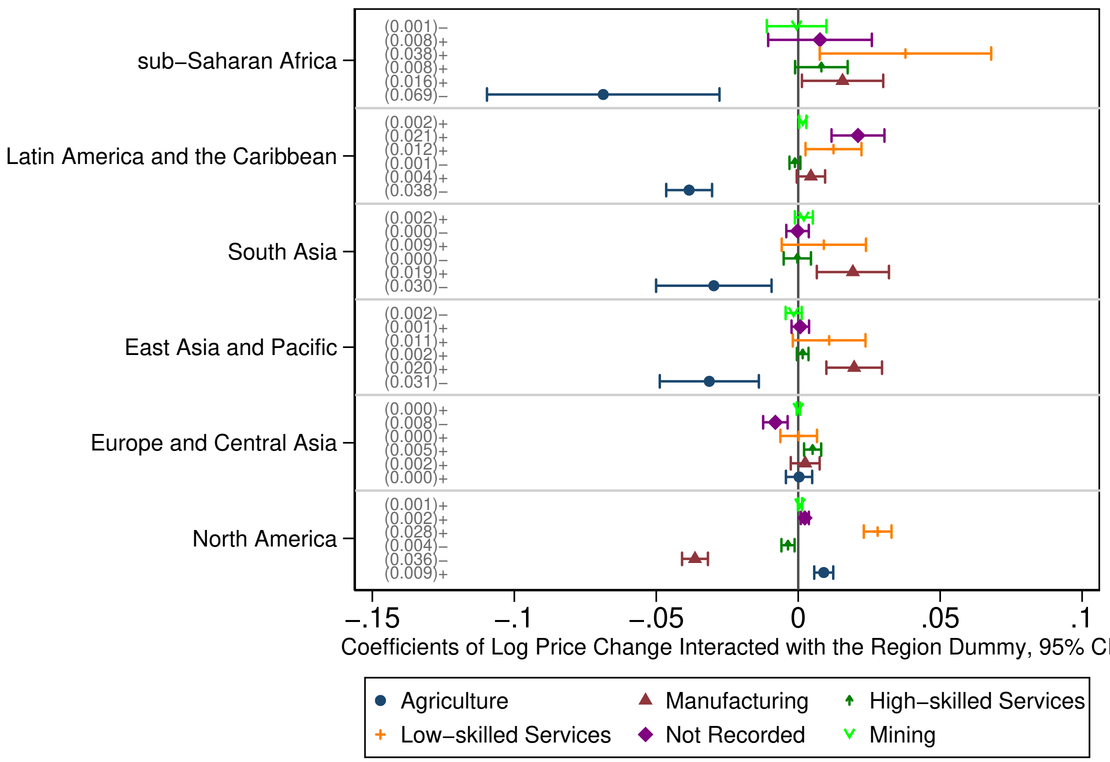
Similar to equation 1, $\Delta Y_{i,t}$ and $\Delta \log Price_{it}^R$ are changes in the outcome variable and changes in mineral prices for city i. $\mathbb{1}(Country_{i,c} \in Group_g)$ are dummy variables that equal 1 if city i of country c belongs to country group g; and zero otherwise. The coefficient of interest is β_{1g}, which captures the average effect of mineral price shocks on population growth for cities in country group g. We exclude North Africa due to insufficient sample size. For the other continents, we plot the coefficient estimates by region and by sector in Figure 1, where we use the 60-km city buffer zone and 120-km mine buffer zone. We obtain similar results when using the 30-km city buffer zone and the 120-km mine buffer zone, as shown in Figure A8 in the appendix.

We highlight two main findings regarding heterogeneous responses in structural transformation across regions. 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 two times larger compared to those in the rest of the world. Specifically, the average annual price change of minerals is about 3.0% among mines within 120 km of city centroids worldwide and about 5.7% 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 0.28 percentage points in SSA. After performing 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 10.6% on a global average and 75.6% for SSA cities. We delve into the distinctive response of Africa to mineral price shocks in detail in 6.

Second, 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, South Asia, and SSA, the manufacturing sector expanded in the presence of mining booms, suggesting that cities in these regions 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 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 may stem from the different natural resources analyzed in each study.

Finally, we show that our core results hold under various robustness checks. 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 measurement error in mines' open/close status in our data; (4) whether the results are robust to alternative sample restriction rules,

Figure 1: 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, mining, high-skilled services, and low-skilled services 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 insufficient observations. Standard errors are clustered at the city level.

fixed effects, control variables, and weighting methods. Our main estimates are not sensitive to any of the above checks. The details of the discussion and the related results are provided in Appendix A.3.

4.3 Mechanisms Behind Structural Transformation

Thus far, we have shown that positive mineral price shocks induce structural transformation out of agriculture and primarily toward low-skilled services. We now investigate the main mechanism driving such changes. One key channel proposed by Gollin et al. (2016) is that mining booms generate higher local income, which will then be spent disproportionately on local non-tradable goods and services. In this subsection, we provide evidence for the income effect channel in our study context.

First of all, focusing on single countries or individual regions, existing studies provide ample evidence that the discoveries of natural resources and the expansion of mining activities lead to increases in local income (or proxies for income).[26] Then, to examine the presence of an income effect from mining booms in our global study, we utilize additional variables from the IPUMS microdata. Although income data is absent for many countries in the IPUMS sample, we can utilize the censuses with available income data (11 out of 73 countries) for our 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.[27] 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 4 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 examines the income changes within the city cores (<60 km of city centroids), while Panels B examines 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 16.1% significant increase in the average total income of local workers living in the city core areas. Identifying a positive income effect in city core areas is crucial as it supports a key assumption of the consumption city hypothesis: a significant 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 3), these results indicates that mining booms not only lead to expansions and income growth in the mining sector itself but also raise the incomes and

[26]We briefly review the related literature on local income effects here. 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.

[27]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.

employment in other sectors. Comparing Panel A (core) with Panel B (periphery), we find that the 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.

Table 4: 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						
$\Delta \log Price$	0.161***	0.112***	0.076**	0.134***	0.139***	0.169***
	(0.019)	(0.027)	(0.030)	(0.018)	(0.019)	(0.019)
N	520	520	505	520	512	520
Adj. R^2	0.957	0.914	0.827	0.960	0.885	0.916
Panel B. Global Sample, City Ring Zone = 60 - 120 km						
$\Delta \log Price$	0.220***	0.173***	0.108***	0.193***	0.199***	0.217***
	(0.020)	(0.024)	(0.026)	(0.015)	(0.017)	(0.015)
N	463	463	461	463	460	463
Adj. R^2	0.951	0.919	0.869	0.959	0.913	0.940

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 employment share and income changes, we examine how the characteristics of the workers change in response to mining booms. In particular, we focus on the average years of schooling of the labor force. Table 5 reports the results of this analysis. Again, Panel A reports the effect in the city core areas, whereas Panel B reports the effect in the periphery areas. In Column (1) where we use the entire labor force sample, we find a significantly positive effect in both the city core and periphery areas, suggesting that a 100% increase in mineral prices increases the average years of schooling by 0.27-0.29 years. This result reflects two effects: first, a compositional effect, in the sense that the inflow and outflow of people with different skills change the average skill level; and second, a human capital accumulation effect, in the sense that higher resource rents could allow parents to invest more in their children's education or allow local governments to build more schools and provide more educational services. In our context, both effects could be present. Comparing the coefficients from Column (2) to Column (6), we find large and positive estimates on the average years of schooling, in both manufacturing and low-skilled services. This suggests that relatively higher-skilled workers have reallocated to these two sectors. The increase in the average skill level of manufacturing employment also potentially explains the lack of a crowding-out effect, previously discussed in Panel E of Table 3.

Table 5: 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						
$\Delta \log Price$	0.273***	0.048	-0.181***	0.161***	0.057	0.178***
	(0.036)	(0.032)	(0.067)	(0.038)	(0.039)	(0.034)
Sample Mean of the Outcome	0.932	0.740	0.821	0.795	0.550	0.735
N	2,432	2,432	2,432	2,432	2,432	2,432
Adj. R^2	0.571	0.442	0.396	0.405	0.619	0.528
Panel B. Global Sample, City Ring Zone = 60 - 120 km						
$\Delta \log Price$	0.285***	0.095***	-0.010	0.204***	-0.021	0.222***
	(0.039)	(0.030)	(0.061)	(0.043)	(0.046)	(0.034)
Sample Mean of the Outcome	0.912	0.723	0.801	0.776	0.549	0.715
N	2,401	2,401	2,401	2,401	2,401	2,401
Adj. R^2	0.598	0.523	0.343	0.433	0.625	0.569

Notes: In Panel A, the dependent variables are calculated within the 60-km city buffer zone. In Panel B, 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.

To summarize our findings on the mechanisms behind resource-led structural transformation, mineral price booms lead to increases in local residual income. Such increases occur for workers in almost every sector including workers living in the city core areas. These facts suggest that the structural transformation process observed in Section 4.1 is likely driven by a local income effect. The educational improvement overall, and especially in manufacturing, indicates a potentially positive impact of mining booms. This also offers insights into why mining booms do not lead to a crowding-out effect on manufacturing activities.

5 The Effect of Mineral Price Changes on Local Population

In Section 4, we have found that mineral price shocks lead to significant changes in local employment shares across sectors, highlighting its broad effect on structural transformation. This leads us to a related question: do mineral price surges also drive urbanization, a process often assumed to be synonymous with structural transformation? Similar as before, we approach this macro-development question using a microdata approach, identifying the causal impact of exogenous mineral price shocks on the local city population. We start by estimating the global average effect in Subsection 5.1. Upon establishing a positive relationship, in Subsection 5.2, we explore the heterogeneous effects across the country groups. Finally, in Subsection 5.3, we discuss whether the observed population increase can be attributed to migration.

5.1 The Global Effect

Table 6: The Effect of Price Shocks on Local Population: Global Analysis

	(1)	(2)	(3)	(4)	(5)	(6)
	Outcome: $\Delta \log$ 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
$\Delta \log Price$	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. Standard errors in parentheses are clustered at the city level. ***, **, * denote statistical significance at the 1%, 5%, 10% levels, respectively.

Table 6 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 (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, and Column (6) examines the 30-120 km ring zones.

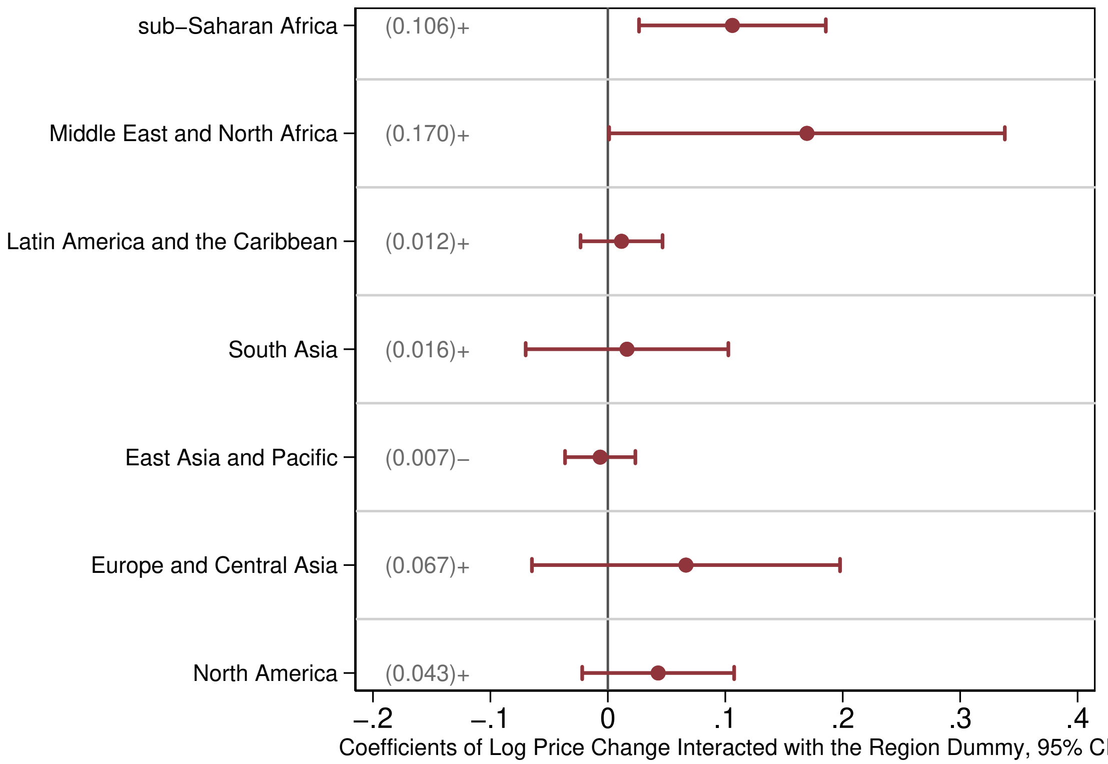
Across most specifications, we find that mining booms are significantly associated with city population growth. Consider Column (1) as an example, the estimated impact suggests a 100% increase in mineral prices from mines within 60 km of a city center leads to a 3.1% increase in population within 10 km of the city center. 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), 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.

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. The population increases could be either driven by the in-migration of the population from elsewhere or driven by natural increases in local areas. We further explore the mechanisms behind this result in Section 5.3. As a preview of our conclusion, we do not find substantial evidence for migration response to mineral price shocks. Comparing the estimates in Column (2) with those in Column (3), and Column (5) with Column (6) in Table 6, we see that the coefficients are of similar magnitudes. This indicates that mineral price changes from mines located within a specific distance from city centers have similar impacts in both the city core and peripheral areas. There are two interpretations. One potential scenario is that mining booms induce migration inflows to the broader local areas rather than specifically to the city core areas. Another possibility is that mining booms may result in similar natural increase rates in both core and peripheral areas. In either case, we cannot conclude that mining booms directly cause urbanization. If they did, we would expect to observe a significantly higher population growth within the city core areas compared to the periphery.

5.2 Heterogeneous Effects By Country Group

Having presented global estimates, we now investigate the heterogeneous impacts of mineral price shocks on urban population across different continents. The empirical specification follows equation (2), where the outcome variable is the changes in city population.

Figure 2: The Effect of Price Shocks on Local Population: 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 2 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 6). There are two main findings. First, the effect of mineral price shocks on urban population growth is significant only in North African and SSA cities, coinciding with 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. 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 of mining booms on urban population growth in other continents, including Latin America and the Caribbean, South Asia, East Asia, Europe and Central Asia, and North America. Similar results hold using an alternative larger city buffer zone—specifically, 30 km—to calculate the urban population, as shown in Figure A7. To summarize, results in this subsection suggest that mineral price shocks of nearby mines lead to significant increases in the population of nearby cities, and the impact is the largest for African cities. In Section 6, we delve deeper into understanding why African cities exhibit these distinct patterns.

5.3 Evidence on Migration Response to Mineral Price Shocks

As shown in Table 6, mineral price booms induce city population growth. How significant are migration inflows as a driving factor behind such changes? To answer this question, we further exploit the migration information in IPUMS.[28] We use country-years for which migration information is available 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:

$$\log Flow_{o,d,t} = \beta_0 + \beta_1 \Delta \log Price_{o,t} + \beta_2 \Delta \log Price_{d,t} + \lambda_{o,d} + \eta_t + \epsilon_{o,d,t}, \tag{3}$$

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, $\Delta \log Price_{o,t}$ ($\Delta \log Price_{d,t}$) is the average log price change of minerals extracted from mines located at origin o (destination d) from $t-1$ to t. We also control for origin-by-destination fixed effects

[28] Among all the 265 country-years in our census sample, 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.

and survey year fixed effects.

Table 7: The Effect of Price Shocks on Migration Flows: Gravity Equation

	(1)	(2)	(3)	(4)
	Outcome: log **Migration Flow from O to D**			
	Panel A. SSA			
	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		
N	1,021	50	162	
Adj. R^2	0.955	0.990	0.988	
	Panel B. Latin America and the Caribbean			
	Brazil	Dominican	Ecuador	Guatemala
$\Delta \log Price$ in Origin	-0.026	0.418	-0.109	-0.028
	(0.074)	(2.104)	(0.254)	(0.187)
$\Delta \log Price$ in Destination	-0.031	-3.736***	-0.294	-0.082
	(0.066)	(1.080)	(0.228)	(0.179)
FE		Year, O×D		
N	1,575	142	351	609
Adj. R^2	0.970	0.976	0.977	0.942
	Panel C. Asia			**Panel D. US**
	Indonesia	Malaysia	Vietnam	
$\Delta \log Price$ in Origin	-0.250**	-0.863**	0.893**	-0.241***
	(0.114)	(0.314)	(0.407)	(0.068)
$\Delta \log Price$ in Destination	-0.109	-0.178	-0.163	0.138**
	(0.102)	(0.177)	(0.234)	(0.057)
FE		Year, O×D		
N	3,194	126	588	5,803
Adj. R^2	0.901	0.975	0.853	0.976

Notes: This table reports the regression coefficients of equation 3. In Panel A, the outcome is the log migration flow in the previous one year. In Panels B-D, the outcome is the log migration flow in the previous five years. 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 7 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 origins tend to retain individuals in those areas in Kenya and Mozambique, but the estimate is insignificant in Botswana. Concurrently, positive price shocks in the destination areas induce migration inflows in all three SSA countries."

On the contrary, we observe insignificant effects or sometimes even opposite effects when using the sample of cities from Brazil, the Dominican Republic, Ecuador, Guatemala, Indonesia, Malaysia, and Vietnam (Panels B-D in Table 7, which use migration flows within the 5 years prior to the census as the outcome variable).[29] A plausible explanation for the disparity is that mineral price shocks exert a substantially more significant influence on individuals' migration decisions in Sub-Saharan African (SSA) countries compared to other regions. This finding can also elucidate the patterns illustrated in Figure 2, where we show that the population of African cities is particularly responsive to mineral price shocks.

Taken together, the results in Sections 4 and 5 offer insights into whether resource rents drive urbanization and structural transformation. On one hand, mineral price shocks significantly contribute to labor reallocation from agriculture to the low-skilled service sector at the local level, explaining a substantial share of observed employment share changes by sector. The mechanism aligns with an income effect. On the other hand, mineral price shocks account for relatively a smaller fraction of observed changes in city populations. For most countries in the IPUMS sample, individuals do not seem to migrate significantly in response to mineral price changes. Hence, based on micro-level evidence using cities as the units of the analysis, we conclude that resource rents induced by mining booms could drive structural transformation at the national level, but they likely do not spur large-scale urbanization. Noteably, African cities exhibit exceptionally high sensitivities to mineral price shocks—a pattern that we further investiagte in the next section.

6 The Uniqueness of Africa

So far, we have observed that African countries demonstrate distinct patterns in response to mineral price shocks across various outcomes. In this subsection, we begin by presenting the summary statistics of key economic variables for the countries across the seven regions in our data sample. Then, after noting some distinct characteristics of SSA countries, we empirically estimate which of these country characteristics plays the most important 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 inquiry regarding Africa's uniqueness. Table A14 presents the descriptive statistics. First, 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

[29] Except for the U.S., where the signs on both coefficients are expected.

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. Fifth, 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. Lastly, African city sizes are on average much smaller than the rest of the world. In summary, we find significant differences between African countries and the rest of the world across various development indicators, ranging from agricultural productivity, human capital, governance, conflict risks, democracy, and urbanization stage.

We then investigate whether and which of these country characteristics might help elucidate Africa's unique patterns of urbanization and structural transformation in response to mineral price shocks. Our empirical strategy is the following:

$$\begin{aligned}\Delta Y_{i,t} = \beta_0 + \beta_1 \Delta \log Price^R_{it} + \beta_2 \Delta \log Price^R_{it} \times \mathbb{1}(Cnty_{i,c} \in Africa) + \\ \beta_3 \Delta \log Price^R_{it} \times X_{i,c} + \alpha Y_{i,t0} + \gamma \log NumMines^R_i + \delta_m + \lambda_c + \eta_{gt} + \epsilon_{i,t},\end{aligned} \tag{4}$$

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 or city 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 characteristics on price elasticity. Ultimately, we are interested in whether the inclusion of the interaction term $\Delta \log Price^R_{it} \times X_{i,c}$ impacts the coefficient on the Africa-sepcific interaction term $\Delta \log Price^R_{it} \times \mathbb{1}(Cnty_{i,c} \in Africa)$.

Table 8 reports the estimation results. Country characteristics are initially omitted in the regressions in Column (1). They are subsequently added one by one from Column (2) to Column (10). Panel A and Panel B report the effects of 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 A15 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 use 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. This indicates 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)-(10) in Table 8, we investigate which city (or country) characteristics interacted with prices could explain the distinct responses in African cities. In Panel A, we focus on the city population as the outcome. Three results stand out: First, across all nine country (or city) characteristics, only the initial population size of the city, the share of natural resource exports in GDP, and agricultural productivity interact significantly with mineral prices. 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). Intuitively, farmers living in low-agricultural-productivity countries face lower opportunity costs to transition out of agriculture (Henderson and Turner, 2020; Lin et al., 2024). Third, accounting for the share of natural resource exports in GDP demonstrates the most significant explanatory power for the exceptional responsiveness of North African cities: 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 a 66% decrease. With a higher share of natural resource exports in GDP, resource rents lead to faster structural transformation through a stronger income effect. In comparison, controlling for 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, except for initial population size (Column 2), all country characteristics interact positively and significantly with mineral prices. This implies that in the presence of mineral price booms, cities in countries characterized higher levels of resource reliance, agricultural productivity, education, GDP per capita, and institutional quality experience a lesser decrease in their agricultural employment share.

Second, the above measures—including resource reliance, agricultural productivity, GDP per capita, and rule of law—all contribute to explaining SSA cities' exceptional responsiveness in terms of industrial structure. The most significant drop occur in Columns (3) (natural resource export) and (4) (agricultural productivity), decreasing from -0.046 (Column 1) to -0.006 (Column 3) or -0.026 (Column 4). This broadly aligns with the results in Panel A. Taken together, Panels A and B of Table 8 indicate that high resource reliance and low agricultural productivity are the two most influential factors determining Africa's exceptional responsiveness to mineral price shocks in terms of agricultural employment share and population changes.

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

	(1) Baseline	(2) Initial Population Size, 1975 (in log)	(3) Natural Resource Exports % of GDP	(4) Agriculture Yield (in log)	(5) Years of Schooling	(6) GDP Per Capita (in log)	(7) Rule of Law	(8) Control of Corruption	(9) Conflict	(10) Democracy
Panel A. Outcome: $\Delta \log$ Population										
$\Delta \log Price \times$ North Africa	0.161*	0.190**	0.054	0.157*	0.190**	0.157*	0.163*	0.163*	0.176*	0.161*
	(0.086)	(0.090)	(0.037)	(0.087)	(0.084)	(0.087)	(0.086)	(0.086)	(0.093)	(0.086)
$\Delta \log Price \times$ Sub-Saharan Africa	0.096**	0.062	0.080	0.050	0.091*	0.086*	0.076*	0.074*	0.099**	0.095**
	(0.043)	(0.039)	(0.057)	(0.041)	(0.049)	(0.045)	(0.040)	(0.040)	(0.043)	(0.043)
$\Delta \log Price$	0.008	0.108***	0.007	0.313***	-0.007	0.016	0.010	0.010	0.008	0.008
	(0.012)	(0.037)	(0.012)	(0.105)	(0.017)	(0.042)	(0.012)	(0.012)	(0.012)	(0.012)
$\Delta \log Price \times$ Characteristic		-0.025***	0.005***	-0.038***	0.003	-0.001	-0.003	-0.007	-0.004	0.000
		(0.008)	(0.001)	(0.013)	(0.002)	(0.005)	(0.006)	(0.006)	(0.007)	(0.001)
N	3,195	3,195	2,715	3,168	3,000	3,114	3,153	3,153	3,195	3,186
Adj. R^2	0.581	0.593	0.579	0.581	0.597	0.581	0.580	0.580	0.581	0.581
Panel B. Outcome: Δ Agricultural Emp. Share										
$\Delta \log Price \times$ Sub-Saharan Africa	-0.046**	-0.043**	-0.006	-0.026	-0.039*	-0.029	-0.032	-0.036*	-0.050**	-0.037*
	(0.021)	(0.021)	(0.023)	(0.022)	(0.021)	(0.021)	(0.020)	(0.020)	(0.021)	(0.021)
$\Delta \log Price$	-0.022***	-0.028***	-0.025***	-0.210***	-0.049***	-0.113***	-0.028***	-0.026***	-0.024***	-0.038***
	(0.003)	(0.010)	(0.003)	(0.046)	(0.006)	(0.020)	(0.003)	(0.003)	(0.003)	(0.006)
$\Delta \log Price \times$ Characteristic		0.001	0.005***	0.023***	0.004***	0.0102***	0.024***	0.019***	0.011**	0.003***
		(0.002)	(0.002)	(0.006)	(0.001)	(0.002)	(0.002)	(0.002)	(0.005)	(0.001)
N	2,484	2,484	2,442	2,484	2,484	2,464	2,478	2,478	2,484	2,484
Adj. R^2	0.260	0.260	0.261	0.262	0.264	0.265	0.274	0.270	0.260	0.268

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, mining, high-skilled services, and low-skilled services within the corresponding city buffer zone. In Panel B, the Middle East and North Africa region is excluded due to insufficient observations. Standard errors in parentheses are clustered at the city level. ***, **, * denote statistical significance at the 1%, 5%, 10% levels, respectively.

7 Conclusion

Both urbanization and structural transformation are crucial topics in economic development and growth. While, historically, urbanization has been accompanied by industrialization in developed nations, many developing countries have recently undergone rapid urbanization with minimum levels of industrialization. This paper investigates the role of mineral resource rents in driving this diverging pattern of urbanization and structural transformation, leveraging 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 integrating several spatially granular data sets.

Overall, there are four main findings. First, we show that mining booms in nearby areas promote structural transformation out of agriculture and toward low-skilled services in the cities. The effect is more pronounced in SSA cities. Using cities' 60-km buffer zones, the mining booms between 1975 and 2015 contributed to 10.6% of the increase in the low-skilled services employment share on a global average and 75.6% of the increase in the low-skilled services employment share in SSA cities alone. The mechanism is consistent with an income-effect-driven structural transformation. Second, 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. 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. Fourth, high resource reliance and low agricultural productivity emerge as the two most significant factors explaining Africa's exceptional sensitivity to mineral price shocks in terms of labor reallocation.

As the global search for critical minerals continues, it offers potential economic opportunities for mineral-rich countries. Our results show that mining booms facilitate employment growth as well as labor reallocation from agriculture to the service sector in the cities surrounded by mines. Should the prices of natural resources continue to surge in the future, our results imply that resource-rich developing countries may follow structural transformation trajectories that diverge significantly from the historical paths observed for today's developed countries. Moreover, we show that such a process does not necessarily crowd out manufacturing activities. While the adverse effects of mining booms, including their impact 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) deserve close scrutiny, it is crucial to promote policies that support the sustainable development of mineral resources in developing countries.

Our findings prompt three further areas of inquiry. First, while our results align with the consumption city hypothesis in a qualitative sense, the impact of mineral prices on local city population is insufficient to account for the differences in the population growth rates between resource-booming cities and cities with mineral resources but no booms. This indicates that other factors beyond the scope of our study also significantly influence the distinct urbanization 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, with low agricultural productivity and high resource reliance playing crucial roles. Yet, there remains a considerable gap in our understanding of African cities' distinct responses, unexplained by these factors alone. 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 are still to be determined, highlighting the need for future research that use more detailed microdata to further explore these mechanisms. We view all these areas as fruitful avenues for future research.

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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 249 rounds of population censuses from 73 countries spanning the years 1970 to 2017. Table A4 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 six industry categories: agriculture, mining, 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 gather other sources of spatial data to control for city-specific location characteristics, including distances to the nearest ports from the World Port Index, terrain ruggedness index and average slope within a 60-km city buffer zone from Nunn and Puga (2012), elevation (median altitude) within a 60-km city buffer zone from FAO-GAEZ database, longitude and latitude of each city. 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.[30] 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

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

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 (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 A8.

The different panels report different outcomes. 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, Panels A, B, E, F). 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,[31] 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

[31] For example, in Column (2) of Table A8, 3,209 / 4,740 = 67.7% of city-years in Panel A (regressions on population) have positive price changes.

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 A9, the coefficients of the two interactions between price change and dummies in capital cities are very close, suggesting that mineral 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.[32] 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.[33] 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.[34]

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 A10, A11 and A12 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 A10; Panels A-D in Tables A11 and A12). Second, we show that our results are robust to country-specific time trends by adding country×period fixed effects (Panel E in Table A10; Panel F in Tables A11 and

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

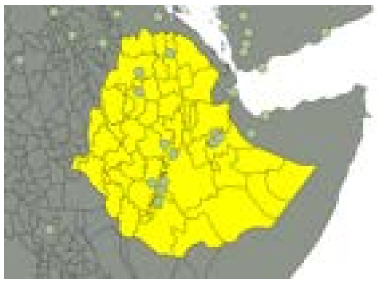
[33] We define the "opening" year as the year when each mine was first mentioned.

[34] 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).

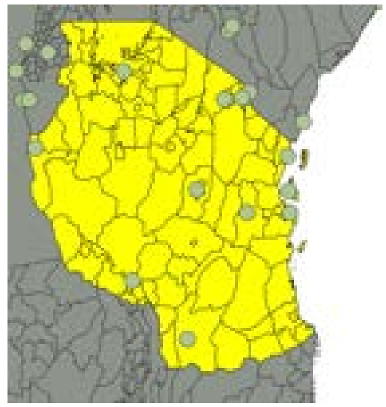
A12). Third, we consider spatial correlations between cities and estimate standard errors following the approach proposed by Conley (1999) (Panel D in Table A10; Panel E in Tables A11 and A12). Fourth, because the lengths of the census periods vary, we weight each city-period unit by period length (Panel F in Table A10; Panel G in Tables A11 and A12). 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. Fifth, we show that our results remain unchanged after excluding commodity fixed effects (Panel G in Table A10; Panel H in Tables A11 and A12). Sixth, we check that city-specific location characteristics don't change our results. We control for distances to the nearest ports, terrain ruggedness index, average slope, and elevation (median altitude) within a 60-km city buffer zone, longitude and latitude of each city (Panel H in Table A10; Panel I in Tables A11 and A12). Finally, we interact the mineral price changes with the number of mines. We find that the estimates on mineral price changes don't change too much (Panel I in Table A10; Panel J in Tables A11 and A12). In short, we find similar results under all of these robustness checks.

A.3 Supplemental Tables and Figures

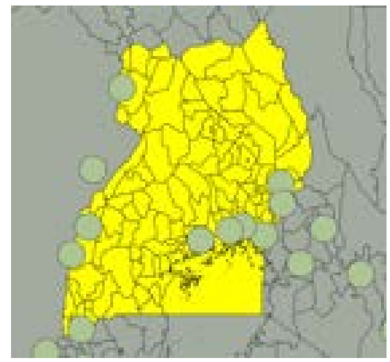
Figure A1: Illustration of City Buffer Zones (30 Km) and Administrative Boundaries



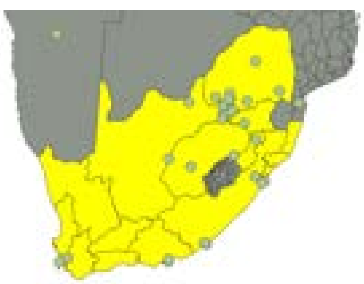
(a) Ethiopia



(b) Tanzania



(c) Uganda



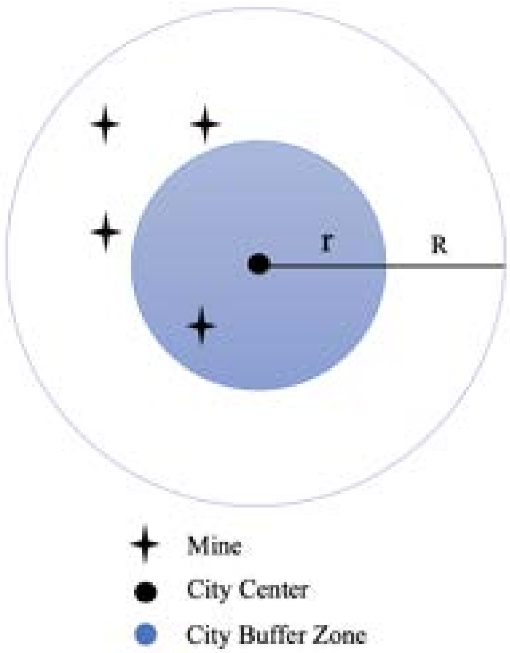
(d) South Africa

(e) Brazil

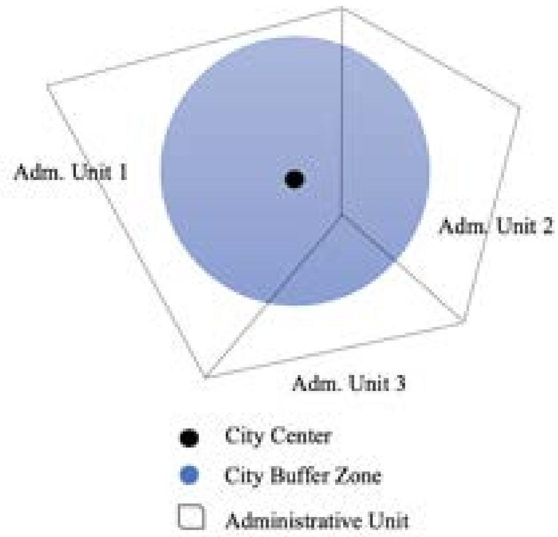
(f) Indonesia

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

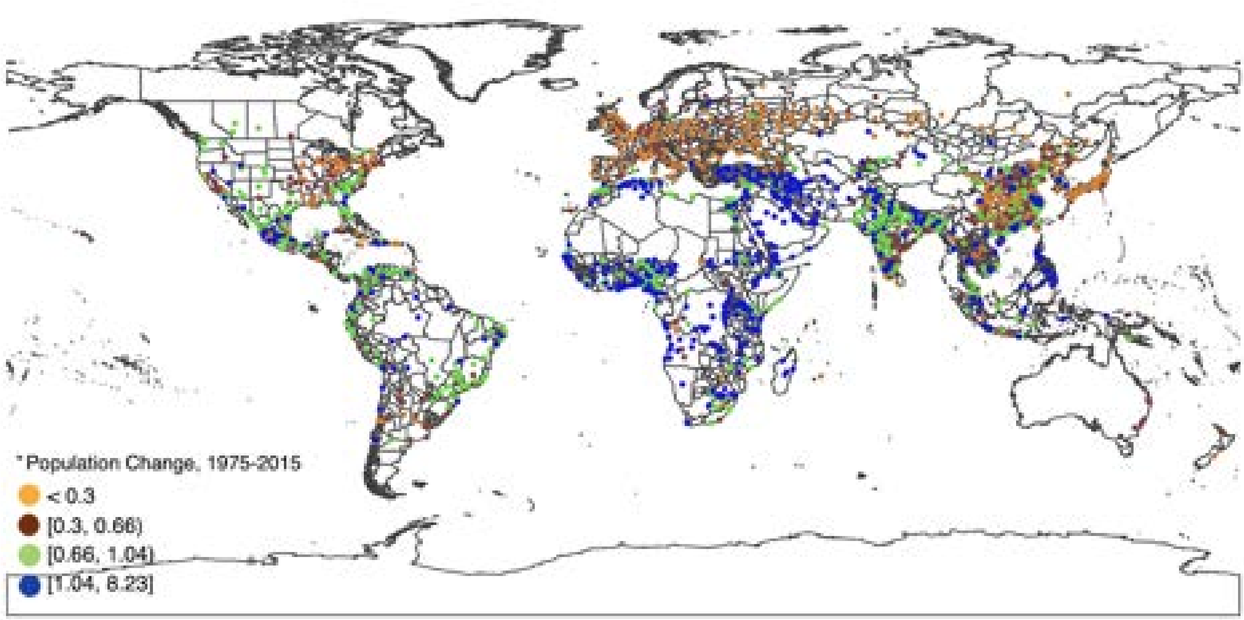
Notes: Panel A shows how to map mining sites with cities. Panel B shows how to calculate employment by industry within city buffer zones.

Table A1: Population Distribution of The World, By Rural/Urban Area of Residence and Size Class of Urban Settlement, 1970 and 2015

Area of residence and size class of urban settlement (number of inhabitants)	#cities	Population (millions) 1970	2015	2015-1970	Percentage of Total Pop. 1970	2015	2015-1970
Total		3701	7383	3682	100.00	100.00	0.00
Urban		1354	3981	2627	36.58	53.92	17.34
Cities with a population of over 300K in 2018	1860	624	2470	1846	16.86	33.46	16.59
Cities with a population of over 300K in 2018 and a population of over 50K in 1970	1483	761	2127	1366	20.56	28.81	8.25
Cities with a population of over 300K in 2018 and a population of over 100K in 1970	1199	739	1980	1241	19.97	26.82	6.85
Cities with a population of over 300K in 2018 and a population of over 200K in 1970	794	681	1717	1036	18.40	23.26	4.86
Cities excluding those with a population of over 300K in 2018		730	1511	781	19.72	20.47	0.74
Rural		2347	3402	1055	63.42	46.08	-17.34

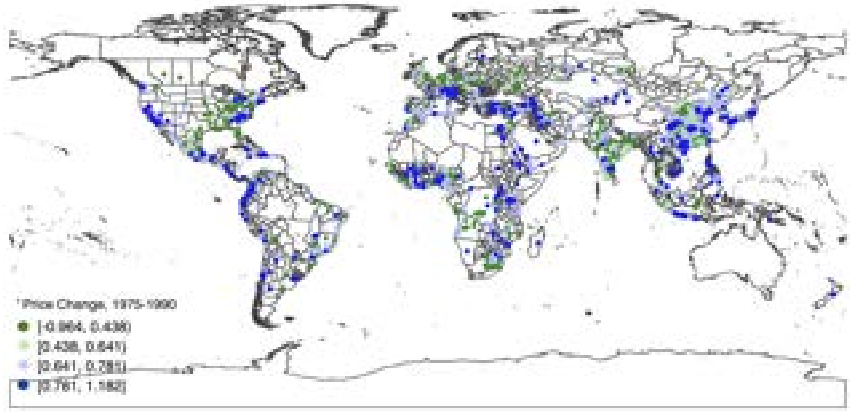
Notes: Calculated by authors. All the data are from World Urban Prospects (2018).

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

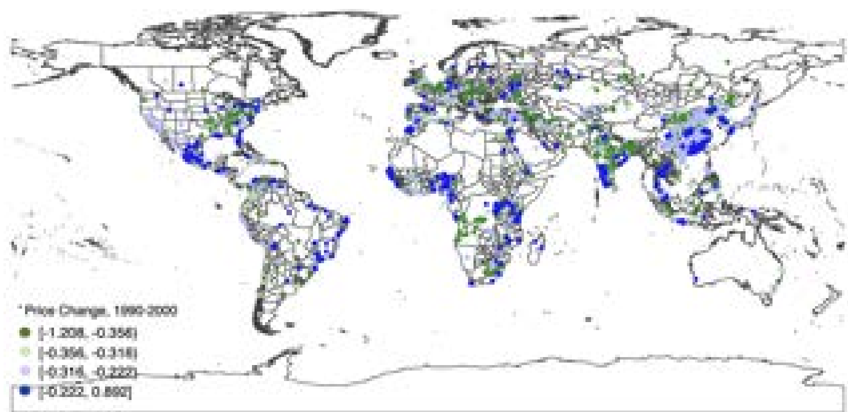


Notes: Figure A3 plots the location of cities globally ($N = 2{,}041$), and their respective population changes from 1975 to 2015. Population change is calculated by the difference in log population density within a radius of 10 km from a city centroid. Data source: GHSL population raster and WUP 2018.

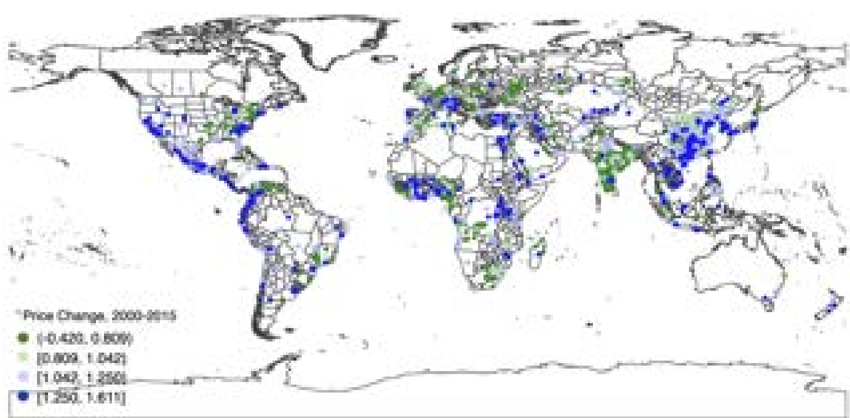
Figure A4: Spatial Distribution of Mineral Price Changes at the City Level



(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

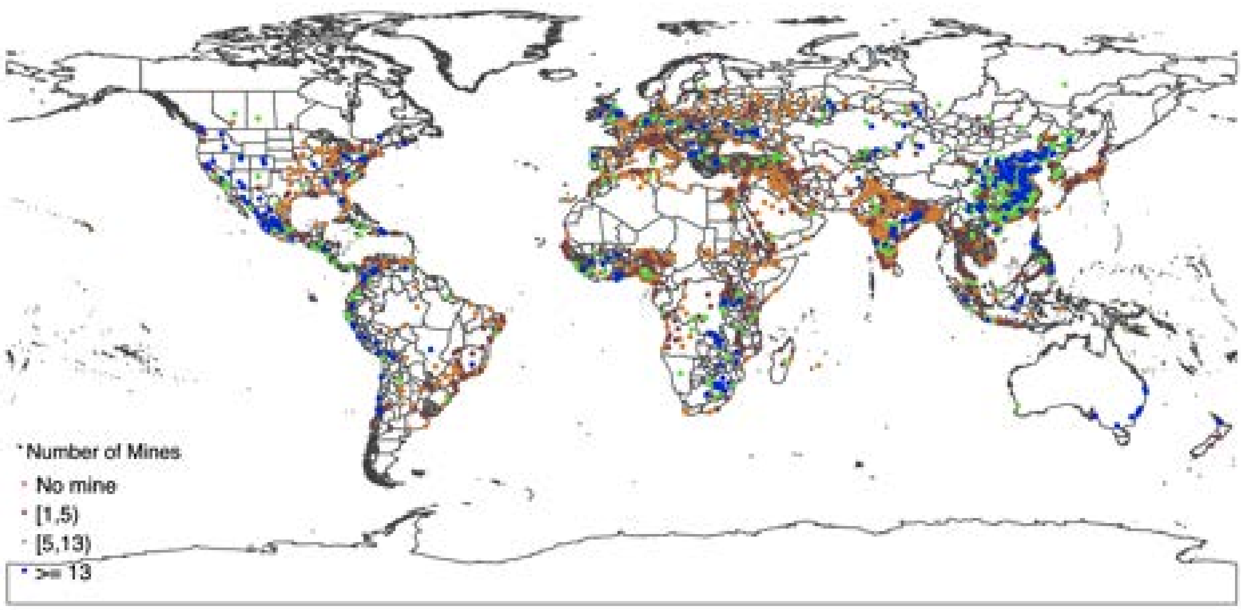
Notes: This figure plots the spatial distribution of mineral price changes experienced by cities globally ($N = 2{,}041$). Mineral price change is computed by taking the simple average of the log price changes of the primary minerals extracted from mines located within a radius of 120 km of a city centroid.

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

	Commodity	Price Series Range First Year	Price Series Range Last Year	Number of Mines	Source
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



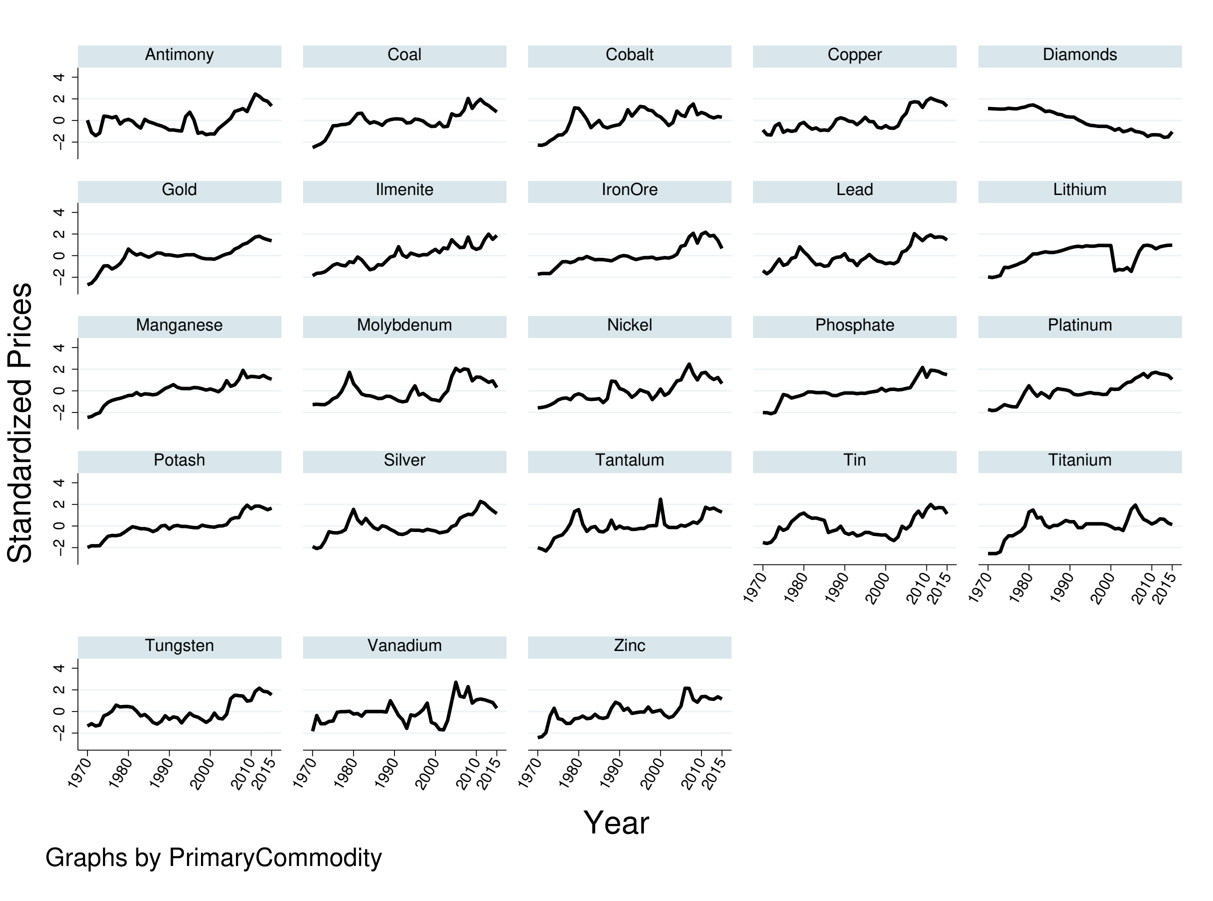
Notes: Figure A5 plots the distribution of cities globally (N = 2,041), and the number of mines located within a 90-km radius of the city centers.

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	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
		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.

Table A5: Summary Statistics: Dependent Variables, Independent Variables, and Control Variables

	N	Mean	Min	Max
Dependent Variables				
Δ log Population in the City, Buffer, 10 km	4,737	0.250	-1.853	4.737
Δ log Population in the City, Ring, 10-120 km	4,740	0.221	-0.850	2.798
Δ log Population in the City, Buffer, 30 km	4,740	0.245	-1.949	2.962
Δ log Population in the City, Ring, 30-120 km	4,740	0.216	-0.847	2.799
Δ log Total Employment Level, Buffer, 60 km	2,536	0.155	-0.712	1.566
Δ log Total Employment Level, Ring, 60 -120 km	2,504	0.139	-0.801	1.000
Δ Agriculture Emp. Share, Buffer, 60 km	2,536	-0.043	-0.555	0.361
Δ Agriculture Emp. Share, Ring, 60 -120 km	2,504	-0.045	-0.412	0.327
Δ Mining Emp. Share, Buffer, 60 km	2,536	-0.002	-0.271	0.258
Δ Mining Emp. Share, Ring, 60 -120 km	2,504	-0.002	-0.271	0.257
Δ Manufacture Emp. Share, Buffer, 60 km	2,536	-0.003	-0.227	0.291
Δ Manufacture Emp. Share, Ring, 60 -120 km	2,504	-0.001	-0.218	0.271
Δ High-skilled Services Emp. Share, Buffer, 60 km	2,536	0.009	-0.075	0.106
Δ High-skilled Services Emp. Share, Ring, 60 -120 km	2,504	0.009	-0.062	0.073
Δ Low-skilled Services Emp. Share, Buffer, 60 km	2,536	0.035	-0.408	0.549
Δ Low-skilled Services Emp. Share, Ring, 60 -120 km	2,504	0.038	-0.363	0.468
Δ Not-recorded Emp. Share, Buffer, 60 km	2,536	0.002	-0.585	0.604
Δ Not-recorded Emp. Share, Ring, 60 -120 km	2,504	0.002	-0.687	0.638
Independent Variables				
Δ log Price, mine buffer, 60 km	3,195	0.442	-1.208	1.895
Δ log Price, mine buffer, 120 km	4,740	0.443	-1.208	1.611
Control Variables				
Distance to the nearest port, km	1,580	272.265	0.004	2,456.408
Slope, percent	1,580	2.748	0.016	15.513
Elevation, meters	1,580	464.384	1.126	3,927.162
Longtitude	1,580	43.338	-123.369	174.776
Latitude	1,580	22.978	-43.533	64.56
Terrain ruggedness index, hundreds of meters	1,580	0.966	0.008	5.415

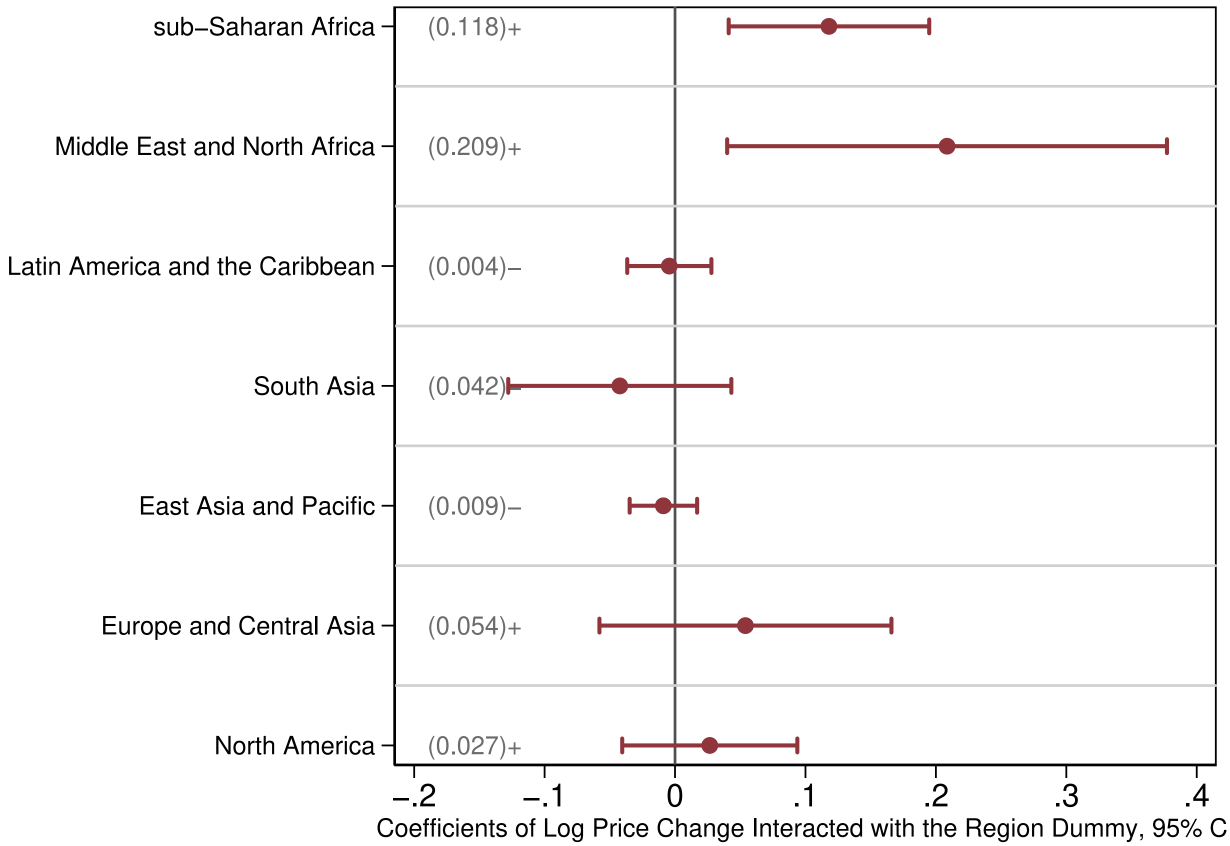
Notes: Calculated by authors.

Table A6: The Effect of Price Shocks on Local Population: Global Analysis, Different City Samples

	(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
Panel A. Cities with a population of over 300K in 2018 and a population of over 50K in 1970						
$\Delta \log Price$	0.042***	0.031**	0.026**	0.040***	0.023	0.024**
	(0.014)	(0.015)	(0.011)	(0.014)	(0.015)	(0.012)
log Initial Population	-0.084***	-0.095***	-0.035***	-0.035***	-0.052***	-0.030***
	(0.020)	(0.014)	(0.007)	(0.010)	(0.008)	(0.007)
FE	Country-group×period, Country, Commodity					
N	2,460	3,771	3,771	2,460	3,771	3,771
Adj. R^2	0.593	0.590	0.572	0.602	0.588	0.557
Panel B. Cities with a population of over 300K in 2018 and a population of over 100K in 1970						
$\Delta \log Price$	0.047***	0.028*	0.020	0.042***	0.016	0.020
	(0.017)	(0.017)	(0.012)	(0.016)	(0.017)	(0.012)
log Initial Population	-0.058***	-0.074***	-0.036***	-0.027***	-0.045***	-0.030***
	(0.011)	(0.011)	(0.008)	(0.010)	(0.009)	(0.008)
FE	Country-group×period, Country, Commodity					
N	2,043	3,096	3,096	2,043	3,096	3,096
Adj. R^2	0.626	0.603	0.566	0.601	0.585	0.553
Panel C. Cities with a population of over 300K in 2018 and a population of over 200K in 1970						
$\Delta \log Price$	0.032*	0.039**	0.023	0.037**	0.023	0.025*
	(0.018)	(0.019)	(0.015)	(0.017)	(0.019)	(0.014)
log Initial Population	-0.033**	-0.054***	-0.026***	0.0052	-0.025**	-0.021***
	(0.013)	(0.013)	(0.009)	(0.011)	(0.011)	(0.008)
FE	Country-group×period, Country, Commodity					
N	1,434	2,142	2,142	1,434	2,142	2,142
Adj. R^2	0.625	0.595	0.657	0.639	0.605	0.640

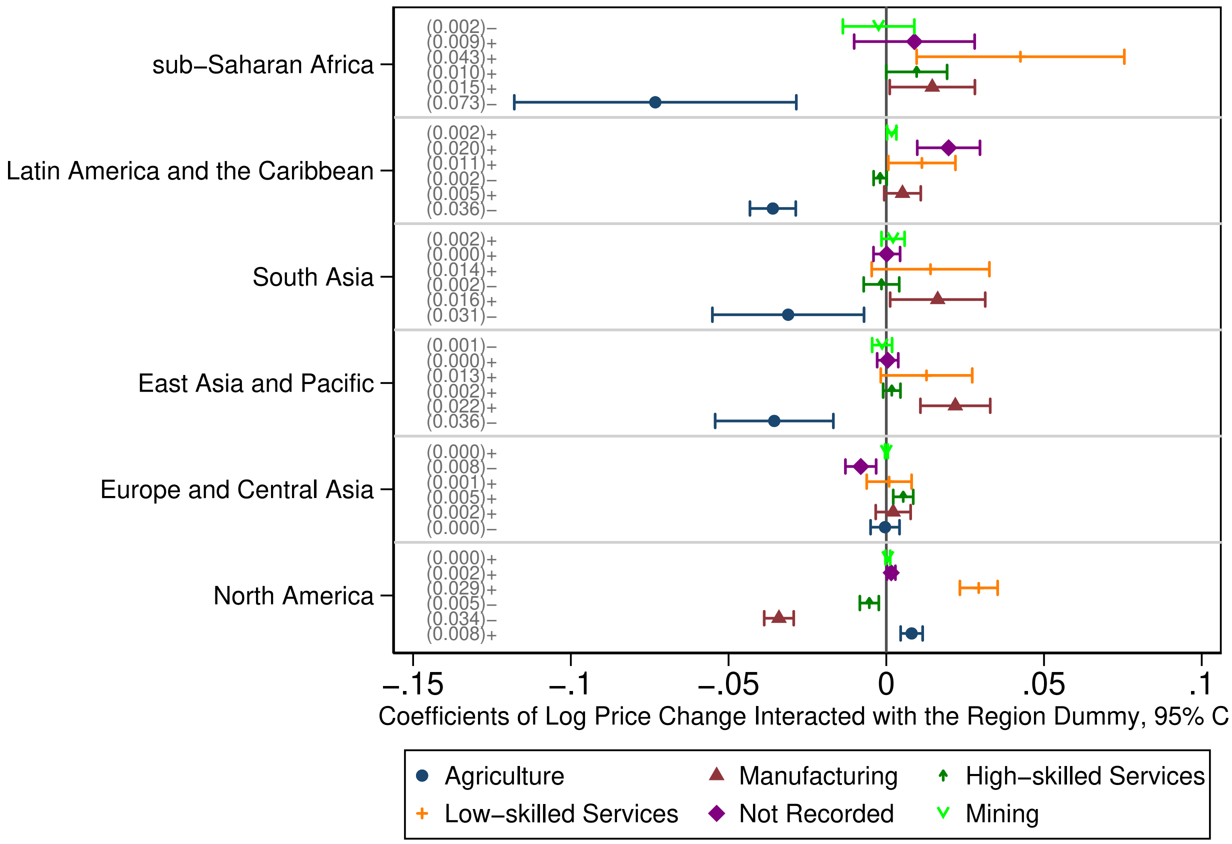
Notes: This table reports the regression coefficients of equation 1. The dependent variables are changes in log population (density) in the corresponding city zones. The independent variable (changes in log price) and the control variable (log number of mines) draw on all mines within the mine buffer zone. The buffer zone used to calculate the log initial population is consistent with the city zone of the dependent variable. Standard errors in parentheses are clustered at the city level. ***, **, * denote statistical significance at the 1%, 5%, 10% levels, respectively.

Figure A7: The Effect of Price Shocks on Local Population: 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$\times$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, mining, high-skilled services, and low-skilled services within the radius of 30 km of a city, log number of mines within the radius of 120 km of a city, country–group $\times$ period fixed effects, country fixed effects, and commodity fixed effects. We exclude the Middle East and North Africa region due to insufficient observations. Standard errors are clustered at the city level.

Table A7: 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
$\Delta \log Price$	0.097*	0.055	0.081***	0.086*	0.038	0.077**
	(0.051)	(0.044)	(0.031)	(0.046)	(0.037)	(0.033)
Initial log Mining Employment Level	-0.361***	-0.368***	-0.282***	-0.318***	-0.369***	-0.280***
	(0.031)	(0.024)	(0.024)	(0.031)	(0.028)	(0.022)
FE	Country-group×period, Country, Commodity					
N	1,607	2,383	2,473	1,635	2,461	2,472
Adj. R^2	0.253	0.251	0.330	0.283	0.280	0.333

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. Standard errors in parentheses are clustered at the city level. ***, **, * denote statistical significance at the 1%, 5%, 10% levels, respectively.

Table A8: The Asymmetric Effects of Mining Booms and Busts

	(1)	(2)
	Panel A. $\Delta\log$ Population	**Panel B. Δ Agriculture Emp. Share**
$\Delta \log Price \times$(Positive=1)	0.060***	-0.026***
	(0.018)	(0.004)
$\Delta \log Price \times$(Negative=1)	-0.026	-0.010
	(0.035)	(0.013)
FE	Country-group×period, Country, Commodity	
N	3,195	2,531
Adj. R^2	0.580	0.259
	Panel C. Δ Manufacturing Emp. Share	**Panel F. Δ High-skilled Serv. Emp. Share**
$\Delta \log Price \times$(Positive=1)	-0.002	0.001
	(0.002)	(0.001)
$\Delta \log Price \times$(Negative=1)	0.016*	-0.001
	(0.009)	(0.002)
FE	Country-group×period, Country, Commodity	
N	2,531	2,531
Adj. R^2	0.247	0.562
	Panel E. Δ Low-skilled Serv. Emp. Share	**Panel F. Δ Not-Recorded Emp. Share**
$\Delta \log Price \times$(Positive=1)	0.016***	0.010***
	(0.004)	(0.003)
$\Delta \log Price \times$(Negative=1)	0.001	-0.004
	(0.009)	(0.006)
FE	Country-group×period, Country, Commodity	
N	2,531	2,531
Adj. R^2	0.548	0.763

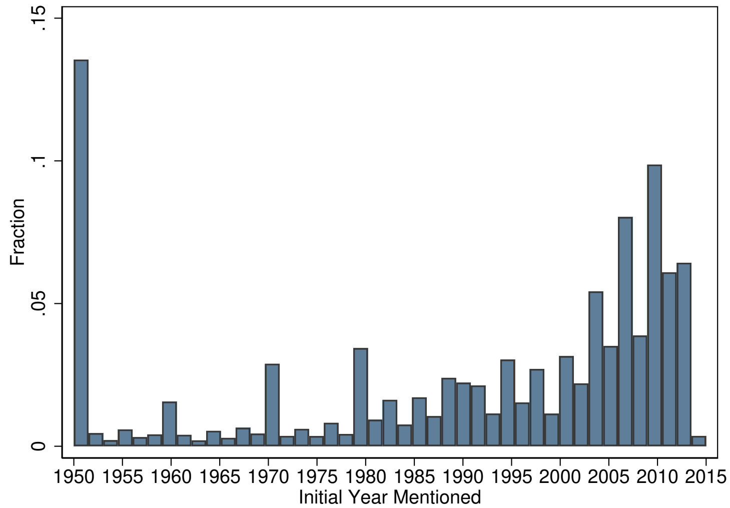
Notes: This table reports the coefficients of equation 1. The dependent variables are changes in log population in the 10-km city buffer zone or employment shares by sector in the 60-km city buffer zone. (Positive=1) is the dummy variable equal 1 if $\Delta \log Price$ is positive; otherwise, 0. (Negative=1) is the dummy variable equal 1 if $\Delta \log Price$ is negative; otherwise, 0. Mine buffer zone is 60 km in Panel A and 120 km in other Panels. 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 Panel B-F controls for the initial employment share of agriculture, manufacturing, mining, high-skilled services, and low-skilled services within the corresponding city buffer zone. Standard errors in parentheses are clustered at the city level. ***, **, * denote statistical significance at the 1%, 5%, 10% levels, respectively.

Table A9: The Effect of Price Shocks on Capital Cities and Non-Capital Cities

	(1)	(2)
	Panel A. $\Delta \log$ Population	**Panel B. Δ Agriculture Emp. Share**
$\Delta \log Price \times$(Capital=1)	0.041*	-0.018***
	(0.022)	(0.005)
$\Delta \log Price \times$(Capital=0)	0.030**	-0.023***
	(0.014)	(0.003)
FE	Country-group×period, Country, Commodity	
N	3,195	2,531
Adj. R^2	0.582	0.259
	Panel C. Δ Manufacturing Emp. Share	**Panel F. Δ High-skilled Serv. Emp. Share**
$\Delta \log Price \times$(Capital=1)	-0.001	0.002
	(0.004)	(0.002)
$\Delta \log Price \times$(Capital=0)	0.002	0.000
	(0.002)	(0.001)
FE	Country-group×period, Country, Commodity	
N	2,531	2,531
Adj. R^2	0.246	0.562
	Panel E. Δ Low-skilled Serv. Emp. Share	**Panel F. Δ Not-Recorded Emp. Share**
$\Delta \log Price \times$(Capital=1)	0.007	0.011*
	(0.006)	(0.006)
$\Delta \log Price \times$(Capital=0)	0.013***	0.007***
	(0.003)	(0.002)
FE	Country-group×period, Country, Commodity	
N	2,531	2,531
Adj. R^2	0.548	0.763

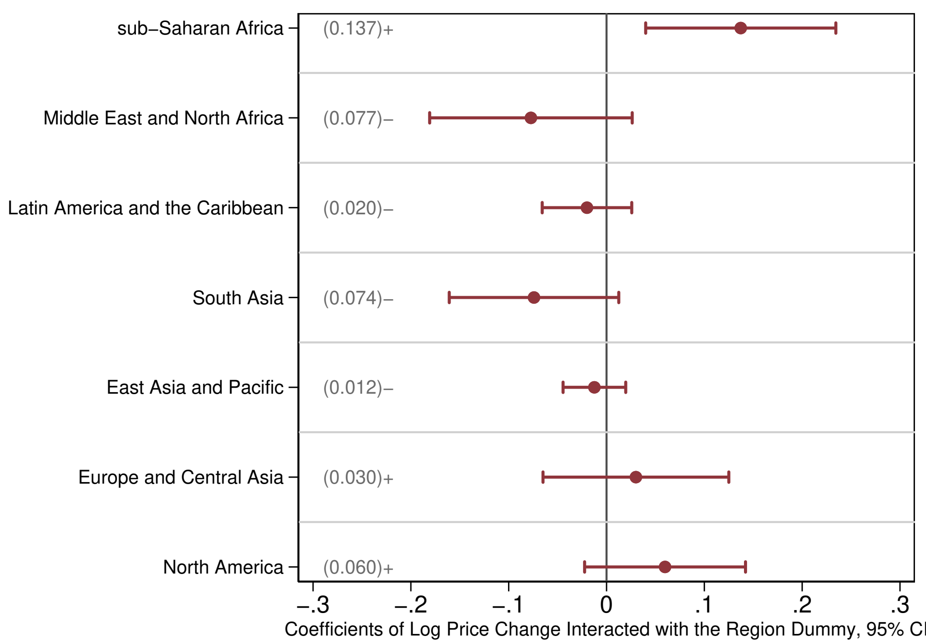
Notes: This table reports the coefficients of equation 1. The dependent variables are changes in log population in the 10-km city buffer zone or employment shares by sector in the 60-km city buffer zone. (Capital = 1) is the dummy variable equal to 1 if the city is the capital of any country; otherwise, 0. (Capital = 0) is the dummy variable equal to 1 if the city is not the capital of any country; otherwise, 0. Mine buffer zone is 60 km in Panel A and 120 km in other Panels. 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 Panel B-F controls for the initial employment share of agriculture, manufacturing, mining, high-skilled services, and low-skilled services within the corresponding city buffer zone. 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 on Local Population Since 1990



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

Table A10: The Effect of Price Shocks on Local Population: Global Analysis

	(1)	(2)	(3)
	$\Delta \log Population$ in the City		
City Zone	Buffer, 10 km		Ring, 10 -120 km
Mine Buffer Zone	60 km	120 km	120 km
Panel A. Cities With and Without Mines			
$\Delta \log Price$	0.014***	0.012*	0.006
	(0.005)	(0.007)	(0.005)
N	6,120	6,120	6,123
Panel B. Only Cities from WHP 2018			
$\Delta \log Price$	0.038**	0.024*	0.028***
	(0.015)	(0.014)	(0.010)
N	2,970	4,356	4,359
Panel C. WHP 2018+African Cities With Pop. Threshold Above 100,000			
$\Delta \log Price$	0.032**	0.032**	0.028***
	(0.013)	(0.012)	(0.010)
N	3,753	5,612	5,616
Panel D. Spatial Correlation			
$\Delta \log Price$	0.031*	0.024	0.023
	(0.018)	(0.021)	(0.017)
N	3,195	4,737	4,740
Panel E. Country×Period FE			
$\Delta \log Price$	0.022*	0.008	0.006
	(0.013)	(0.015)	(0.011)
N	3,066	4,602	4,605
Panel F. Varying Period Length			
$\Delta \log Price$	0.033**	0.020	0.023**
	(0.014)	(0.015)	(0.010)
N	3,195	4,737	4,740
Panel G. Exclude Commodity FE			
$\Delta \log Price$	0.042***	0.030*	0.030**
	(0.016)	(0.016)	(0.014)
N	3,195	4,737	4,740
Panel H. Other Controls			
$\Delta \log Price$	0.027**	0.020	0.023**
	(0.013)	(0.013)	(0.010)
N	3,195	4,737	4,740
Panel I. Interact Price Change with Mine Intensity			
$\Delta \log Price \times \log$ Number of Mines	-0.004	0.008**	0.003
	(0.004)	(0.003)	(0.003)
$\Delta \log Price$	0.030**	0.025*	0.023**
	(0.013)	(0.013)	(0.010)
log Number of Mines	0.008	0.006	0.007*
	(0.006)	(0.005)	(0.004)
N	3,195	4,737	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, and in Panel G, which controls for country–group×period fixed effects and country 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. In Panel H, we additionally control for distances to the nearest ports from the World Port Index, terrain ruggedness index and average slope within a 60-km city buffer zone from Nunn and Puga (2012), elevation (median altitude) within a 60-km city buffer zone from FAO-GAEZ database, longitude and latitude of each city. ***, **, * denote statistical significance at the 1%, 5%, 10% levels, respectively.

Table A11: The Effect of Price Shocks on Local Employment Shares by Sector: City Buffer 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				Buffer, 60 km		
Mine Buffer Zone				120 km		
Panel A. Cities With and Without Mines						
$\Delta \log Price$	-0.019***	0.000	0.002	-0.000	0.008***	0.009***
	(0.003)	(0.000)	(0.002)	(0.001)	(0.003)	(0.002)
N	3,117	3,117	3,117	3,117	3,117	3,117
Panel B. Only Cities from WHP 2018						
$\Delta \log Price$	-0.022***	0.000	0.001	0.000	0.012***	0.008***
	(0.003)	(0.000)	(0.002)	(0.001)	(0.003)	(0.002)
N	2,476	2,476	2,476	2,476	2,476	2,476
Panel C. Cities from WHP 2018 and African Cities With Population Threshold Above 100,000						
$\Delta \log Price$	-0.023***	0.001	0.002	0.000	0.013***	0.007***
	(0.003)	(0.000)	(0.002)	(0.001)	(0.003)	(0.002)
N	2,648	2,648	2,648	2,648	2,648	2,648
Panel D. Exclude Censuses with Only GEOLEV1 Available						
$\Delta \log Price$	-0.027***	0.001	0.001	-0.000	0.015***	0.010***
	(0.003)	(0.000)	(0.002)	(0.001)	(0.003)	(0.002)
N	2,419	2,419	2,419	2,419	2,419	2,419
Panel E. Spatial Correlation						
$\Delta \log Price$	-0.023***	0.001	0.002	0.000	0.013***	0.007***
	(0.004)	(0.001)	(0.003)	(0.001)	(0.003)	(0.002)
N	2,536	2,536	2,536	2,536	2,536	2,536
Panel F. Country×Period FE						
$\Delta \log Price$	-0.025***	0.001	0.003	0.000	0.018***	0.003**
	(0.004)	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)
N	2,511	2,511	2,511	2,511	2,511	2,511
Panel G. Varying Period Length						
$\Delta \log Price$	-0.027***	0.001	0.004**	-0.001	0.014***	0.009***
	(0.003)	(0.001)	(0.002)	(0.001)	(0.003)	(0.003)
N	2,531	2,531	2,531	2,531	2,531	2,531
Panel H. Exclude Commodity FE						
$\Delta \log Price$	-0.022***	-0.000	0.003	0.000	0.012***	0.007***
	(0.003)	(0.000)	(0.002)	(0.001)	(0.003)	(0.002)
N	2,531	2,531	2,531	2,531	2,531	2,531
Panel I. Other Controls						
$\Delta \log Price$	-0.022***	0.001	0.001	0.000	0.013***	0.007***
	(0.003)	(0.000)	(0.002)	(0.001)	(0.003)	(0.002)
N	2,531	2,531	2,531	2,531	2,531	2,531
Panel J. Interact Price Change with Mine Intensity						
$\Delta \log Price \times \log numberofmines$	-0.009***	-0.001*	0.003*	-0.000	0.005***	0.002
	(0.003)	(0.000)	(0.001)	(0.001)	(0.002)	(0.001)
$\Delta \log Price$	-0.025***	0.000	0.002	0.000	0.014***	0.008***
	(0.003)	(0.000)	(0.002)	(0.001)	(0.003)	(0.002)
log number of mines	0.004***	0.002***	-0.002**	-0.000	-0.003**	-0.001
	(0.002)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
N	2,531	2,531	2,531	2,531	2,531	2,531

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, mining, high-skilled services, and low-skilled services 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, and in Panel I, which controls for country–group×period fixed effects and country 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. In Panel J, we additionally control for distances to the nearest ports from the World Port Index, terrain ruggedness index and average slope within a 60-km city buffer zone from Nunn and Puga (2012), elevation (median altitude) within a 60-km city buffer zone from FAO-GAEZ database, longitude and latitude of each city. ***, **, * denote statistical significance at the 1%, 5%, 10% levels, respectively.

Table A12: 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						
$\Delta \log Price$	-0.021***	0.001***	0.004**	-0.000	0.003	0.013***
	(0.003)	(0.000)	(0.002)	(0.000)	(0.002)	(0.002)
N	3,073	3,073	3,073	3,073	3,073	3,073
Panel B. Only Cities from WHP 2018						
$\Delta \log Price$	-0.023***	0.001***	0.004**	0.000	0.006***	0.011***
	(0.003)	(0.000)	(0.002)	(0.000)	(0.002)	(0.002)
N	2,444	2,444	2,444	2,444	2,444	2,444
Panel C. Cities from WHP 2018 and African Cities With Population Threshold Above 100,000						
$\Delta \log Price$	-0.024***	0.001***	0.004**	0.001	0.008***	0.011***
	(0.003)	(0.000)	(0.002)	(0.000)	(0.002)	(0.002)
N	2,616	2,616	2,616	2,616	2,616	2,616
Panel D. Exclude Censuses with Only GEOLEV1 Available						
$\Delta \log Price$	-0.025***	0.001***	0.003*	0.000	0.008***	0.013***
	(0.003)	(0.000)	(0.002)	(0.000)	(0.003)	(0.003)
N	2,415	2,415	2,415	2,415	2,415	2,415
Panel E. Spatial Correlation						
$\Delta \log Price$	-0.024***	0.001***	0.004	0.001	0.007**	0.011***
	(0.005)	(0.001)	(0.00)	(0.001)	(0.003)	(0.003)
N	2,504	2,504	2,504	2,504	2,504	2,504
Panel F. Country×Period FE						
$\Delta \log Price$	-0.024***	0.002***	0.006**	0.001*	0.009***	0.006***
	(0.004)	(0.001)	(0.003)	(0.000)	(0.002)	(0.002)
N	2,476	2,476	2,476	2,476	2,476	2,476
Panel G. Varying Period Length						
$\Delta \log Price$	-0.028***	0.001**	0.007***	-0.001*	0.008***	0.013***
	(0.003)	(0.001)	(0.002)	(0.001)	(0.003)	(0.003)
N	2,499	2,499	2,499	2,499	2,499	2,499
Panel H. Exclude Commodity FE						
$\Delta \log Price$	-0.022***	0.001***	0.003*	0.000	0.007***	0.011***
	(0.003)	(0.000)	(0.002)	(0.000)	(0.002)	(0.002)
N	2,499	2,499	2,499	2,499	2,499	2,499
Panel I. Other Controls						
$\Delta \log Price$	-0.024***	0.001***	0.004**	0.000	0.007***	0.011***
	(0.003)	(0.000)	(0.002)	(0.000)	(0.002)	(0.002)
N	2,499	2,499	2,499	2,499	2,499	2,499
Panel J. Interact Price Change with Mine Intensity						
$\Delta \log Price \times$ log number of mines	-0.012***	0.001	0.003**	-0.000	0.007***	0.001
	(0.002)	(0.000)	(0.001)	(0.000)	(0.002)	(0.001)
$\Delta \log Price$	-0.025***	0.001***	0.004**	0.001	0.008***	0.011***
	(0.003)	(0.000)	(0.002)	(0.000)	(0.002)	(0.002)
log number of mines	0.003**	0.001***	-0.002*	-0.000	-0.002*	-0.001
	(0.002)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
N	2,499	2,499	2,499	2,499	2,499	2,499

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, mining, high-skilled services, and low-skilled services 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, and in Panel I, which controls for country–group×period fixed effects and country 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. In Panel J, we additionally control for distances to the nearest ports from the World Port Index, terrain ruggedness index and average slope within a 60-km city buffer zone from Nunn and Puga (2012), elevation (median altitude) within a 60-km city buffer zone from FAO-GAEZ database, longitude and latitude of each city. ***, **, * denote statistical significance at the 1%, 5%, 10% levels, respectively.

Table A13: 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 A14: 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
Population density, 1975, city buffer = 10 km	104	129	96	44	63	111	51
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 include 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 the 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 A15: The Uniqueness of Africa: The Role of Country Characteristics–Complementary

	(1) Baseline	(2) Initial Population Size, 1975 (in log)	(3) Natural Resource Exports % of GDP	(4) Agriculture Yield (in log)	(5) Years of Schooling	(6) GDP Per Capita (in log)	(7) Rule of Law	(8) Control of Corruption	(9) Conflict	(10) Democracy
Panel A. Outcome: Δ Manufacturing Emp. Share										
$\Delta \log Price \times$ Sub-Saharan Africa	0.012	0.018**	0.020	0.004	0.004	-0.004	0.004	0.005	0.014*	0.005
	(0.007)	(0.008)	(0.014)	(0.008)	(0.008)	(0.009)	(0.007)	(0.008)	(0.008)	(0.008)
$\Delta \log Price$	0.002	-0.021***	-0.000	0.071**	0.030***	0.090***	0.005**	0.004**	0.003	0.014***
	(0.002)	(0.007)	(0.002)	(0.034)	(0.004)	(0.013)	(0.002)	(0.002)	(0.002)	(0.003)
$\Delta \log Price \times$ Characteristic		0.005***	0.003*	-0.009**	-0.004***	-0.010***	-0.013***	-0.013***	-0.006	-0.002***
		(0.002)	(0.002)	(0.004)	(0.000)	(0.001)	(0.002)	(0.002)	(0.006)	(0.000)
N	2,484	2,484	2,442	2,484	2,484	2,464	2,478	2,478	2,484	2,484
Adj. R^2	0.247	0.250	0.247	0.248	0.259	0.259	0.258	0.258	0.247	0.259
Panel B. Outcome: Δ High-skilled Services Emp. Share										
$\Delta \log Price \times$ Sub-Saharan Africa	0.008*	0.009*	-0.017***	0.004	0.007	0.007	0.008	0.008	0.009*	0.008
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$\Delta \log Price$	0.000	-0.002	-0.002*	0.036**	0.003**	0.009**	0.000	0.000	0.000	0.001
	(0.001)	(0.003)	(0.001)	(0.017)	(0.001)	(0.004)	(0.001)	(0.001)	(0.001)	(0.001)
$\Delta \log Price \times$ Characteristic		0.000	0.002***	-0.004**	-0.000**	-0.001**	-0.001	-0.001	-0.002	-0.000
		(0.001)	(0.001)	(0.002)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
N	2,484	2,484	2,442	2,484	2,484	2,464	2,478	2,478	2,484	2,484
Adj. R^2	0.563	0.564	0.572	0.564	0.564	0.568	0.568	0.568	0.563	0.563
Panel C. Outcome: Δ Low-skilled Services Emp. Share										
$\Delta \log Price \times$ Sub-Saharan Africa	0.026*	0.018	-0.002	0.038**	0.031*	0.029*	0.026	0.026*	0.033**	0.024
	(0.016)	(0.016)	(0.018)	(0.017)	(0.017)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
$\Delta \log Price$	0.013***	0.037***	0.020***	-0.103**	-0.006	-0.007	0.013***	0.012***	0.015***	0.016***
	(0.003)	(0.009)	(0.003)	(0.044)	(0.006)	(0.015)	(0.003)	(0.003)	(0.003)	(0.004)
$\Delta \log Price \times$ Characteristic		-0.006***	-0.014***	0.014***	0.003***	0.002	0.000	0.001	-0.017**	-0.001
		(0.002)	(0.004)	(0.005)	(0.001)	(0.002)	(0.002)	(0.002)	(0.007)	(0.000)
N	2,484	2,484	2,442	2,484	2,484	2,464	2,478	2,478	2,484	2,484
Adj. R^2	0.546	0.547	0.555	0.547	0.548	0.542	0.545	0.545	0.547	0.546

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, mining, high-skilled services, and low-skilled services within the corresponding city buffer zone. The Middle East and North Africa region is excluded due to insufficient observations. Standard errors in parentheses are clustered at the city level. ***, **, * denote statistical significance at the 1%, 5%, 10% levels, respectively.