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Mining and Economic Development

Did China's WTO Accession Affect African Local Economic Development?

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Abstract

This paper investigates China's influence on local economic development in 37 African countries between 1997 and 2007. The analysis compares the average changes in economic growth, migration, spatial inequality, and welfare for mineral-rich districts, pre- and post-accession, to the corresponding changes in districts without any mineral endowment. Using this exogenous variation, the paper shows that over 2002–07, mining activities in response to the global commodity price boom increased welfare as measured by spatial Sen Index but were insignificant for local economic growth, migration, and spatial inequality. The findings suggest that policy needs to do more to improve the local benefits of positive external shocks (such as China's World Trade Organization accession): it is not enough to assume, given Africa's high spatial inequality, that local economies will automatically benefit from higher national growth.

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Mining and Economic Development:
Did China's WTO Accession Affect African Local Economic Development?‡

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1. INTRODUCTION

Africa has been achieving much higher rates of growth, with the 'super-cycle' in commodity prices constituting a positive economic shock for much of the region, and especially for those with mineral resources (Andersen et al. 2014; Beny and Cook, 2009). Although there has recently been a sharp drop in world prices, the post-2000 commodity boom has been one of the most powerful since 1945 (see for example Radetzki, 2006; Humphreys, 2013).

The accession of China to the multilateral trading system, under the World Trade Organization (WTO), in December 2001 has been one of the main drivers of the recent commodities price boom, especially over 2002-08 (Erten and Ocampo, 2013). While China has its own mining sector (metals and coal), it is a net importer of most metals (as well as most of the oil and gas that it uses). World metals prices almost tripled over 2001-06, with China accounting for more than 50 per cent of the increased demand (Francis, 2007: 20). China's WTO accession accelerated China's already high economic growth rate, adding further to its appetite for Africa's bauxite, copper, iron ore, nickel, uranium and other minerals (Pigato and Tang, W., 2015).

This leads to an important issue: what has been the economic impact on Africa of the increased demand for metals associated with China's growth surge after its WTO Accession? Much of the policy debate focuses on China's impact on Africa at the *national* level, and specifically the overall economic growth impact.[5] However, success in raising economic growth may not translate into success at the local economic level, and the existing pattern of spatial development is highly uneven in Africa. Mining projects may have few local economic linkages even though they contribute to higher levels of GDP, export earnings, and government revenues. Accordingly, our aim is to evaluate the impact of China's WTO accession – via the channel of world mineral prices – on indicators of local development in Africa, namely: economic growth; migration; spatial inequality; and welfare.

Our paper makes four main contributions. First, it provides fresh empirical evidence on the development of China's WTO accession, as Henderson et al. (2013) notes, there is a shortage of research evidence regarding China's impact on African economies. Second, previous studies examining the impact of accession have been theoretical or simulation-based, mainly due to a lack of data, especially when the study was undertaken only a few years after 2001 (see for example Wang, 2003; Wong, 2003). As we explain in detail later, the present study utilizes novel night lights and spatial mineral data to circumvent this limitation. Third, the spatial dimension of Africa's growth, which is a major determinant of the overall income distribution, and whether growth is 'inclusive' or not, needs more robust evidence given its high policy importance

[5] China impacts Africa's economies through both direct bilateral relations (in trade, finance and investment) and via indirect effects (Henderson et al., 2013). The present paper focuses on the latter category, the impact of which can be much larger than that of direct bilateral relations (Ibid).

(Henderson et al., 2013). Finally, our analysis is not just confined to a few countries nor to a few districts: our coverage is 2339 districts in 37 African countries[6] – thus providing evidence that is more useful for policy than studies with more restricted geographical coverage.

Several reasons motivated our choice of districts as the units of analysis. First, district-level analysis identifies the impacts of WTO Accession in close proximity to the sites where mining deposits are available and mining activities are taking place. This disaggregated analysis helps understand the extent to which mineral resources are locally beneficial. Second, by focusing on districts, we capture the impacts in a much more 'fine-grained' way than taking administrative regions as the unit of analysis (for these regions can be very large in Africa). This gives us a clearer picture of the depth to which an important global event, China's WTO accession, has penetrated (and indicates how future studies of the local impact of large global shocks, whether positive or negative, might be undertaken). Third, the empirical analysis of economic development at the local level has generally been elusive for Africa, and most empirical studies have relied on country-level analysis. Our study fills an important knowledge gap, and one which is central to policy.

As we explain below, to provide meaningful answers to our research question, the paper's empirical strategy uses the difference-in-difference (DID) estimators (similar in spirit to Lu and Yu (2015) and Andersen et al. (2014)) to quantify the causal impacts of WTO accession on local economic development in Africa. Using accession as an exogenous temporal variation, we consider two main periods. The first period (1997–2001) is the pre-accession period. The second period (2002–2007) is the post-accession period before the full-blown effects of the 2008 global financial crisis were felt. Our identification of the treatment effects relies on comparing the average changes in economic development indicators in mineral-rich districts, both pre- and post-accession, to the corresponding changes in districts without mineral endowments.

Our main findings show that China's WTO accession improved local welfare (as measured by lights-based spatial Sen Index) in Africa, but did not lead to more local economic growth, migration opportunities, and or lower spatial inequality. The results were similar when we analyzed the heterogeneous effects of accession on various exogenous variations sources (namely, the scale of mining operations, values of minerals extracted, and the nature of mining activities). The positive effect on welfare was predominant in the districts with large-scale mining operations, low-value minerals, and those that engaged in mining transformation activities. Overall, these results suggest that China's influence on Africa's local economic development was rather limited in the 2002–2007 period. Given that this was a time when China's demand for Africa's commodities was having substantial positive impact on the overall growth rate, as well as raising public revenues (and foreign exchange reserves) this suggests that policy needs to look to improving the impact at the local level.

[6] See Table 8 in Appendix II for a list of countries, and Figure 4 in Appendix I for the spatial distribution of mineral deposits across these countries.

The present study relates to a large body of empirical literature on mining and development in Africa. Addison et al. (2015) found that, overall, mining activities increase district-level inequality and show differential effects on inequality based on such characteristics as minerals values, scale of mining operations, and the nature of mining activities. Moreover, our study echoes the recent debate on natural resources and management in developing countries (see Venables, 2016; Van der Ploeg 2011; Beny and Cook, 2009). We also add to the recent growing literature on the local economic effects of natural resource wealth (e.g. Aragón and Rud, 2013; Caselli and Michaels, 2013; Fafchamps, et al., 2015; and Aragón, et al., 2015; and Chuhan-Pole, et al., 2015); in contrast to earlier cross-country studies on the resource curse (e.g. Sachs and Warner, 1995, 1997, 2001; Gleason, Herbert son and Sega, 1999; Mehlum et al., 2006; Brunnschweiler, 2008; Chambers D, and Guo J, 2009; and Arezki and Van der Ploeg 2011).

Our paper is closest to that of Andersen et al. (2014), who estimated that the increase in average annual real economic growth in sub-Saharan Africa induced by China's accession to WTO was approximately 14.6 percent of total (actual) growth. In contrast to our findings, Bhattacharyya et al. (2015) found that mineral production significantly improved district-level economic development in sub-Saharan Africa between 1992 and 2012. Similarly, Tolonen (2015) combined panel data on industrial mines with DHS household survey data for women aged 15-49 and found that the opening of a new gold mine increases women's income earning opportunities by 41 percent within the service sector and halves infant mortality rate, despite risks of environmental pollution from gold mining. Kotsadam and Tolonen (2013) showed that gold mines increase local female employment in service sectors when a mine opens up, but that the effect dissipates upon the mine's closure.

The remainder of this paper is organized as follows. Section 2 summarizes the key features on the economic implications of China's WTO accession for developing nations. That section also provides an account of China–Africa bilateral and regional trade relations in recent decades. Section 3 describes the data and section 4 presents the empirical model. Section 5 presents the main results, robustness checks, and the results on the heterogeneous effects, before Section 6 calls for further studies of the local economic impact of China on Africa.

2. BACKGROUND

A. Economic implications of China's WTO accession to the developing world

Table 1 shows the patterns of economic growth, income, trade, and resource rents across the income groupings in the developing world, divided into periods before accession (that is, 1991–1995 and 1996–2001) and after accession (2002–2007 and 2008–2013). Except for the Middle East and North Africa (MENA) region, the growth, income, and trade performance of countries in the remaining groups was relatively low before accession. For 1991–1995, sub-Saharan Africa (SSA) experienced an average income growth of -1.73 percent, with per capita income averaging as low as US$2335 and trade-GDP shares surging at 53 percent, below the leading MENA countries. However, a slightly different story emerges when comparing resources (minerals, gas, and oil) rents during 1991–1995: SSA countries dominated GDP shares of mineral rents at 0.84 percent, while MENA countries had larger GDP shares in gas rents (1.96 percent) and oil rents (19.33 percent).

Table 1: China's WTO accession and it's economic and trade implications in the developing world.

Category	GDP growth (%)	GDP per capita, PPP (2011 US$)	Trade (% of GDP)	Mineral rents (% of GDP)	Gas rents (% of GDP)	Oil rents (% of GDP)
1991-1995						
Least developed countries	-0.08	1249	45.44	0.51	0.31	3.10
Low income	-2.10	1024	49.58	1.15	0.00	0.12
Middle East & North Africa	0.53	11303	65.86	0.03	1.96	19.33
Sub-Saharan Africa	-1.73	2335	53.29	0.84	0.15	5.42
1996-2001						
Least developed countries	2.15	1362	55.77	0.24	0.45	4.12
Low income	1.23	1059	51.21	0.39	0.00	0.20
Middle East & North Africa	2.04	12423	62.99	0.03	2.92	16.72
Sub-Saharan Africa	0.77	2365	62.85	0.36	0.31	6.39
2002-2007						
Least developed countries	3.44	1595	58.66	0.82	1.00	11.07
Low income	2.30	1148	62.41	0.96	0.29	1.66
Middle East & North Africa	3.46	14410	80.91	0.12	5.70	26.95
Sub-Saharan Africa	3.53	2699	64.25	1.05	0.88	11.15
2008-2013						
Least developed countries	2.50	1942	62.42	2.19	1.06	11.72
Low income	2.77	1374	65.32	2.84	0.31	1.63
Middle East & North Africa	1.38	16866	88.26	0.44	4.21	27.57
Sub-Saharan Africa	1.68	3151	65.28	2.26	0.67	11.65

Source: Authors' construction using World Development Indicators, World Bank 2014

The period from 1996 to 2001 saw two major patterns in the developing world. The first was positive increase in income growth and modest increases in both per capita income and trade shares with SSA countries experiencing a positive average increase of 0.77 percent in income growth, a mild 1.3 percent average increase in income per capita (from US$ 2335 during 1991–1995 to US$2365 during 1996–2001), and a 9.56 percent increase (from 53.29 percent to 62.85 percent) in trade-GDP shares. The second pattern was a significant decline in mineral rents (to 0.36 percent), a doubling of gas rents (to 0.31 percent), and a modest increase in oil rents (to 6.39 percent). As explained below, income, trade, and resource rents indicators improved considerably after accession, arguably affirming the influence of China's WTO accession on economic and trade outcomes in the developing world and in SSA countries in particular.

The 2002–2007 period showed a remarkable turnaround in the patterns of income, trade, and minerals indicators in the developing world. A unique feature to note during this period is SSA's growth surge, which averaged 3.53 percent. Yet per capita income increasing modestly from an average of US$2365 during 1996–2001 to US$2699, and trade-GDP shares increasing, albeit modestly, from 62.85 percent to 64.25 percent. GDP shares of resource rents show sizeable improvements: mineral rents increased to 1.05 percent from 0.36 percent, gas rents more than doubled from 0.31 percent to 0.88 percent, and oil rents almost doubled to 11.15 percent from 6.39 percent. There is no doubt that these improvements (especially in income, trade, and GDP shares of mineral rents) overlap with the accession in 2001, a fact that has been attributed to 2002–2008 surges in global mineral prices. Arguably, it is not unreasonable to associate the improved economic, trade, and resource rent indicators to the accession during 2002–2007. For-example, Figure 1 in Appendix I shows a sharp rise in mineral commodities prices post-accession, reaffirming the hypothesis that the accession was associated with the improvement in economic, trade, and resource rent indicators across SSA countries during 2002–2007.

The 2008–2013 period shows the patterns after the on-set of the recent global financial crisis. Except for a decline in income growth and GDP shares of gas rents, SSA countries performed remarkably well, on average, in other indicators during the financial crisis of 2009-10 (China pursued a counter-cyclical fiscal policy, and the fiscal expansion further stimulated its demand for Africa's commodities). In fact, per capita income and GDP-trade shares increased during this period. Similarly, GDP shares of mineral and oil rents increased over and above the 2002–2007 shares. The patterns of income, trade, and resource rent indicators during 2008–2013 are certainly interesting in their own way. But, as we previously noted, to avoid the contaminating effects of the financial crisis our analysis is confined over 1997–2007 periods.

B. China–Africa trade relations in perspective

In order to understand the association between China's accession and its impact on African economies, we now turn to the trade relations between China and Africa. We present our discussions in two ways. First, we use data on metals and mineral production to show the average patterns of metals and minerals production across African countries during the 1996–2013 period. Similarly, we present the patterns of metals and minerals imports by China during the same period. We have two aims: (i) to show the general patterns of metals and minerals production from Africa and imports by China, and (ii) to infer the behavior of associations from these patterns. Second, we bring to bear the analysis of average trade flows on several commodities between China and Africa. For a meaningful comparison, we break up this analysis into four successive periods: 1990–1995, 1996–2001, 2002–2007, and 2008–2014. This analysis shows the magnitude of average trade flows between the two trading partners. Our end goal is to empirically document the association between China's WTO accession and its potential impacts on trade flows – and thus economic outcomes – across African countries.

Figures 2a and 2b, in Appendix I, depict the patterns of the main metals (aluminum, copper, iron ore, and steel), minerals (coal, chromite, and manganese), and petroleum production in Africa in the 1996–2012 period. Reported in constant 2000 levels, both figures indicate substantial rises in the production of metals, minerals and petroleum after 2001. Similarly, Figures 3a, 3b, and 3c, also in Appendix I, show that the patterns of Chinese imports for the same commodities during 1996–2013 and distinctively mirror the African production levels.

Table 2: Average product trade flows shares between China and Africa, 1990–2014

Periods	1990-95		1996-2001		2002-2007		2008-2014	
Product	Exports (%)	Imports (%)	Exports (%)	Imports (%)	Exports (%)	Imports (%)	Exports (%)	Imports (%)
Agricultural	17.12	0.65	25.40	0.33	10.35	0.48	6.07	0.57
Chemical	1.62	7.06	2.39	12.33	2.21	7.26	1.37	8.08
Food	29.81	12.97	9.32	8.06	3.23	4.76	3.35	3.17
Fuel	4.00	2.50	31.21	2.00	56.84	1.15	39.43	0.50
Machinery	24.20	20.65	3.18	28.98	1.65	38.53	1.29	46.96
Manufactures	28.01	82.47	10.31	88.19	11.73	91.20	9.12	93.66
Ores and Metals	20.74	1.21	23.36	1.09	17.40	1.22	41.69	1.46
Textiles	15.95	21.85	6.57	15.95	5.02	16.06	2.34	8.99
Total	17.54	18.63	13.97	19.62	13.55	20.08	13.08	20.42

* These include raw materials. ** Includes transport equipment.

Notes:

(1) Exports refers to products' shares exported to China.

(2) Imports refers to products' shares imported from China.

Source: Authors' calculations using World Integrated Trade Solutions, (WITS)

Table 2 contextualizes the production and imports patterns described above. A few important facts become noticeable when we decompose the patterns. On the one hand, Africa imported more manufactured goods from China (import shares range from 82.47 percent during 1990–1995 to 91.20 percent and 93.66 percent during 2002–2007 and 2008–2014, respectively), suggesting that Africa has been a growing consumer market for Chinese industrial products. A similar dominant pattern is noticeable for Africa's imports of chemicals, machinery, and textiles, albeit in relatively small magnitudes.

On the other hand, exports from Africa to China were predominantly agricultural products (including raw materials), food items, fuel products, and ores and metals. The export shares of agricultural products have dropped steadily, from an average of 17.12 percent during 1990–1995 to 10.35 percent and 6.07 percent during 2002–2007 and 2008–2014, respectively. A similar pattern is visible for food items: export shares plummeted from 29.81 percent to 3.23 percent during 2002–2007 and a modest increase (but still a significant decline) to 3.35 percent during 2008–2014.

However, a reversal pattern is evident on the exports of fuel products and ores and metals. Fuel product export shares from Africa surged from 4 percent only during 1990–1995 to 56.84 percent during 2002–2007 and then dipped to 39.43 percent during 2008–2014. The export rates of ores and metals indicate that the amount of metals and minerals that Africa has exported to China has increased. Though smaller in magnitude during 2002–2007 than in the preceding periods, Africa's positive trade balance in ores and metals is in line with the production and imports patterns described above (cf. Figures 2a and 2b, and Figures 3a, 3b, and 3c in Appendix I).

In sum, while the overall trade balance between Africa and China had been negative, there was still a positive balance in average trade flows for commodities such as fuel products and ores and metals. Second, this positive balance reflected the patterns of metals and minerals production and imports from Africa and to China, respectively, which have been more distinct since China's WTO accession in 2001. In the next section, we describe the data we used for the empirical analysis.

3. DATA AND VARIABLES

A. Data

We combined several data sources in order to carry out the empirical analysis. The first source is the National Oceanic and Atmospheric Administration, National Geophysical Data Center (NOAA-NGDC),[7] which provides satellite data on night-time light intensity, recorded daily between 8.30 p.m. and 10.00 p.m. local time, across countries around the world. We cleaned[8] and used this data to approximate measures of local economic development in Africa, consistent with Mveyange, (2015), Alesina et al., (2015), Gennaioli et al. (2014), and Henderson et al. (2012), among others.

Our second source is the United States Geological Survey (USGS),[9] which provides data on spatial location of mineral deposits and mining activities in Africa (see Table 8 in Appendix II for the list countries). This data enabled us to identify the spatial references of the places where mineral deposits are present and in which mining is active relative to places with no such deposits. As explained below, these differential variations in mineral deposits and mining activities inform the baseline empirical strategy. Further, with the USGS data we were able to identify three interesting sources of exogenous variations. We identified mining sites with different attributes such as those involved in minerals extraction or transformation; those with high- or low-value minerals extracted; and those where the scale of mining operations is large or small. As described later, we

[7]The data are available at: https://www.ngdc.noaa.gov/eog/dmsp/downloadV4composites.html

[8] Lights data are derived in three different formats: cloud-free, average visible, and stable light composites. Consistent with other studies, we employed the stable light composites, which are free from background noises, summer lights, ephemeral events, and gas flares.

[9] The data are available at: http://minerals.usgs.gov/minerals/pubs/country/africa.html.

use these differential mining sites attributes for estimating the heterogeneous effects of post-WTO accession on local economic development. Ultimately, the constructed dataset contains over 40 mineral types matched across 2339 districts in 37 countries in Africa.

One key feature of the USGS data is the presence of historical mineral prices data (measured at 1998 constant US dollars and average US prices) available since 1900 for the United States. We employ[10] these data to control for the volatility in world mineral prices as we later detail in the empirical specification. Two facts guide the choice of US historical prices data. First, the US has a large economy whose mineral prices are good proxies for world mineral prices. Second, compared to the commonly used World Bank Global Economic Monitor (GEM) price data, the USGS price data covers a wider range of mineral commodities. The overall (unreported) price correlations between GEM and USGS, when matched across minerals, is 0.93, which suggests that the use of US minerals' prices is not unreasonable. However, we use the GEM price data for robustness checks of our main regression estimates.

The third data source is the Satellite Assessment of Rainfall for Agriculture in Tropical Africa (TAMSAT),[11] which provides monthly rainfall data in Africa since 1983. We use this data source to construct a measure of rainfall (mean and standard deviations) and later use them as proxies for climatic shocks and agricultural productivity variations; this is similar in spirit to Miguel et al. (2004).

The fourth data source is the Gridded Population of the World (GPW. V4).[12] At a grid cell resolution of 30 arc-seconds (approximately 1 km at the equator), this source contains two main sub-sources: population count grids for the years 1990, 1995, and 2000, and population count grid future estimates for the years 2005, 2010, 2015 and 2020 and the data are adjusted to reflect the historical, current, and future projections of the United Nations World Population estimates. Following Holder and Rascky (2014), we extracted these data at the district level and linearly interpolated them to estimate population counts for the missing years. Thus, we were able to construct a dataset with population count estimates over the period from 1990 to 2015.

The Armed Conflict Location and Event Data (ACLED)[13] is our fifth source, providing disaggregated spatial conflict data that identifies the locations in which conflicts have taken place around the world since 1997. We exploit the spatial nature of the ACLED data to identify places where conflicts occurred in Africa between 1997 and 2007 before pairing them (at the district

[10] Note, however, that the key limitation of using the USGS dataset is the lack of information on the levels of mineral productions at the mining site, and opening and closure of such sites.

[11] The data are available at: http://www.met.reading.ac.uk/~tamsat/cgi-bin/data/rfe.cgi

[12] From the Socio-Economic Data and Application Centre (SEDAC) hosted by the Centre for International Earth Science Information Network (CIESIN) at Columbia University which are available at: http://beta.sedac.ciesin.columbia.edu/data/collection/gpw-v4

[13] Available at: www.acleddata.com/

level) with all the other data. We assign a conflict dummy of 1 for districts that experienced at least a single instance of civil unrest or war in a given year during this period, and 0 otherwise. For analysis, we use the conflict dummy as a control for the disruptive nature of conflict on economic activity (Addison, 2003).

Finally, to merge all the data together at the district level, we extracted geo-spatial referenced data from global administrative areas database (GADM),[14] which provides spatial references for geographical administrative data to as low a level as IV across countries around the globe.

B. Main variables

Our key outcome variables include measures of economic growth, migration, spatial inequality, and welfare, all of which are measured annually across districts from 1997 to 2007. We construct a proxy for economic growth by using the following formula:

$$Annual\ per\ capita\ growth^{15} = ln\left(\frac{Lights_{dct}}{Population_{dct}} \Big/ \frac{Lights_{dct-1}}{Population_{dct-1}}\right) \qquad [1],$$

where d, c, and t stand for district, country, and time, respectively, and y is lights per capita growth. Our measure of migration exploits the temporal variations in population densities sizes across districts.

To estimate the spatial Gini, we first identify and cut countries' districts into 0.01 square decimal degrees' grid-cells (about 1.1 sq. km at the equator – equivalent to the size of a town or village). Following Mveyange (2015), we then exploit the spatial and temporal variation of the grid cells' light intensity to estimate average spatial inequality using the following formula:

$$Spatial\ Gini^{16} = \frac{n}{n-1} * \left(\frac{\sum_{i=1}^{n}(2i-n-1)*y_i}{n^2\chi}\right) \qquad [2],$$

where i is grid cell rank order, n is total number of grid cells, y_i is the grid cell value of average light intensity, and χ is the grid cell population count. For the robustness checks on the coefficients of Spatial Gini we employed two more measures of spatial inequality: Theil[17] and MLD.[18] Haughton and Khandker, (2009) argue that all of these spatial inequalities measures have several

[14] Available at: http://www.gadm.org/

[15] We also calculated lights growth as a proxy for annual economic growth as $ln\left(\frac{Lights_{dct}}{Lights_{dct-1}}\right)$ and used it for robustness checks.

[16] Similar to Damgaard and Weiner (2000).

[17] Theil is calculated using the following formula: $Theil = \frac{1}{N}\sum_{i=1}^{N}\frac{y_i}{\bar{y}}ln\left(\frac{y_i}{\bar{y}}\right)$, where y_i is grid cell value (that is, light intensity per capita), $\bar{y}$ is the average grid cell lights, and $N$is the population size within the grid cells.

[18] The mean logarithmic deviation (MLD) is calculated using the following formula: $MLD = \frac{1}{N}\sum_{i=1}^{N} ln\left(\frac{y_i}{\bar{y}}\right)$

desirable properties, such as symmetry, mean independence, Pigou-Dalton Transfer sensitivity, and population size independence.

To estimate the welfare effects, we constructed a lights-based spatial Sen Index. The calculation of the Sen Index is given as:

$$Spatial\ Sen\ Index = m(1 - G) \qquad [3],$$

where m stands for the arithmetic mean in lights intensity and G stands for Spatial Gini coefficient in equation [2]. In the next section, we present the empirical strategy that guided our empirical estimation and analysis.

EMPIRICAL STRATEGY

A. Specification

Our model specification explores the idea that natural resource extraction, is important to the recent impressive economic growth performance in Africa (see Beny and Cook, 2009). To identify the impacts of post-WTO accession on local economic development in Africa, we rely on the facts presented in Table 1 and 2. Thus, it is unsurprising that, after the accession, mineral-rich African countries increased their mining activities (cf. Figures 2a and 2b in Appendix I). As noted above, the underlying argument is that China's accession to WTO led to higher world mineral prices (cf. Figure 1 in Appendix I) which, arguably, had positive economic benefits for mineral-rich countries in Africa (cf. Table 1).

The differences in mineral endowments (and therefore mining activities) and the timing of China's WTO accession offer an interesting opportunity to conduct a quasi-experimental analysis, which enables us to employ a difference-in-difference (DID) technique to identify the causal impacts of the post-WTO accession of China on local economic activities in Africa. The DID estimator enables us to compare the changes in our indicators of economic development (economic growth, migration, spatial inequality, and welfare) in mineral-rich districts (the treatment group) pre- and post-WTO accession to the corresponding changes in districts with no mineral endowment (the control group) across 37 countries in Africa. Our approach is similar in spirit to that of Andersen et al. (2014) and Lu and Yu (2015).

To capture the impacts of mineral endowments and mining activities, we specify the baseline models in two different ways. First, we consider whether the discovery and hence the presence of mineral deposits has any implications for our outcomes of interest. We specify the model such that we are able to separately identify the overall effect of mineral endowment on economic outcomes. This enables us to compare the changes in outcome variables between the treatment group and the control group. The specifications for the DID estimator takes the following forms:

$$\begin{aligned} Y_{dct} = {} & \beta_0 Post_t + \beta_1 Deposit_{dct} + \beta_2 Post_t \cdot Deposit_{dct} \\ & + \boldsymbol{X'_{dct}}\beta_3 + \boldsymbol{\gamma}_d + \boldsymbol{\Phi}_t + \boldsymbol{\Gamma}_{ct} + \varepsilon_{dct}, \end{aligned} \qquad [4],$$

where d, c, and t represent the district, country, and year, respectively. Y_{dct} is the measure of the above-mentioned outcome indicators in a district across countries over time. $Post_t$ denotes a post-accession dummy, taking the value of 1 if it is year 2002 and onwards, and 0 otherwise. $Deposit_{dct}$ is a dummy for the presence of mineral deposits, taking the value of 1 if mineral deposits are present, and 0 otherwise. β_0 picks the separate average effects of time before and after the accession. β_1 captures the average effect of being in the treated versus control group. β_2 captures the average treatment effect. $\boldsymbol{\gamma}_d$ is the district fixed effect controlling for all unobserved district specific time-invariant effects. Examples include districts' geographical locations and natural resource wealth; the timing and opening of mines; the level of technology employed in the mining sector; trade relations between districts; the cross-border movement of people (either for job search, trading, or other economic motives); and other unobserved factors such as ethnicity, which, as Fum and Hodler (2010) argued, are also likely to affect economic outcomes. $\boldsymbol{\Phi}_t$ is the year fixed effect, controlling for all unobserved time relevant shocks common to districts (such as trade booms and busts within and across districts). $\boldsymbol{\Gamma}_{ct}$ is the country-year fixed effect, which controls for country-wide unobserved yearly shocks (for example, the timing of the privatization of the mining sector, which has been widespread in Africa, the institutional differences in policy packages aimed to attract foreign investment in the mining sector, unpredictable changes in world commodities prices, and other institutional and policy changes that affect individual countries over time). ε_{dct} is an error term.

The vector $\boldsymbol{X}_{cdt}$ captures time-varying observables that would otherwise confound the coefficient estimates of the treatment effects. Since we are estimating the impact of mineral deposit presence, we included three main variables as controls to address the potential underlying bias: mineral prices, measures of rainfall dispersion, and a conflict dummy. Mineral prices enable us to account for mineral price volatility that can otherwise bias our estimates. We use rainfall to account for both observed climatic changes and also as a proxy of agricultural production. The conflict dummy controls for the potential impacts of war, civil unrest, and other forms of fragility that can differentially and separately affect our outcome variables, thereby biasing our estimates. Following Betrand et al. (2004), we also control for potential serial correlation and heteroscedasticity by clustering all the standard errors at the country level. Note that, unless otherwise stated, we use similar notations for all model specifications.

The second model specification is similar to equation [4], except that we refine it to focus on active mining activities rather than mere mineral endowment. We argue that having mineral deposits is necessary but not sufficient enough to fully understand the underlying impacts of mining on economic development; unless actual extraction takes place to generate meaningful interactions amongst economic agents, it is difficult to identify the impacts of mining on development. Our model specification adapts to this fact: districts with active mining activities become the treatment group, while those with none become the control group (these include districts with closed mines).

In the end, we were able to compare changes in the outcome variables between the treatment and control groups before and after China's WTO accession. The DID estimator takes the following form:

$$Y_{dct} = \delta_0 Post_t + \delta_1 Active_{dct} + \delta_2 Post_t \cdot Active_{dct} + \boldsymbol{X}'_{\boldsymbol{dct}}\boldsymbol{\delta_3} + \boldsymbol{\gamma}_d + \boldsymbol{\Phi}_t + \boldsymbol{\Gamma}_{ct} + \varepsilon_{dct}, \qquad [5],$$

where, $Active_{dct}$ is a dummy taking the value of 1 for active mining and 0 otherwise. The rest of the variables are described as above. δ_0 , δ_1, and δ_3 are interpreted similar to equation [4].

B. Treatment Effects Identification

The treatment effects identification relies on two key assumptions. The first assumption is that the error term, ε_{dct}, has a mean of zero and is uncorrelated with each of the other covariates in a correctly specified model. That is,

$$\mathrm{E}\left[\varepsilon_{dct}|x_j\right] = 0, \qquad [6],$$

$$\mathrm{Cov}\left[x_j, \varepsilon_{dct}\right] = 0, \qquad [7],$$

where $x_j \in [Treat, \boldsymbol{\gamma}_d, \boldsymbol{X}_{cdt}, \boldsymbol{\Phi_t}, \boldsymbol{\Gamma}_{dct}]$ and $Treat$ represents the treatment regressors in equations [4] and [5]. To identify the treatment effects, Stock and Watson (2010) asserted that equation [6] allows for endogeneity of $\gamma_{\boldsymbol{d}}$, X_{cdt}, Φ_t, and Γ_{dct}. However, the estimated coefficients of such regressors are not causal and cannot be interpreted as such. Equation [7] suggests the presence of common pre-treatment trends (see Khandker (2010) and Betrand et al. (2004) for detailed explanations), commonly referred to as the *parallel trends*. In other words, identifying the treatment effect equation [7] requires that the treatment and control groups exhibit parallel trends in outcome variables prior to China's WTO accession; thus, the unobserved characteristics affecting the selection into treatment or control are time invariant.

The second assumption, proposed by Mora and Regio (2012, 2014), extends the parallel trends assumption and requires further checking of the pre-treatment dynamic trends, especially in the presence of several pre-treatment periods, as is the case here. According to Mora and Regio (2014), in the presence of multiple pre-treatment periods it is possible for the pre-treatment trends to differ between the treatment and control group. Therefore, it is necessary to check the equivalence in both pre- and post-treatment trends (and adjust for trends accordingly if necessary) in order to correctly identify the treatment effects.

C. Identification Checks

In this part, we provide consistency checks to the identifications strategy in order to ensure that the treatment effects are indeed causal and not driven by other factors outside the baseline framework. The checks are motivated by several concerns that can potentially bias the baseline treatment effects. One of the concerns, which was also noted by Lu and Yu (2015), is that the timing of China's WTO accession may have had unobserved anticipatory effects that also affected the outcome variables. In view of the extended negotiations that took 15 years to complete, in which each WTO member had to agree to China's accession, we argue that it was difficult to pre-determine that 2001 would have been the year of China's WTO accession. However, following Lu and Yu (2015) strategy, we also include $Mine^{0}_{dct}\ x\ Year_{2000}$ and $Active^{0}_{dct}\ x\ Year_{2000}$ in our DID specifications in order to address this concern. The inclusion of this extra control enables us to check whether the expectation effect on the coefficient of the treatment effect a year before WTO accession. $Mine^{0}_{dct}$ and $Active^{0}_{dct}$ refer to dummies for districts that have neither mineral deposits nor active mining, respectively.

China-Africa relations have further deepened since 2000 when the forum on China-Africa cooperation (FOCAC) was created. It is possible that the creation of this forum had unobserved biases on the pre-treatment trends of our outcome variables. FOCAC has convened every three years since 2000, which means that two meetings were convened during the 2002–2007 period: one in 2003 (in Ethiopia) and one in 2006 (in Beijing). It is not unreasonable to assume that resolutions arrived at in these forums might have had some direct and indirect effects on our outcome variables. To address such concerns, we argue that the country-year fixed effects suffice to account for any potential unobserved bias.

The last concern is the likelihood that the accession impacts within the treated group also affect the control group; for example, through intra-districts trade or cross-border interactions – the violation of the classical stable unit treatment value assumption (SUTVA).[19] Indeed, we expect the treated and control districts to have been trading even before China's WTO accession. Nonetheless, we do not have district-level trade data with which to squarely address this concern. As a way to control for this violation, we rely on both district and country-year fixed effects controls. We argue that these fixed effects implicitly capture the unobserved intra-trade or cross-border interactions between the treated and control districts.

4. RESULTS

A. *Descriptives*

Table 3a reports the descriptive statistics for annual lights growth, population density, spatial Gini, and the spatial Sen Index from 1997 to 2007. The table shows that, on average, annual light growth was around 0.03 percent. Population density averaged 288 people per square kilometer. Spatial Gini and Sen Index averaged 0.254 and 4.003, respectively. Except for spatial Gini, the rest of the outcome variables show considerable variations around their mean.

[19] We rule out the second SUTVA assumption, variations in treatment, since the treatment does not vary across the treated group: all districts are subject to the same post-WTO accession dummy for the treatment period 2002–2007.

Table 3a: Descriptive statistics

Variables	Obs.	Mean	Std. Dev	Min	Max
Annual lights growth	24856	0.029	1.625	-10.585	10.790
Population density	24957	288	3388	0.007	197924
Spatial Gini	20315	0.254	0.206	-0.000	0.887
Spatial Sen Index	20315	4.003	8.213	0.007	62.955

Source: Authors' calculations.

Table 3b: Mean comparisons pre-WTO accession.

Variables	Obs. control	Mean - control	Obs. treatment	Mean - treatment	Mean difference
Light per capita growth	9060	0.071	2214	0.033	0.039
Population density	9149	241.6	2219	264.5	-22.89
Spatial Gini	7144	0.249	2012	0.370	-0.121***
Spatial Sen Index	7144	3.059	2012	5.246	-2.186***

Source: Authors' calculations.

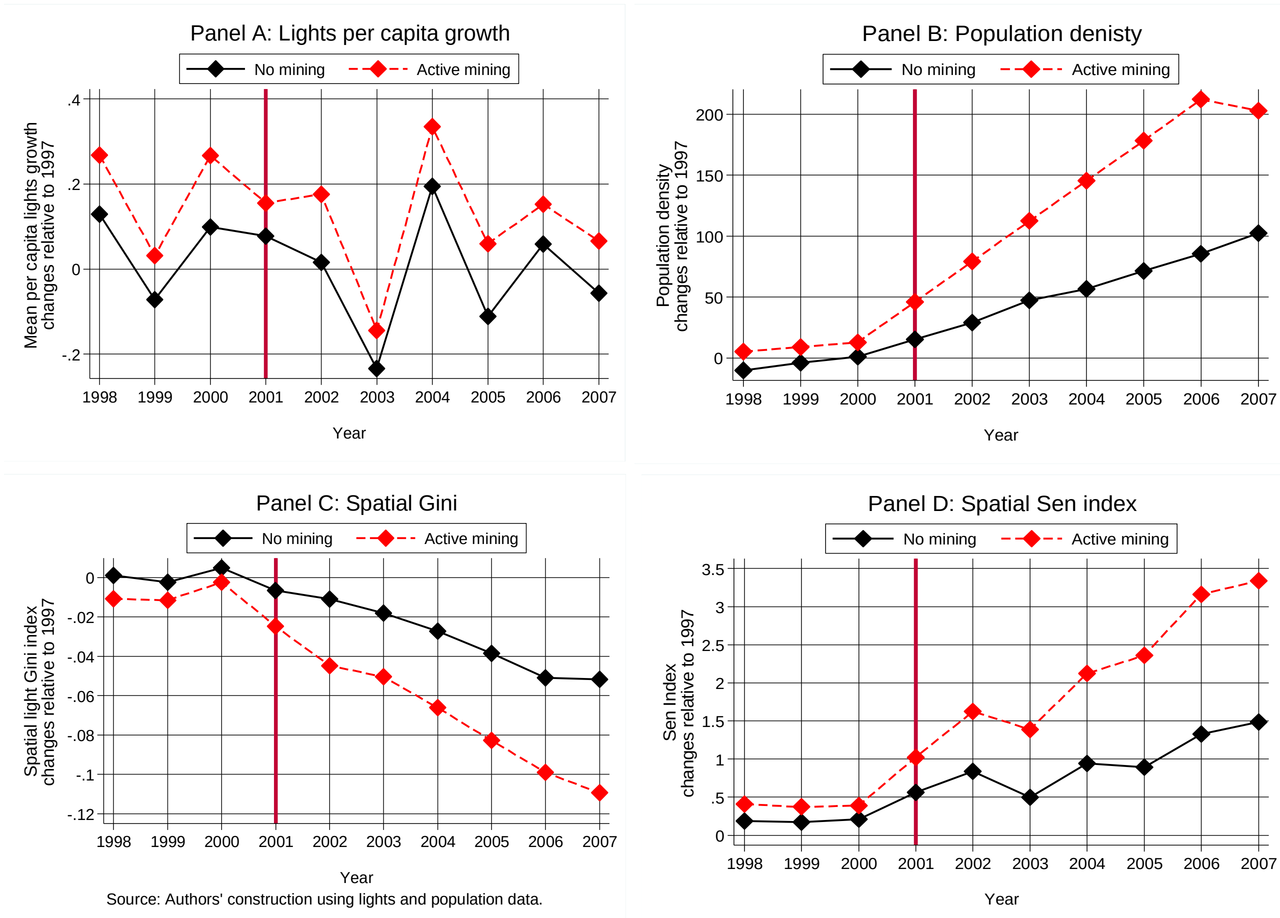
Table 3b provides a snapshot of the mean comparisons of the outcome variables between control and the treatment districts during the 1997–2001 period. The table shows that the number of controls exceeded that of treatment districts across all three outcome variables. However, it is worth noting that the mean difference in lights per capita growth between control and treated districts prior to accession was insignificant, which indicates the non-existence of measurable economic growth and population density differences. On the contrary, mean differences of the spatial Gini and the Sen welfare index were negative and significant, suggesting a reduction in both inequality and welfare between control and treatment districts prior to China's WTO accession.

B. Parallel trends and pre-treatment dynamics tests

Figure 4 reveals trends in annual changes in the outcome variables before and after China's WTO accession. Panel A shows the average annual changes in lights per capita growth – our economic growth proxy – relative to 1997. The pre-accession annual changes in lights per capita growth show similar trends[20] between the treated and control districts. While the trends are consistent with the assumption stated in equation [7], it is not implausible to disassociate the changes in annual lights per capita growth during 2002–2007 to China's WTO accession: the average annual changes in the intensity of lights per capita growth are consistently high with roughly the same gap in the treated than in the control districts during 1997–2007.

[20] Almost similar trends hold when the district selection into treatment is based on the presence of mineral deposits.

Figure 4: Parallel trends assumption



Panel B of Figure 4 shows the average annual changes in population density – our migration measure – relative to 1997. That panel shows that the annual population density changes before the accession were steady and trending in parallel between the treated and control districts. Significant changes in population densities are observed in the treated districts in the post-accession period. These upward trends suggest that in the wake of booming mining activities, treated districts experienced increased inflows of people; these people were, arguably, migrating in search of jobs in the mining sector (as well as into other occupations in the local economy, which benefits from the rise in purchasing power induced by mining operations). Surges in population density are typically induced by agglomeration and spillover effects common in economically booming areas.

Panel C shows the average annual changes in spatial Gini – a measure of district level inequality. The panel reveals similar pre-accession trends, followed by a widening gap in inequality between the treated and control districts post-accession: treated districts experienced significant reductions in inequality relative to control districts. With a rise in mining activities, it is not implausible to conjecture that the treated districts had more economic activities than the control districts, allowing more widespread income distribution within and across the districts, thus the gap in the declining patterns in spatial inequality.

Panel D portrays the annual changes in the proxy for welfare levels, the spatial Sen Index. Close parallel trends were prevalent in the three years preceding accession to WTO. However, post-accession trends were remarkably divergent, with treated districts showing significant improvements in the welfare index relative to control districts. These welfare trends resonate with those in Panels A and C: the increases in average lights and declines in spatial Gini reflect the positive welfare trends across both the treated and control districts.

Table 4: P-values for parallel growth paths tests

Parallel-q	*Years*	*Annual growth*	*Population density*	*Spatial Gini*	*Spatial Sen Index*
Panel A - H0: Common pre-treatment dynamics					
		0.489	0.693	0.927	0.979
Panel B - H0: q=q-1					
q=1	1997	-	-	-	-
q=2	1998	0.960	0.847	0.369	0.794
q=3	1999	0.781	0.894	0.405	0.992
q=4	2000	0.665	0.989	0.536	0.809
q=5	2001	0.790	0.946	0.659	0.729
Panel C - H0: s=s-1					
q=1	1997	0.274	0.992	0.811	0.985
q=2	1998	0.282	1.000	0.987	0.999
q=3	1999	0.259	1.000	0.971	0.999
q=4	2000	0.332	1.000	0.976	0.996
q=5	2001	0.359	1.000	0.978	0.996

Notes: (1) q refers to all pre-treatment periods; (2) q=q-1 is a null hypothesis of equivalent parallel pre-treatment paths; (3) s=s-1 is a null of hypothesis of a test on the equality of the effect on all post-treatment periods.

Source: Authors' calculations.

As previously mentioned, Mora and Regio (2012) proposed that when there are multiple pre-treatment periods, as is the case here, it is necessary to check the pre-and post-treatment dynamic growth paths in order to safely rule out threats to our main identifying assumption – the parallel path. In order to do as Mora and Regio (2014) suggested, we ran three tests: one for the presence of common pre-treatment dynamics in our outcome variables, one for the equivalence in average acceleration of these common pre-treatment dynamics, and one for the equivalence of the effects on all post-treatment periods. The last test is very useful in drawing correct inferences associated with the causal effects of an intervention (in this case, the post-WTO accession by China). In Table 4, Panel A shows the results of the first test. All four outcomes variables fail to reject a null hypothesis on the presence of common pre-WTO accession dynamics. Panels B and C show the results for the second and third tests. Both tests also fail to reject their null hypotheses.

C. Main Results

Table 5a and 5b, in Appendix II, report our main results. Columns 1, 3, 5, and 7 show the regression estimates without other relevant controls except for time and fixed effects. Columns 2, 4, 6, and 8 show the estimates after controlling for all the relevant controls such as climate, time, and fixed effects, the conflict dummy, and a control for expectation effects.

Table 5a reports the estimates of the post-accession impacts based on the presence of mineral deposits. Columns 1 and 2 show that the average impacts of post-accession on annual per capita growth in the treated compared to control districts are statistically insignificant. Columns 3 and 4 show the average impacts on migration. Similar to growth impacts in columns 1 and 2, the impacts on migration are also statistically insignificant. Columns 5 and 6 show the average impacts on spatial inequality. Columns 5 shows a statistically significant 3 percent reduction in spatial inequality in the treated compared to control districts. However, this effect is before the inclusion of the relevant controls; when these are included, the reduction becomes statistically no different from zero (column 6). Columns 7 and 8 depict the welfare impacts. Column 7 shows statistically significant gain of 1.04 index points on welfare in the treated districts relative to the control districts. When the regressions take into account the relevant controls, in column 8, this effect is reduced to 0.716 index points. With regard to the effects of mineral prices, Table 5a suggests that their coefficients are insignificant across the board. Similarly, the coefficients of the expectation effects are insignificant for all outcome variables except welfare, which suggests indirect spillover pre-accession impacts to control districts.

Table 5b reports estimates of the post-accession impacts based on the presence of active mining activities. Columns 1 and 2 show that the average impacts of post-accession on annual per capita growth in the treated compared to control districts were statistically not different from zero. Columns 3 and 4 show the average impacts on migration. Similar to growth impacts in columns 1 and 2, the impacts on migration are also statistically insignificant. Columns 5 and 6 show the average impacts on spatial inequality. Similar to Table 5a, Column 5 shows a statistically significant 3 percent reduction in spatial inequality in the treated compared to control districts. However, this effect is not different from zero when the relevant controls are accounted for in column 6. Columns 7 and 8 show the welfare impacts. Column 7 shows a statistically significant gain of 1.10 index points on welfare in the treated relative to the control districts. When the regressions take into account the relevant controls, in column 8, this effect is reduced to 0.744 index points. The effects on mineral prices and expectation effects are similar to those in Table 5a.

D. Robustness Checks

Tables 6a–6d, in Appendix II, report the robustness checks to our main results. Columns 1-4 present the estimates using USGS historical average prices as controls while columns 5-8 use the World Bank’s real prices data. Tables 6a and 6b replicate similar estimates as in Tables 5a and 5b, respectively. Tables 6c and 6d re-estimate the baseline model with different outcome variables;

that is, average annual light growth (a measure of overall economic growth), population sizes (a measure of migration changes), and Mean Logarithmic Deviation (MLD) and Theil index as measures of spatial inequality.

The results in Table 6a and 6b indicate similar statistically insignificant effects as those in Tables 5a and 5b, respectively, even when we used average and real prices as controls; this also suggests the important role of prices in affecting our outcome variables. The same results hold for the coefficients of expectation effects. The results also hold for the coefficients of mineral prices, except for a positive and significant World Bank's real price coefficient on welfare estimates.

Table 6c shows the post-accession impacts on districts with mineral endowments using the different outcome variables. The results indicate insignificant effects on overall economic growth, migration, and spatial inequality alternative measures regardless of the mineral prices used as controls. The findings confirm the robustness of those in Table 5a. Similar to Table 6c, Table 6d reports the post-accession impacts on districts with active mining activities. Again, the results show insignificant effects on overall economic growth, migration, and spatial inequality alternative measures, regardless of the source of mineral prices data. The results thereby reaffirm the robustness of those in Table 5b.

E. Heterogeneous Effects

In order to identify the heterogeneous local economic effects of post-accession, as described in section 3, we exploited the exogenous spatial variation from the scale (small or large) of mining operations, the value (high or low) of minerals extracted, and the nature (extractive or transformative) of mining activities. The main goal is to estimate and evaluate the treatment effects across these difference exogenous variations. Therefore, we specified and estimated the following model:

$$\begin{aligned} Y_{dct} = \eta_0 Post_t + \eta_1 Active_{dct}^{status} + \eta_2 Post_t \cdot Active_{dct}^{status} \\ + \boldsymbol{X_{dct}}'\eta_3 + \boldsymbol{\gamma}_d + \boldsymbol{\Phi}_t + \boldsymbol{\Gamma}_{ct} + \varepsilon_{dct}, \end{aligned} \quad [8],$$

where $status$ represents a dummy for an active large or small mining scale operations, a dummy for active high or low value minerals extracted, and a dummy for extractive or transformative mining activities. The coefficient of interest here is η_2, which captures a vector of the treatment effects post-WTO accession. The rest of the variables are interpreted in the same fashion as in equations [4] and [5].

Tables 7a–7c, in Appendix II, show the estimated results. As above, columns 1-4 present the estimates based on constant USGS mineral prices, while columns 5-8 report the estimates based on the World Bank's real prices data.

Table 7a reports the regressions based on the scale of mining operations. When we estimate the models using the USGS data, the results show statistically insignificant effects on per capita growth, population density, spatial Gini and Sen Index in treated districts with small-scale mining operations. With the exception of the significant negative effect on population density, the results in districts with small-scale mining operations remain the same for other outcome variables when we estimated the models using the World Bank's real prices data. The table also shows that, when fitting the model using the USGS data, the estimates on treated districts with large-scale mining operations are statistically not different from zero for average annual lights per capita growth, population density, and spatial inequality, but positive and different from zero for the Sen Index. Similarly, when we use the World Bank's real prices data, the lights per capita growth, population, and spatial inequality remain statistically insignificant, while the Sen Index remained significant, albeit at the margins. Moreover, when we use the World Bank price data the coefficients of real prices remain insignificant for all variables except the Sen Index, indicating the significant welfare impacts of changing real mineral prices. The expectation effect remains the same as before, but at the 10 percent significance level with the USGS data compared to a 1 percent significance level with the World Bank data.

Table 7b reports the regressions based on the aggregate extracted minerals' values. When we fit the models using the USGS data, the results show insignificant effects on the average annual lights per capita growth, population density, spatial Gini, and Sen Index in the treated districts engaged in extracting the high-value minerals. Similar results hold when we fit the models using the World Bank's real price data. Additionally, the table, using USGS price data, reports statistically insignificant impacts on average annual lights per capita growth, population density, and spatial inequality in the treated districts engaged in extraction of low-value minerals. Nonetheless, the impacts on the Sen Index are positive and statistically significant. Similar to Table 7a, when we fit the models using the World Bank's real price data, the results remain qualitatively unchanged. Further, except for the changes in coefficient sizes, the sign of the impacts of minerals prices and the expectation effects remain similar to those in Table 7a.

We now turn our attention to the heterogeneous effects based on the different types of mining activities; namely, extraction or transformation activities. Table 7c presents these results again, indicating statistically insignificant impacts on all our outcome variables in the treated districts compared to control districts engaged in the minerals extraction activities. These results remain qualitatively robust using both the USGS and the World Bank data. Furthermore, when we fit the models using both the USGS and the World Bank data, the results indicate similar insignificant impacts on all the outcome variables in the treated relative to control districts engaged in minerals' transformation activities. Again, except for the changes in coefficient sizes, the sign of the impacts of minerals prices and the expectation are qualitatively similar to those in Tables 7a and 7b.

In general, the examination of the heterogeneous effects confirms our main findings that China's WTO accession significantly improved welfare across African districts with large-scale mining operations, low-value minerals, and engaging in minerals transformation activities. We speculate that the positive effect on welfare could be related to China's significant efforts in building mega infrastructures (such as roads, dams, railways) in Africa. Further, our results indicate insignificant impacts on economic growth, migration, and spatial inequality. The findings in the present paper offer one key lesson: except for the welfare effects, China's influence on Africa's local economic development was rather limited in 2002–2007, repudiating the widespread anecdotal claims in favor of China's positive economic influence in Africa. The findings also resonate with the on-going disquieting policy debates on the extent of China's influence on Africa's economic development.

5. CONCLUSION

In this paper we have sought to answer the question of whether China's WTO accession affected local economic development in Africa. Our pursuit is motivated by three recent empirical facts. The first is the contention that the recent (and just ended) commodities super-cycle had, among other factors, been a driver of Africa's impressive growth performance. The second is a claim that the accession of China to the multilateral trading system, under the WTO, in late 2001 was the main driver of the recent commodities price boom around the world, particularly during 2002–2008. Third, although it waned, the 2002–2008 commodity price boom has been the most powerful since World War II.

Thus, our study evaluates the impacts that China's WTO accession had, through its impact on world mineral commodity prices, on indicators of local development in Africa; namely, economic growth, migration, spatial inequality, and welfare. Using accession to the WTO as an exogenous temporal variation, our empirical strategy used difference-in-difference (DID) estimators to quantify the causal impacts of accession on local economic development in Africa. Therefore, by confining our empirical framework to the district level, we divided our analysis into two periods, the pre-accession period between 1997 and 2001 and the post-accession period between 2002 and 2007. We identified the treatment effects by comparing the average changes in economic development indicators in mineral-rich districts pre- and post-accession to the corresponding changes in districts that had no such mineral endowment or activities.

We found statistically significant welfare gains post-China's WTO accession in the treated relative to control districts. We speculated that the positive effect on welfare could be related to China's significant efforts in building mega infrastructure (such as roads, dams, railways) in Africa. Moreover, our findings indicate statistically insignificant effects on economic growth, migration, and spatial inequality. The analysis of the heterogeneous effects shows insignificant impacts on economic growth, migration, and spatial inequality across the different variants of heterogeneous effects, but statistically significant effects on welfare across the districts with large-scale mining operations, low-value minerals, and engagement in minerals' transformation activities. Overall, the findings indicate that, except for the welfare effects, China's influence on Africa's local economic development was rather limited in 2002–2007, invalidating the widespread anecdotal claims in favor of China's positive economic influence in Africa.

To summarize, the present study provides important insights that can be useful for influencing policy, mostly because China's influence in Africa has been widespread but mired with scant empirical evidence on its effects on Africa's development. Thus, the finding that China has less influence on economic growth than on welfare in Africa can indeed be useful for African policy makers. However, this study has certain limitations. The analysis is somewhat limited by the lack of data on mineral production at the mining sites. Also, the lack of accurate information on the precise opening and closing of mining sites years has limited our analysis, compelling us to make a rather strong implicit assumption that all active mines were open between 1997 and 2007. Going forward, we propose that future research should focus on isolating the individual minerals and investigate their respective roles in explaining local economic development outcomes in order to uncover the specific effects that these mineral commodities bring to bear in Africa.

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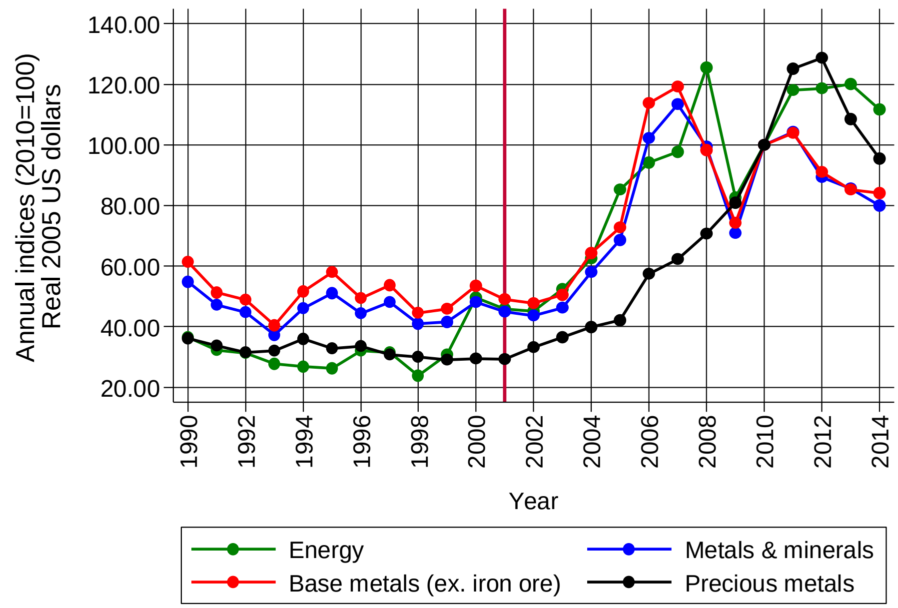
APPENDIX I: *Figures*

Figure 1: Mineral price trends: pre- and post- China's WTO accession



Source: Authors' construction using World Bank Commodity Price Data

Figure 2a: Africa's production of metals and minerals, 1996–2012

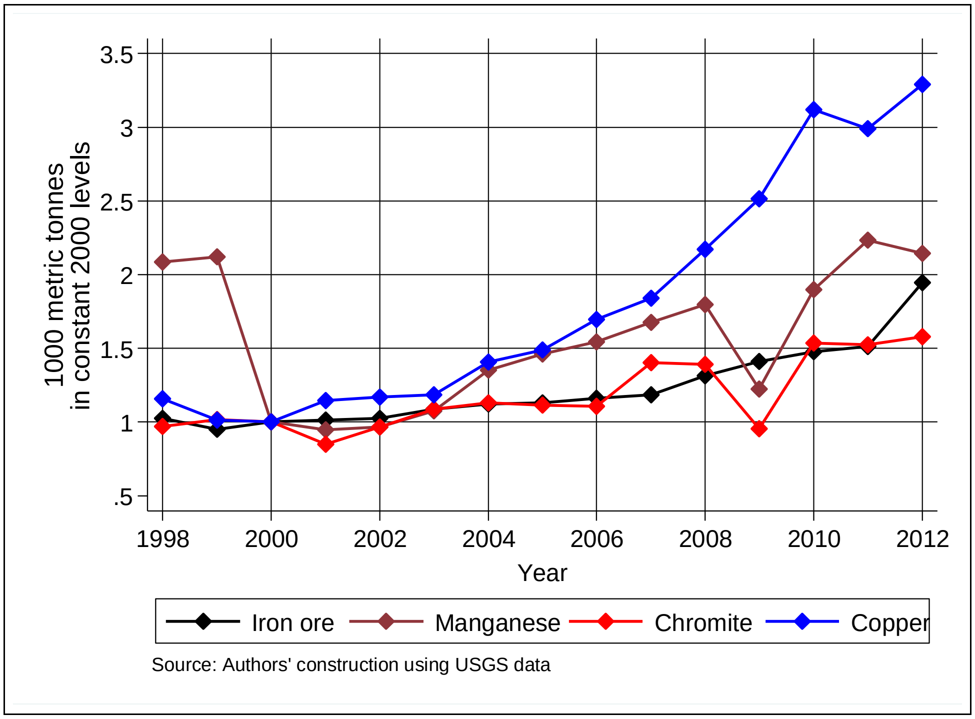


Figure 2b: Africa's production of metals and minerals, 1996–2012

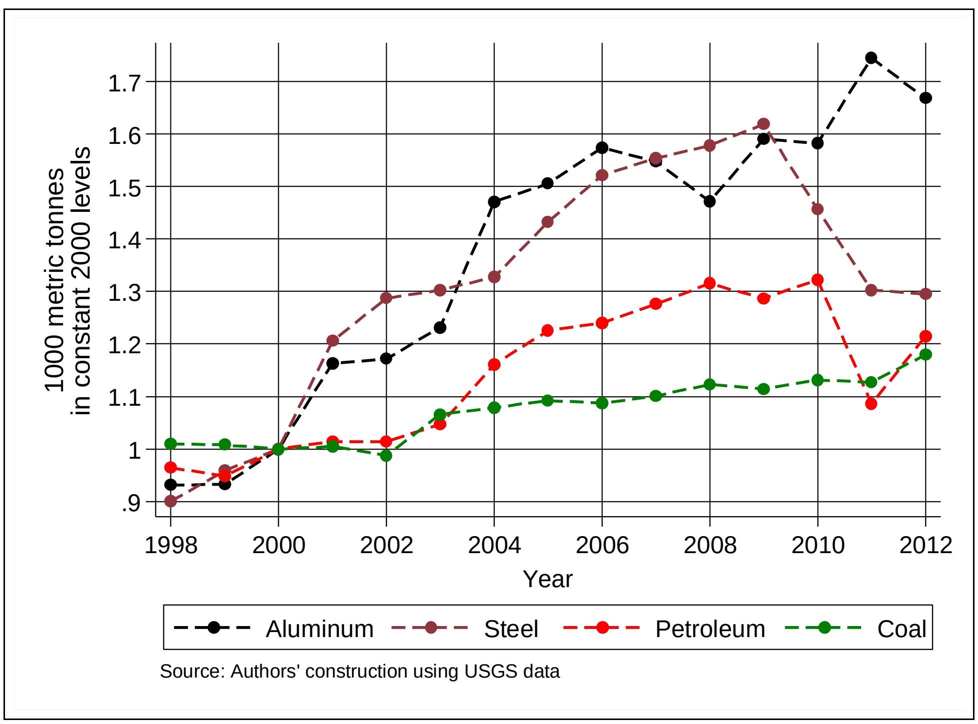


Figure 3a: China's imports of metals and minerals, 1996–2013

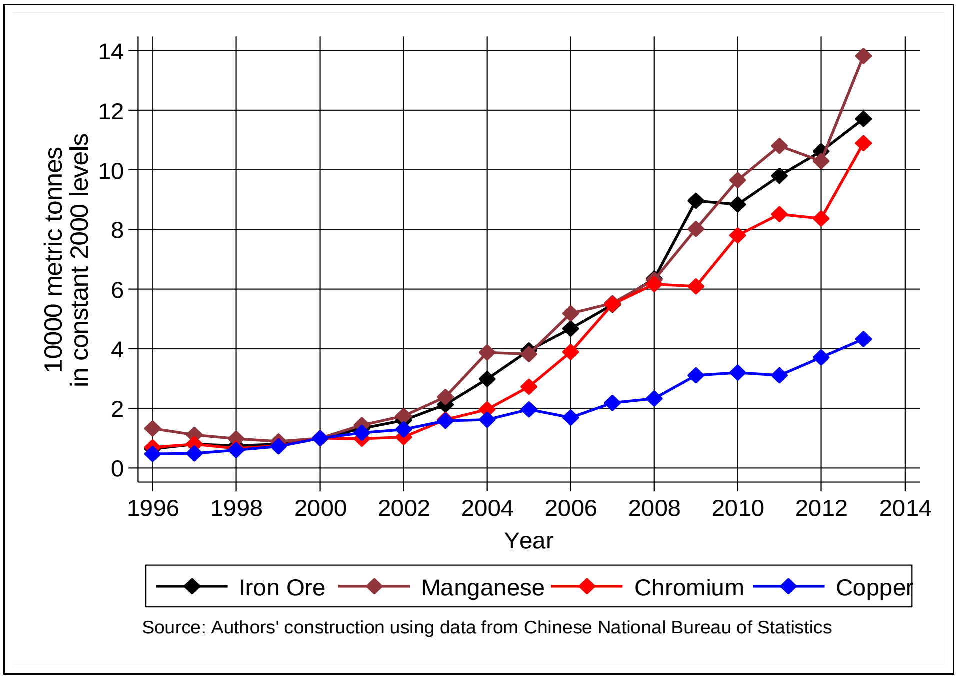


Figure 3b: China's imports of metals and minerals, 1996–2013

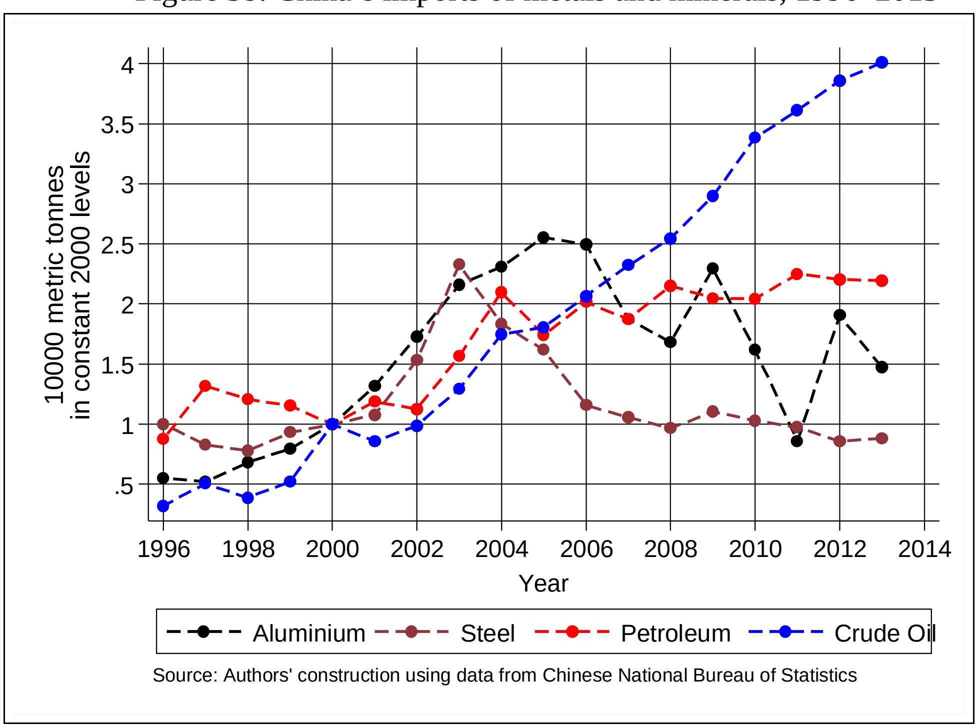


Figure 3c: China's imports of metals and minerals, 1996–2013

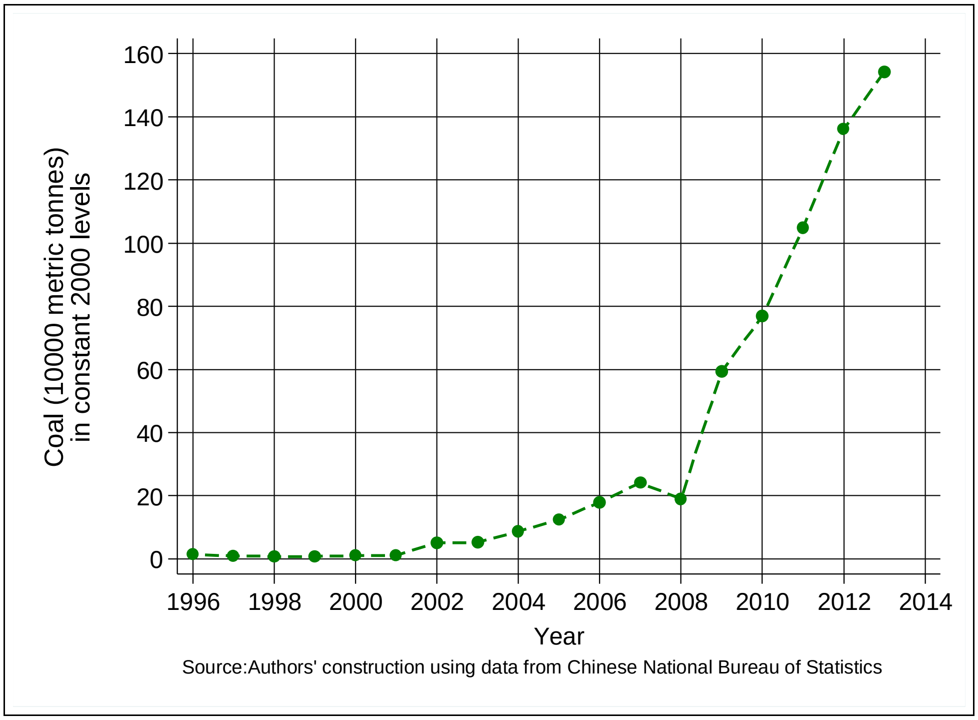
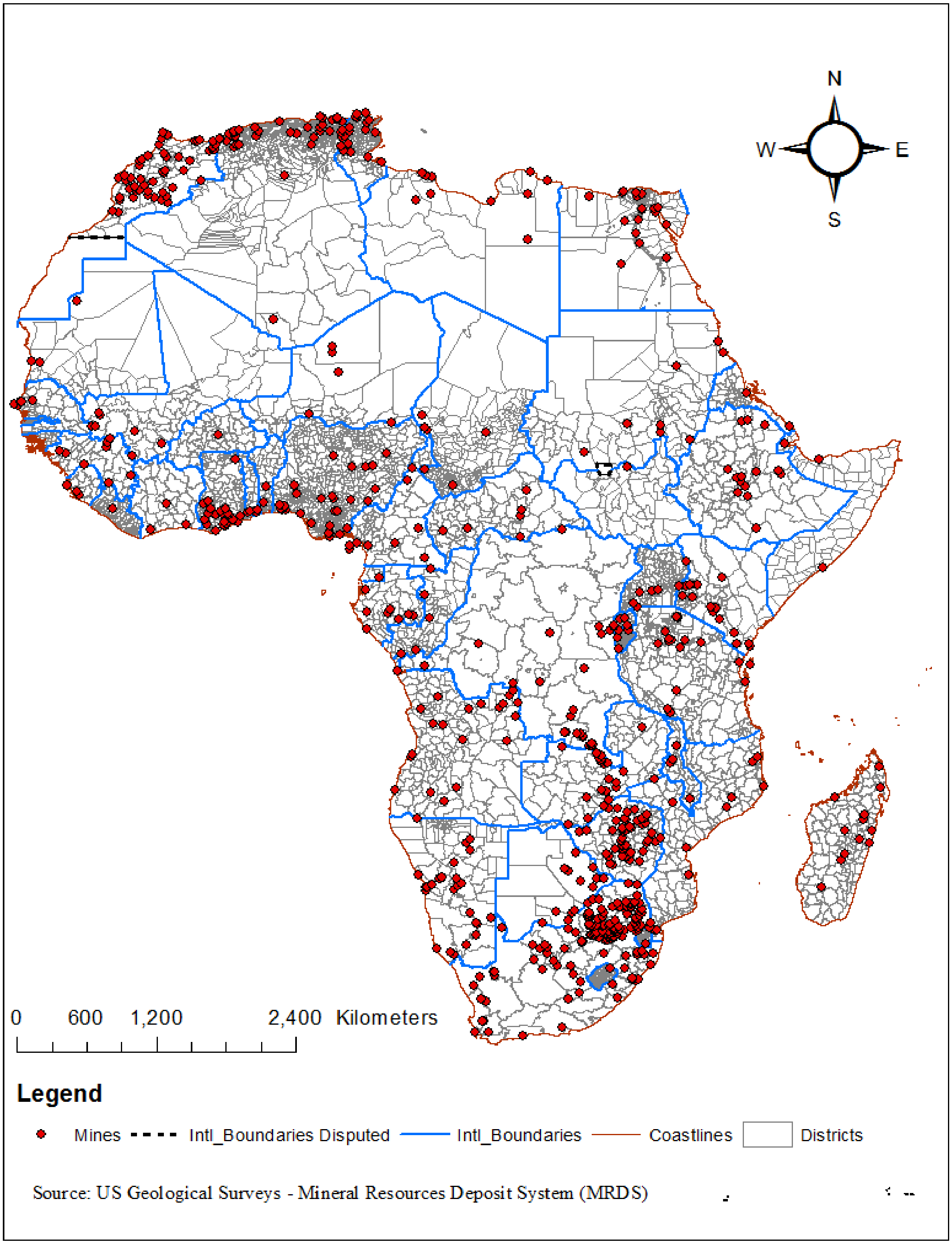


Figure 4: Distribution of mineral deposits in Africa



APPENDIX II: *Tables*

Table 5a: Local economic impacts based on presence of mineral deposits.

Dependent variables:	*Per capita Growth*		*Population density*		*Spatial Gini*		*Spatial Sen Index*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post *x* Deposit	0.068	0.058	75.381	106.864	-0.030**	-0.018	1.040***	0.716**
	[0.043]	[0.063]	[62.894]	[85.422]	[0.012]	[0.015]	[0.232]	[0.272]
No. Deposits *x* Year 2000		-0.059		9.408		-0.008		0.103**
		[0.142]		[8.593]		[0.009]		[0.050]
Log (Constant Prices)		0.096		-54.523		-0.008		0.386
		[0.071]		[63.127]		[0.014]		[0.268]
Climate	No	Yes	No	Yes	No	Yes	No	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Conflict dummy	No	Yes	No	Yes	No	Yes	No	Yes
N	24856	22764	24957	22864	20315	18378	20315	18378
R-squared	0.074	0.076	0.969	0.969	0.795	0.791	0.951	0.950
Dep. Variable [mean]	0.029	0.029	288.423	283.912	0.254	0.247	4.003	3.626

Notes: (1) The table shows the regression results across districts in Africa during 2002–2007. (2) The results show the local economic impacts of China's WTO accession in the presence of mineral deposits in Africa. (3) The standard errors, clustered at the country level, are in brackets; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. (4) Growth, Spatial Gini, and Sen Index are measured using lights data as described in the data section. (5) Population density is measured as population per square kilometer. (6) Prices are reported in 1998 constant US dollars. (7) Fixed effects include time-fixed effects, district-fixed effects, and country-year-fixed effects. (8) Climate is measured using the standard deviation of rainfall distribution at the district level.

Source: Authors' estimations.

Table 5b: The local economic impacts of active mining activities.

Dependent variables:	*Per capita Growth*		*Population density*		*Spatial Gini*		*Sen Index*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post *x* Active mines	0.066	0.072	86.988	129.015	-0.029**	-0.019	1.099***	0.744**
	[0.044]	[0.068]	[67.306]	[90.002]	[0.012]	[0.015]	[0.246]	[0.297]
Inactive mines *x* Year 2000		-0.124		10.962		-0.002		0.110*
		[0.145]		[9.272]		[0.007]		[0.055]
Log (Constant Prices)		0.100		-55.337		-0.009		0.412
		[0.071]		[62.318]		[0.014]		[0.277]
Climate	No	Yes	No	Yes	No	Yes	No	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Conflict dummy	No	Yes	No	Yes	No	Yes	No	Yes
N	24856	22764	24957	22864	20315	18378	20315	18378
R-squared	0.074	0.076	0.969	0.969	0.795	0.791	0.951	0.950
Dep. Variable [mean]	0.029	0.029	288.423	283.912	0.254	0.247	4.003	3.626

Notes: (1) The table shows the regression results across districts in Africa during 2002–2007. (2) The results show the local economic impacts of China's WTO accession in the presence active mining activities in Africa. (3) The standard errors, clustered at the country level, are in brackets; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. (4) Population density is measured as population per square kilometer. (5) Prices are reported in 1998 constant US dollars and are in logarithmic form. (6) Growth, Spatial Gini, and Sen Index are measured using lights data as described in the data section. (7) Fixed effects include time-fixed effects, district-fixed effects, and country-year-fixed effects. (8) Climate is measured using the standard deviation of rainfall distribution at the district level.

Source: Authors' estimations

Table 6a: Robustness checks – the local economic impacts of the presence of mineral deposits.

	USGS average prices				*World Bank GEM real prices*			
Dependent variables:	*Per capita Growth*	*Pop. density*	*Spatial Gini*	*Sen Index*	*Per capita Growth*	*Pop. density*	*Spatial Gini*	*Sen Index*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
Post *x* Deposit	0.041	111.856	-0.017	0.645**	0.076	-30.848	-0.033	0.674*
	[0.069]	[88.718]	[0.016]	[0.242]	[0.110]	[26.118]	[0.020]	[0.380]
No Deposit *x* Year 2000	-0.057	7.403	-0.008	0.114**	-0.134	-1.795	0.007	0.148***
	[0.142]	[6.880]	[0.009]	[0.049]	[0.195]	[3.128]	[0.011]	[0.047]
Log(Prices)	0.106	-44.683	-0.009	0.438	0.154	23.617	-0.022	0.876**
	[0.075]	[57.909]	[0.013]	[0.277]	[0.194]	[22.835]	[0.015]	[0.392]
Climate	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Conflict dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	22764	22864	18378	18378	21451	21547	17201	17201
R-squared	0.076	0.969	0.791	0.950	0.076	0.972	0.796	0.953
Dep. Variable [mean]	0.029	283.912	0.247	3.626	0.030	273.537	0.240	3.642

Notes: (1) The table shows the regression results across districts in Africa during 2002–2007. (2) The results show the local economic impacts of China's WTO accession in the presence of mineral deposits in Africa. (3) The standard errors, clustered at the country level, are in brackets; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. (4) Growth, Spatial Gini, and Sen Index are measured using lights data as described in the data section. (5) Population density is measured as population per square kilometer. (6) Prices are reported as average US dollars. (7) Fixed effects include time-fixed effects, district-fixed effects, and country-year-fixed effects. (8) Climate is measured using the standard deviation of rainfall distribution at the district level. (9) Analysis based on World Bank GEM data has fewer observations because the GEM prices data covers fewer mineral products than in the USGS data.
Source: Authors' estimations

Table 6b: Robustness checks – the local economic impacts of active mining.

	USGS average prices				*World Bank GEM real prices*			
Dependent variables	*Per capita Growth*	*Pop. density*	*Spatial Gini*	*Sen Index*	*Per capita Growth*	*Pop. density*	*Spatial Gini*	*Sen Index*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
Post x Active mines	0.055	134.561	-0.018	0.671**	0.068	-24.982	-0.034	0.787**
	[0.072]	[93.083]	[0.015]	[0.267]	[0.114]	[28.253]	[0.020]	[0.355]
Inactive mines x Year 2000	-0.121	8.969	-0.002	0.121**	-0.169	-2.349	0.005	0.132**
	[0.145]	[7.503]	[0.007]	[0.051]	[0.211]	[3.553]	[0.011]	[0.057]
Log(Prices)	0.108	-47.181	-0.010	0.469	0.171	16.011	-0.024	0.850*
	[0.074]	[57.252]	[0.014]	[0.279]	[0.197]	[23.692]	[0.015]	[0.433]
Climate	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Conflict dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	22764	22864	18378	18378	21451	21547	17201	17201
R-squared	0.076	0.969	0.791	0.950	0.076	0.972	0.796	0.953
Dep. Variable [mean]	0.029	283.912	0.247	3.626	0.030	273.537	0.240	3.642

Notes: (1) The table shows the regression results across districts in Africa during 2002–2007. (2) The results show the local economic impacts of China's WTO accession in the presence active mining activities in Africa. (3) The standard errors, clustered at the country level, are in brackets; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. (4) Population density is measured as population per square kilometer. (5) Prices are reported as both average and real US dollars. (6) Growth, Spatial Gini, and Sen Index are measured using lights data as described in the data section. (7) Fixed effects include time-fixed effects, district-fixed effects, and country-year-fixed effects. (8) Climate is measured using the standard deviation of rainfall distribution at the district level. (9) Analysis based on World Bank GEM data has fewer observations because the GEM prices data covers fewer mineral products than in the USGS data.
Source: Authors' estimations

Table 6c: Robustness checks – the local economic impacts of the presence of mineral deposits, other variables.

	USGS Average prices				*World Bank (GEM) real prices*			
Dependent variables:	*Growth*	*Log(Pop)*	*MLD*	*Theil*	*Growth*	*Log(Pop)*	*MLD*	*Theil*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
Post *x* Deposit	0.045	0.100	-0.017	-0.023	0.074	-0.024	-0.045	-0.043
	[0.067]	[0.066]	[0.030]	[0.021]	[0.107]	[0.042]	[0.038]	[0.028]
No Deposit *x* Year 2000	-0.049	0.009	-0.006	-0.012	-0.138	-0.003	0.031	0.007
	[0.143]	[0.008]	[0.019]	[0.013]	[0.197]	[0.007]	[0.028]	[0.014]
Log(Prices)	0.100	-0.035	-0.005	-0.014	0.160	0.024	-0.055	-0.028
	[0.076]	[0.025]	[0.026]	[0.019]	[0.194]	[0.055]	[0.032]	[0.021]
Climate	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Conflict dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	22764	22864	18378	18378	21451	21547	17201	17201
R-squared	0.074	0.954	0.705	0.727	0.075	0.952	0.706	0.732
Dep. Variable [mean]	0.042	10.973	0.335	0.215	0.042	10.922	0.321	0.206

Notes: (1) The table shows the regression results across districts in Africa during 2002–2007. (2) The results show the local economic impacts of China's WTO accession in the presence of mineral deposits in Africa. (3) The standard errors, clustered at the country level, are in brackets; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. (4) Growth, Spatial Gini, and Sen Index are measured using lights data as described in the data section. (5) Population density is measured as population per square kilometer. (6) Prices are reported as both average and real US dollars. (7) Fixed effects include time-fixed effects, district-fixed effects, and country-year-fixed effects. (8) Climate is measured using the standard deviation of rainfall distribution at the district level. (9) Analysis based on World Bank GEM data has fewer observations because the GEM prices data covers fewer mineral products than in the USGS data.

Source: Authors' estimations

Table 6d: Robustness checks – the local economic impacts of active mining, other variables

	USGS Average prices				*World Bank (GEM) real prices*			
Dependent variables	*Growth*	*Log(Pop)*	*MLD*	*Theil*	*Growth*	*Log(Pop)*	*MLD*	*Theil*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
Post x Active mines	0.059	0.092	-0.014	-0.020	0.063	-0.025	-0.041	-0.040
	[0.070]	[0.068]	[0.030]	[0.020]	[0.110]	[0.047]	[0.041]	[0.030]
Inactive mines x Year 2000	-0.113	0.009	-0.000	-0.005	-0.173	-0.003	0.020	0.002
	[0.146]	[0.009]	[0.015]	[0.008]	[0.214]	[0.007]	[0.032]	[0.015]
Log(Prices)	0.103	-0.026	-0.008	-0.017	0.180	0.023	-0.059^{*}	-0.033
	[0.074]	[0.026]	[0.027]	[0.021]	[0.196]	[0.055]	[0.032]	[0.021]
Climate	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Conflict dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	22764	22864	18378	18378	21451	21547	17201	17201
R-squared	0.074	0.954	0.705	0.727	0.075	0.952	0.706	0.732
Dep. Variable [mean]	0.042	10.973	0.335	0.215	0.042	10.922	0.321	0.206

Notes: (1) The table shows the regression results across districts in Africa during 2002–2007. (2) The results show the local economic impacts of China's WTO accession in the presence active mining activities in Africa. (3) The standard errors, clustered at the country level, are in brackets; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. (4) Population density is measured as population per square kilometer. (5) Prices are reported as both average and real US dollars. (6) Growth, Spatial Gini, and Sen Index are measured using lights data as described in the data section. (7) Fixed effects include time-fixed effects, district-fixed effects, and country-year-fixed effects. (8) Climate is measured using the standard deviation of rainfall distribution at the district level. (9) Analysis based on World Bank GEM data has fewer observations because the GEM prices data covers fewer mineral products than in the USGS data.

Source: Authors' estimations.

Table 7a: Heterogeneous effects by the scale of mining operations

	USGS Constant prices				World Bank (GEM) real prices			
Dependent variables:	*Per capita Growth*	*Pop. density*	*Spatial Gini*	*Sen Index*	*Per capita Growth*	*Pop. density*	*Spatial Gini*	*Sen Index*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
Post x Small Scale	-0.522	-59.260	0.042	2.203	-0.268	-37.802**	0.009	5.375
	[0.375]	[58.193]	[0.063]	[2.776]	[0.296]	[17.473]	[0.101]	[5.679]
Post x Large Scale	0.094	117.424	-0.021	0.654**	0.096	-30.461	-0.034	0.504*
	[0.066]	[90.463]	[0.016]	[0.246]	[0.118]	[27.695]	[0.020]	[0.295]
Log(Prices)	0.093	-56.479	-0.008	0.404	0.151	23.590	-0.022	0.887**
	[0.072]	[63.154]	[0.013]	[0.279]	[0.195]	[22.774]	[0.015]	[0.402]
Inactive mines x Year 2000	-0.157	9.817	-0.008	0.106*	-0.231	-1.687	0.006	0.154***
	[0.144]	[8.899]	[0.010]	[0.054]	[0.204]	[3.185]	[0.011]	[0.048]
Climate	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Conflict dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	22764	22864	18378	18378	21451	21547	17201	17201
R-squared	0.076	0.969	0.792	0.950	0.076	0.972	0.796	0.953
Dep. Variable [mean]	0.029	283.912	0.247	3.626	0.030	273.537	0.240	3.642

Notes: (1) The table shows the regression results across districts in Africa during 2002–2007. (2) The results show the local economic impacts of China's WTO accession based on the scale of mining operations. (3) The standard errors, clustered at the country level, are in brackets; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. (4) Population density is measured as population per square kilometer. (5) Growth, Gini, and Sen Index are measured using lights data as described in the data section. (6) Fixed effects include time-fixed effects, district-fixed effects, and country-year-fixed effects. (7) Climate is measured using the standard deviation of rainfall distribution at the district level. (8) Analysis based on World Bank GEM data has fewer observations because the GEM prices data covers fewer mineral products than in the USGS data.

Source: Authors' estimations

Table 7b: Heterogeneous effects by minerals' values.

	USGS Constant prices				World Bank (GEM) real prices			
Dependent variables:	*Per capita Growth*	*Pop. density*	*Spatial Gini*	*Sen Index*	*Per capita Growth*	*Pop. density*	*Spatial Gini*	*Sen Index*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
Post x High	0.071	-11.582	-0.024	0.601	0.114	-5.159	-0.002	0.391
	[0.145]	[39.568]	[0.023]	[0.447]	[0.164]	[40.038]	[0.020]	[0.691]
Post x Low	0.052	154.146	-0.016	0.763**	0.060	-41.405	-0.046*	0.797*
	[0.045]	[112.815]	[0.016]	[0.333]	[0.107]	[26.671]	[0.024]	[0.403]
Log(Prices)	0.099	-74.459	-0.009	0.367	0.151	21.681	-0.024	0.895**
	[0.067]	[68.539]	[0.012]	[0.253]	[0.195]	[20.436]	[0.015]	[0.387]
Inactive mines x Year 2000	-0.066	12.829	-0.010	0.108	-0.068	-3.383	0.009	0.148***
	[0.139]	[11.245]	[0.011]	[0.067]	[0.137]	[3.429]	[0.008]	[0.054]
Climate	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Conflict dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	22764	22864	18378	18378	21451	21547	17201	17201
R-squared	0.076	0.969	0.791	0.950	0.076	0.972	0.796	0.953
Dep. Variable [mean]	0.029	283.912	0.247	3.626	0.030	273.537	0.240	3.642

Notes: (1) The table shows the regression results across districts in Africa during 2002–2007. (2) The results show the local economic impacts of China's WTO accession based on the mineral values. (3) The standard errors, clustered at the country level, are in brackets; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. (4) Population density is measured as population per square kilometer. (5) Growth, Gini, and Sen Index are measured using lights data as described in the data section. (6) Fixed effects include time-fixed effects, district-fixed effects, and country-year fixed effects. (7) Climate is measured using the standard deviation of rainfall distribution at the district level.

Source: Authors' estimations

Table 7c: Heterogeneous effects by the nature of mining activities

	USGS Constant prices				World Bank (GEM) real prices			
Dependent variables:	*Per capita Growth*	*Pop. density*	*Spatial Gini*	*Sen Index*	*Per capita Growth*	*Pop. density*	*Spatial Gini*	*Sen Index*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
Post x Extract	0.018	66.288	-0.022	0.451	0.034	-33.500	-0.031	0.493
	[0.068]	[85.842]	[0.016]	[0.310]	[0.094]	[24.096]	[0.020]	[0.451]
Post x Transform	0.178*	240.262	-0.008	1.523**	0.281	-18.436	-0.039	1.398***
	[0.090]	[219.465]	[0.035]	[0.566]	[0.246]	[57.794]	[0.024]	[0.471]
Log(Prices)	0.089	-79.908	-0.009	0.212	0.146	23.437	-0.022	0.872**
	[0.071]	[62.417]	[0.011]	[0.274]	[0.196]	[22.827]	[0.015]	[0.385]
Inactive mines x Year 2000	-0.365	16.149	-0.024	0.138	-0.559	-4.189	0.006	0.237**
	[0.248]	[19.272]	[0.015]	[0.145]	[0.599]	[7.002]	[0.009]	[0.092]
Climate	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Conflict dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	22764	22864	18378	18378	21451	21547	17201	17201
R-squared	0.076	0.969	0.792	0.950	0.076	0.972	0.796	0.953
Dep. Variable [mean]	0.029	283.912	0.247	3.626	0.030	273.537	0.240	3.642

Notes: (1) The table shows the regression results across districts in Africa during 2002–2007. (2) The results show the local economic impacts of China's WTO accession based on the nature of mining activities in Africa. (3) The standard errors, clustered at the country level, are in brackets; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. (4) Population density is measured as population per square kilometer. (5) Growth, Gini, and Sen Index are measured using lights data as described in the data section. (6) Fixed effects include time-fixed effects, district-fixed effects, and country-year-fixed effects. (7) Climate is measured using the standard deviation of rainfall distribution at the district level.

Source: Authors' estimations

Table 8: List of countries

Algeria	Gabon	Mozambique	South Sudan
Angola	Gambia	Namibia	Sudan
Benin	Guinea-Bissau	Niger	Tanzania
Botswana	Kenya	Nigeria	Togo
Cameroon	Liberia	Republic of Congo	Tunisia
Chad	Madagascar	Rwanda	Uganda
Côte d'Ivoire	Malawi	Senegal	Zambia
Democratic Republic of the Congo	Mali	Sierra Leone	Zimbabwe
Djibouti	Mauritania	Somalia	
Ethiopia	Morocco	South Africa	

Source: USGS data.

Table 9: Names of mineral commodities and their SITC codes by countries of production

SITC code	Minerals names	Price data	List of production countries
120	Helium	Yes	Algeria
264	Garnet (industrial)	Yes	Kenya
273	Stones (crushed, dimension), limestone, gypsum, marble, and silicon	Yes	Algeria, Angola, Ethiopia, Madagascar, Malawi, Mauritania, Mozambique, Rwanda, South Africa, Sudan, Tunisia, Uganda, and Zambia
274	Sulfur	Yes	Ethiopia, Kenya, Malawi, Namibia, South Africa, Zambia, and Zimbabwe
277	Diamond	Yes	Angola, Botswana, Cameroon, Liberia, Namibia, Sierra Leone, South Africa, Tanzania, and Zimbabwe
278	Barite, bentonite, clay, dolomite, fluorspar, graphite, salt, vermiculite, fluorine, and graphite	Yes	Algeria, Botswana, Chad, Djibouti, Ethiopia, Kenya, Madagascar, Morocco, Mozambique, Namibia, South Africa, Tanzania, Tunisia, Uganda, and Zimbabwe
281	Iron ore	Yes	Sierra Leone, South Africa, Tunisia, Zambia, and Zimbabwe
283	Copper	Yes	Algeria, Democratic Republic of Congo, Mauritania, Morocco, Namibia, Nigeria, Republic of Congo, South Africa, Zambia, and Zimbabwe
287	Cobalt, chromium, niobium (columbium), tantalum, titanium, zirconium, and tungsten	Yes	Botswana, Burundi, Ethiopia, Gambia, Madagascar, Mozambique, Nigeria, Rwanda, Sierra Leone, South Africa, Uganda, and Zimbabwe
522	Arsenic trioxide, lithium, manganese, pyrophyllite, soda ash, sodium silicate, and wollastonite	Yes	Chad, Cote d'Ivoire, Kenya, Morocco, Namibia, South Africa, Zambia, and Zimbabwe
523	Phosphate rock, and phosphoric acid	Yes	Malawi, South Africa, Tanzania, Togo, and Tunisia
661	Cement	Yes	Algeria, Angola, Benin, Burundi, Cameroon, Chad, Democratic Republic of Congo, Ethiopia, Gabon, Kenya, Liberia, Malawi, Mauritania, Morocco, Mozambique, Niger, Nigeria, Republic of Congo, Senegal, Sierra Leone, Somalia, South Africa, Sudan, Tanzania, Togo, Tunisia, and Zimbabwe

662	Diatomite	Yes	Kenya and Mozambique
681	Platinum	Yes	Botswana, Ethiopia, South Africa, and Zimbabwe
683	Nickel	Yes	Zimbabwe
686	Zinc	Yes	Algeria and South Africa
687	Tin	Yes	Nigeria, Rwanda, and Uganda
971	Gold	Yes	Algeria, Burundi, Cote d'Ivoire, Ethiopia, Kenya, Liberia, Mali, Republic of Congo, South Africa, Tanzania, Uganda, Zambia, and Zimbabwe
282	*Steel*	*No*	*Kenya, Mozambique, Nigeria, South Africa, Sudan, and Uganda*
289	*Gemstones*	*No*	*Botswana, Ethiopia, Madagascar, Mozambique, and Rwanda*
321	*Coal*	*No*	*Botswana, Burundi, Ethiopia, Malawi, Morocco, Mozambique, Niger, Nigeria, South Africa, Tanzania, Zambia, and Zimbabwe*
525	*Uranium*	*No*	*Namibia and Niger*
663	*Chromite*	*No*	*South Africa, Sudan, and Zimbabwe*
684	*Aluminum, ammonia, and bauxite*	*No*	*Cameroon, Mozambique, Nigeria, and South Africa*
*728***	*Asbestos*	*No*	*South Africa*

Source: Authors' construction using USGS data.