Connective Financing

Chinese Infrastructure Projects and the Diffusion of Economic Activity in Developing Countries

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Abstract

This paper studies the causal effect of transport infrastructure on the spatial distribution of economic activity within subnational regions in a large number of developing countries. To do so, we introduce a new global dataset of geolocated Chinese development finance projects over the period from 2000 to 2014 and combine it with measures of spatial concentration based on remotely-sensed data. We find that Chinese-financed transportation projects reduce spatial concentration within regions. Transport projects decentralize economic activity particularly strongly in regions that are more urbanized, located closer to a city, and less developed.

Keywords: development finance, transport costs, infrastructure, foreign aid, spatial concentration, China

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1 Introduction

In 2009, the Export-Import Bank of China (China Eximbank) approved a loan to the Kenyan government to substantially widen and improve the Nairobi-Thika Highway—a 50.4 km dual carriageway that extends from the center of Nairobi to the town of Thika. The project, locally known as the "Thika Super-Highway," sought to reduce congestion and travel times between Nairobi and a set of satellite towns along a critically important transportation corridor (African Development Fund 2007). Upon completion in 2012, traffic flows increased by 45 percent, journey speeds rose from 8 km per hour to at least 45 km per hour in sections with the highest registered traffic, and average commuting times from Thika to Nairobi fell from 2-3 hours to 30-45 minutes (KARA and CSUD 2012, African Development Bank 2014b,a, 2016, 2019). Economic activity spread out along the transport corridor and became substantially less concentrated in the core of Nairobi as a result (see Figure 1). The case of the Nairobi-Thika Highway fits within a broader pattern: Starting with Baum-Snow (2007), a series of studies in a variety of countries shows that major transport infrastructure investments can decentralize economic activity.[1]

[Figure 1 about here.]

The key contribution of this study is to examine whether and to what extent Chinese-financed infrastructure projects are decentralizing economic activity in recipient regions in developing countries.[2] We focus specifically on the provision of transport infrastructure financing from China's government, as it has assumed a dominant role in the construction and rehabilitation of transportation infrastructure around the world during the 21st century. Most of our analysis centers on the concentration[3] of economic activity within regions, as China's local footprint within a region is often sizable, but we also present results relating to infrastructure financing and concentration across regions. Our study thus tests whether the results from the existing, usually country-specific, literature can be generalized across a large sample of developing countries that host projects provided by the largest provider of infrastructure financing in the world.

Since 2000, China's government has financed many of the largest transport infrastructure projects in developing countries. The short- and long-run consequences of China's infrastructure financing activities—including the US$1 trillion Belt and Road

[1]See, for example, Baum-Snow et al. (2017) and Banerjee et al. (2020) on China, Bayes (2007) on Bangladesh, Bird and Straub (2014) on Brazil, Donaldson (2018) on India, Henderson and Kuncoro (1996) on Indonesia, Garcia-López et al. (2015) on Spain, Gibbons et al. (2019) on the United Kingdom, and Duranton and Turner (2012) on the United States. Redding and Turner (2015) as well as Baum-Snow and Turner (2017) provide recent surveys of this literature.

[2]These subnational units are first-order administrative (ADM1) regions, i.e., one layer below the national level. They correspond, for example, to provinces, states, oblasts, governorates, or emirates, depending on the administrative divisions in place in a given country.

[3]We use the terms *spatial concentration* and *spatial centralization* of economic activity interchangeably, as they both refer to changes in the distribution of people and output across space.

Initiative (BRI)—are the subject of considerable debate in the media and within policy circles. A growing number of studies focus on the expected impact of the BRI in different regions (e.g., Perlez and Huang 2017, Bandiera and Tsiropoulos 2020, Bird et al. 2020, de Soyres et al. 2020, Lall and Lebrand 2020).[4] Beijing's critics claim that it finances poorly-designed and hastily-executed projects that provide few economic benefits, while Western donors and lenders have learned through decades of experience to design and implement infrastructure projects in more careful and sustainable ways. In response to mounting criticism that it finances politically motivated and economically unsustainable projects, the Chinese government has doubled down on its leadership role in the market for global infrastructure finance.[5]

Many developing countries have unmet infrastructure financing needs, and the leaders of these countries are quick to point out that China is willing and able to swiftly finance and build roads, bridges, railways, and ports at a time when Western donors and lenders are not (Swedlund 2017).[6] For example, during his tenure as the President of Senegal, Abdoulaye Wade admonished traditional donors and creditors for their cumbersome bureaucratic procedures, noting that: "[w]ith direct aid, credit lines and reasonable contracts, China has helped African nations build infrastructure projects in record time. [...] I have found that a contract that would take five years to discuss, negotiate and sign with the World Bank takes three months when we have dealt with Chinese authorities" (Wade 2008).

We introduce the first global dataset of geo-located Chinese government-financed projects that were undertaken in developing countries between 2000 and 2014.[7] The dataset includes 3,485 projects that took place in 6,184 subnational locations across 138 countries during this fifteen-year period. For the purposes of our analysis, we focus on 269 Chinese government-financed transportation infrastructure projects that were undertaken in 1,211 subnational locations across 86 countries. The lower bound for the total financial value of these projects is US$64 billion. We estimate the effects of these projects on the spatial concentration of economic activity—both within and across

[4]As explained by Mauk (2019), "China has never released any official map of Belt and Road routes nor any list of approved projects, and it provides no exact count of participating nations or even guidelines on what it means to be a participant."

[5]At the 2017 Belt and Road Forum for International Cooperation, President Xi emphasized that "[i]nfrastructure connectivity is the foundation of development through cooperation. We should promote land, maritime, air and cyberspace connectivity, concentrate our efforts on key passageways, cities and projects and connect networks of highways, railways and sea ports [...]" (Xi 2017).

[6]An important reason for these infrastructure financing gaps follows from the fact that "Western donors have by and large gotten out of hard infrastructure sectors [...] and [t]hey [instead] channel their assistance overwhelmingly to social sectors or to infrastructure sectors such as water supply and sanitation that have direct effects on household health" (Dollar 2008).

[7]Though the Belt and Road Initiative (BRI) was not officially launched until late 2013, the Chinese government had already begun providing a significant number of large-scale financing for transport infrastructure in developing countries by the turn of the century. These pre-2014 projects share most of the characteristics of transport infrastructure projects that are now formally part of the BRI.

subnational jurisdictions—with satellite data on the geographical dispersion of nighttime light output (similar to Henderson et al. 2018).

To identify the causal effect of Chinese government-financed projects on spatial concentration, we circumvent the problem of missing instrumental variables for infrastructure for a large number of countries by focusing on the availability of *resources* for the construction of infrastructure projects.[8] This approach has the advantage that comparable data are available for a large number of countries, and plausibly exogenous instruments can be applied across these diverse empirical settings. We introduce an instrumental variable that uses an exogenous supply push variable interacted with a local exposure term: China's domestic production of potential project inputs interacted with each recipient region's probability of receiving projects. We use China's annual production of aluminum, cement, glass, iron, steel, and timber to proxy its capacity to provide physical project inputs.[9] The intuition behind this approach is that the Chinese government has long considered these production materials as strategic commodities and therefore produced them in excess of domestic demand. This policy results in large surpluses, some of which China redirects to overseas infrastructure projects.[10] We therefore expect China to be more lenient towards countries that request financing for transport infrastructure projects in the years when such inputs are abundant and less lenient in the years when such inputs are scarce. We also expect subnational localities that frequently receive Chinese government-financed transport projects to be more severely affected by year-to-year fluctuations in the supply of project inputs.

Our results show that regions which are frequent recipients of projects receive larger amounts of Chinese government financing in years of overproduction than subnational localities that infrequently receive Chinese government-financed transport projects. This difference presumably occurs because existing local capacity and relationships make it easier to implement additional projects. This estimate can be interpreted as a difference-in-differences estimate, similar to those reported in the "China shock" literature or the literature on aid and conflict (e.g., Autor et al. 2013, Nunn and Qian 2014). We essentially compare the effects of Chinese transport projects induced by annual changes in the production of raw materials in subnational localities with a high probability of receiving such projects and subnational localities with a low probability of receiving such projects.

[8] The literature typically uses historical transport networks or other country-specific historical circumstances (such as minimum spanning trees connecting the largest cities).

[9] Exporting excess capacity in a variety of materials through infrastructure investments abroad is one of the secondary motives often ascribed to the Chinese government's BRI initiative. For example, the Economist writes "Mr Xi [...] hopes to [...] export some of his country's vast excess capacity in cement, steel and other metals" (see `www.economist.com/the-economist-explains/2017/05/14/what-is-chinas-belt-and-road-initiative`). Our approach extends the strategy proposed in Dreher et al. (2021a) which exclusively used the level of steel production.

[10] Chinese infrastructure projects usually require construction inputs that are oversupplied in China, and Chinese state-owned banks usually obligate their borrowers to import these inputs on a preferential basis (Dreher et al. 2021b).

We find that Chinese-financed infrastructure projects reduce spatial concentration within first-order regions and accelerate the diffusion of economic activity around cities (in line with Figure 1 and Baum-Snow 2007). Specifically, we find that the Gini coefficient measuring the spatial concentration of economic activity is reduced by about 2.2 percentage points. Similar specifications for concentration between regions suggest that Chinese-financed infrastructure cannot be robustly linked to changes in the concentration of economic activity across regions. This absence of an overall effect is in line with the recent studies which emphasize that transport infrastructure has heterogeneous and context-specific impacts on the distribution of economic activity across regions (Baum-Snow et al. 2020, Fajgelbaum and Redding 2018, Jedwab and Storeygard 2020, He et al. 2020). Our main results hold under a variety of perturbations, such as the choice of control variables to strengthen identification or variations of the instrumental variable.

In line with predictions from land use theory, we find that transport projects shift activity from dense locations to less densely developed places, that is, from the highest quintile of the light distribution to lower quintiles. We find no evidence that light intensity increases at the extensive margin or that per capita output increases, but we do find evidence that overall light intensity increases in response to Chinese-financed infrastructure projects. The results also show that the impact of these projects on the concentration of activity within regions is heterogeneous. Chinese-financed transport infrastructure reduces concentration more strongly in regions with more urban areas, low travel time to cities, and higher road density. We take this as indirect evidence suggesting that our results are driven by a relocation of workers to the outskirts of cities rather than an increase in economic activity in peripheral cities of a region. We also provide evidence that these effects are largest in African countries and poorer regions within developing countries, which tend to experience rapid population growth and have high demand for infrastructure.

The remainder of the paper proceeds as follows. Section 2 briefly discusses what theory and the existing empirical literature suggest about the relationship between transport projects and the spatial concentration of economic activity within and across regions. Section 3 introduces a subnationally georeferenced dataset of Chinese government-financed projects around the world, and discusses the remotely-sensed measure of spatial concentration. Section 4 describes the empirical strategy. Section 5 presents and discusses the results. Section 6 concludes.

2 Transport infrastructure and the concentration of economic activity

Urban land use theory suggests that transport infrastructure should reduce spatial concentration *within* subnational regions if these jurisdictions primarily consist of urban areas and their surroundings. This is a key prediction of the canonical monocentric city model (Alonso et al. 1964, Mills 1967, Muth 1969), in which all workers commute to a single location in a central business district (CBD). In this model, agglomeration benefits and rents are highest in the city center but decline with distance from the CBD. Initially, many people choose to live near the center and pay higher rents in order to reduce their commuting times. Subsequent investments in transportation infrastructure increase the speed of transportation, reduce commuting costs, and increase the supply of readily accessible land, shifting this gradient outwards. Transportation infrastructure thus facilitates urban sprawl—the flow of people out of the city center—by turning a city's agricultural surroundings into valuable locations to live in. The model also implies that people should spread out along newly created highways (Baum-Snow 2007), just as we document above for the case of Nairobi. Firms also have incentives to move out of cities in response to new transportation infrastructure but this depends on a number of factors, including the degree to which a particular industry benefits from agglomeration economies.[11] Beyond the monocentric city model, as people and firms move out of existing urban centers, new sub-centers emerge and create replicas of CBDs that lure even more people and firms away from existing urban centers (Ogawa and Fujita 1980, Fujita and Ogawa 1982, Henderson and Mitra 1996).

While the model is highly stylized, its prediction that new or upgraded transportation infrastructure disperses economic activity away from urban agglomerations is supported by a large and growing body of empirical evidence. Consider suburbanization in 20th-century America, where researchers have documented urban sprawl and strong population growth in cities with more developable surroundings (Burchfield et al. 2006, Saiz 2010). The construction of highways in the United States dramatically lowered commuting times and increased demand for suburban relative to urban residential space (Baum-Snow 2007). There is also evidence for similar processes of diffusion around urban areas in developing countries (e.g., Bayes 2007, Zárate 2020). Baum-Snow et al. (2017) examine the effect of road and railway infrastructure on the spatial distribution of economic activity in China, and find that ring road investments displaced 50 percent of industrial GDP from central cities to outlying areas. As Chinese-financed infrastructure projects in developing

[11]Firms have weaker incentives than individuals since they face a more complex set of costs when leaving city centers. They trade agglomeration benefits off against a variety of costs, giving rise to a pattern where manufacturing firms and other firms that require less-skilled jobs decentralize more than other firms (Rossi-Hansberg et al. 2009, Baum-Snow 2014).

countries often represent a substantial proportion of local infrastructure investment in a given year, we expect them to similarly decentralize economic activity around urban areas. We also expect these projects to spur the formation of new sub-centers as businesses, workers, and other economic actors relocate into the periphery.

Transport projects may also affect the concentration of economic activity across regions, a central concern of economic geography research. The classic core-periphery model stresses the role played by increasing returns to scale when economic activity starts to concentrate in a particular region. When trade costs are high or prohibitive, firms are spread out evenly across regions to locate themselves close to consumer demand. When transport projects increase connectivity between leading and lagging regions, labor and capital should move from the periphery to the better connected core, creating a core-periphery split until there is almost complete specialization (Krugman 1991). However, some of these forces reverse at high levels of concentration. Puga (1999), for example, shows how a lack of migration with low trade costs implies that firms will again locate closer to final demand. This gives rise to a bell shape for regional inequalities in relation to trade costs. The advantage of being in a central location that is well-connected with other markets erodes when very low trade costs make it easy to reach the periphery. While the bell-shaped curve is a robust prediction, it requires additional heterogeneity in agricultural trade costs, urban congestion, or migration decisions that make the overall relationship difficult to identify.

Empirical evidence on how transport costs shape regional concentration reflects this heterogeneity. Brülhart et al. (2019) show that the advantages of market potential are shrinking in the developed world but remain an important determinant of employment growth in developing countries. In terms of infrastructure investments, Bird and Straub (2014) find that investments in Brazil's road network increased economic agglomeration in the already prosperous population centers of the South, while also facilitating economic agglomeration in less developed areas of the North. On balance, these investments reduced spatial inequality across the country's municipalities.[12] However, Faber (2014) provides evidence that China's National Trunk Highway System—a major inter-regional transportation infrastructure project—reduced levels of economic activity in the newly connected peripheral regions relative to non-connected peripheral regions. Given these mixed findings and the cross-national scope of our study, we do not have strong reasons to believe that Chinese-financed transportation projects will uniformly increase or decrease concentration between regions.

Developing countries are an important and useful application of these theories. Most developing countries face major transportation infrastructure gaps in both urban and

[12] In a related study of Argentina's steam railroad network and the agricultural sector, Fajgelbaum and Redding (2018) suggest that lower transport costs can enable economic actors located in remote, interior regions to participate in structural transformation.

rural regions. Internal transport costs are four to five times higher within Ethiopia or Nigeria than within the United States (Atkin and Donaldson 2015). The total length of the road network per 1,000 people is roughly 10 times lower for South Asia, East Asia and the Pacific, Sub-Saharan Africa, and the Middle East and North Africa than for North America (Andrés et al. 2014). Many of these countries have both rapidly expanding populations and underfunded, poorly designed transportation systems (Cervero 2013). Major infrastructure financing gaps make it difficult for developing countries to overcome the spatial bottlenecks created by high levels of urban concentration and rural neglect.

Moreover, subnational regions within developing countries are often defined by dense central cities surrounded by underdeveloped hinterlands.[13] Large cities in many African countries, for example, tend to be highly congested relative to overall levels of infrastructure, industry, and economic opportunity (Lall et al. 2017), while Africa's secondary cities tend to be isolated from world markets (Gollin et al. 2016). In our setting, high levels of urban congestion in developing economies are a latent force for spatial dispersion as new transportation options become available.

3 Data

New geocoded dataset of Chinese government-financed projects

The Chinese government considers the details of its overseas development program to be a "state secret" (Bräutigam 2009, p. 2). It does not publish a country-by-country breakdown of its expenditures or activities. Nor does it systematically publish project-level data on its less concessional and more commercially-oriented financial expenditures and activities in developing countries. In order to overcome this challenge, Dreher et al. (2021b) collaborated with AidData, a research lab at William & Mary, to build a global dataset of Chinese government-financed projects committed between 2000 and 2014. This project-level dataset uses a publicly documented method called Tracking Underreported Financial Flows (TUFF) to facilitate the collection of detailed and comprehensive financial, operational, and locational information about Chinese government-financed projects (Strange et al. 2017, 2018). The TUFF method triangulates information from four types of open sources—English, Chinese and local-language news reports; official statements from Chinese ministries, embassies, and economic and commercial counselor offices; the aid and debt information management systems of finance and planning ministries in counterpart countries; and case study and field research undertaken by scholars and non-governmental organizations (NGOs)—in order to minimize the

[13] As Baum-Snow et al. (2017) point out, the urban distribution of economic activity in many developing countries today largely resembles that of early 20th century America, in which industry was initially overwhelmingly concentrated in urban centers.

impact of incomplete or inaccurate information.[14] Economists, political scientists, and computational geographers have used these data—so far limited to Africa or country-level data—to explain the nature, allocation and effects of Chinese government-financed projects (e.g., BenYishay et al. 2016, Hernandez 2017, Dreher et al. 2018, Eichenauer et al. 2021, Isaksson and Kotsadam 2018a,b, Gehring et al. 2022, Horn et al. 2021, Anaxagorou et al. 2020, Isaksson 2020, Martorano et al. 2020, Dreher et al. 2021b).[15]

In this paper, we build on these project-level data to create a first-of-its-kind geocoded dataset of China's project locations around the globe. In contrast to previous versions, our new data enable subnational analyses of Chinese-financed projects in five regions of the world (Africa, the Middle East, Asia and the Pacific, Latin America and the Caribbean, and Central and Eastern Europe) over a 15-year period (2000–2014). Our dataset takes all officially committed projects from Dreher et al. (2021b) that entered implementation or reached completion as a starting point.[16] We then subjected all of these projects to a double-blind geocoding process (Strandow et al. 2011), in which two trained coders independently employ a defined hierarchy of geographic terms and assign uniform latitude and longitude coordinates and standardized place names to each location where the project in question was active. Coders also specify a precision code for each location. Precision code 1 corresponds to an exact location; precision code 2 corresponds to locations within 25 kilometers of the exact project site; precision code 3 corresponds to a second-order region; and precision code 4 corresponds to a first-order region.[17] If the coordinates and precision codes do not match, a senior "arbitrator" identifies the source of the discrepancy and assigns a final set of geocodes for all sites. The purpose of this double-blind coding process is to minimize the risk of missed or incorrect locations.[18] In total, the resulting dataset covers 3,485 projects (worth at least US$273.6 billion in constant 2014 dollars) in 6,184 discrete locations across 138 countries.[19]

[14] The method is organized in three stages: two stages of primary data collection (project identification and source triangulation) and a third stage to review and revise individual project records (quality assurance). The TUFF data collection and quality assurance procedures are described at length in Strange et al. (2017, 2018).

[15] One exception is Marchesi et al. (2021) who investigate the effects of Chinese aid on the level of firms. See also Chauvet and Ehrhart (2018).

[16] We build on earlier georeferenced datasets that cover Africa, the Tropical Andes, and the Mekong Delta for fewer years only (BenYishay et al. 2016, Dreher et al. 2019). Note that we exclude all suspended and cancelled projects as well as projects that reached the (non-binding) pledge stage or (binding) official commitment stage but never reached implementation or completion during the period of study (2000-2014).

[17] We exclude all projects with precision codes between 5 and 9 from the regression analysis below. Such projects (e.g., country-wide projects) were not able to be geocoded with a sufficient level of spatial precision to be included in the regional-level data.

[18] Note that the point-based method used to geocode these projects is not designed to measure the exact linear path of transportation infrastructure. This implies that one cannot 'connect the dots' and look for effects alongside the roads, railways etc. However, it is useful for measuring the effects within treated subnational regions as we do in the present paper.

[19] For comparison, the Africa-specific data provided in Dreher et al. (2019) include 1,650 projects across 2,969 locations in the 2000-2012 period. Note that, in contrast to our dataset, they also cover

In order to merge these geocoded project data with our outcome measures of spatial concentration within and across subnational regions, we aggregate all projects with precision codes 1-4 to first-order regions. Figure 2 shows the locations of projects that can be placed within first-order regions over the 2000-2014 period. The resulting subsample includes 2,140 Chinese government-financed projects at 4,420 discrete locations (collectively worth US$201 billion) that were completed or being implemented in 883 first-order regions within 129 countries between 2000 and 2014.[20] Our data can be disaggregated by financial flow type and sector. With respect to the former, we distinguish between Official Development Assistance and other forms of concessional and non-concessional financing from Chinese government institutions.[21] For the purposes of the latter, we use the OECD's three-digit sector classification scheme, which categorizes projects according to their primary objectives.[22]

269 of these projects were assigned to the "transport and storage" sector, implemented in 1,211 different locations (with a combined value of at least US$64 billion, when counting those projects for which financial values are available). The vast majority of these projects focused on building transportation infrastructure, such as roads, railways, bridges, seaports, and airports. With 651 project locations, long-distance roads are most frequent, followed by long-distance railways (245), and urban roads (123) (see Table A-2 in the Appendix). These projects are the ones we exploit for most of our analyses. We also use a larger sample of projects that supported economic infrastructure and services, which includes roads, railways, bridges, seaports and airports but also power grids, power lines, cell phone towers, and fiber optic cable lines (514 projects at 1,897 locations with a value of about US$165 billion).

[Figure 2 about here.]

projects that have not (yet) reached implementation stage.

[20] We only focus on low-income and middle-income countries. More precisely, we include countries that the World Bank does not classify as high-income countries in a given year (see `https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lendinggroups`, last accessed September 13, 2017). We also exclude small states with a population size that falls below a threshold of 1,000,000 inhabitants. Table A-1 in the Appendix lists all countries included in the analysis.

[21] More precisely, we code all Chinese government-financed projects as Official Development Assistance ("ODA-like"), Other Official Flows ("OOF-like"), or "Vague Official Finance." Chinese ODA-like projects refer to projects financed by Chinese government institutions that have development intent and a minimum level of concessionality (a 25 percent or higher grant element). Chinese OOF projects refer to projects financed by Chinese government institutions that have commercial or representational intent and/or lack a grant element of 25 percent or more. Projects assigned to the Vague Official Finance category are Chinese government-financed projects where there is insufficient information in the public domain about concessionality and/or intent to make a clear determination as to whether the flows are more akin to ODA or OOF. Total Chinese Official Finance (OF) is therefore the sum of all projects coded as ODA-like, OOF-like, or Vague (Official Finance). For more detailed discussion of the distinction between these types of Chinese development finance, see Dreher et al. (2018).

[22] There are 24 of these OECD sector codes (see `www.oecd.org/development/financing-sustainable-development/development-finance-standards/purposecodessectorclassification.htm` for details).

Figure 2 illustrates the global reach of Chinese official finance in the 21st century. Consistent with earlier periods of Chinese aid giving (Dreher and Fuchs 2015), Chinese projects cover almost all developing countries (with countries recognizing the Chinese government in Taiwan as a notable exception).[23] Chinese-financed development projects are densely concentrated in African and Asian countries. The figure also illustrates that many Chinese government-financed projects are situated in coastal regions, including some of the highest-value transportation projects.

Measuring concentration within and across subnational regions

Reliably measuring local economic activity across the globe with official data is difficult. Few countries collect and report comprehensive data at the individual or plant/establishment level at regular intervals and subnational GDP data are generally only available in highly developed countries. To circumvent this problem, we follow recent literature that uses nighttime light intensity as a proxy for local economic activity (Henderson et al. 2012, Hodler and Raschky 2014, Michalopoulos and Papaioannou 2014). While nighttime lights were initially proposed as a measure of income for countries with weak statistical capacity, they were quickly adopted as a measure of subnational economic activity in developing countries more broadly. Subsequent studies have demonstrated that changes in light emissions correlate strongly with traditional measures of welfare down to the village level (Bruederle and Hodler 2018, Weidmann and Schutte 2017).

One of the main purposes of infrastructure investments is to enable the relocation of economic activity. Hence we are primarily interested in shifts in total activity rather than per capita measures. We follow Henderson et al. (2018), who use nighttime light intensity at the grid-cell level as a measure of aggregate economic activity—i.e., the product of population and light output per capita—and then calculate a spatial Gini coefficient based on the distribution of this proxy for total GDP.

We obtain data on nighttime light intensity from the Defense Meteorological Satellite Program's (DMSP) Operation Line Scan satellites. The DMSP satellites circle the earth in sun-synchronous orbit and record evening lights between 8:30 and 9:30 pm on a 6-bit scale ranging from 0 to 63. The National Oceanic and Atmospheric Administration (NOAA) processes these data, creates annual composites of the daily images at a resolution of 30 arc seconds, and makes them available to the general public. We use the so-called "stable lights" product, which filters out most background noise, forest fires, and stray lights. Even though there are well-known issues in these data with bottom and top coding (see Jean et al. 2016, Bluhm and Krause 2018), nighttime lights are measured in a consistent manner around the globe and avoid many of the measurement errors involved

[23] For recent work that studies the allocation of China's development finance, see Dreher et al. (2022) or Hoeffler and Sterck (2022).

in more traditional survey data.

We proceed in four steps to calculate our measure of spatial concentration. First, we divide the entire world into a grid of 6 arc minute cells (i.e., an area of about 9.3 km by 9.3 km at the equator)[24] and align the grid with lights data. Second, we intersect this grid with the global first-order administrative boundaries, which creates "squiggly" cells along the regional borders.[25] Third, for all squiggly cells in this grid and all years in the nightlights data, we compute the sum of light (s_i), the land area of each cell in km^2 (a_i), and the light intensity in the cell ($x_i = s_i/a_i$).[26] We average the resulting light intensities whenever more than one satellite is available and turn off all pixels that do not fall on land before aggregating the lights to the grid level. Finally, we compute the Gini coefficient of light intensities over all cells (including cells with zero light intensity) within an administrative region as

$$\textsc{Gini} = \frac{\sum_{i=1}^{n} w_i \sum_{j=1}^{n} w_j |x_i - x_j|}{2 \sum_{i=1}^{n} w_i \sum_{i=1}^{n} w_i x_i}, \tag{1}$$

where $w_i = \frac{a_i}{\sum_{i=1}^{n} a_i}$ is an area-based weight and n is the total number of cells in a region. We also construct Gini coefficients for concentration *between* first-order regions. The formula remains the same only that it is based on the average light intensity of a region (swapping $\bar{x}_i$ for x_i) and w_i is then defined as the land area of the entire region.

Our spatial Gini coefficient can be interpreted as the average (weighted) difference between the light intensities of all possible pairs of cells within an administrative region. Geometrically, it is the area under the Lorenz curve plotting the cumulative distribution of weighted light intensities against the cumulative distribution of cell areas (in km^2). Including cells with zero light intensity means the Lorenz curve will remain at zero before sloping up to one, but ensures that the Gini coefficient is a proper measure of economic concentration, which not only decreases when the distribution of light becomes more equal among already illuminated cells but also when new cells become illuminated. As can be seen from the long differences in the spatial Gini coefficient presented in a world map of first-order regions in Figure 3, our dependent variable shows considerable variation over the time period under analysis, both within and across countries (2000–2013).

[Figure 3 about here.]

[24] Although the nominal resolution of the DMSP-OLS system is 30 arc seconds, geolocation errors and on-board processing of fine-resolution pixels lead to a true ground footprint of 5 km by 5 km (Elvidge et al. 2013). Taking about twice this resolution reduces the influence of this mechanical spatial autocorrelation, reduces the influence of top coding and bottom coding, and limits the computational burden. The newer Visible Infrared Imaging Radiometer Suite (VIIRS) data, which have superior technical properties, do not span a significant portion of our sample.

[25] We obtained the regional borders from the Database of Global Administrative Areas (GADM) vector dataset (version 2.8). The same data were used to geocode the Chinese-financed projects.

[26] Dividing by the land area adjusts for the fact that 6 arc minute cells do not have a uniform area across the globe and may be covered by water. We calculate the land area of each cell using the Gridded Population of the World (v4) land/water raster.

It is important to emphasize that the Gini coefficient captures the overall dispersion of economic activity, which is a product of the population distribution and the distribution of light per capita.[27] Henderson et al. (2018) show that the cross-sectional variation in population density across administrative regions is substantially larger than the variation in income per capita. If this holds across time, then a significant proportion of observed changes in the within-region distribution of light intensities should be attributable to shifts in the population distribution rather than differences in per-capita income. This is precisely the type of variation we are interested in and expect to be affected by transport infrastructure investments. Moreover, since the time period of our study is relatively short, relocation of people is perhaps more likely to drive the results rather than the (somewhat slower) relocation of firms.

We prefer using nighttime lights over data for population density as our main outcome measure. Population data at comparable resolutions–such as the Global Human Settlement Layer, Gridded Population of the World, or Landscan–are based on rarely available censuses, which are then disaggregated in space and interpolated over time. They would not allow us to exploit annual variation in the commitment of transport projects and changes in economic activity, which are the basis of our identification strategy. Census data are also less frequently available in poorer developing countries that host many Chinese-financed development projects.

4 Empirical strategy

We are interested in permanent changes in spatial concentration of economic activity as a result of infrastructure investments. Denoting first-order administrative regions by j, countries by i,[28] and years by t, our main equation relates our luminosity-based measure of spatial concentration, $\textsc{Gini}_{jit}$, to the total number of years in which transportation projects have been committed to a region until $t-2$, $N_{ji,t-2}$. We lag this variable by two years to account for the difference between the commitment date and the expected finalization of a project.[29] We begin with a flexible specification which allows the effect

[27]To see this, consider that x_i is defined as $\frac{p_i}{a_i} \times \frac{s_i}{p_i}$, where $\frac{p_i}{a_i}$ is population density and $\frac{s_i}{p_i}$ is light per capita in each cell.

[28]Going below the first-order level would change many characteristics of the sample. We would lose a significant share of projects that have only been accurately coded to first-order regions and the exposure variable we introduce below would be based on substantially fewer projects per region as well. What is more, in countries with a smaller land mass, second-order regions often correspond to administrative boundaries of cities, which would effectively exclude their surroundings from a within-unit analysis.

[29]This lag duration corresponds to the difference between actual project start and end dates for a subset of projects where both data points are available. In our data set, approximately 1,100 Chinese government project records had enough information to calculate the average time between project start and finish. The average time from start to completion within this subset is about 2.1 years; historical data on Chinese development projects also reveal a median of two years between project start and completion (Dreher et al. 2021b, based on data from Bartke 1989). When we use one rather than two lags, the results we report below are very similar. The estimates become smaller for longer lags, and are

of a Chinese-financed project to be arbitrarily correlated with region-specific fixed effects and region-specific time trends:

$$\text{GINI}_{jit} = \beta N_{ji,t-2} + \mu_{ji} + \theta_{ji} \times t + \lambda_{it} + +\epsilon_{jit}, \tag{2}$$

where μ_{ji} are region-fixed effects, $\theta_{ji} \times t$ are region-specific linear time trends, and λ_{it} are country-year-fixed effects that absorb a variety of potential shocks to all regions of a country in a particular year.

A more tractable version of this model can be estimated in first differences:

$$\Delta\text{GINI}_{jit} = \beta \Delta N_{ji,t-2} + \theta_{ji} + \tau_{it} + \Delta\epsilon_{jit}, \tag{3}$$

where $\tau_{it} = \lambda_{it} - \lambda_{i,t-1}$ is a new set of country-year-fixed effects and wherein region-specific trends in levels are now captured by the region-fixed effects in first differences, $\theta_{ji} = \theta_{ji} \times t - \theta_{ji} \times (t-1)$. In both equations, β measures the effect of committing at least one new project two years prior on contemporary changes in spatial concentration. The model nests less flexible approaches with a strict parallel-trends assumption since all θ_{ji} could be zero.

We allow a wide range of dependency structures to occur in $\Delta\epsilon_{jit}$. Transportation infrastructure projects often connect more than one administrative region. Clustering standard errors on the country level permits arbitrary spatial and temporal correlation among all regions within a country. To account for connections across countries, we also report Conley errors with a spatial cutoff of 500 km and a heteroskedasticity- and autocorrelation-consistent (HAC) structure with a lag cutoff of 1,000 years in the time-series dimension.[30] While our "treatment-control" strategy does not account for general equilibrium effects, spillovers to untreated regions would have to systematically raise or lower concentration there (which has not been established in the literature) to introduce significant bias into our within-region estimates.

Our preferred measure of transportation infrastructure projects, $\Delta N_{ji,t-2}$, is thus a binary variable indicating that at least one new project is committed to a particular region in a year.[31] Clearly, the size of the projects is not necessarily homogeneous across locations, and thus the effects of projects on spatial concentration might differ along

imprecisely estimated.

[30] Using a long lag cutoff in the HAC part of the errors implies that the weight of a time-series shock is almost constant, which is equivalent to clustering on regions in the time-series dimension. We also used higher spatial cutoffs to estimate Conley errors but found no substantive changes beyond 500 km (and a very small subset of standard errors could not be computed beyond 500 km). Alternatively, we clustered at the region level or at region level *and* year. None of this changes our qualitative results.

[31] This measure does not count the number of projects or project locations in a particular year. This is because projects are often co-located, e.g., different sections of a highway, and are coded with multiple locations per project. Both do not necessarily capture the intensive margin of infrastructure investments but rather reflect the definitions adopted during the geocoding process.

the intensive margin. Unfortunately, we lack comprehensive information on the financial values for more than a third of these projects (see Dreher et al. 2021b), so we prefer the binary indicator and present additional results using (logged) aggregate dollar values for comparison. We define our dependent variable based on commitment years rather than actual disbursement dates as comprehensive data on disbursements are not available and virtually impossible to estimate through open-source data collection. With first differences, a two-year lag, and a lack of nighttime lights data after 2013 (from the DMSP-OLS system), our sample effectively covers the period from 2002 until 2013.

The subnational allocation of Chinese development projects is almost certainly endogenous to spatial concentration. For example, China may allocate more resources to poorer and less connected regions. After all, an official goal of Chinese development financing is to make "great efforts to ensure its aid benefits as many needy people as possible" (State Council 2011). Previous studies also demonstrate that the allocation of Chinese funding is correlated with per-capita income and population size (Dreher and Fuchs 2015, Dreher et al. 2018). Reverse causality could also stem from commercially motivated projects that either get sited in economic centers to exploit agglomeration effects, or locate in suburban areas out of cost concerns.

Apart from reverse causality, our parsimonious specification omits a number of variables which are likely to be correlated with Chinese infrastructure funding as well as with spatial concentration. Some of these covariates vary across regions and over time in a non-linear fashion, so that they are not captured by our battery of fixed effects and region-specific trends. Such unobserved variation could, for example, arise when the decision to finance an infrastructure project in a particularly abundant region is driven by an increased demand for natural resources (or other commodities) in China (Guillon and Mathonnat 2020). More broadly, Chinese development projects have been linked to deteriorating political institutions and higher levels of corruption at the local level (Brazys et al. 2017, Isaksson and Kotsadam 2018a). Chinese development financing also directly affects subnational and national development in Africa (Dreher et al. 2021a,b) but how this relates to the spatial distribution of economic activity is not clear ex ante. Greater local growth could lead to a reduction of spatial concentration within regions—both directly and indirectly through positive spillovers—or it could increase the within-region concentration of economic activity at the expense of poorer cities and villages in the region. In the context of this paper, local growth is a mediating factor and therefore a "bad control" (Angrist and Pischke 2008). The same holds for population or population density, which we do not include as a control (although doing so hardly affects our results).

[Figure 4 about here.]

To address concerns about endogeneity, we use an instrumental-variables strategy. We instrument Chinese infrastructure projects with the interaction of two variables.

The first is China's production of raw materials that are typically used in transport infrastructure projects—aluminum, cement, glass, iron, steel, and timber—which proxy China's capacity to provide physical project inputs. The second is the regional probability of receiving a Chinese-financed transport infrastructure project in a given year.[32] We calculate this (endogenous) probability as the fraction of years over the 2000–2014 period in which at least one Chinese government-financed transport infrastructure project has been committed, $\sum_t \Delta N_{ijt}/15$, and denote this variable by $\bar{N}_{ji}$. We measure China's production of aluminum, cement, iron, and steel in 10,000 tons, glass in 10,000 weight cases, and timber in 10,000 cubic meters.[33] Given that the production of these raw materials trends upwards over time, we detrend the individual time series. We then extract the first common factor from these six inputs, F_t, resulting in one variable that maximizes the variation of the underlying components. Figure 4 reports the corresponding graphs, including the original and detrended input materials, and the first factors of both to emphasize the non-linear time variation that we exploit for identification. Rather than using six separate interactions as instruments, which are strongly correlated, we interact the first common factor of the detrended (logged) inputs with the probability to receive aid to form a single instrumental variable.

We lag this series by one year (relative to the timing of project commitments) so that domestic overproduction in China translates into transport infrastructure projects abroad approximately one year later. In this setup, the production of Chinese raw materials only varies over time (and is exogenous to spatial concentration within any particular region), while the probability of receiving projects varies only across regions. This is how our instrument resembles the supply-shock instruments commonly used in trade and development economics, such as the recent literature on the impact of the rise of Chinese manufacturing on local US labor markets (e.g., Autor et al. 2016) or studies on aid and civil conflict (e.g., Nunn and Qian 2014). Putting these elements together, we estimate the following first-stage regression:

$$\Delta N_{ji,t-2} = \delta(F_{t-3} \times \bar{N}_{ji}) + \omega_{ji} + \phi_{i,t-2} + \nu_{ji,t-2}, \tag{4}$$

where F_{t-3} is the first common factor of the (detrended and logged) raw materials

[32] Our description of the instrument draws in part on Dreher et al. (2021a), where the level of steel production in China was first introduced as a supply shock in the time-series dimension. The original instrument has been used in a number of studies, including Brazys and Vadlamannati (2021), Humphrey and Michaelowa (2019), Ping et al. (2020), Iacoella et al. (2021), Marchesi et al. (2021), and Zeitz (2021). Since we have introduced our variant of the instrument with multiple detrended inputs, it has been used in Gehring et al. (2022) and Dreher et al. (2021b, 2022).

[33] We use USGS data on annual production of aluminum (`https://www.usgs.gov/centers/nmic/aluminum-statistics-and-information`, last accessed 12 October 2019). We have retrieved the annual production volumes of cement, glass, pig iron, steel, and timber via Quandl and complemented them with information from the website of the National Bureau of Statistics of China (`http://www.stats.gov.cn/english/statisticaldata/yearlydata/YB1999e/m12e.htm`; last accessed 12 October 2019).

produced in China, and $\phi_{i,t-2}$ are country-year-fixed effects. Equations (3) and (4) are estimated using Two-Stage Least Squares (2SLS).[34] When we include controls for various robustness checks, they always enter both equations in first differences (i.e., $\Delta \mathbf{x}_{jit}$).

The intuition behind this identification approach resembles that of a generalized difference-in-differences design. Intuitively, we effectively compare the effects of Chinese transport infrastructure projects on spatial concentration induced by changes in domestic production of potential project inputs in China across two groups: regions that are regular and irregular recipients of Chinese transport infrastructure financing. In other words, we use differences in the local exposure to the common overproduction shock originating in China to identify the effects of transport infrastructure projects on the spatial distribution of economic activity.

We investigate the validity of this approach in several steps. First, the identifying assumptions inherent in this approach could be violated if other unobserved variables drive the allocation of Chinese-financed infrastructure projects *and* these variables have heterogeneous effects on spatial concentration that coincide with our distinction between regular and irregular recipient regions. Hence, in comparison to a standard panel difference-in-differences setting, our instrument ensures that the timing of the intervention is exogenous but still requires parallel pre-treatment trends across regions that are regular versus irregular recipients of Chinese transport projects.

Figure 5 compares the trends in spatial concentration before China became active in 2000 among future recipient regions. It shows that spatial concentration among regions that will ultimately receive a project runs parallel to concentration in regions that will not receive a project from 2000 to 2014. There is some narrowing towards the end of the pre-period, which is why we allow linear departures from parallel trends in our specifications. However, there is no evidence in favor of different non-linear trends between treated and non-treated regions. After 2000, we observe a steeper fall in spatial concentration in regions with transport projects as China becomes increasingly active towards the middle of the 2000s. In any case, this type of graphical analysis cannot entirely rule out that there is dynamic selection in the period after 2000, that is, once China's government had become a major global infrastructure supplier, which is why we pursue an instrumental variables strategy.

In Figure A-1 in the Appendix, we visually examine the variation in the transport project indicator and spatial concentration for different terciles of the indicator during our period of interest. The results also give little reason to believe that the parallel pre-trends assumption is violated. There are notable global trends—a secular decline in spatial concentration and a rise in the number of projects—but the probability-specific trends in project numbers and concentration appear broadly parallel across terciles of

[34] Note that we cannot estimate the level equation directly, as our instrument is linked to new project commitments, i.e., differences in $N_{ji,t-2}$, and has no counterpart which could be used in Equation (2).

$\bar{N}_{ji}$. Importantly for our identification strategy, there is no obvious *non-linear* trend in a particular tercile that resembles the trend in Chinese production of input materials—shown in Figure 4—more than in another (see Christian and Barrett 2017). Figure A-2 in the Appendix provides another piece of evidence along these lines. The figure reports results from an event study based on the first time a region receives an infrastructure project. Here too, we find no evidence of pre-trends but effect sizes and a timing pattern that echos the results presented below.

[Figure 5 about here.]

Second, allowing for correlated random trends implies that we do not need to assume parallel pre-treatment trends. The key identification assumption is $Cov(F_{t-3} \times \bar{N}_{ji}, \Delta\epsilon_{jit}) = 0$ conditional on region-specific time trends, as well as region- and country-year-fixed effects. This leaves few sources of confounding variation with heterogeneous non-linear effects. Commodity price shocks and commodity cycles are known to affect local incomes heterogeneously (e.g., Berman and Couttenier 2015). The detrended input series might be correlated with the production volumes and prices of other commodities. If their time-varying effect on spatial concentration is uniform across regions in a country, then it is fully captured by detrending the raw series and including country-year-fixed effects. If instead their time-varying effect is heterogeneous across regions but linear, then it is captured by the region-specific trends. Only if their time-varying effect is non-linear and heterogeneous across regions would we need to control for these shocks (which we do in the robustness checks).

Third, the production of physical project inputs could also be correlated with overall trade volumes or foreign direct investment (FDI). China's share of world manufacturing value added rose steadily over the sample period and this rise coincided with a large demand shock for raw materials (Autor et al. 2016). It could be that frequent recipients of Chinese transport infrastructure projects are also frequent host regions of investment projects and have close trade ties with China. If this is the case, then the differences in the spatial concentration of economic activity might be the result of trade or investment rather than transport infrastructure projects. To address this concern, we later present robustness checks where we control for the yearly volume of exports to China, imports from China, and Chinese FDI, interacted with a set of variables that makes it more or less likely that a region is affected by changes of these variables.

Finally, our empirical strategy is related to a large shift-share literature, in which instruments are usually constructed as sums of shocks to a variety of industries with varying local exposures. Absent parallel trends, there are two ways to achieve identification in such settings under an alternative set of assumptions. Local industry shares can be interpreted as instruments, provided that they are exogenous (Goldsmith-Pinkham et al. 2020). As Borusyak et al. (2020) demonstrate, identification can also be purely based on exogenous variation in the time-series shocks, even when variation in local exposures is endogenous.[35] Contrary to this literature, our setting does not involve many shocks in different industries but a single endogenous exposure to a single, potentially endogenous, shock. Rather than trying to convince the reader that one of these shocks is—unconditionally—exogenous, we rely on the alternative assumptions outlined above (and test their validity below).

5 Results

Baseline results

Table 1 reports our main results on the relationship between Chinese-financed transport infrastructure projects and economic concentration. We consider two different types of concentration—within regions and between regions—which we estimate in two different ways. Columns 1 and 2 show results when concentration is measured within regions. Column 1 focuses on the binary project indicator, column 2 on (logged) annual dollar amounts.[36] Columns 3 and 4 turn to between-regional concentration and report results with concentration computed over average light intensities in first-order regions, resulting in an analysis at the level of countries, which is the level of analysis typically presented in studies of between-region concentration (e.g., Lessmann and Seidel 2017).

[Table 1 about here.]

We report four specifications in each of the four columns. Panel a shows the results from least-squares fixed-effects regressions. Although the coefficient estimates are negative in two of four regressions, they are imprecisely estimated and small in magnitude.

Panel b reports the reduced-form estimates for the same specifications. Here we regress the change in the spatial Gini coefficient on our instrumental variable and the full set of fixed effects. If our identification strategy works and there is an effect of transportation infrastructure on spatial concentration at any of these levels, we should observe a strong reduced-form effect as well. Indeed, columns 1 and 2 show that there is a significant and negative effect of the instrument on changes in spatial concentration within regions. This effect will be passed through with the same sign in our 2SLS regressions below if

[35] For the panel case, Borusyak et al. (2020) establish that our estimator is consistent when the covariance between the detrended input series and a weighted average of the within-location time variation in unobserved factors affecting spatial concentration approaches zero in large samples. This is likely to work with reasonably large T, together with a battery of fixed effects, and can be supported by including proxies for the remaining unobserved variation. However, in our case T is too small to rely on this approach.

[36] Project amounts have the advantage that we can account for the size of projects, but come with the drawback that we lack information on the financial amounts for more than a third of these projects. Note that we have added a value of one before taking logs.

the corresponding first-stage regression is sufficiently strong and the coefficient on the instrument in those regressions is positive. Columns 3 and 4 show that we do not find a significant reduced-form relationship for the between-region regressions.

Panel c in Table 1 presents our main results where the two-period lag of the project variables ($\Delta N_{ji,t-2}$) is instrumented by the detrended project input series (F_{t-3}) times our local exposure variable ($\bar{N}_{ij}$). Recall that we expect to find a negative effect on spatial concentration within regions and have no clear prior on the effect of transport projects on concentration between regions. Our results are in line with these expectations. For concentration within regions, the 2SLS coefficients are negative, statistically significant at conventional levels, and of substantial magnitude. A possible interpretation is that a combination of measurement errors, simultaneous causality, and the omission of potential confounders biases the least-squares estimates toward zero, which may have been addressed by instrumenting Chinese project locations. The 2SLS point estimate in column 1 indicates that the Gini coefficient is permanently reduced by 2.2 percentage points in regions where at least one Chinese government-financed transport project has been committed two years before.[37] Column 2 shows very similar results. Though the coefficient initially appears small, note that the average value of a project at a particular location is about US$7.6 million (or 15.84 log points). This implies that such an increase leads to a decrease in the Gini coefficient by 2.2 percentage points.[38] This effect is thus economically meaningful but moderate compared to the decreases in concentration observed in the case of Nairobi discussed in the introduction. While we have not yet tested how much of this result is driven by urban areas, it is in line with the notion that building or upgrading transport infrastructure allows economic activity to decentralize around congested cities (e.g., Baum-Snow 2007, Baum-Snow et al. 2017). Moreover, our Local Average Treatment Effect (LATE) uses variation induced by the production of physical input factors in China and will thus have a greater impact on big infrastructure projects requiring large volumes of steel, cement, and other physical inputs.

Turning to the results in columns 3 and 4, we find no evidence that Chinese-financed transport projects affect concentration between regions. However, the magnitude and direction of the coefficients are similar to those estimated for within-region concentration. We thus cannot rule out that substantive effects exist but are imprecisely estimated due to the much lower number of observations.

Panel d in Table 1 reports the associated first-stage regressions. Reassuringly, none

[37] Recall that the average project duration is about 2.1 years, suggesting that the effects we find here result from projects that have, on average, just been completed. While we do not find significant results for deeper lags (not reported in the table but available on request), note that the availability of project construction materials is unlikely to affect the supply of projects only exactly one year later. To the extent that project commitments in other years are also affected, the Local Average Treatment Effect (LATE) reflects the effects of projects in these years as well.

[38] Note that the average Gini coefficient within regions is 0.54. Table A-3 in the Online Appendix reports summary statistics.

of the above estimates suffer from a weak-instrument problem. The coefficients are highly significant and all associated first-stage F-statistics are considerably larger than the conventional rule-of-thumb value of 10. They remain strong when computing F-statistics that are robust to heteroskedasticity, autocorrelation, and clustering (Olea and Pflueger 2013).[39] As expected, we observe a positive relationship between the supply-push instrument and the probability of hosting a Chinese transport project. Domestic production of aluminum, cement, glass, iron, steel, and timber within China translates into more transport projects abroad at a meaningful rate. While it does not map directly into the growth rates of the underlying inputs, a typical change in F_{t-3} is about 0.4 in either direction. Such an annual increase raises the probability of receiving a Chinese-funded transport project by about 8.8 percentage points ($0.4 \times \frac{7}{14} \times 0.44$) for a region which has been getting at least one new project location in half of all years—the maximum we observe in the data—but only by 1.3 percentage points in a region which received a Chinese project in only one year ($0.4 \times \frac{1}{14} \times 0.44$).

Our main results do not depend on the choice of country-clustered standard errors or Conley errors, although the latter tend to be a little smaller and the corresponding first-stage F-statistics (not reported) somewhat higher. Adão et al. (2019) point out that inference in shift-share designs may be biased downwards if we ignore that regions with the same probability of receiving a Chinese-funded transport project have similar regression residuals (no matter which cluster they are located in). While we cannot use their variance estimator in our application with one sector, the estimated standard errors barely change if we cluster them on distinct values of $\bar{N}_{ji}$ to account for some of this bias.

Placebo tests and robustness checks

Our robustness checks focus on spatial concentration within regions.[40] Table 2 presents alternative measures of our variable of interest. Column 1 uses the annual number of new project locations within a region rather than the binary project indicator as variable of interest. Considering that the average project has 2.4 locations, the estimated effect corresponds roughly to our baseline estimate in column 1 of Table 1, where the coefficient is about two-and-a-half times larger. The corresponding first stage weakens noticeably but is still above the rule-of-thumb value of ten.

[Table 2 about here.]

Column 2 uses a binary indicator for projects that are known to have been completed, which pertains to about 60 percent of the projects in our sample. It shows that the effect of

[39] The Montiel-Pflueger effective F-statistic is 30.0, which is significantly above the corresponding critical value for a 10% "worst-case" bias of 23.1 in column 1 (Olea and Pflueger 2013).

[40] We do not report results for concentration between regions as we find no robust association with Chinese-financed transport projects.

finished projects is almost twice as large. However, these results are based on substantially fewer observations and the confidence interval includes our baseline estimate. In column 3, we broaden the definition of what constitutes an infrastructure project by including all projects that are defined as "economic infrastructure and services" according to OECD definitions.[41] The estimated coefficient is smaller and less precisely estimated, but stays significant at the ten-percent level. It is not surprising that our result holds given that our LATE loads heavily on physical infrastructure.

Next, we narrow our definition of a transport project. We expect decentralization effects to be particularly pronounced for roads and railways. Specifically, we include only road projects (urban roads and long-distance roads) in column 4, both road and rail projects (where the latter includes urban railways, tram lines, and long-distance railways) in column 5, and all urban transport projects (urban roads, urban railways, and tram lines) in column 6. The estimated coefficients are larger in all three cases compared to the baseline.[42] In line with theory, it appears that the expansion of the road and rail network (in and around cities) leads to a relocation of activity from the center and generates more sprawl. Finally, column 7 of Table 2 replicates our baseline regression with an additional control variable for the construction phase. This binary indicator $\Delta N_{ji,t-1}$ takes a value of one if a Chinese government-financed transport project has been committed in the previous year. The resulting estimate of $\Delta N_{ji,t-2}$ is only slightly smaller and remains statistically significant at conventional levels. This suggest that our finding is not primarily driven by light emitted during the construction process of new transport infrastructure. In summary, these variants of our baseline regression reinforce our main results.

Table 3 further probes the robustness of our results in two dimensions. First, we control for other potentially important shocks that could influence project allocation. For example, rising Chinese exports or commodity demand shocks may have influenced the regions to which China allocated projects. As we have discussed above, commodity price shocks and commodity cycles heterogeneously affect local incomes and to the extent that such time-varying effects on spatial concentration move systematically with the incidence of Chinese transport projects, they might bias our estimates. Most importantly, a skeptical reader might be concerned that the allocation of Chinese transport projects could be highly correlated with the allocation of other Chinese projects, so that our LATE reflects the effect of all projects rather than just transport projects. Second, we use randomization inference to test the underlying assumptions of our instrument, alter the instrument in various ways, and construct a falsification test to further probe the

[41]In addition to transportation infrastructure, i.e., projects such as roads, railways, and airports, this category includes energy production and distribution projects, and information and communication technology (ICT) projects (e.g., broadband internet and mobile phone infrastructure).

[42]Note however the much-reduced first-stage F-statistic associated with the results we report in column 6.

validity of our approach.

[Table 3 about here.]

Columns 1 to 5 focus on four time-varying shocks: Chinese FDI, imports from China, exports to China, and the presence of a Chinese non-transport project in a country.[43] While we do not have location-specific estimates for FDI and trade, they are typically linked to China's demand for natural resources or increasing trade integration with China, both of which are uneven across regions. We construct time-varying and location-specific proxies for these shocks similar to our instrument by interacting these variables with two proxies for openness and market size (distance to the coast and urbanization) and two proxies for the existence of natural resources in a region (large mines and oil fields).[44] Columns 1 to 5 in Table A-4 show that these results hold when we flexibly allow for non-linear trends that vary with these four proxies for differential exposure to Chinese influence.

For Chinese-financed development projects outside the transport sector, we run instrumental-variable regressions with two endogenous variables (transport projects, $\Delta N_{ji,t-2}$, and non-transport projects, $\Delta M_{ji,t-2}$) and two instruments. The instrument for the second endogenous variable is constructed in analogy to our baseline, i.e., the time-varying component is the first factor of the six production inputs and the cross-sectional component is the fraction of years over the 2000–2014 period in which a Chinese non-transport project has been committed ($F_{t-3} \times \bar{M}_{ji}$). We find that our results are robust to controlling for these four time-varying shocks, either individually (columns 1–4) or in combination (column 5). The coefficients remain significant and hardly vary in magnitude. Columns 4 and 5 show that our results for transport projects hardly change once we control for non-transport projects and control for the four time-varying shocks at the same time. This implies that our results do not reflect the effect of all projects but those of transport projects specifically.[45]

The next set of tests focus on the instrument itself. Christian and Barrett (2017) suggest tests to probe the validity of the assumptions underlying our instrumental variable approach. In addition to visual inspection of trends in Figures 4 and A-1, we conduct a randomization inference test where we reassign the transport project indicator and instrumental variable to different countries and years in the sample. As can be seen from the results of 999 Monte Carlo simulations shown in Figure A-3, the resulting coefficient

[43] More specifically, we use Chinese FDI outflows (in logs of current US$) from UNCTAD. We measure imports and exports to and from China using bilateral trade flows (in logs of current US$) from the IMF Direction of Trade Statistics.

[44] All variables and sources are defined in the table notes.

[45] For brevity, we only report the first-stage equation for our primary variable of interest but note that the first F-statistics remain relatively high (for an equation with two endogenous variables), the estimated coefficient on our primary instrumental variable hardly changes, while the instrument for non-transport projects only predicts those types of projects.

estimates center around zero. According to an exact Fisher test, the coefficient from our main estimate (introduced below, and indicated by the vertical dashed line) is significantly different from the randomized coefficients (p-value = 0.016). The same holds when we break the timing structure required for identification less radically and instead randomize (i) the entire time series between regions, (ii) years within regions, and (iii) regions within years (also shown in Figure A-3). It is thus unlikely that omitted variables correlate with our key variables in a way that spuriously brings about our main result.

To further test the robustness of our instrument, column 6 modifies our detrending method and residualizes each input series via a regression on the log of GDP at constant local currency units (to measure input growth that is faster or slower than GDP growth, as opposed to linear detrending). The estimate is robust to this perturbation, and, if anything, becomes slightly larger. Column 7 shows results using the detrended production of Chinese steel as the time-series shock rather than the first factor of all six project inputs. The first-stage and second-stage estimates are similar to our baseline results. The main purpose of using steel only is to facilitate a comparison with column 8, which reports results from a placebo regression using United States steel production rather than Chinese production values. This presents a falsification test as US steel production should be unrelated to Chinese-financed infrastructure projects around the world. As expected, the first stage collapses and is extremely weak, with a Kleibergen-Paap F-statistic of just 0.63, while the 2SLS estimate is positive and loses statistical significance at conventional levels. The 2SLS estimate is somewhat smaller (about -0.095) and equally insignificant when we do not control for the other China shocks (not reported). In short, US steel production does not help to predict the commitment of Chinese-financed transport projects. Taken together, these estimates give us confidence that our results do not hinge on the specific choice of how we define Chinese production shocks, and that the time-series component is not driven by spurious trends. Finally, we replace the second component of our instrument—a region's probability to receive a project—with the analogous measure calculated by excluding contemporaneous projects (i.e., where we calculate it excluding $\Delta N_{ji,t-2}$ from the cross-sectional average).[46] Column 6 of Table A-4 shows that our results remain qualitatively similar when we instrument projects with the "leave-one-out" instrument.

Extensions

Our finding that Chinese-financed transport projects reduce the concentration of economic activity within subnational regions raises the question of where exactly this diffusion takes place. The monocentric city model implies that we should observe a shift

[46] We also replaced the probability to receive a project with data from the Cold War period, taken from Dreher et al. (2021a). However, the first-stage F-statistic is too low (< 5), so we do not report these results here.

in activity from central cities to their immediate periphery. The model has little to say about whether this should also increase overall activity in a region or whether this kind of development occurs by leap-frogging into undeveloped areas or integrating less densely developed areas.

[Table 4 about here.]

To probe this question, Table 4 examines different moments of the distribution. Columns 1 and 2 show a strong effect of transport projects on overall economic activity but not on our proxy for per capita incomes. A new transport project increases the average light density in a region by about 15 percent (column 1), which is both economically and statistically significant. When we instead focus on light per capita (column 2), we cannot reject the null hypothesis that Chinese transport projects have no effect on changes in light per capita and estimate a coefficient close to zero. This is in line with the results of Dreher et al. (2022), who also report no effect of Chinese development finance at large on lights per capita in a global sample. The insignificant coefficient for the world sample stands in contrast to results for the African continent, where previous work finds positive effects of aid on development (Dreher et al. 2021a, 2022). Since the per capita data use interpolated population data in the denominator, we cannot rule out that this occurs due to added noise in the dependent variable. Column 3 uses the fraction of illuminated pixels as the dependent variable. It shows that economic activity does not seem to primarily expand into previously undeveloped areas. To summarize, columns 1 to 3 show that Chinese transport projects increase economic activity in a recipient region. This may represent an increase in population rather than welfare, and appears to be primarily occurring in areas that are already somewhat developed.

The remaining columns of Table 4 focus on relative changes in economic activity across quintiles of the light distribution. This allows us to directly trace which type of changes reduce the Gini coefficient. The pattern is consistent with predictions from urban land use theory. We find that Chinese transport projects significantly reduce nighttime lights in the highest quintile, while they raise the share of activity taking place in the lower quintiles (though estimated imprecisely for the second quintile and with borderline significance for the first). It thus appears that Chinese transport projects gradually redistribute activity from the most densely developed parts of regions, that is, the city centers, to less densely developed places. The magnitudes of the estimated coefficients suggest that this process benefits the higher quintiles more relative to the least developed parts of a region.

[Table 5 about here.]

Table 5 presents a more direct approach to measuring from where to where the relocation of activity takes place. We report a series of regressions that split the sample along the median of several variables typically linked with rapid urban growth. The results provide further support for the conjecture that these effects occur around cities. We find a sizable decentralization of activity in regions with below-median travel time to cities, high urbanization rates, high road density, and above-median proximity to the coast. The estimated effects are substantial in these sub-samples. By contrast, they are imprecisely estimated and typically of the opposite sign or lower in magnitude in the other sub-samples (the exception being below-median proximity to the coast, with similar estimated magnitudes and standard errors in both samples). Last but not least, we also find that the effect seems to be driven by relatively poor regions as measured by below-median light per capita. This is not surprising given that some of the poorest regions have some of the highest population growth rates and are home to many of the fastest growing cities. The evidence presented here is in line with literature focusing on individual countries or regions discussed above. For example, in their study of the expansion of China's highway system, Baum-Snow et al. (2017) find that reductions in spatial concentration were larger within coastal and richer central regions. Similarly, although they do not focus on decentralization within regions per se, studies focusing on modelling the spatial impact of the Belt and Road Initiative typically estimate that coastal regions, border crossings, and urban hubs will benefit more (Lall and Lebrand 2020).[47]

Next, we investigate major world regions separately. China's global infrastructure footprint is uneven and most of its transportation projects are located in Africa and Asia (recall Figure 2). Urban population growth is rapid and infrastructure constraints are most severe in these regions. As can be seen from the sub-samples in columns 1 to 3 of Table 6, our main findings are driven by regions in African countries, where the effect is larger than our baseline estimates. The coefficient on Chinese transport projects is insignificant or substantially smaller for Asia and the Americas, although the first stage remains about equally powerful in all three regions. This is not surprising given that Africa lags behind the other two world regions in terms of infrastructure development. It is also the region where urban primacy is most pronounced and where deficiencies in urban infrastructure have been linked to slower economic growth at the national level (Castells-Quintana 2017). Chinese-financed projects in Africa therefore appear to mitigate congestion which, eventually, could enable cities to reap the benefits of agglomeration economies.

[Table 6 about here.]

Column 4 restricts the sample to countries classified by the World Bank as low-income economies in 2000. It highlights that the diffusion effects of Chinese transport

[47] This literature suggests that BRI projects will lead to an increasing specialization among regions and hence more concentration of economic activity in regions with better access to world markets but does not consider the distribution of activity within regions.

projects also occur in the poorest countries of the world. Finally, in column 5, we restrict our analysis to only those subnational regions that have received at least one transport project from China over the entire sample period. This addresses one last identification challenge that would arise if regions that received any development-related project from China experience different non-linear trends than those which did not. Our results become substantially stronger.

Finally, Table A-5 explores the issue of co-location with other types of projects. Our results remain similar when we control for the presence of World Bank projects in the transport sector (or in any sector) and for Chinese-financed projects in other sectors.

6 Conclusion

The monocentric city model predicts that transport infrastructure decentralizes economic activity within subnational regions, at least to the extent that such regions primarily consist of urban areas and their surroundings. The theory has previously been tested for single countries and by relying on identification strategies that make use of historical transport networks or other country-specific circumstances. Whether this process occurs generally across developing countries, many of which face severe infrastructure gaps, has not been tested.

We overcome the challenge of missing data on comparable infrastructure projects across countries and how to estimate their causal effect by focusing on infrastructure projects financed by China—a single but massive source of infrastructure financing across the developing world since 2000. While many scholars and policymakers are skeptical about the quality and effects of China's development projects, its commitment to financing infrastructure is unambiguous. Connectivity has been a central focus of China's Belt and Road Initiative (BRI) from its announcement in 2013, and projects financed prior to BRI similarly focus on connective infrastructure. Transport projects such as roads, highways, railways, harbors, and airports are at the heart of this approach. China's government has financed hundreds of big-ticket transport and other infrastructure projects in developing countries in recent years (Dreher et al. 2022).

One of our key contributions is to provide a new geocoded dataset of China's emerging footprint around the world, much of which comes in the form of large scale infrastructure investments but extends across a variety of sectors. While our data cover the period from 2000 to 2014, and thus mostly precede the BRI, the projects we focus on share many of the characteristics of the more recent initiative. Using these data, we test whether infrastructure projects influence the spatial concentration of economic activity within and between recipient regions. Our identification strategy relies on commodity inputs produced in China that affect the availability of projects over time in tandem with a variable that measures the likelihood that countries receive a smaller or larger share of

China's projects.

Our results show that Chinese government-financed transportation projects reduce the concentration of economic activity within regions in developing countries. More specifically, our results imply that the Gini coefficient measuring the spatial concentration of economic activity is reduced by 2.2 percentage points within first-order regions. These results are robust in a large number of different specifications, to the choice of control variables, and variations of the instrumental variable. The effect increases for completed projects, holds for projects financing economic infrastructure more broadly, and is largest in poor regions and African countries, who are most in need of infrastructure financing. In line with urban land use theory, we find that our results are driven by changes in economic activity in and around urban areas.

In financing major transport projects, China's government appears to be helping cities and regions in developing countries in their transformation from dense, crowded and unproductive places towards hubs of productivity. While these results are encouraging, they do not imply that Chinese government-financed transport infrastructure has only positive effects. There is growing evidence that Chinese development projects also produce negative externalities. For example, in related work, we have shown that China's "aid on demand" approach is vulnerable to domestic political capture wherein incumbent government leaders steer Chinese development projects toward their home regions, often at the expense of poorer regions with greater material need (Dreher et al. 2019). There are many other concerns about the consequences of China's development finance, ranging from their impact on the environment to questions of debt sustainability (BenYishay et al. 2016, Horn et al. 2021). In short, Chinese-financed transportation projects may help deal with congestion in developing countries, but our study should not be read as a comprehensive assessment of their costs and benefits. This leaves considerable scope for future research.

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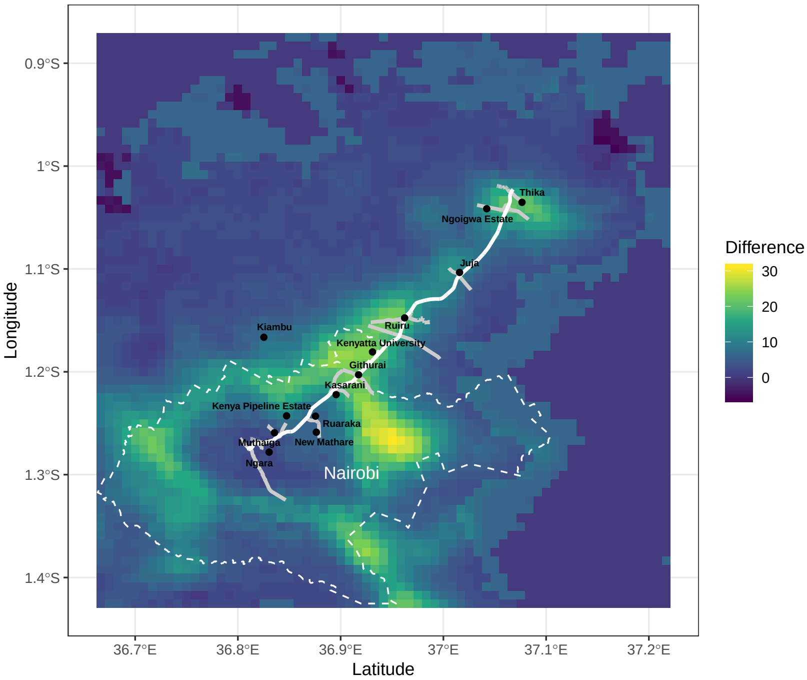
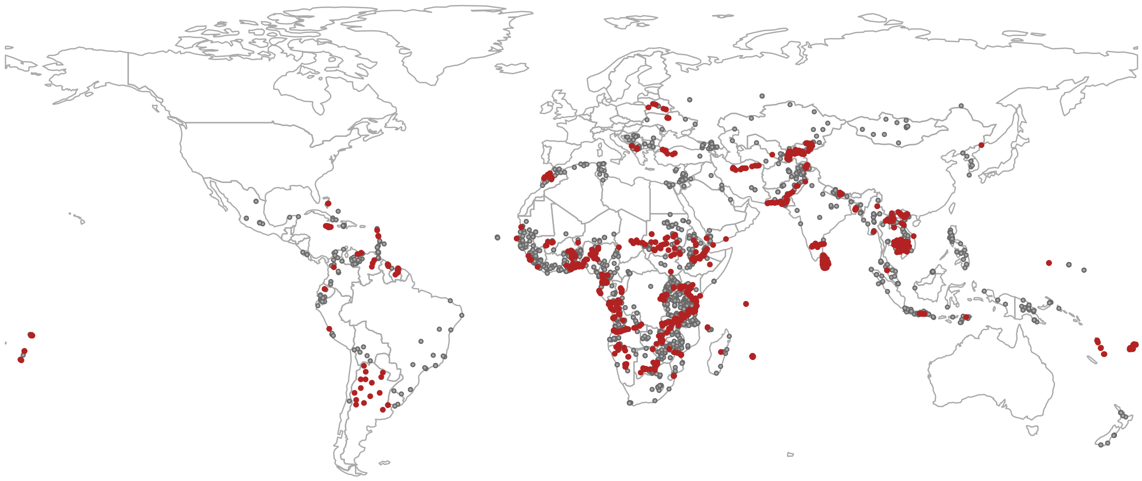
Figure 1 – Nairobi-Thika Highway, change in nighttime lights, 2008–2013



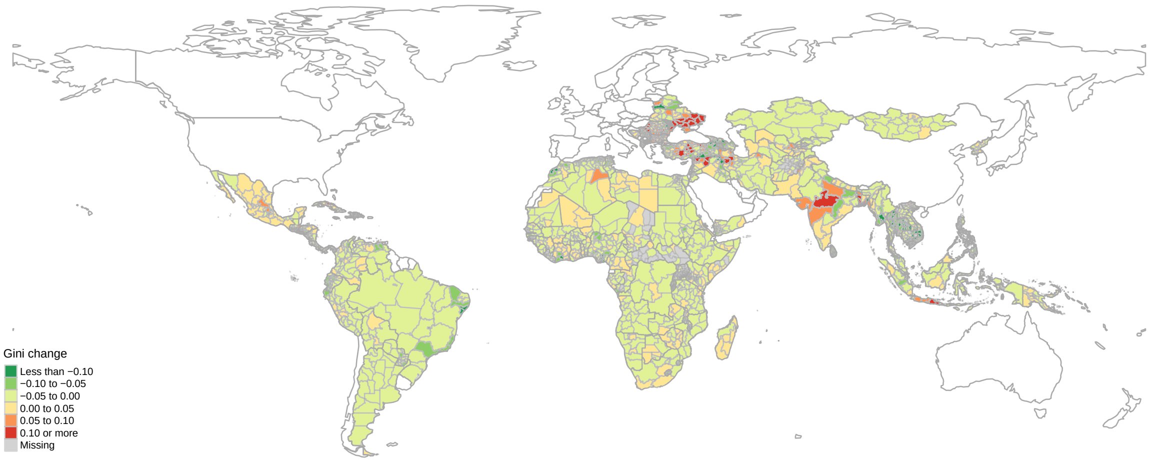
Notes: The figure illustrates the change in nighttime lights from 2008 to 2013 along the route of the Nairobi-Thika Highway in Kenya, which was constructed from January 2009 until October 2012. Major intersections and points of interest are highlighted along the highway. The change in nighttime lights is the difference between the F18 2013 image (in DN from 0 to 63) and the F16 2008 image (in the same units). The differences have a range from -6 to 31 DN. The expansion of light around Nairobi is related to other infrastructure projects, many of which are also Chinese-financed but not highlighted here. Between 2008 and 2013, the geographical areas within a 4 km buffer of the highway experienced a 27 percent reduction in the spatial concentration of nighttime light intensity. Spatial concentration, as measured by the Gini coefficient introduced later in this paper, fell from 0.425 in 2008 to 0.31 in 2013 in the 4 km buffer. At the same time, land values doubled in Thika and rose even faster in areas closer to Nairobi (like Kasarani, where land values increased from US$46,000 per acre to US$500,000 per acre), farmgate prices for dairy products and horticulture rose due to increased access to markets, and trade and investment alongside the road corridor expanded (KARA and CSUD 2012, African Development Bank 2014b, 2016, 2019).

Figure 2 – Locations of Chinese-financed projects, transport and non-transport, 2000–2014



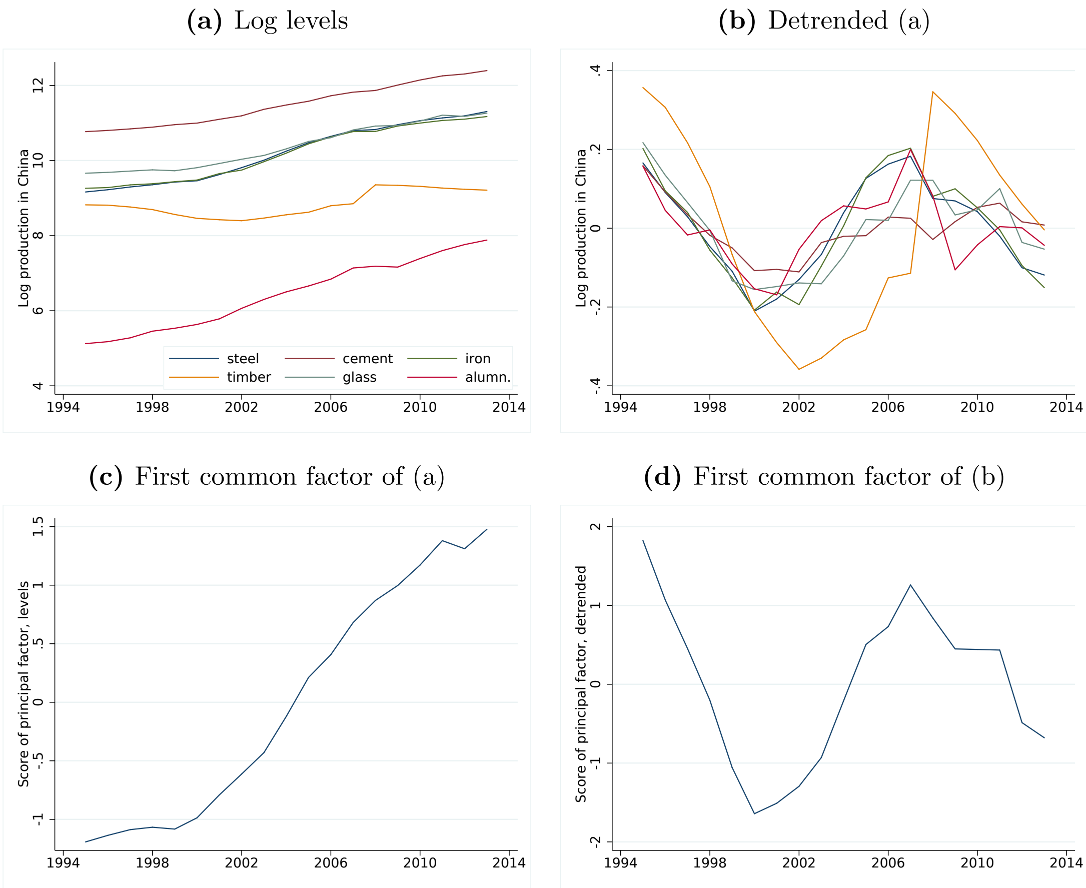
Notes: The figure illustrates all Chinese-financed transport (red) and non-transport projects (grey) which were committed and implemented in the period from 2000 to 2014. It shows a total of 2,140 projects in 4,420 discrete locations which have a precision accuracy of (at least) a first-order administrative division. 1,345 projects have a precision accuracy less than the first-order region (not shown). Although there are "only" 269 transportation projects, 1,211 of the 4,420 locations shown in the figure have directly received (some part) of a larger transportation project.

Figure 3 – Long differences in spatial concentration, within ADM1, 2000–2013



Notes: The figure illustrates the cross-regional and temporal variation in spatial concentration. It shows long differences in the Gini coefficient for spatial concentration within first-order regions, that is, a region's value in 2013 minus the value in 2000. Only countries that are not classified as high-income by the World Bank are shown. Missing values occur when there were too few lit cells to compute the Gini coefficient in the initial or final period.

Figure 4 – Variations in physical project inputs, 1995–2013



(a) Log levels

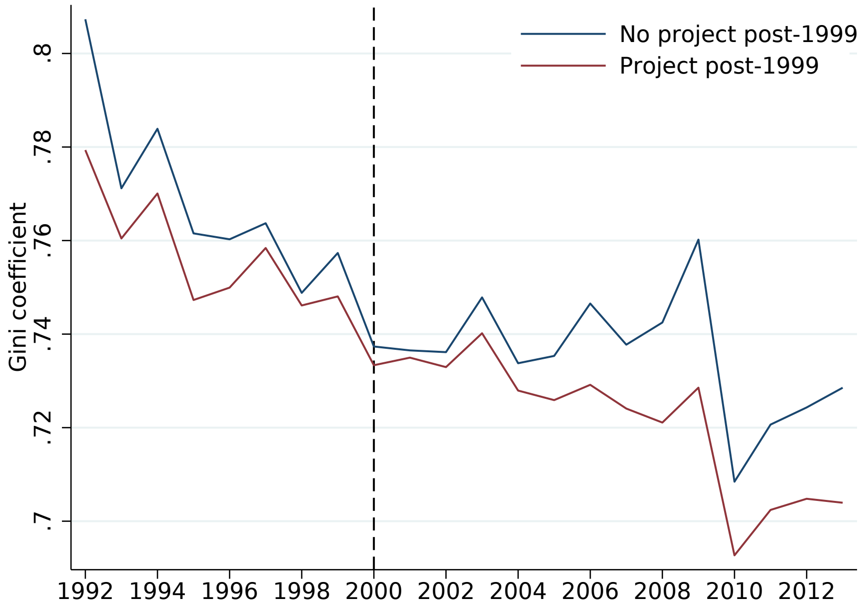
(b) Detrended (a)

(c) First common factor of (a)

(d) First common factor of (b)

Notes: The figure illustrates the time variation in the production of physical project inputs in China. Panel a shows the raw data over time (in logarithms). Panel b shows the linearly detrended series. Panel c shows the first common factor of all level series in panel a. Panel d shows the first common factor of all detrended series in panel b. The annual data for steel, cement, pig iron, timber, and glass have been obtained from the National Bureau of Statistics of China. The time series for aluminum has been obtained from the Minerals Yearbook by the US Geological Survey.

Figure 5 – Parallel pre-trends, 1992–1999



Notes: The figure illustrates the average Gini coefficient of light intensity within first-order administrative regions over time in the period before and after China became increasingly active in funding transport projects in other countries. The time series is reported separately for regions which will eventually receive a project in the 2000–2014 period and those regions which will not.

Table 1 – Transport projects and concentration within and between regions, 2002–2013

	Spatial concentration, $\Delta\textsc{Gini}_{jit}$, measured ...			
	Within first-order regions		Between first-order regions	
	Projects	Values	Projects	Values
	(1)	(2)	(3)	(4)
	Panel a) OLS estimates			
Projects ($\Delta N_{ji,t-2}$)	0.0026	0.0002	-0.0042	-0.0002
	(0.0020)	(0.0001)	(0.0043)	(0.0002)
	[0.0021]	[0.0001]	[0.0043]	[0.0002]
	Panel b) Reduced-form estimates			
IV ($F_{t-3} \times \bar{N}_{ji}$)	-0.0096	-0.0096	-0.0075	-0.0075
	(0.0049)*	(0.0049)*	(0.0073)	(0.0073)
	[0.0032]***	[0.0032]***	[0.0073]	[0.0073]
	Panel c) 2SLS estimates			
Projects ($\Delta N_{ji,t-2}$)	-0.0218	-0.0014	-0.0224	-0.0012
	(0.0097)**	(0.0006)**	(0.0215)	(0.0011)
	[0.0073]***	[0.0005]***	[0.0216]	[0.0011]
	Panel d) First-stage estimates			
IV ($F_{t-3} \times \bar{N}_{ji}$)	0.4400	6.8244	0.3361	6.0497
	(0.0747)***	(1.1363)***	(0.0638)***	(1.1467)***
	[0.0688]***	[1.1546]***	[0.0636]***	[1.1359]***
Level of analysis	ADM1	ADM1	ADM0	ADM0
First-stage F-Stat	34.70	36.07	27.73	27.83
Observations	27,162	27,162	1,386	1,386
Regions	2,406	2,406	–	–
Countries	122	122	122	122

Notes: The table reports regression results. Panel a shows least-squares fixed-effects regressions where the dependent variable is indicated in the column header. Panel b shows reduced-form regressions where the dependent variable is indicated in the column header. Panel c shows two-stage least squares fixed effects regressions where the dependent variable is indicated in the column header. Panel d shows the corresponding first-stage regressions where the dependent variable is a binary indicator for new project commitments ($\Delta N_{ji,t-2}$) in a region. Columns 1 and 2 include region-fixed effects and country-year-fixed effects; columns 3 and 4 includes country-fixed effects and year-fixed effects. Standard errors clustered at the country level are reported in parentheses. Conley errors with a spatial cutoff of 500 km and a time-series HAC with a lag cutoff of 1,000 years are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table 2 – Variants of baseline regression, within ADM1, 2002–2013

	Variations of the variable of interest ($\Delta N_{ji,t-2}$)						
	Location count	Completed	Economic infra.	Roads	Roads & rail	Urban transport	Transport
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel a) 2SLS estimates						
Projects ($\Delta N_{ji,t-2}$)	-0.0086	-0.0412	-0.0165	-0.0274	-0.0230	-0.0355	-0.0155
	(0.0037)**	(0.0201)**	(0.0092)*	(0.0087)***	(0.0131)*	(0.0118)***	(0.0091)*
	[0.0031]***	[0.0143]***	[0.0095]*	[0.0118]**	[0.0083]***	[0.0153]**	[0.0065]**
	Panel b) First-stage estimates						
IV ($F_{t-3} \times \bar{N}_{ji}$)	1.1205	0.2329	0.3600	0.4723	0.4086	0.4886	0.4895
	(0.3243)***	(0.0545)***	(0.0468)***	(0.1067)***	(0.0912)***	(0.2555)*	(0.0879)***
	[0.2782]***	[0.0591]***	[0.0555]***	[0.0988]***	[0.0857]***	[0.2390]**	[0.0798]***
Construction phase ($\Delta N_{ji,t-1}$)	–	–	–	–	–	–	✓
First-stage F-stat	11.94	18.26	59.16	19.59	20.06	3.66	31.03
Observations	27,162	27,162	27,162	27,162	27,162	27,162	27,162
Regions	2,406	2,406	2,406	2,406	2,406	2,406	2,406
Countries	122	122	122	122	122	122	122

Notes: The table reports regression results. Panel a shows two-stage least-squares fixed-effects regressions where the dependent variable is the first difference of the Gini coefficient of light intensity within first-order administrative regions. Panel b shows least squares fixed effects regressions where the dependent variable is indicated in the column header. 'Location count' is the number of project locations of newly committed projects in a region. 'Completed' is a binary indicator for completed projects in a region. 'Economic infrastructure' broadens the definition of our base measure by including all economic infrastructure projects (transportation, energy production and distribution, and information and communication technology). 'Roads' narrows the definition of our base measure by including only road projects (urban roads and long-distance roads). 'Roads & rail' narrows the definition of our base measure by including only road and railroad projects (urban roads, long-distance roads, urban railways and tram lines, and long-distance railways). 'Urban transport' narrows the definition of our base measure by including only urban transport projects (urban roads and urban railways and tram lines). Whenever we change the dependent variable, the cross-sectional component of the instrument follows the same definition of projects. The last column uses the baseline measure of transport projects and adds a control variable for the construction phase, which is a binary indicator $\Delta N_{ji,t-1}$ that takes a value of one if a Chinese government-financed transport project has been committed in the previous year. All specifications include region-fixed effects and country-year-fixed effects. Standard errors clustered at the country level are reported in parentheses. Conley errors with a spatial cutoff of 500 km and a time-series HAC with a lag cutoff of 1,000 years are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table 3 – Identification: Other "China shocks" and variants of the instrumental variable, within ADM1, 2002–2013

	Accounting for other "China shocks"					*Altering the instrument*		
	FDI (1)	Imports (2)	Exports (3)	Projects (4)	All (5)	Overprod. (6)	Det. steel (7)	US placebo (8)
				Panel a) 2SLS estimates				
Projects ($\Delta N_{ji,t-2}$)	-0.0218	-0.0208	-0.0211	-0.0205	-0.0195	-0.0301	-0.0247	0.1083
	(0.0097)**	(0.0096)**	(0.0096)**	(0.0106)*	(0.0105)*	(0.0113)***	(0.0108)**	(0.1435)
	[0.0073]***	[0.0071]***	[0.0071]***	[0.0083]**	[0.0083]**	[0.0099]***	[0.0086]***	[0.1368]
				Panel b) First-stage estimates				
IV ($F_{t-3} \times \bar{N}_{ji}$)	0.4400	0.4571	0.4604	0.4374	0.4570	0.3493	0.3635	-0.0604
	(0.0746)***	(0.0747)***	(0.0748)***	(0.0749)***	(0.0750)**	(0.0606)***	(0.0648)***	(0.0763)
	[0.0715]***	[0.0726]***	[0.0726]***	[0.0727]***	[0.0740]***	[0.0625]***	[0.0642]***	[0.0764]
IV ($F_{t-3} \times \bar{M}_{ji}$)				0.0040	0.0009			
				(0.0099)	(0.0095)			
				[0.0096]	[0.0095]			
Δ (Shock $\times$ Distance)	✓	✓	–	–	✓	✓	✓	✓
Δ (Shock $\times$ Urbanization)	✓	✓	–	–	✓	✓	✓	✓
Δ (Shock $\times$ Large mines)	–	–	✓	–	✓	✓	✓	✓
Δ (Shock $\times$ Oil fields)	–	–	✓	–	✓	✓	✓	✓
First-stage(s) F-stat	34.79	37.43	37.84	8.74	7.44	33.27	31.45	0.63
Observations	27,162	26,491	26,491	27,162	26,491	26,491	26,491	26,491
Regions	2,406	2,348	2,348	2,406	2,348	2,348	2,348	2,348
Countries	122	116	116	122	116	116	116	116

Notes: The table reports regression results. Panel a shows two-stage least-squares fixed-effects regressions where the dependent variable is the first difference of the Gini coefficient of light intensity within first-order administrative regions. Panel b shows least-squares fixed-effects regressions where the dependent variable is a binary indicator for new project commitments ($\Delta N_{ji,t-2}$) in a region. 'FDI' are Chinese FDI outflows (in logs of current US$) from UNCTAD. 'Distance' is the average "as-the-crow-flies" distance from the region to the nearest coastline from Natural Earth. 'Urbanization' is the fraction of land which is defined as an urban cluster or urban center in 2000 by the Global Human Settlement Layer (Pesaresi et al. 2019). 'Imports' are bilateral imports from China; 'Exports' are the value of donor-country exports to China (both in logs of current US$ and from the IMF Direction of Trade Statistics). 'Large mines' indicate if the region has at least one major mineral deposit in 2005 according to the United States Geological Survey. 'Oil fields' indicate if the region has at least one major on-shore oil or gas field (Lujala et al. 2007). 'Projects' is binary and indicates the presence of a Chinese non-transport project in the region in $t-2$. The instrument is constructed in analogy to our baseline, i.e., the cross-sectional component is the fraction of years over the 2000–2014 period in which a Chinese non-transport project has been committed. 'Overproduction' implies that the factor inputs were residualized by running a regression of each input on the log of Chinese GDP at constant local currency units before the first factor was extracted. 'Det. steel' uses the linearly detrended log of Chinese steel production from the National Bureau of Statistics of China as the time-series shock. We standardize this variable before multiplying it with the exposure term so that the coefficient is comparable with that using the first common factor of all inputs. 'US placebo' uses a US construction steel production index from FRED hosted by the Federal Reserve Bank of St. Louis (Series `IPN3311A2BS`) as a placebo instrument. We log, detrend, and standardize the series, just like Chinese steel production in the previous column. All specifications include region-fixed effects and country-year-fixed effects. Standard errors clustered at the country level are reported in parentheses. Conley errors with a spatial cutoff of 500 km and a time-series HAC with a lag cutoff of 1,000 years are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table 4 – Light intensity and quintile shares, within ADM1, 2002–2013

	Moments of spatial concentration							
	Light	Light	Extensive	Quintile shares				
	density	per capita	margin	0–20%	20–40%	40–60%	60–80%	80–100%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel a) 2SLS estimates							
Projects ($\Delta N_{ji,t-2}$)	0.1462	-0.0005	0.0122	0.0028	0.0032	0.0102	0.0191	-0.0353
	(0.0476)***	(0.0028)	(0.0173)	(0.0015)*	(0.0027)	(0.0040)**	(0.0075)**	(0.0114)***
	[0.0516]***	[0.0028]	[0.0104]	[0.0019]	[0.0024]	[0.0043]**	[0.0078]**	[0.0116]***
	Panel b) First-stage estimates							
IV ($F_{t-3} \times \bar{N}_{ji}$)	0.4505	0.4498	0.4505	0.4394	0.4394	0.4394	0.4394	0.4394
	(0.0732)***	(0.0732)***	(0.0732)***	(0.0749)***	(0.0749)***	(0.0749)***	(0.0749)***	(0.0749)***
	[0.0688]***	[0.0688]***	[0.0688]***	[0.0716]***	[0.0716]***	[0.0716]***	[0.0716]***	[0.0716]***
First-stage F-stat	37.86	37.72	37.86	34.44	34.44	34.44	34.44	34.44
Observations	28,037	28,025	28,037	26,877	26,877	26,877	26,877	26,877
Regions	2,440	2,439	2,440	2,379	2,379	2,379	2,379	2,379
Countries	122	122	122	122	122	122	122	122

Notes: The table reports regression results. Panel a shows two-stage least-squares fixed-effects regressions where the dependent variable is indicated in the column header. Panel b shows least-squares fixed-effects regressions where the dependent variable is a binary indicator for new project commitments ($\Delta N_{ji,t-2}$) in a region. We use the inverse hyperbolic sine transformation in columns 1 and 2, which is defined as $ihs(z) = log(z + \sqrt{z^2+1})$, for light density and light per capita to include regions with zero light and retain an interpretation similar to logs. The extensive margin is defined as the (untransformed) fraction of pixels with a non-zero light density. All specifications include region fixed effects and country-year fixed effects. Standard errors clustered at the country level are reported in parentheses. Conley errors with a spatial cutoff of 500 km and a time-series HAC with a lag cutoff of 1,000 years are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table 5 – Sample splits, within ADM1, 2002–2013

	Splitting at the median of . . .				
	Travel time to cities (1)	Urbanization rate (2)	Road density (3)	Distance to coast (4)	Light per capita (5)
	Panel a) Below median, 2SLS estimates				
Projects ($\Delta N_{ji,t-2}$)	-0.0306	0.0044	-0.0101	-0.0207	-0.0276
	(0.0147)**	(0.0087)	(0.0099)	(0.0154)	(0.0089)***
	[0.0104]***	[0.0103]	[0.0107]	[0.0090]**	[0.0056]***
	Panel b) Above median, 2SLS estimates				
Projects ($\Delta N_{ji,t-2}$)	0.0003	-0.0222	-0.0262	-0.0232	-0.0288
	(0.0105)	(0.0180)	(0.0121)**	(0.0096)**	(0.0287)
	[0.0097]	[0.0129]*	[0.0112]**	[0.0098]**	[0.0312]
First-stage F-stat a)	11.74	20.15	22.60	23.23	21.01
First-stage F-stat b)	39.68	12.11	16.90	16.33	13.76
Observations a)	13,016	13,642	13,527	13,509	13,142
Observations b)	13,875	13,254	13,451	13,545	13,672

Notes: The table reports regression results. Panel a shows two-stage least squares fixed effects regressions for first-order regions with below median values of the variable indicated in the column header. Panel b shows two-stage least squares fixed effects regressions for first-order regions with above median values of the variable indicated in the column header. 'Travel time to cities' is measured as the travel time to the nearest city of 50,000 or more people in the year 2000 (Nelson 2008). The 'urbanization rate' is measured as the fraction of land in the region which is defined as an urban cluster or urban center in 2000 by the Global Human Settlement Layer (Pesaresi et al. 2019). 'Road density' is measured as the total road length over the area of the region where road length is derived from the gROADS data set (CIESIN and ITOS 2013). 'Distance to coast' is the average "as-the-crow-flies" distance to the nearest coastline (from Natural Earth). 'Light per capita' is the sum of light in a region divided by its population in 2000 (from the Global Human Settlement Layer). All specifications include region fixed effects and country-year fixed effects. Standard errors clustered at the country level are reported in parentheses. Conley errors with a spatial cutoff of 500 km and a time-series HAC with a lag cutoff of 1,000 years are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table 6 – Regional variation, within ADM1, 2000–2013

	Regional subsets and related sample perturbations				
	Africa	Asia	Americas	Low income	$\bar{N}^{\text{all}} > 0$
	(1)	(2)	(3)	(4)	(5)
	Panel a) 2SLS estimates				
Projects ($\Delta N_{ji,t-2}$)	-0.0252	-0.0134	-0.0084	-0.0204	-0.0301
	(0.0076)***	(0.0244)	(0.0079)	(0.0117)*	(0.0073)***
	[0.0100]**	[0.0112]	[0.0019]***	[0.0058]***	[0.0100]***
	Panel b) First-stage estimates				
IV ($F_{t-3} \times \bar{N}_{ji}$)	0.4413	0.4171	0.7981	0.4327	0.4348
	(0.1123)***	(0.1020)***	(0.2285)***	(0.0897)***	(0.0753)***
	[0.0997]***	[0.1096]***	[0.3355]**	[0.0826]***	[0.0744]***
First-stage F-Stat	15.45	16.72	12.20	23.28	33.31
Observations	8,401	9,191	4,954	11,357	8,639
Regions	729	791	430	982	735
Countries	48	34	22	60	92

Notes: The table reports regression results. Panel a shows two-stage least squares fixed effects regressions where the dependent variable is the first difference of the Gini coefficient of light intensity within first-order administrative regions. Panel b shows least squares fixed effects regressions where the dependent variable is a binary indicator for new project commitments ($\Delta N_{ji,t-2}$) in a region. Columns 1 to 3 report regional subsets as indicated in the column header. Column 4 uses only countries classified as low-income economies by the World Bank in 2000. Column 5 uses only regions which have received any transport or non-transport financing from China over the entire period. All specifications include region-fixed effects and country-year-fixed effects. Standard errors clustered at the country level are reported in parentheses. Conley errors with a spatial cutoff of 500 km and a time-series HAC with a lag cutoff of 1,000 years are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Online Appendix

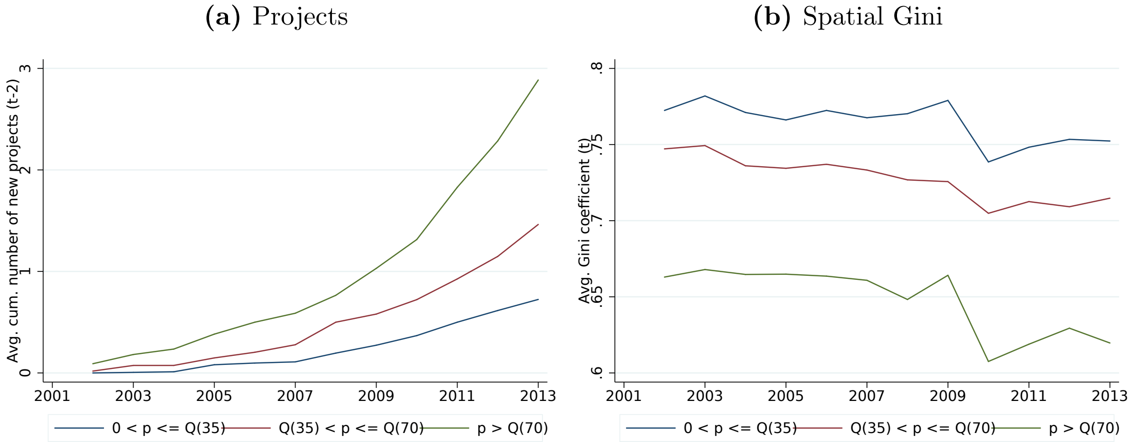
for

"Connective Financing: Chinese Infrastructure Projects and the Diffusion of Economic Activity in Developing Countries"

by

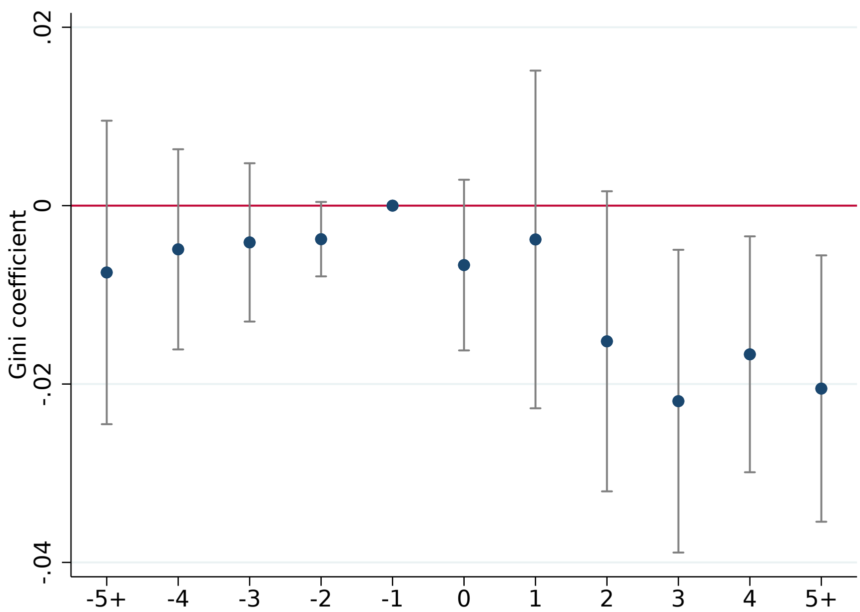
Bluhm, Dreher, Fuchs, Parks, Strange, and Tierney

Figure A-1 – Trends in the count project-years and spatial Gini by terciles of $\bar{N}_{ji}$



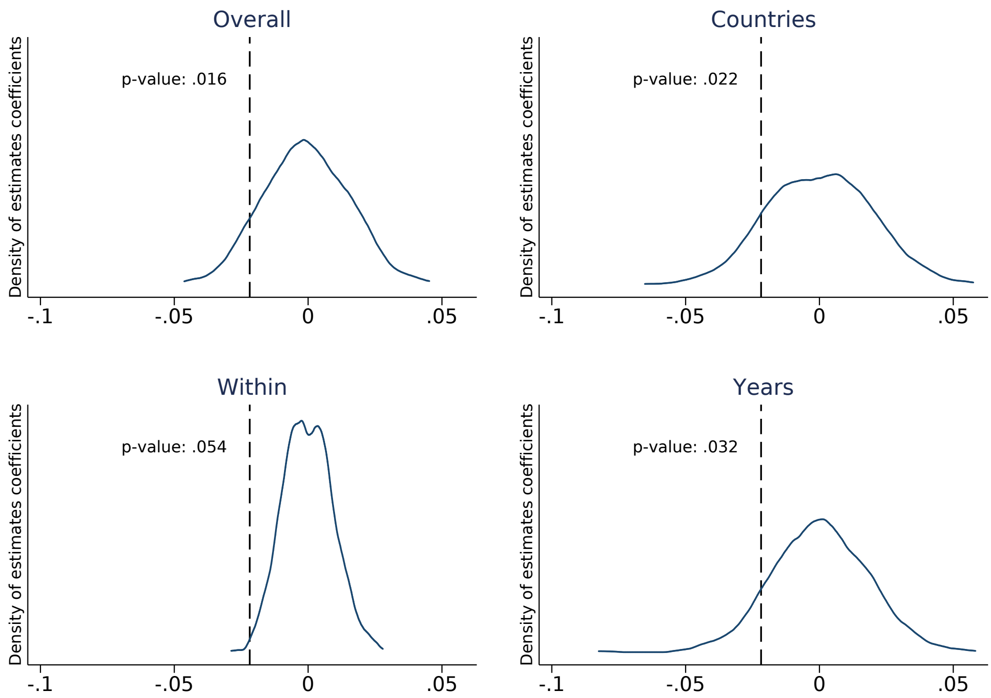
Notes: The figure shows—for ADM1 regions with different "probabilities to receive aid" over the sample period—the number of transport projects in tandem with the regions' spatial Gini coefficient.

Figure A-2 – Event study based on first project in region



Notes: The figure illustrates event-study results from two-way fixed effects regressions of the spatial Gini coefficient on a binned sequence of treatment change dummies (from $t <= -5$ to $t >= 5$). The estimated effect size are relative to $t = -1$. All regressions include region and year fixed effects. The grey error bars indicate 95% percent confidence intervals based on standard errors clustered at the country level.

Figure A-3 – Randomization inference



Notes: The figure shows the distribution of point coefficients of Chinese-financed transport projects based on 999 Monte Carlo replications under different randomization inference tests. Panel a *'Overall'* swaps the project dummy and instrument for all observations, panel b *'Countries'* swaps the entire time series between countries, panel c *'Within'* swaps years within countries, and panel d *'Years'* swaps countries within years. Dashed vertical lines indicate the original estimate from column 1 of Table 1. The p-values are calculated as the proportion of times that the absolute value of the t-statistics in the simulated data exceed the absolute value of the original t-statistic.

Table A-1 – List of countries

Afghanistan	Ghana	North Macedonia
Albania	Guatemala	Oman
Algeria	Guinea	Pakistan
Angola	Guinea-Bissau	Panama
Argentina	Haiti	Papua New Guinea
Armenia	Honduras	Paraguay
Azerbaijan	Hungary	Peru
Bangladesh	India	Philippines
Belarus	Indonesia	Poland
Benin	Iran, Islamic Rep.	Romania
Bolivia	Iraq	Russian Federation
Bosnia and Herzegovina	Jamaica	Rwanda
Botswana	Jordan	Saudi Arabia
Brazil	Kazakhstan	Senegal
Bulgaria	Kenya	Serbia
Burkina Faso	Korea, Dem. People's Rep.	Sierra Leone
Burundi	Kyrgyz Republic	Slovak Republic
Cambodia	Lao PDR	Somalia
Cameroon	Latvia	South Africa
Central African Republic	Lebanon	South Sudan
Chad	Lesotho	Sri Lanka
Chile	Liberia	Sudan
Colombia	Libya	Syrian Arab Republic
Congo, Dem. Rep.	Lithuania	Tajikistan
Congo, Rep.	Madagascar	Tanzania
Costa Rica	Malawi	Thailand
Cote d'Ivoire	Malaysia	Togo
Croatia	Mali	Trinidad and Tobago
Cuba	Mauritania	Tunisia
Czech Republic	Mauritius	Turkey
Dominican Republic	Mexico	Turkmenistan
Ecuador	Moldova	Uganda
Egypt, Arab Rep.	Mongolia	Ukraine
El Salvador	Morocco	Uruguay
Eritrea	Mozambique	Uzbekistan
Estonia	Myanmar	Venezuela, RB
Eswatini	Namibia	Vietnam
Ethiopia	Nepal	Yemen, Rep.
Gabon	Nicaragua	Zambia
Gambia, The	Niger	Zimbabwe
Georgia	Nigeria	

Notes: The table lists all 122 countries included in the regression analysis.

Table A-2 – Number of project locations by sector

Project sector	No. of project-locations
Transport and Storage, of which...	1,215
...long-distance roads	651
...long-distance railways	245
...urban roads	123
...airports	38
...bridges	38
...urban railways and tram lines	35
...several categories	24
...ports and waterways	16
...vehicles	16
...other project types not listed above	29
Health	676
Education	538
Energy Generation and Supply	350
Communications	337
Government and Civil Society	273
Emergency Response	238
Other Social Infrastructure and Services	205
Agriculture, Forestry and Fishing	193
Water Supply and Sanitation	150
Industry, Mining, Construction	107
Other Multisector	68
Developmental Food Aid/Food Security Assistance	18
General Environmental Protection	10
Other sectors not listed above	54
Total	4,432

Notes: The table lists project sectors and project types in the sector Transport & Storage together with their frequency in terms of project locations.

Table A-3 – Descriptive statistics

	N	*Mean*	*SD*	*Min*	*Max*
		Panel a) Dependent variables			
GINI_{jit} (within first-order regions)	26,759	0.535	0.159	0.000	0.849
GINI_{jit} (between first-order regions)	22,664	0.453	0.194	0.000	0.985
Log light per capita	26,759	-3.301	0.942	-4.604	1.793
Extensive margin	26,759	0.466	0.344	0.001	1.000
Quintile share (0-20%)	25,092	0.026	0.031	0.000	0.330
Quintile share (20-40%)	25,092	0.058	0.037	0.000	0.232
Quintile share (40-60%)	25,092	0.109	0.046	0.000	0.318
Quintile share (60-80%)	25,092	0.198	0.053	0.000	0.536
Quintile share (80-100%)	25,092	0.609	0.134	0.168	1.000
		Panel b) Variables of interest			
Projects ($N_{i,t-2}$)	26,759	0.047	0.272	0.000	6.000
Projects (log 1 + financial values)	26,759	0.177	1.769	0.000	21.61
Projects (location count)	26,759	0.027	0.317	0.000	10.000
Projects (completed)	26,759	0.029	0.211	0.000	5.000
Projects (economic infrastructure)	26,759	0.099	0.417	0.000	8.000
Projects (construction phase)	26,759	0.013	0.112	0.000	1.000
		Panel c) Instruments			
IV ($F_{t-3} \times \bar{N}_{ji}$)	26,759	-0.003	0.044	-0.821	0.630
IV ($F_{t-3} \times \bar{M}_{ji}$)	26,759	-0.009	0.118	-1.525	1.170
IV (Det. steel)	26,759	0.000	0.048	-0.889	0.773
IV (US placebo)	26,759	0.000	0.054	-1.782	0.561
		Panel d) Other variables			
Log FDI	26,759	10.04	1.300	7.831	11.59
Log imports	26,098	6.924	2.093	0.000	11.12
Log exports	26,098	5.492	2.835	0.000	10.74
Distance to coast	26,759	0.313	0.385	0.001	2.455
Urbanization	26,759	0.072	0.151	0.000	1.000
Large mines	26,759	0.262	0.440	0.000	1.000
Oil fields	26,759	0.306	0.461	0.000	1.000
Travel time to cities	26,747	326.5	384.3	4.418	4,984
Road density	26,759	0.143	0.297	0.000	8.805
Light per capita	26,759	0.044	0.062	0.000	1.207
Africa	26,759	0.303	0.460	0.000	1.000
Asia	26,759	0.340	0.474	0.000	1.000
Americas	26,759	0.185	0.388	0.000	1.000
Developing	26,108	0.825	0.380	0.000	1.000
$\bar{N}^{\text{all}} > 0$	26,759	0.320	0.466	0.000	1.000

Notes: The table provides descriptive statistics for the regressions using data at the level of first-order regions.

Table A-4 – Non-linear trends and instrument robustness

	Non-linear trends, i.e., year dummies times ...					*IV pertub.*
	Distance to coast	Urbanization rate	Large mines	Oil fields	All	Leave-one-out instrument
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel a) 2SLS estimates					
Projects ($\Delta N_{ji,t-2}$)	-0.0218	-0.0145	-0.0218	-0.0218	-0.0149	-0.0156
	(0.0102)**	(0.0107)	(0.0098)**	(0.0097)**	(0.0108)	(0.0094)*
	[0.0076]***	[0.0073]**	[0.0072]***	[0.0073]***	[0.0074]**	[0.0078]**
L-o-o. prob. ($\widetilde{N}_{jit}$)						0.0086
						(0.0312)
						[0.0312]
	Panel b) First-stage estimates					
IV ($F_{t-3} \times \bar{N}_{ji}$)	0.4393	0.4389	0.4400	0.4400	0.4390	
	(0.0748)***	(0.0745)***	(0.0744)***	(0.0747)***	(0.0741)***	
	[0.0716]***	[0.0718]***	[0.0714]***	[0.0715]***	[0.0716]***	
Alt. IV ($F_{t-3} \times \widetilde{N}_{jit}$)						0.5058
						(0.1043)***
						[0.0930]***
L-o-o. prob. ($\widetilde{N}_{jit}$)						0.8865
						(0.2476)***
						[0.2237]***
First-stage F-Stat	34.53	34.75	34.99	34.68	35.07	23.53
Observations	27,162	27,162	27,162	27,162	27,162	24,797
Regions	2,406	2,406	2,406	2,406	2,406	2,392
Countries	122	122	122	122	122	121

Notes: The table reports regression results. Panel a shows two-stage least-squares fixed-effects regressions where the dependent variable is the first difference of the Gini coefficient of light intensity within first-order administrative regions. Panel b shows least-squares fixed-effects regressions where the dependent variable is a binary indicator for new project commitments ($\Delta N_{ji,t-2}$) in a region. Columns 1 to 5 add interactions of a cross-sectional variable (either a dummy for above-median value or a dummy that indicates the presence of something) with year dummies to allow general non-linear "China shocks" to affect some regions more than others. Column 6 uses a modified "leave-one-out" ("L-o-o.") instrument, where we compute the exposure variable, $\widetilde{N}_{jit}$, as the cross-sectional average minus the value of $\Delta N_{i,t-2}$ in each period. While this removes the contemporaneous correlation between the IV and the endogenous variable, the probability is now time-varying and no longer absorbed by the unit fixed effects (which is why we control for it in both stages of the regression). 'Distance to coast' is the average "as-the-crow-flies" distance from the region to the nearest coastline from Natural Earth. 'Urbanization rate' is the fraction of land which is defined as an urban cluster or urban center in 2000 by the Global Human Settlement Layer (Pesaresi et al. 2019). 'Large mines' indicate if the region has at least one major mineral deposit in 2005 according to the United States Geological Survey. 'Oil fields' indicate if the region has at least one major on-shore oil or gas field (Lujala et al. 2007). All specifications include region-fixed effects and country-year-fixed effects. Standard errors clustered at the country level are reported in parentheses. Conley errors with a spatial cutoff of 500 km and a time-series HAC with a lag cutoff of 1,000 years are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table A-5 – Controlling for co-location, within ADM1, 2002–2013

	Controlling for other projects committed at $t-2$				
	World Bank	World Bank	China	China	China
	(1)	(2)	(3)	(4)	(5)
	Panel a) 2SLS estimates				
Projects ($\Delta N_{ji,t-2}$)	-0.0215	-0.0214	-0.0211	-0.0218	-0.0219
	(0.0092)**	(0.0097)**	(0.0100)**	(0.0098)**	(0.0099)**
	[0.0071]***	[0.0073]***	[0.0074]***	[0.0072]***	[0.0073]***
	Panel b) First-stage estimates				
IV ($F_{t-3} \times \bar{N}_{ji}$)	0.4400	0.4396	0.4353	0.4400	0.4381
	(0.0747)***	(0.0746)***	(0.0759)***	(0.0747)***	(0.0753)***
	[0.0716]***	[0.0715]***	[0.0722]***	[0.0715]***	[0.0718]***
World Bank Transport	✓	–	–	–	–
World Bank Any	–	✓	–	–	–
China Social	–	–	✓	–	–
China Production	–	–	–	✓	–
China Energy	–	–	–	–	✓
First-stage F-Stat	34.68	34.70	32.86	34.65	33.81
Observations	27,162	27,162	27,162	27,162	27,162
Regions	2,406	2,406	2,406	2,406	2,406
Countries	122	122	122	122	122

Notes: The table reports regression results. Panel a shows two-stage least-squares fixed-effects regressions where the dependent variable is the first difference of the Gini coefficient of light intensity within first-order administrative regions. Panel b shows least-squares fixed-effects regressions where the dependent variable is a binary indicator for new project commitments ($\Delta N_{ji,t-2}$) in a region. Columns 1 to 2 control for World Bank projects using the World Bank Geocoded IBRD-IDA Projects (v1.4.2). Columns 3 to 5 include dummies for projects in different sectors based on the geocoded China data presented in this paper. All specifications include region-fixed effects and country-year-fixed effects. Standard errors clustered at the country level are reported in parentheses. Conley errors with a spatial cutoff of 500 km and a time-series HAC with a lag cutoff of 1,000 years are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.