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

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Abstract

How do development projects influence the geographic distribution of economic activity within low-income and middle-income countries? Existing research focuses on the effects of Western development projects on inter-personal inequality and inequality across different subnational regions. However, China has recently become a major financier of economic infrastructure in Africa, Asia, Latin America, the Middle East, and Central and Eastern Europe, and it is unclear if these investments diffuse or concentrate economic activity. We introduce an original dataset of geo-located Chinese Government-financed projects in 138 countries between 2000 and 2014, and analyze the effects of these projects on the spatial distribution of economic activity within host countries. We find that Chinese development projects in general, and Chinese transportation projects in particular, reduce economic inequality within and between subnational localities. Our results suggest that Chinese investments in "connective infrastructure" produce positive economic spillovers that lead to a more equal distribution of economic activity in the localities where they are implemented.

Keywords: foreign aid, inequality, China, Official Development Assistance, georeferenced data, spatial analysis, GINI, aid effectiveness

JEL classifications: F35, P33, R11, R12

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1. Introduction

In the early 1960s, the Government of Tanzania approached foreign donors and lenders with a proposal to finance an ambitious project: an 1860-kilometer railway connecting copper mines in landlocked Zambia to the port of Dar es Salaam. Two feasibility studies commissioned by the World Bank and the United Nations questioned the technical feasibility and economic viability of the proposal (Monson 2009: 15). Shortly thereafter, the United Kingdom, the United States, Japan, Canada, France, West Germany, and the Soviet Union signaled that they would not finance the project (Harden 1987; Song 2015). China, however, agreed to bankroll the US$415 million project—worth approximately US$3 billion in current dollars—in 1967. At the time, the TAZARA railway represented China's single largest foreign aid project.[1] The project was an extraordinary engineering challenge. It required blasting through or moving 89 million cubic meters of earth, and constructing 320 bridges, 2,225 culverts, and 22 tunnels (Harden 1987). Yet it was completed less than three years after construction activities commenced.[2]

The newly established corridor had far-reaching and long-lasting effects on the spatial distribution of economic activity in Tanzania. Monson (2009: 8) notes that "[u]pon its completion, the TAZARA railway formed the backbone of a new spatial orientation for agrarian production and rural commerce." It promoted a large-scale resettlement of rural villages alongside the rail line, attracted migrants in search of wage labor opportunities to these villages, increased agricultural intensification near the settlements along the railway corridor, and strengthened ties between rural and urban markets. Song (2015: 59) elaborates on this point, writing that "[t]he operation of the [TAZARA] railway facilitated the flourishing development of an agricultural economy along its route, and local areas changed dramatically after its completion. Wastelands and jungles were transformed into farms of rice, corn, and bananas. The railway also promoted the circulation of commodities. Besides effectively solving the problems confronting the export of copper, the TAZARA railway […] revitalized domestic trade by speeding up the transportation of light industrial products between different localities and made travel much easier than before for

[1] For ease of exposition, we will use the term "aid" in this paper to refer broadly to any types of official finance from a donor (or lender) to a recipient (or borrower). In cases when we wish to reference the narrower (OECD-DAC) definition of aid, we use the term Official Development Assistance (ODA). In cases when we wish to reference concessional and non-concessional official financing that does not qualify as ODA, we use the term Other Official Flows (OOF). Finally, when we wish to reference the sum of ODA and OOF, we use the term Official Finance (OF).

[2] The project was initiated in October 1970, and an estimated 30,000-40,000 Chinese workers traveled to the country by boat to co-labor alongside tens of thousands of Tanzanian workers. Monson (2009: 52) writes that "[s]trenuous working conditions were made more difficult by the determination of the Chinese authorities to finish the project well ahead of schedule. The Chinese management was willing to push the workforce night and day to show what could be achieved—and to build African confidence—at a time when the world was watching." By the end of 1973, just 27 months after construction began, the railroad was nearly complete on the Tanzanian side of the border.

the local people." According to Monson (2009: 122), "economic development in the TAZARA corridor […] radiated outwards into the surrounding regions."

Mao-era construction of the TAZARA railway foreshadowed Beijing's rise as a major international financier of transportation infrastructure.[3] Since 2000, China has assumed an increasingly dominant role in the construction and rehabilitation of transportation infrastructure around the globe.[4] In Sub-Saharan Africa, it has funded a US$320 million ring road around Ethiopia's capital, Addis Ababa; a US$3 billion railroad that runs from Addis Ababa to Djibouti's seaside port of Doraleh; a US$4 billion railroad that connects Kenya's capital with the port city of Mombasa; a US$600 million road that connects Gabon's leading seaport (Port-Gentil) with its capital, Libreville; and a US$500 million road in Cameroon that connects the port city of Douala with the capital, Yaoundé. In Asia, China's government has funded a US$7 billion high-speed railway from Laos' capital city, Vientiane, to the capital of China's Yunnan Province (Kunming) and a US$2 billion highway from Karachi to Lahore in Pakistan, while pouring billions of dollars into the construction and rehabilitation of roads in Cambodia, Sri Lanka, and Indonesia. In Latin America, it has provided US$2 billion in support of the rehabilitation of a 1500 km railway in Argentina, US$350 million for suburban mass transit extensions in Venezuela, and hundreds of millions of dollars for highways and bridges in Jamaica, Suriname, Ecuador, and Bolivia. In the Middle East and North Africa, it has invested US$2 billion in the electrification of a 926 km railway from Mashhad to Tehran and US$250 million in Morocco's Berchid-Beni Mellal highway.[5]

Notwithstanding criticism that it finances politically motivated and economically unsustainable projects, the Chinese Government has recently doubled down on its leadership role in the global infrastructure finance market. In his keynote address at the 2017 Belt and Road Forum for International Cooperation, President Xi Jinping emphasized that "[i]nfrastructure connectivity is the foundation of development through cooperation. We should promote land, maritime, air and

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[3] It also provided an early indication of Beijing's unique interest, possibly rooted in its own development experience, in building transportation networks that connect inland or otherwise isolated areas with coastal regions and ports (Bonfatti and Poelhekke 2017).

[4] In 1999, China adopted a "Going Out" strategy, which called upon government institutions to more aggressively encourage Chinese firms to invest and do business in overseas markets. The implementation of this strategy has fundamentally altered the scale and scope of China's state-sponsored financial transfers to other countries (Djankov 2016; Dreher et al. 2017). Foreign direct investment, development finance, and export finance from China have soared since 2000 (Dong and Fan 2017; Morgan and Zheng 2017).

[5] In the dataset that we introduce in Section 3, we identify 342 Chinese Government-financed transportation projects that were underway at 1331 locations in 86 countries around the globe over the 2000-2014 period. The total financial value of these projects amounts to US$ 69.5 billion. 61% of these projects were fully complete by 2014.

cyberspace connectivity, concentrate our efforts on key passageways, cities and projects and connect networks of highways, railways and sea ports ...” (Xi 2017).

The short- and long-run consequences of China’s infrastructure financing activities—including the US$1 trillion Belt and Road Initiative—are sources of growing speculation and debate (e.g., Perlez and Huang 2017). Western politicians and public intellectuals claim that China prioritizes speed over quality and often funds “white elephant” projects. However, 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 finance roads, bridges, railways, and ports at a time when Western donors and lenders are not (Dollar 2018).[6]

Existing studies have evaluated the effects that Chinese development projects have on economic development, literacy, environmental degradation, trade union participation, and corruption (BenYishay 2016; Dreher et al. 2016, 2017; Brazys et al. 2017; Isaksson and Kotsadam 2018a, 2018b; Martorano et al. 2018). However, a key question that remains unanswered is whether and to what extent Chinese development projects widen or narrow inequalities within low-income and middle-income countries.[7] Inequality is one of the defining issues of our time. Left unattended, it can limit inter-generational mobility, increase political polarization, undermine social cohesion, erode trust in public institutions, and elevate the risk of violent unrest (Dreier et al. 2004; Østby et al. 2009; Khwaja 2009; Alesina et al. 2004, 2016; Cederman et al. 2013; Chetty et al. 2014; Chetty and Hendren 2018a, 2018b; Ahlerup et al. 2016, 2017).

Many international development organizations claim that they are tackling this problem. The World Bank, for example, has redefined its mission “as ending extreme poverty by 2030 and *boosting prosperity among the poorest 40 percent in low- and middle-income countries.*”[8] Aid agencies and development banks also claim that they are making special efforts to address economic disparities that exist within and across subnational localities (van de Walle and Mu.

[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). Indeed, Western aid agencies and multilateral development banks have become significantly more risk averse about bankrolling large-scale infrastructure projects because of the environmental, social, and financial risks that they pose (Nielson and Tierney 2003; Hicks et al. 2008; Buntaine 2016).

[7] By contrast, a growing “China shock” literature explores analogous distributional questions in the context of Chinese economic engagement in the United States and other developed economies (Autor et al. 2016).

[8] The U.N. Sustainable Development Goals also identify targets for the growth rate of the bottom 40% of the population and for the social, economic and political inclusion of ethnicities and different social groups under the broad goal of “reducing inequalities.”

2007; Chen et al. 2009; Wagstaff 2011).[9] But existing empirical research demonstrates a yawning gap between donor rhetoric and action in this regard. By various measures and methods, economists and political scientists have found that international development organizations do a poor job of targeting economically disadvantaged regions within countries (Öhler and Nunnenkamp 2014; Öhler et al. 2017).[10] In fact, a growing number of studies find that international development organizations actually site their projects in *wealthier* areas within countries (Zhang 2004; Nunnenkamp et al. 2016; Briggs 2017, 2018, forthcoming).[11]

However, China is a unique source of development finance that merits special attention given its revealed preference for funding "connective infrastructure" at home and abroad. Economic theory suggests that these types of investments can increase the mobility of people, goods and capital, which begs the broader question of whether Chinese Government-financed connective infrastructure might help developing countries escape inefficient spatial equilibria—that is, transition away from the status quo of excessive concentration of economic activity in a small number of cities or regions.

To analyze this question, we introduce an original dataset of geo-located Chinese Government-financed projects situated in 138 countries between 2000 and 2014, and examine the effects of these projects on the spatial distribution of economic activity in host countries. We estimate the overall and sector-specific effects of these projects on spatial inequality within and across subnational jurisdictions, which we measure using the dispersion in nighttime light intensity (as in Henderson et al. 2018). We conduct this analysis at the second-order administrative region (ADM2) level, first-order administrative region (ADM1) level, and country level (ADM0).[12] We also briefly compare the distributional effects of development projects financed by China to those of the World Bank, a financier of large-scale infrastructure projects that is—at least

[9] Spatial inequality is an important component of overall inequality (Elbers et al. 2005; Yemtsov 2005); household inequality and spatial inequalities within and between regions often move in the same direction (Kim 2008; Lessmann and Seidel 2017). An unequal distribution of economic activity is not necessarily harmful. It may simply reflect the comparative advantages of particular regions. However, in many developing countries, it is the result of excessive concentration of economic activity in primate cities and rural neglect (Ades and Glaeser 1995; Sahn and Stifel 2003). Also, when spatial inequality coincides with ethnic or other social cleavages, it can fuel violent conflict (Kanbur and Venables 2005; World Bank 2009; Kuhn and Weidmann 2015; Alesina et al. 2016; Ezcurra and Andrés Rodríguez-Pose 2017). Cases in point are Kenya's 2008-election violence or the downfall of the Shah's regime in Iran.

[10] Cross-country research on the impact of aid on inequality is mixed and largely inconclusive (Chong et al. 2009; Bjørnskov 2010; Herzer and Nunnenkamp 2012; Tezanos et al. 2013).

[11] One reason why this may be the case is that the poorer regions within countries are often rural and remote and it tends to be costlier and challenging to deliver aid to such places (Custer et al. 2017). There may also be political reasons why wealthier regions get more aid (Dreher et al. 2016).

[12] Typically, ADM1 regions are provinces, states, or governorates, while ADM2 regions are counties, districts, or municipalities. For example, Sri Lanka is divided into 9 provinces (ADM1s) and 25 districts (ADM2s).

rhetorically—committed to the idea that the benefits of economic growth ought to be shared broadly across society.

To estimate the causal effect of Chinese Government-financed projects on spatial inequality, we use the instrumental variable (IV) developed in Dreher et al. (2016), who study the effects of Chinese aid on subnational development in Africa. Our instrument uses an exogenous supply push variable interacted with a local exposure term: China's domestic production of potential aid inputs interacted with each recipient region's probability of receiving aid. We use China's annual production of steel (in thousand tons) to proxy for its capacity to produce physical aid inputs. The intuition behind this approach is that the Chinese government has long considered steel a strategic commodity and therefore maintains excess production capacity. This policy results in a steel surplus, some of which supplies aid projects in developing countries. As a result, aid inputs are higher about a year after production volumes were high and China's subsequent provision of foreign aid is also higher (see Dreher et al. 2016, 2017, for a detailed description). We proxy for local exposure by the share of years within our study period in which a particular subnational region received Chinese aid. Regions that frequently receive Chinese-financed projects are more severely affected by year-to-year fluctuations in the supply of Chinese aid—and thus overproduction in steel in the prior year—than those regions that infrequently host Chinese-financed projects. This approach is similar to the identification strategies used in the "China shock" literature, which analyzes the effects of Chinese import competition on US labor markets (e.g., Autor et al. 2016) and can be interpreted as a difference-in-difference estimate. We essentially compare the effects of Chinese aid projects on spatial inequality induced by annual variations in steel production in China between regions with a high probability of receiving Chinese aid to those regions with a low level of exposure to Chinese-financed projects. Our local average treatment effect (LATE) is therefore primarily driven by big infrastructure projects requiring large amounts of steel and other physical inputs.

Our results strongly suggest that Chinese-financed connective infrastructure reduces spatial inequalities and accelerates the diffusion of economic activity across geographic space. This finding is robust to a variety of sensitivity checks and perturbations. The results are strongest for transportation infrastructure projects financed by China, but also hold for Chinese-financed development projects more generally. The estimated causal effects using the instrumental variable regressions are larger than the OLS estimates but both consistently point towards a negative effect of Chinese-financed projects on spatial inequality. Remarkably, this pattern holds at all levels of regional aggregation, although the individual significances and effect sizes vary. We also test whether Chinese transportation infrastructure projects are more effective in reducing regional inequality when they are undertaken alongside projects in complementary sectors, such as health or education, but fail to find robust evidence in favor of co-location benefits. Moreover, we cannot confirm that World Bank-financed projects also affect the spatial distribution of economic activity in any systematic manner (but also have to use a different instrument in this setting).

The remainder of the paper proceeds as follows. In the next section, we develop theoretical arguments and put forth a testable hypothesis about how aid affects economic inequality within communities. Section 3 introduces our new subnational dataset of georeferenced Chinese government-financed projects in 138 countries, and discusses the measurement of spatial inequality at the subnational level. Section 4 describes our identification strategy. Section 5 presents and discusses our main results, including a battery of robustness checks and generalizations. Section 6 concludes with a discussion of potential avenues for future research.

2. Theory

2.1 State of the Existing Literature on Aid and Spatial Inequality

Previous research strongly suggests that the way in which aid is distributed across subnational units worsens regional disparities. Hodler and Raschky (2014), for example, provide evidence that autocratic leaders are more likely than democratic leaders to funnel resources to their home regions, thereby widening spatial inequalities, particularly in countries that receive large amounts of aid. This finding may reflect the logic of political survival; that is, when the "selectorate" is sufficiently small, the leader may have an incentive to provide private goods to a small group of individuals rather than public goods that benefit a larger proportion of the population (Bueno de Mesquita et al. 2003). Dreher et al. (2016) suggest that those donors that grant high levels of discretion over project site selection to aid-receiving governments are more vulnerable to this type of domestic political manipulation. Other studies suggest that aid projects may promote a greater skew in the geographic distribution of economic activity if they are subject to high levels of elite capture and corruption (Lessmann and Seidel 2017).

However, the existing literature has not seriously considered the possibility that development projects in different sectors may have heterogeneous effects on the spatial concentration or diffusion of economic activity. Consider projects that finance the construction or rehabilitation of "connective infrastructure." Roads, bridges, railways, and ports increase the mobility of labor, goods, and capital, and theory suggests several reasons why these types of transportation infrastructure investments might disperse rather than concentrate economic activity across geographic space (Henderson 2002; Kanbur and Venables 2005; Baum-Snow 2007; Kim 2008).[13]

Nor has the existing literature seriously engaged with the possibility that the heterogeneous goals and practices of different donors may have distributional implications. China and traditional donors vary along several dimensions that are potentially consequential: the speed with which they implement projects, the level of priority that they assign to different types of connective infrastructure projects, and the degree to which they seek to establish "growth poles" through the co-location of projects in multiple sectors.

Therefore, in the next section of this paper, we briefly consider why transportation infrastructure projects in general, and Chinese Government-financed transportation infrastructure projects in particular, might reduce economic inequalities in the subnational localities where they are implemented.

2.2 Connective Infrastructure and Spatial Inequality

New economic geography (NEG) theory suggests that investments in connective infrastructure set in motion "centripetal" forces that concentrate economic activity and "centrifugal" forces that disperse economic activity (Krugman 1996). Transportation infrastructure investments reduce the costs of trade and migration, making it easier for firms to reach more distant markets and individuals to commute or relocate to places of work that are further afield. Indeed, previous research demonstrates that connective infrastructure can spread economic activity to rural, remote and economically disadvantaged areas by nurturing the development of local markets (Mu and Van de Walle 2012), increasing access to larger (urban) markets where (rural) firms can sell their goods and services (Michaels 2008; Donaldson and Hornbeck 2016), reducing inter-regional price differences and price volatility (Cirera and Arndt 2008; Le Cotty et al. 2017; Donaldson 2018), promoting the entry of new firms (Shiferaw et al. 2015; Ghani et al. 2016), lowering the cost of inputs and consumer goods (Bayes 2007; Parada 2016), increasing land values and agricultural production (Khandker et al. 2009; Donaldson and Hornbeck 2016),[14]

[13] Also, transportation infrastructure is often highlighted as one of the key policy levers that governments can use to influence the spatial distribution of economic activity in both classical and New Economic Geography theory (Kim 2008).

[14] Jacoby (2000) shows that reductions in transportation costs increase the market value of land in previously disconnected, poorer areas.

facilitating knowledge and technology spillovers (Khanna 2016), and enabling commuters to travel longer distances to places of employment (Baum-Snow 2007).[15]

On the other hand, there are increasing returns to scale when economic activity is concentrated in a particular location (Lichtenberg 1960; Henderson 1986; Murphy et al. 1989; Krugman 1991a), so when leading areas are better connected to lagging areas, it is possible that labor and capital will move from the latter to the former and pattern of circular and cumulative causation will ensue.[16] If firms can achieve lower unit costs and higher profits in large markets, they will likely relocate there (when it is feasible to do so), and as new firms and workers enter these large and expanding markets, they will create greater demand for intermediate inputs and final goods, which will in turn attract more firms and workers and make large markets even larger (Krugman 1996; World Bank 2009). Indeed, in Krugman's (1991a) original NEG model, falling transport costs predict the development of a core-periphery split and hence a high level of spatial inequality prevailing in equilibrium.[17]

Spatial inequality outcomes—whether they are defined as inter- or intra-regional differences in economic outcomes—are the net result of these centrifugal and centripetal forces. Empirical research suggests that infrastructure investments generally have the net effect of dispersing rather than concentrating economic activity in developing countries. Baum-Snow et al. (2017) examine the effect of road and railway infrastructure on the spatial distribution of economic activity in China. They find that ring road investments displaced 50 percent of industrial GDP from central cities to outlying areas. They also find that railway investments have similar, but quantitatively smaller impacts. Bayes (2007) provides evidence that a US$1 billion bridge investment in Bangladesh, which connected farmers and firms in the underdeveloped, northwestern division of Rajshahi to the country's more economically developed eastern divisions, expended market access, reduced input prices, facilitated diversification into higher-value crops, and ultimately reduced the level of income inequality within Rajshahi (a first-order

[15] There is also evidence that transportation investments expand firm productivity, output growth, and exports (Faber 2014; Ghani et al. 2016; Martincus et al. 2017), and increase household income in geographically proximate areas (Jacoby 2000; Bayes 2007; Khandker et al. 2009; Jacoby and Minten 2009).

[16] Faber (2014) provides evidence that China's National Trunk Highway System did not diffuse economic activity away from metropolitan areas to peripheral areas. Instead, the investment in inter-regional transportation infrastructure actually reduced levels of economic activity in the newly connected peripheral regions relative to non-connected peripheral regions.

[17] In developing countries, labor may initially be immobile so that firms concentrate close to final demand. If this is the case, then initial investments in infrastructure first permit a greater concentration of economic activity as firms cluster to exploit agglomeration economies, which is then followed by a diffusion of activity as the productive landscape becomes more diverse and firms spread out to exploit local price differentials in immobile factors (Puga 1999). In any case, the presence of increasing returns to scale implies that initial infrastructure investments can be greatly amplified through the forces they set in motion.

administrative region).[18] Bird and Straub (2015) provide evidence 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, but on balance these investments reduced spatial inequality across the country's municipalities (second-order administrative units).

Another important feature of transportation infrastructure projects is that they are public goods. Roads, bridges, railways, and ports are typically non-rival in consumption and non-excludable,[19] meaning that their benefits generally accrue to a wide range of individuals and segments of the economy.[20] Many other types of infrastructure investments (e.g., electricity lines, water pipes, sewerage connections, schools, hospitals, and public housing) are rival in consumption, providing benefits from which specific groups can be—and in developing countries often are—excluded (Burgess et al. 2015; De Luca et al. 2018; Ejdemyr 2018).To the extent that infrastructure projects can be narrowly targeted towards specific geographic areas, or restricted for use by specific groups, they may even adversely affect spatial inequalities (Kasara 2007; Ichino and Nathan 2013).

Connective infrastructure investments are also likely to deliver more immediate and easily detectable reduction in spatial inequality than other types of development projects. Infrastructure projects reduce transportation costs for firms in a wide variety of sectors and increase the relative mobility of firms and households in poorer areas.[21] By contrast, the distributional impacts of other types of development projects—for example, health and education investments that promote the accumulation of human capital among poorer segments of society—likely accrue over longer periods of time (Mayer 2001; Clemens et al. 2012).[22]

2.3 Chinese Government-Financed Connective Infrastructure and Spatial Inequality

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[18] Similarly, Khandker et al. (2009) provide evidence that rural road investments in Bangladesh have reduced poverty and inequality at the village level by reducing agricultural input prices, increasing agricultural output prices, and expanding agricultural production.

[19] Users can only be excluded from connective infrastructure if a toll is imposed, which is rare among the Chinese Government-financed projects that we analyze. Notwithstanding the existence of some poorly designed projects that underestimated levels of usage, rivalry in the use of connective infrastructure is also uncommon.

[20] Previous research suggests that public works projects and other public capital investments tend to narrow the connectivity gap between a region's poor and wealthy, while also reducing the relative production and transaction costs of the poor (Ferreira 1995; Gannon and Liu 1997).

[21] Capital infrastructure projects may also flatten the spatial distribution of economic activity if they create employment on a large scale in poor areas with high levels of unemployment—in particular, during the construction phase of such projects.

[22] It is also worth mentioning that infrastructure lowers the costs of human and capital mobility and thereby makes human capital development cheaper for the poor (Brenneman and Kerf 2002; Leipziger et al. 2003).

There are also several theoretical reasons to believe that China might be more effective than traditional financiers of connective infrastructure at diffusing economic activity across geographic space: its willingness and ability to implement transportation infrastructure projects on an expedited schedule, the extent to which its investments challenge rather than reinforce preexisting spatial distributions of economic activity, and the degree to which it co-locates projects in different sectors to promote agglomeration economies.

First, China might be more efficient than traditional donors and lenders in implementing transportation infrastructure projects. In 2008, the then-President of Senegal Abdoulaye Wade publicly criticized traditional donors and lenders in the *Financial Times* for their disapproval of China's rapidly expanding overseas development program, noting that "China has helped African nations build infrastructure projects in record time… a contract that would take five years to discuss, negotiate and sign with the World Bank takes three months when we have dealt with the Chinese authorities." Similarly, Swedlund (2017: 128-129) reports that "[it] is clearly a dominant perception among many recipient-government officials that the Chinese are much faster than traditional donors at getting things done. One donor official recounted … having it explained to him that, if a traditional donor wants to build a road in 2012, the process needs to start in 2007. If the Chinese are going to build the same road, they start in 2011, and it is finished in 2012" (Swedlund 2017: 128-129).[23] Therefore, inasmuch as transportation infrastructure projects are effective at reducing spatial inequality and China executes these projects more efficiently than others, one would expect Chinese-financed transportation infrastructure projects to have stronger and faster inequality-reducing effects than transportation infrastructure projects backed by traditional donors and lenders.

Second, China might be more willing than traditional donors to fund the types of transportation investments that can help host countries escape inefficient spatial equilibria—e.g., situations in which most economic activity is concentrated in one or few primate cities and there is little economic activity in rural towns and villages. Colonial-era investments were highly localized in many developing countries, setting in motion powerful forces of economic agglomeration and creating spatial inequalities that have persisted over long periods of time (Bonfatti and

[23] These anecdotal accounts are broadly consistent with the empirical evidence presented in Bunte et al. (2018). They find large nighttime light impacts from Chinese investment projects and no impacts from U.S. investment projects in Liberia. They also report that the central authorities were particularly motivated to work with the Chinese because of their reputation for expeditious implementation of projects, including large-scale transport infrastructure projects.

Poelhekke. 2017; Roessler et al. 2018).[24] In other cases, the geographical distribution of economic activity has become highly skewed due to ethnic in-group and out-group dynamics or historical accidents (Krugman 1991a; Posner 2004; Padró i Miquel 2007; Cederman et al. 2010; Wucherpfennig et al. 2011; Alesina et al. 2016; Ezcurra and Rodrıguez-Pose 2017; De Luca et al. 2018; Bommer et al. 2018).[25]

One way to escape such traps is to invest in projects that challenge rather than reinforce preexisting distributions of economic activity—for example, by connecting inland and coastal communities. Bonfatti and Poelhekke (2017) point out that the traditional bilateral and multilateral donors prefer to invest in overland (interior-to-interior) transportation networks between countries, while China prefers to invest in interior-to-coast transportation networks.[26] This preference may reflect China's own experience with spatial inequality (Ravallion 2009: 309; Li et al. 2013: 307). When it opened up its economy to foreign investment during the 1980s, China not only experienced rapid economic growth, but also sharp increases in spatial inequality (Kanbur and Zhang 2005; Fleisher et al. 2010). The government responded with a set of spatial inclusion policies and programs—the "Develop the West Campaign" (西部大开发)—that redirected private and public investment to less economically developed areas in the central and western parts of the country.[27] Several studies suggest that the development of interior-to-coast transportation networks helped reverse a trend of growing inequality within and across the country's subnational localities (Lessmann 2013; Mao 2011; Huang and Wei 2016; Wu et al.

[24] In Ghana, for example, the British invested heavily in two railroad lines in the early 1900s: a Western line that connected the mines of Tarkwa and Obuasi to the coast and an Eastern line that connected Accra with gold mines and cocoa-growing areas in the rural hinterlands. Over time, villages, towns, and economic activity clustered alongside these transportation corridors, and this spatial equilibrium has proven to be remarkably stable because colonial investments created local increasing returns to scale and served as anchors for future rounds of public investment during the post-colonial era, thereby centralizing rather than decentralizing economic activity (Jedwab and Moradi 2016).

[25] Ethiopia—where some ethnic groups (the Tigray, Oromo, Amhara) have significant representation in the central government, and others (Somalis and Afars) face high levels of political discrimination—provides a good example of the former. Public resources and economic activity are concentrated in the geographical areas dominated by the Tigray, Oromo, and Amhara and not in the ethnic homelands of the Somalis and Afars (Argaw 2017). Krugman (1991b) points to the highly concentrated carpet industry in Dalton, Georgia as an example of the latter. A young woman from this town, named Catherine Evans, made a tufted bedspread in 1895 as wedding gift. Tufted bedspreads, in turn, became popular in that geographical area and led to the development of tufting skills and the emergence of a cottage industry, which then led to large-scale manufacturing of tufted carpets in northwestern Georgia after World War II.

[26] Bonfatti and Poelhekke (2017: 105) note that investments in interior-to-interior transportation networks tend to increase trade with neighboring countries, and investments in interior-to-coast transportation networks tend to increase trade with overseas countries, but it is not clear which of these investments most effectively reduce skew in the geographical distribution of economic activity.

[27] China's Ninth Five-Year Plan (1996–2000) identified the country's central and western regions as public investment priorities. Also, under the auspices of the 2000 Western Region Development Strategy and the 2004 Rise of Central China Plan, the central government launched an ambitious effort to lure foreign investors to the country's western and central regions (Huang and Wei 2016).

2018).[28] Therefore, if China has a unique and coherent way of making domestic investments in connective infrastructure, it is possible that the transportation infrastructure projects China finances abroad more effectively diffuse economic activity than similar projects funded by traditional donors.

Third, China places special emphasis on making complementary social sector and productive sector investments in or near the geographical areas where it is implementing transportation projects (Li et al. 2013: 306-307). This is a potentially consequential source of variation between China and traditional donors, as previous research suggests that these types of coordinated public investment strategies are particularly effective at diffusing economic activity across geographic space (Isserman and Rephann 1995; Meng 2013).[29] Coordinated public investment strategies trace their intellectual origins to "growth pole" theory—the idea that the concentration and co-location of a complementary set of investments in specific geographic areas will create clusters of interconnected firms, nurture the development of local markets, set in motion economic agglomeration processes, and reduce local unemployment (Perroux 1950, 1955; Myrdal 1957; Hirschman 1958; Boudeville 1966; Speakman and Koivisto 2014).

In light of these considerations, the core hypothesis that we seek to test is whether Chinese development projects—in particular, transportation infrastructure projects—reduce spatial inequalities within and between subnational jurisdictions. We also explore two auxiliary hypotheses: (a) whether Chinese connective infrastructure financing is more effective at diffusing economic activity in subnational localities where it co-locates these investments with other social sector and productive sector investments, and (b) whether these effects are any different for a "traditional" donor (the World Bank).

3. Data

3.1 A 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: 2). It does not publish a country-by-country breakdown of its

[28] A recent study demonstrates that China invested roughly ten times more than India did in its own highway system, and that India could increase economic growth and lower regional income disparities if it invested in a Chinese-style highway grid that penetrates previously isolated poor regions (Alder 2017).

[29] A quasi-experimental evaluation of the U.S. Government's regional development program in Appalachia has demonstrated that it was effective in reducing spatial inequality: between 1965 and 1991, per capita income increased 17 percentage points faster in the Appalachian counties that benefited from the targeted investment package than a matched set of U.S. counties with otherwise similar baseline economic characteristics (Isserman and Rephann 1995). China observed a similar reduction in spatial inequality under its so-called "8-7" plan, which sought to bring 80 million people in 593 economically disadvantaged counties out of poverty within seven years (1994-2000) through a geographically targeted package of infrastructure, health, education, and public employment interventions (Meng 2013).

expenditures or activities.[30] 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, we collaborated with AidData, a research lab at the College of William & Mary, to build a first-of-its-kind dataset of the subnational locations where Chinese Government-financed projects took place around the globe between 2000 and 2014.[31] This dataset captures all official committed projects that entered implementation or reached completion between 2000 and 2014 in five regions of the world (Africa, the Middle East, Asia and the Pacific, Latin America and the Caribbean, and Central and Eastern Europe) and were supported by Chinese official financing—i.e., foreign aid and other forms of concessional and non-concessional financing from Chinese government institutions.[32]

In total, the dataset captures 3,485 projects (worth US$273.6 billion in constant 2014 dollars) in 6,184 discrete locations across 138 countries. Figure 1 shows the locations of Chinese Government-financed projects over the 2000-2014 period. Figure 2 weights each project by its financial size in constant 2014 US dollars. Figure 1 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 are densely concentrated in African and Asian countries. Figures 1 and 2 also call attention to the fact that many Chinese Government-financed projects are situated in coastal regions, including some of the highest-value projects financed by Beijing.

The underlying project-level data is from Dreher et al. (2017), who use a publicly available method called Tracking Underreported Financial Flows (TUFF) to facilitate the collection of detailed and comprehensive financial, operational, and locational information about Chinese

[30] The Chinese government publishes some data on its foreign aid activities, but they are insufficiently detailed for use in social science research. The State Council has published two "White Papers" on the country's foreign aid program—one in 2011 and another in 2014—that provide summary statistics on the total amount of aid provided to five regions of the world (Information Office of the State Council 2011, 2014). The Ministry of Finance also publishes data on the country's total foreign aid expenditure through its website and a publication called the *Finance Yearbook of China*. However, neither of these official sources provides country-level or project-level data, let alone georeferenced data.

[31] 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. 2016). Note that we exclude all suspended and cancelled programs 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).

[32] More precisely, the dataset codes all Chinese Government-financed projects as ODA-like, 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% 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. 2018a.

government-financed projects. 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 impact of incomplete or inaccurate information.[33] Economists, political scientists, and computational geographers have used this dataset and earlier versions of it—capturing fewer countries and years—to explain the nature, allocation and effects of Chinese Government-financed projects (BenYishay et al. 2016; Kilama 2016; Hernandez 2017; Strange et al. 2017b; Brazys et al. 2017; Isaksson and Kotsadam 2018a, 2018b; Martorano et al. 2018; Bonfatti and Poelhekke 2017).

We limited the scope of our geocoding effort to Chinese Government-financed projects that were completed or in implementation during this period of study. All of these projects were subjected to a double-blind geocoding process (Strandow et al. 2011), in which two trained experts independently employ a defined hierarchy of geographic terms and independently assign uniform latitude and longitude coordinates and standardized place names to each location where the project in questions was active. Coders also specify a precision code for each location where a given project was active. 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 administrative (ADM2) region; and precision code 4 corresponds to a first-order administrative (ADM1) region.[34] These two sets of codes (latitude and longitude coordinates and geographic precision codes) are then checked against each other. If they are identical, they become the final set of codes. If they are not identical, the project in question is assigned to a senior “arbitrator” who identifies the underlying source of the discrepancy or discrepancies and assigns a master set of geocodes for all of the intervention sites described in the project documentation. The purpose of this double-blind coding process is to minimize the risk of missed or incorrect locations.

In order to merge these geocoded project data with our outcome measures of nighttime light inequality within subnational localities, we aggregate all projects with precision codes 1-4 to

[33] 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 Dreher et al. (2017) and Strange et al. (2017a).

[34] We exclude all projects with precision codes between 5 and 9. Such projects (e.g., country-wide projects) were not able to be geocoded with a sufficient level of spatial precision to be included in our ADM1-level dataset or ADM2-level dataset.

ADM1s and all projects with precision codes 1-3 to ADM2 regions. The resulting subsample includes 2,142 Chinese government-financed projects at 4,432 discrete locations (collectively worth US$ 193 billion) that were completed or being implemented in 883 ADM1 regions and 1,319 ADM2 regions within 129 countries between 2000 and 2014. These data can be disaggregated by financial flow type (ODA-like, OOF-like, Vague Official Finance) or sector. For the purposes of the latter, we use the OECD's three-digit sector classification scheme, which categorizes projects according to their primary objectives.[35] 43% of the projects in our sample supported economic infrastructure and services, including roads, railways, bridges, seaports, airports, power grids, power lines, cell phone towers, and fiber optic cable lines.[36] 42% of the projects in our sample focused on the provision of social infrastructure and services, such as hospitals, schools, piped water, and sewerage. Projects in the production sectors (e.g., mining, industry, trade, tourism, agriculture, forestry, and fishing) represent only 7% of our sample.

3.2 Measuring Inequality Within and Across Subnational Jurisdictions

Reliably measuring local economic activity across the globe with official data is incredibly difficult. Few countries collect and report comprehensive data at the individual or establishment level at regular intervals and subnational GDP data are generally only available in highly developed countries.[37] To circumvent this problem, we follow a recent literature that uses nighttime light intensity as a proxy for local economic activity (Henderson et al. 2012; Michalopoulos and Papaioannou 2014; Hodler and Raschky 2014; Pinkovskiy and Sala-i-Martin 2016; Dreher et al. 2016). While night lights were initially proposed as a proxy for GDP in countries with weak statistical capacity, they were quickly adopted as a measure of regional economic activity (Michalopoulos and Papaioannou 2014; Hodler and Raschky 2014). Subsequent studies have demonstrated that changes in light emissions correlate strongly with

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[35] There are 24 of these OECD sector codes: education (110), health (120), population policies/programs and reproductive health (130), water supply and sanitation (140), government and civil society (150), other social infrastructure and services (160), transport and storage (210), communications (220), energy generation and supply (230), banking and financial services (240), business and other services (250), agriculture, forestry and fishing (310), industry, mining, and construction (320), trade and tourism (330), general environmental protection (410), women in development (420), other multisector (430), general budget support (510), developmental food aid/food security assistance (520), non-food commodity assistance (530), action relating to debt (600), emergency response (700), support to NGOs and government organizations (920), and unallocated/unspecified (998).

[36] 27.4% of the projects in our sample were assigned to the "Transport and Storage" sector, and the vast majority of these projects focused on building transportation infrastructure, such as roads, railways, bridges, seaports, and airports.

[37] Nevertheless, there have been many attempts to create and compile such data. For example, the G-Econ database reports a gross cell product for one degree by one degree cells in 1990, 1995, 2000, and 2005, while Gennaioli et al. (2014) compile a heavily unbalanced dataset of regional GDPs for 83 countries from the early 1950s until 2010.

traditional measures of welfare down to the village level (Mellander et al. 2015; Weidmann and Schutte 2017; Bruederle and Hodler 2017; Khomba and Trew 2017).

There are two approaches to measuring spatial inequalities using nighttime light output data. The vast majority of the recent literature focuses on welfare disparities across ethnic groups or administrative regions and proxies for these differences using light per capita (Cederman et al. 2015; Kuhn and Weidman 2015; Alesina et al. 2016). A spatial Gini coefficient based on the distribution of light per capita is meaningful if theory suggests that income differences between groups or regions matter, regardless of their absolute size. However, Henderson et al. (2018) take a different approach. They 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.[38] This second approach is more suitable whenever agglomeration or scale effects play a role and is more relevant to our research question, since a primary objective of connective infrastructure investments is to enable the relocation of economic activity.

We obtain data on nighttime lights 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.

We proceed in four steps to calculate our measure of spatial inequality. First, we divide the entire world into a grid of 6 arc minute cells (area of about 9.3 km by 9.3 km at the equator, decreasing with the cosine of latitude) and align the grid with the lights data. Second, we intersect this grid with the global first-order and second-order administrative boundaries, which creates "squiggly" cells along the regional borders.[39] 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[40] of each cell in km^2 (a_i), and the light intensity in the cell ($x_i = s_i/a_i$). We average the resulting light intensities

[38] Henderson et al. (2012) and Hodler and Raschky (2014) estimate elasticities between nighttime light intensity and GDP at the national and subnational levels, respectively, of around 0.3. In effect, they treat nighttime light intensity as the product of GDP per capita and population (or total GDP). Likewise, Bluhm and Krause (2018) study the fragmentation of African cities—that is, the distribution of economic activity from the city center to the periphery—using nighttime light intensity as a proxy for population density and economic activity.

[39] The regional borders are obtained from the GADM vector dataset (version 2.8).

[40] We calculate the land area of each cell using the Gridded Population of the World (v4) land and water area raster.

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 lit cells[41] within an administrative unit as

$$G = \frac{\sum_{i=1}^{n} w_i \ \sum_{j=1}^{n} w_j |x_i - x_j|}{2 \ \sum_{i=1}^{n} w_i \sum_{i=1}^{n} w_i x_i}$$

where $w_i = a_i / \ \sum_{i=1}^{n} a_i$ is an area-based weight and n is the total number of lit cells in a region. Analogously, we also construct Gini coefficients for inequality *between* first and second-order regions (based on the average light intensity and land area of each 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*, or geometrically, as the area under the Lorenz curve plotting the cumulative distribution of weighted light intensities against the cumulative distribution of cell areas (in km^2).[42] It is important to emphasize again that our index captures the overall dispersion of economic activity, which is a product of the population distribution and the distribution of light per capita. To see this clearly, consider that x_i is defined as $\frac{p_i}{a_i} \times \frac{s_i}{p_i}$, where p_i / a_i is the population density and s_i / p_i is light per capita in each cell. Henderson et al. (2018) show that the temporal variation in population density across administrative regions is greater than the variation in income per capita. In our study context, this implies that, given a reasonable degree of mobility, a significant proportion of observed changes in the *within-region* distribution of light intensities may 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 infrastructure investments.

Several other reasons lead us to prefer a measure of spatial inequality based on light intensity rather than a measure based on light per capita. Even though there are well-known issues with bottom and top coding (see Jean et al. 2016; Bluhm and Krause 2018), nighttime light emissions are measured annually in the same manner for the entire globe at a resolution of less than 1 km by 1 km. 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. Separating changes in income per capita from changes in the population distribution at a resolution below

[41] Note that we exclude unlit cells when computing Gini coefficients; otherwise all larger countries would have Gini coefficients near unity. This is equivalent to assuming that these pixels are unpopulated. Bruederle and Hodler (2017) suggest that focusing only on lit pixels improves the correlation with local welfare.
[42] Figure 3 shows the average spatial Gini coefficient values between 2000 and 2013 for all ADM1s worldwide. Figure 4 presents the changes in ADM1-level spatial Gini coefficient values between 2000 and 2013.

10 km by 10 km is therefore extremely difficult without introducing high levels of measurement error. We also have good reasons to believe that such measurement errors would neither be benign nor random. Census quality and data availability are systematically correlated with development outcomes, so that there will be more spatial interpolation in poorer countries and regions (Henderson et al. 2018), and even if the population distribution at a particular point in time is approximately correct, then temporal interpolation implies that light may react more quickly and non-linearly than the cell-level population estimates. Since our identification strategy relies only on variation over time, focusing on inequality in light per capita would not only close an important channel but also potentially bias our estimates in an unknown direction.

4. Empirical Strategy

Our empirical approach is inspired by Dreher et al. (2016), who use a similar strategy in their analysis of Chinese aid projects and regional development in Africa. We instrument Chinese development projects with a Bartik-style instrument that isolates the supply-driven component of our main explanatory variable (Chinese aid) and then estimates the effect of this exogenous component on the spatial distribution of economic activity.

We use two measures for Chinese aid projects: a binary variable indicating the presence of an active project and an indicator focusing exclusively on transportation infrastructure projects. Clearly, the size of the projects is not homogenous across locations, and thus the effects of projects on spatial inequality might differ along the intensive margin (see Figure 2). Unfortunately, we do not have accurate information on the financial values of more than a third of these projects (see Dreher et al. 2017), so we prefer a binary measure of the presence or absence of a project, and we only present additional results using aggregate dollar values for comparison. We define these dummies based on commitment years rather than actual disbursement dates. Comprehensive data on actual disbursements are not available and virtually impossible to estimate via open-source data collection. We lag the committed project dummy by two years in order to allow for sufficient time for commitments to affect outcomes. 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.[43]

[43] In our dataset, approximately 1,100 Chinese Government project records had enough information to calculate the average time between project start and finish. The average time from commitment to completion within this subsample is about 2.1 years. Large infrastructure projects almost certainly take longer to complete. However, many short-term projects (e.g. disaster relief, cash transfer, technical assistance) have a duration near zero—that is, an

Our main equation of interest is

$$Gini_{irt} = \beta ChnAid_{i,t-2} + \boldsymbol{x}'_{irt}\boldsymbol{\gamma} + \mu_{ir} + \lambda_{it} + \epsilon_{irt}, \quad (1)$$

where $Gini_{irt}$ is the luminosity-based measure of spatial inequality in region r of country i in year t, $ChnAid_{i,t-2}$ is a binary measure of active Chinese development projects that have been committed two years earlier, $\boldsymbol{x}_{irt}$ is a vector of controls (including regional population in the main regressions), μ_{ir} are region fixed effects, and λ_{it} are country-year fixed effects which absorb a variety of potential shocks hitting all regions of a country in a particular year (such as average oil price changes or other commodity shocks). Since transportation infrastructure projects often connect more than one administrative region, we allow for arbitrary spatial and temporal correlation of all regions within a country by clustering standard errors on the country level.[44]

We employ annual data rather than data averaged over several periods. This is mostly out of necessity—the first year for which we have comprehensive global data on Chinese aid is 2000 and our identification strategy derives its power from annual variation.[45] Our results should therefore be interpreted differently than much of the related aid effectiveness literature; we test whether the presence of Chinese development projects affects the spatial distribution of economic activity in the short-run. Also note that, in keeping with the literature, we only focus on low-income and middle-income countries.[46]

The subnational allocation of Chinese development projects is almost certainly endogenous to spatial inequality within and across administrative regions. The official goal of Chinese development financing is to make “great efforts to ensure its aid benefits as many needy people as possible” (Information Office of the State Council 2011), so China may allocate more resources to poorer cities and villages. Previous studies also demonstrate that Chinese aid allocation is correlated with population density (Dreher and Fuchs 2015).

Apart from reverse causality, our parsimonious specification omits a large number of variables, which are likely to be correlated with Chinese aid as well as with spatial inequality. Typical

identical commitment and end year, which works in the opposite direction. Historical Chinese aid data also reveal a median of two years between project start and completion (Dreher et al. 2017, based on data from Bartke 1989) while aid from the average Western donor exhibits longer lags (Dreher et al. 2018b).

[44] We alternatively clustered at the region-level or country-year- and region-level. Qualitative results are unchanged.

[45] Chinese aid volumes are also available for years prior to 1987 (Dreher and Fuchs 2015) but these values are not comparable to post-2000 aid as they are gathered based on different data collection procedures and are less comprehensive.

[46] 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). Appendix A3 lists all countries included in the analysis.

regressions in the aid effectiveness literature include additional control variables such as ethnic fractionalization, institutional quality, and macroeconomic policies (e.g., Burnside and Dollar 2000).[47] Most of these variables are not available at the regional level and their country-year values are captured by fixed effects. Chinese aid projects have also been linked to deteriorating political institutions and higher levels of corruption at subnational scales.[48] We consider all of these variables as "bad controls" in the sense that they may close important transmission channels and they are not predetermined (Achen 2005). For instance, Chinese development financing directly affects subnational and national development in Africa (Dreher et al. 2016; 2017) 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 inequalities 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.[49] Including average nightlight intensity as a control would close this potentially important channel.

Our instrumental variables strategy addresses these concerns. We instrument Chinese aid projects by the interaction of Chinese steel production with the regional probability of receiving a Chinese-financed development project in a given year.[50] We calculate this probability as the fraction of years over the period from 2000-2014 in which a region had Chinese Government-financed projects underway and denote this variable by $\bar{p}_{ir}$.[51] Chinese production of crude steel is measured as the log of thousands of metric tons and obtained from the World Steel Association (2000, 2010, 2016). We lag these data by one additional period to allow for a delay in how domestic overproduction translates into international development projects. In this set-up, the production of Chinese steel only varies over time (and is exogenous to spatial inequality within any particular region) while the probability of receiving aid varies only across regions. In this way, our instrument resembles the supply shock instruments commonly used in trade and labor economics, such as the recent literature on the impact of the rise of Chinese manufacturing on local US labor markets (Autor et al. 2016). Putting these elements together, we then estimate the following first-stage regression:

[47] For recent surveys of the aid effectiveness literature see Dreher et al. (2018c) and Doucouliagos (forthcoming). Dreher and Lohmann (2015) investigate the subnational effect of World Bank projects on development and find no significant effects at the ADM1- or ADM2-level.

[48] See Brazys et al. (2017) and Isaksson and Kotsadam (2018) on the link between Chinese aid and local corruption.

[49] Empirical research on Chinese aid allocation demonstrates a strong, negative correlation between Chinese ODA and the per-capita income of recipient countries (Dreher and Fuchs 2015; Dreher et al. 2018a). However, Chinese OOF (in Africa) tends to favor creditworthy countries (with higher loan repayment capacity) and countries that have higher levels of imports to China (Dreher et al. 2018a).

[50] Our description of the instrument draws heavily on Dreher et al. (2016, 2017).

[51] This directly follows the analyses in Nunn and Qian (2014), Dreher and Langlotz (2017), and Dreher et al. (2016). Also see Werker et al. (2009).

$$ChnAid_{ir,t-2} = \delta(Steel_{t-3} \times \bar{p}_{ir}) + \boldsymbol{x}'_{irt}\boldsymbol{\pi} + \omega_{ir} + \phi_{i,t-2} + \upsilon_{ir,t-2}, \quad (2)$$

where $\boldsymbol{x}_{irt}$ are the controls from the main equation, ω_{ir} are region fixed effects and $\phi_{i,t-2}$ are country-year fixed effects. Equations (1) and (2) are estimated jointly using 2SLS.

The intuition behind this identification approach resembles a difference-in-difference design. We compare the effects of Chinese aid on spatial inequality induced by changes in domestic steel production in China across two groups: regions that are regular and irregular recipients of Chinese Government financing. Or, in other words, we use differences in the local exposure to the common overproduction shock originating in China to identify the effects of aid projects on the spatial distribution of economic activity. The identifying assumptions inherent in this approach would be violated if a change in the domestic steel production in China would lead to a different change in the propensity of receiving an aid project in regular recipient regions as opposed to irregular recipient regions *and* if this change, in turn, would have a different effect on spatial inequality in regular and irregular recipients. Hence, in comparison to a standard panel difference-in-difference setting, our instrument ensures that the timing of the intervention is exogenous but still requires parallel pre-treatment trends across regular and irregular recipient regions.

To examine this issue in detail, we visually examine the variation in Chinese steel production in tandem with variation in the location of aid projects and spatial inequality for different quartiles of the probability to receive aid. Appendix A1 reports the corresponding figures, including a linearly detrended steel series to emphasize the annual variation. The results give little reason to believe that the parallel pre-trends assumption is violated in this case. There are notable global trends—a secular decline in spatial inequality and a rise in Chinese aid projects—but the probability-specific trends in aid and inequality appear broadly parallel across all quartiles. Importantly for our identification strategy, there is no obvious non-linear trend in a particular quartile that resembles the trend in Chinese steel production more than in another.

Our steel instrument might pick up changes in the spatial concentration of economic activity that are not exclusively due to Chinese aid projects and could have a greater effect in regions more (or less) exposed to Chinese aid. Steel production in China follows an almost linear trend, which is likely to be correlated with the production volumes and prices of other commodities.[52] Commodity price shocks and commodity cycles are known to affect local incomes heterogeneously (e.g., Berman and Couttenier 2015). If their time-varying effect on spatial

[52] The correlation of steel production with a linear trend is 0.92.

inequality is unrelated to the probability of receiving Chinese aid, then it is fully captured by the country-year fixed effects. If they vary systematically with the incidence of Chinese aid, then we need to control for these shocks in the robustness checks that follow. Steel production is also certainly correlated with most other projects inputs, such as cement or timber. Our local average treatment effect (LATE) should be interpreted as capturing the combined effects of these physical aid inputs.

The production of steel and other physical aid inputs could be correlated with overall export volumes or foreign direct investment. China's share of world manufacturing value added rose steadily over the same period and this rise coincided with a large demand shock for raw materials (Autor et al. 2016). Quite plausibly, frequent recipients of Chinese aid 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 and investment, not aid. To address this concern, we control for the yearly volume of Chinese exports (from the IMF's Direction of Trade Statistics, DOTS) to other countries and Chinese foreign direct investment (FDI) outflows (from UNCTAD),[53] both interacted with the regional probability of receiving Chinese aid in later robustness checks. In keeping with Dreher et al. (2017), we also test robustness to the inclusion of an interaction of a linear trend with the probability to receive aid, so that we exploit deviations in steel production from its trend rather than the trend itself in predicting Chinese aid.[54]

Finally, we run similar estimations for World Bank projects to compare effects of Chinese and World Bank aid projects on spatial inequality. Broadly following Lang (2016) and Dreher et al. (2017), we calculate a proxy for the World Bank's aid "budget" using measures of its financial resources. Lang (2016) suggests the IMF's liquidity ratio interacted with the probability of a country to be under an IMF program as instrument for IMF loans. We use this idea and design a similar proxy for the World Bank. We rely on the IBRD's equity-to-loans ratio,[55] which is a measure of the World Bank's "ability to issue loans without calling its callable capital" (Bulow

[53] Specifically, we used data from the World Investment Report's 2017 Annex table 01 (see http://unctad.org/en/Pages/DIAE/World%20Investment%20Report/Annex-Tables.aspx, last accessed October 6, 2017).

[54] Dreher et al. (2017) offer two additional placebo tests, testing whether the instrument significantly predicts Chinese FDI or exports (at the country level). Given that trade and FDI data are not available at the regional level we cannot offer such test here. Dreher et al. (2017) also offer a placebo test where they test whether Chinese aid projects that do not rely on physical inputs from China (such as budget aid or debt relief) can be predicted with the steel-based instrument. They show that there is no strong first-stage relationship between the instruments and projects that do not make use of steel and other physical aid inputs.

[55] Equity is defined as the sum of usable paid-in capital, general reserves, special reserves, and cumulative translation adjustments. It does not include the callable capital that the IBRD's shareholders are legally obligated to provide if and when it is needed. Loans are defined as the sum of outstanding loans and the present value of guarantees.

2002: 245) that has been consistently reported in the IBRD's annual financial statements since 1994. We then interact this liquidity proxy with the recipient-region-specific probability of receiving World Bank aid and use this interaction as an instrument for the effect of World Bank projects on spatial inequalities.[56]

5. Analysis and Results

Table 1 reports the results from our baseline regressions at the ADM1 level. Panel a shows the OLS results. Although the coefficient estimates are consistently negative in columns 1 to 4, we cannot reject the null that between Chinese Government-financed projects and inequality within ADM1 regions are unrelated. This result is consistent whether we examine all projects (column 1) or separately investigate ODA-like flows (column 2) and OOF-like flows (column 3). However, we find a negative and highly significant effect of transportation infrastructure projects on spatial inequality (column 4). Chinese Government-financed transport projects in a given ADM1 region are associated with a reduction in the spatial Gini coefficient of light by one percentage point. The results are qualitatively and quantitatively similar if we control for the presence of projects outside the transport sector (not reported). The baseline OLS results thus tentatively confirm our expectation that regions receiving Chinese-financed transportation infrastructure projects experience a greater diffusion of economic activity within their territory compared to regions without any such projects.

Panel b reports the *reduced form* estimates for the same set of project types. Here we directly regress the spatial Gini coefficient on lagged Chinese steel production interacted with the relevant probabilities, population and the full set of fixed effects.[57] Columns 1 to 4 clearly reveal a sizable, highly significant and negative effect of the instrument on spatial inequality, which will be passed through with the same sign if the corresponding first-stage regressions are sufficiently strong and the coefficient on the instrument in those regressions is positive.

Panel c in Table 1 turns to our main results estimated via 2SLS. All of the previous findings become substantially stronger once we address the endogeneity of Chinese project locations. The estimated coefficients are negative and significantly different from zero at the one-percent level in each column. Their size also increases substantially (by about an order of magnitude in

[56] Appendix A3 show definitions and sources of all variables while Appendix A4 reports descriptive statistics.
[57] Note that we use the category- or sector-specific probability to receive aid projects for the interactions rather than the probability to receive any aid project. For example, the instrument for ODA-like projects is the interaction of the number of years with ODA-like projects in a region in all years with China's logged steel production.

absolute terms), which suggests that the OLS estimates were attenuated due to measurement error and/or upwardly biased due to simultaneity. Our results suggest that a first-order administrative region obtaining a Chinese aid project can expect a reduction of within-region spatial inequality—varying from 4 percentage points for OOF-like projects to 10 percentage points in the transport sector. The effect of transportation infrastructure projects is about 3 percentage points larger than the average Chinese Government-financed project and much larger than that of OOF-like projects.[58]

The estimated effect sizes resulting from the 2SLS model are large but plausible. Our LATE uses variation induced by steel production in China and will thus move observations (projects) requiring a lot of steel and many other physical inputs. These projects are likely to be the kinds of large infrastructure projects that can have substantial effects on the spatial diffusion of economic activity. This may explain why the estimated effects of Chinese ODA-projects and transportation infrastructure projects are so similar. Nevertheless, this effect may be the upper bound of what can be expected from receiving a Chinese Government-financed transportation infrastructure project.

Reassuringly, the 2SLS estimates do not suffer from a weak-instrument problem. Panel d in Table 1 reports the associated *first stage* regressions. As expected, we observe a positive relationship between the supply-push instrument and the probability of hosting a Chinese aid project a year later. The coefficients are highly significant and all associated first-stage F-statistics are considerably larger than the conventional rule-of-thumb value of 10. Domestic overproduction in China translates into more aid projects abroad at a meaningful rate. To see this, consider that Chinese steel production grew on average by about 13.5% per annum from 2000 to 2013. Such a production increase raises the probability of receiving a Chinese aid project by about 5.1 percentage points (0.135×0.3783) in a region that always receives Chinese aid projects, but only by half a percentage point in a region that receives Chinese aid in 10% of all years. The estimates for OOF-like projects and transportation infrastructure projects are twice as large, but this is probably due to greater co-location of similar projects within the same sector occurring in these categories.

Our baseline results thus clearly establish that Chinese transportation infrastructure projects cause a diffusion of economic activity within the regions in which they are located. In the

[58] Appendix A5 reports results for a number of additional sectoral aggregates. As can be seen, Chinese aid reduces inequality in the broad OECD-defined sectors “social” and “economic” (which includes the transport sector), as well as in education and health. Water, energy and projects in the “production” sector show no significant effects of Chinese aid.

remainder of this section, we probe the robustness of these results and examine how these findings generalize to other spatial units; however we no longer distinguish ODA-like from OOF-like projects and omit the auxiliary reduced forms and first-stage regressions to reduce clutter.

Table 2 presents additional OLS results that investigate the timing of projects in more detail and reports results from alternative measures of Chinese Government-financed projects. Columns 1 and 2 show that allowing for different lags with which Chinese aid could affect the distribution of economic activity does not change the qualitative results. As before, we only find significant partial correlations between the concentration of economic activity and projects in the transport sector. Chinese Government-financed projects in the aggregate remain insignificant with our preferred timing of a two-year delay and alternative lag structures. Projects in the transport sector are negatively associated with spatial inequality with a one- and two-year lag at the ten- and five-percent level of significance, respectively. These regressions also include an important placebo test: a significant correlation between future aid commitments and spatial inequality would cast serious doubt on the causal interpretation of our findings. But our results show that the effects of future and contemporaneous aid projects are not significant at conventional levels (and generally estimated to be small in absolute value).

In the remaining columns of Table 2, we (i) replace the binary project indicators with the logged financial size of Chinese aid projects,[59] (ii) add a lagged dependent variable to account for persistence in inequality levels (ignoring Nickell bias), and (iii) focus on completed projects rather than also including projects that had only reached the implementation stage during our period of study. None of these adjustments alter our main conclusion. Transportation infrastructure projects are associated with the greatest reduction in within-region inequality.

We return to our instrumental variables approach in Table 3. As our instrumental variable approach does not allow us to instrument different lags or leads of the project dummies at the same time, we instead add a number of tests examining the power of our instrument and the plausibility of the exclusion restriction. Columns 1 and 2 show that using the financial values of projects in lieu of the dummy variable produces similar results. A doubling of a project's financial value leads to a reduction in the spatial concentration of economic activity by about 0.7

[59] We add a value of "one" before we take logs. Most studies in the aid effectiveness literature focus on either aid per capita or aid as a share of GDP. One disadvantage of this approach is that it restricts the effect of population or GDP to be the same as those of aid. As Annen and Kosempel (2018) point out, there are no obvious theoretical reasons for using this approach. Their simulations also show that using aid-over-GDP ratios introduces a downward bias relative to using levels of aid. Following Ahmed (2016) and Dreher et al. (2017), among others, we instead use (logged) aid in levels as variable of interest and control for population size.

percentage points.[60] Columns 3 and 4 add lagged values of spatial inequality on the right hand side, while columns 5 and 6 examine the effects of completed projects. Our results remain remarkably stable, consistently indicating that both transport sector projects and all aid projects combined lead to a diffusion of economic activity.

The last three columns of Table 3 probe the strength of our instrument. Given that Chinese steel production roughly follows a linear trend over time, one might be concerned that the interaction of logged steel with the probability of a region receiving aid is highly correlated with similar interactions of other variables exhibiting such a development over time. For example, rising Chinese exports or commodity demand shocks may have influenced the regions to which China allocated aid projects. While we cannot include interactions of such variables with the probability of receiving a Chinese aid project directly (since the high degree of collinearity does not allow us to distinguish our hypothesis from alternative explanations), we create proxies that are less strongly correlated and still capture plausible variation in the exposure to other external shocks.

Columns 7 to 8 in Table 3 address this problem in three different ways. Column 7 includes the interaction of a linear trend with the probability of receiving any Chinese aid project (rather than any Chinese transportation infrastructure project). Following a similar intuition, column 8 includes the interaction of the probability of receiving (any) Chinese aid with logged Chinese FDI in the country that receives the aid, and column 9 includes the interaction of this probability with logged Chinese exports to the country. Only in column 9, where we control for trade interacted with the probability of receiving aid, the coefficient on transportation projects falls relative to its standard error. The effect is no longer significant at conventional levels but the estimated effect remains about three times larger than the coefficient on the trade interaction. Recall that this is an exceptionally strict test. It only considers the (unlikely) limiting case where the exposure to trade shocks and the probability of receiving aid are identical. Given the high degree of collinearity, we do not consider the loss of efficiency much cause for concern.

Next, we test whether projects in the transport sector are more effective at reducing inequality when complemented by geographically proximate projects in other sectors in Table 4. Column 1 shows that the interaction of transportation infrastructure projects with projects in the production sector is not significant at conventional levels using OLS. Column 2 offers some evidence that transportation infrastructure projects are more effective at spreading economic activity when

[60] This may seem small compared to our earlier estimates but understates the typical effect sizes considerably. The standard deviation of the financial value of all projects in places with a project is about 7.5, so that a standardized change in the regional project volume leads to a 5.4 percentage point reduction in spatial inequalities, in line with previous estimates.

they are co-located with education projects, but the effects are very small. A similar picture emerges using a modified version of our instrumental variables approach.[61] However, the first stage F-statistics are extremely weak, which explains the implausibly large coefficients on the interaction of transport and education in column 4. On balance, we interpret this as a lack of robust evidence for our interaction hypothesis.

In Table 5 we continue to focus on within-region inequality and turn to a more fine-grained analysis of second-order administrative regions (ADM2). Columns 1-4 repeat our baseline specifications using both OLS and 2SLS. In general, the results are quantitatively and qualitatively similar to those at the first-order level with minor deviations. The coefficients in the 2SLS regressions are only marginally smaller than those reported earlier: a transportation infrastructure project reduces spatial inequalities by about nine percentage points.[62] The remaining columns of Table 5 add interactions of transportation infrastructure projects with projects in the production or education sectors. None of these interactions are significant, providing further evidence against our hypothesis that project co-location is an important aspect of how Chinese aid flattens the spatial distribution of economic activity.

In Table 6, we seek to explain inequality *between* subnational regions. In columns 1 to 6, the dependent variable is the area-weighted Gini coefficient of average light intensities between first-order regions. Naturally, this implies that we are now analyzing the data at the cross-country level. Columns 1 to 4 consistently report a negative sign of Chinese aid projects on inter-regional inequalities. While these results are only significant at the ten percent level in the instrumental variables estimates of transport sector aid, the consistency of the effect sizes across different levels of aggregation is striking. Again, the results for project co-location in columns 5 and 6 are not strongly indicative of interaction effects.[63] Columns 7 to 12 mirror this approach but analyze spatial inequality *between* second-order regions within their parent (first-order) regions. While most of the coefficients of interest are not significant in this setting, we once again observe coefficients for all projects and transport infrastructure projects that are remarkably similar to previous estimates. In summary, although the evidence at the within-region level is much stronger than the evidence at the between-region level, Chinese aid projects, and Chinese transportation infrastructure projects in particular, seem to accelerate the diffusion of economic activity across the board.

[61] We include the interaction of the instruments for transport- and education-sector-projects as additional instrument.
[62] We again investigated a number of additional sectors. As can be seen in Appendix A6, results are in analogy to those at the ADM1 level above.
[63] What is more, the instruments are too weak in this setting, which may overstate the coefficient sizes of the interaction terms.

Finally, Table 7 compares the effects of Chinese aid projects to projects financed by the World Bank. The results for first-order administrative regions are reported in panel a, while panel b repeats the analysis for second-order administrative regions. At both levels of regional aggregation, we cannot reject the null that World Bank projects have no effect on the spatial distribution of economic activity. This is true for World Bank projects in the aggregate and for World Bank projects in the transport sector. However, the first stage F-statistics are too low to interpret these results definitively. We are also are unable to directly compare the causal effects obtained here to those of Chinese Government-financed projects since they are based on very different local average treatment effects. Our World Bank budget instrument captures a broader array of projects, whereas the overproduction of Chinese steel primarily fuels infrastructure investments. In summary, our results offer some evidence that Chinese Government-financed projects are effective at reducing spatial inequality, while evidence for World Bank-financed projects is less conclusive and not directly comparable with our China-specific results.

6. Conclusion

Many scholars and policymakers are skeptical about the existence of a “China model” or “Beijing Consensus” that coherently outlines China’s development recipe for other countries (Ramo 2004; Kennedy 2010; Ferchen 2013; Beeson and Li 2015). Whether or not such an alternative paradigm exists, China’s commitment to financing connective infrastructure is unambiguous. Connectivity has been a central focus of China’s Belt and Road Initiative (BRI) since the government first announced the plan in 2013 (Blanchard and Flint 2017). A key policy document that outlines that scope and ambition of BRI (entitled “Vision and Actions on Jointly Building Silk Road Economic Belt and 21st Century Maritime Silk Road”) also mentions “connectivity” (互联互通) more than a dozen times (NDRC 2015). Our findings suggest that this commitment to connective infrastructure has far-reaching distributional consequences in low-income and middle-income countries that are not yet fully understood or appreciated.

We find that Chinese development projects in general, and Chinese transportation projects in particular, reduce economic inequality within and between regions. These results suggest that Chinese investments in “connective infrastructure” produce positive economic spillovers that flatten the spatial distribution of economic activity. To the extent that China is helping developing countries escape inefficient spatial equilibria in which most economic activity concentrates in a small number of urban centers and gravitates away from rural towns and villages, this is an outcome that ought to be celebrated.

However, readers should also not harbor any illusions that Chinese infrastructure finance is a development panacea. Dreher et al. (2016) provide evidence that China's "aid on demand" approach is vulnerable to domestic political manipulation in that government leaders in recipient countries steer Chinese aid to their home and ethnic regions.[64] Previous studies also demonstrate that Chinese development projects, including infrastructure projects, produce a number of negative externalities, including local corruption, environmental degradation, and lower levels of trade union participation (BenYishay et al. 2016; Brazys et al. 2017; Isaksson and Kotsadam 2018a, 2018b). There are also some indications that Chinese connective financing may saddle recipient governments—and their taxpayers—with unsustainable debt burdens (Hurley, Morris and Purtelance 2018). Therefore, Chinese connective financing may help narrow spatial inequalities, but its overall impact is a more complex question.

We suggest five potentially useful avenues for future research, First, the robustness and precision of our results could be reexamined with alternative measures of treatment (e.g., line- rather than point-based data that characterize the spatial scope of Chinese transportation investments, more precise data on the construction start and end dates of individual road and railway segments) and a broader set of outcome measures (e.g., nighttime light inequality across ethnic groups within countries, inequality of asset ownership and human development via Demographic and Health Surveys). Second, in order to further probe the "growth pole" hypothesis, one could test for possible interaction effects between Chinese transportation investments and stocks (rather than flows) of human capital investment.

Third, several potential moderating variables—that could amplify or attenuate the effect of transportation investments on the spatial distribution of economic activity—merit examination. These include baseline levels of economic development, the nature of the political regime that is in power, the extent to which power has been devolved from the central government to subnational localities, and the extent to which a country's political leaders have an incentive to extend their patronage network to subnational localities and ethnic groups other than those that are within their "winning coalition." Fourth, in light of the tentative nature of our World Bank

[64] Additionally, to the extent that Chinese connective financing abroad is modeled on China's own post-reform experience, it is important to note that China's domestic strategy is not without flaws. For example, China's investment in its domestic highway system has been prone to regional political bias that alters the allocation of highway placement, moving it closer to the birthplaces of leaders (Alder and Kondo 2018). Also, while many of its domestic economic policies have helped spread the gains of globalization to inland provinces, China remains highly unequal.

findings, additional effort should be made to determine whether our findings apply to transportation infrastructure projects financed by donors and lenders other than China.

Fifth and finally, to the extent that Chinese development projects narrow spatial inequalities within weak and conflict-prone states, it is also possible that they have second-order effects on social capital, political stability and violence, and state legitimacy at subnational and national scales. The growing availability of subnationally georeferenced governance data opens up new opportunities to explore these effects over the long run (BenYishay et al. 2017).

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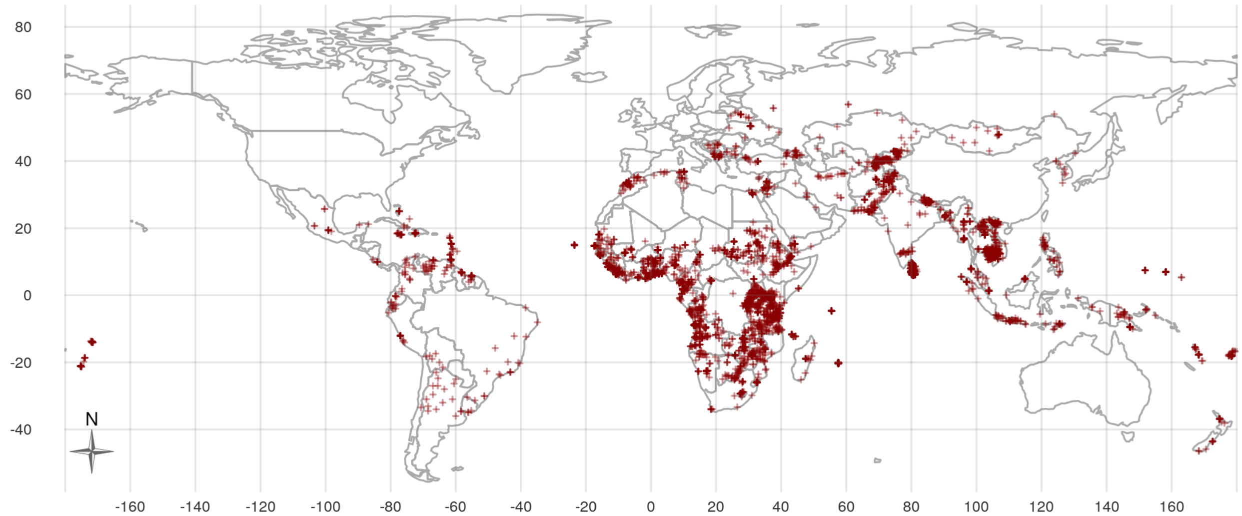
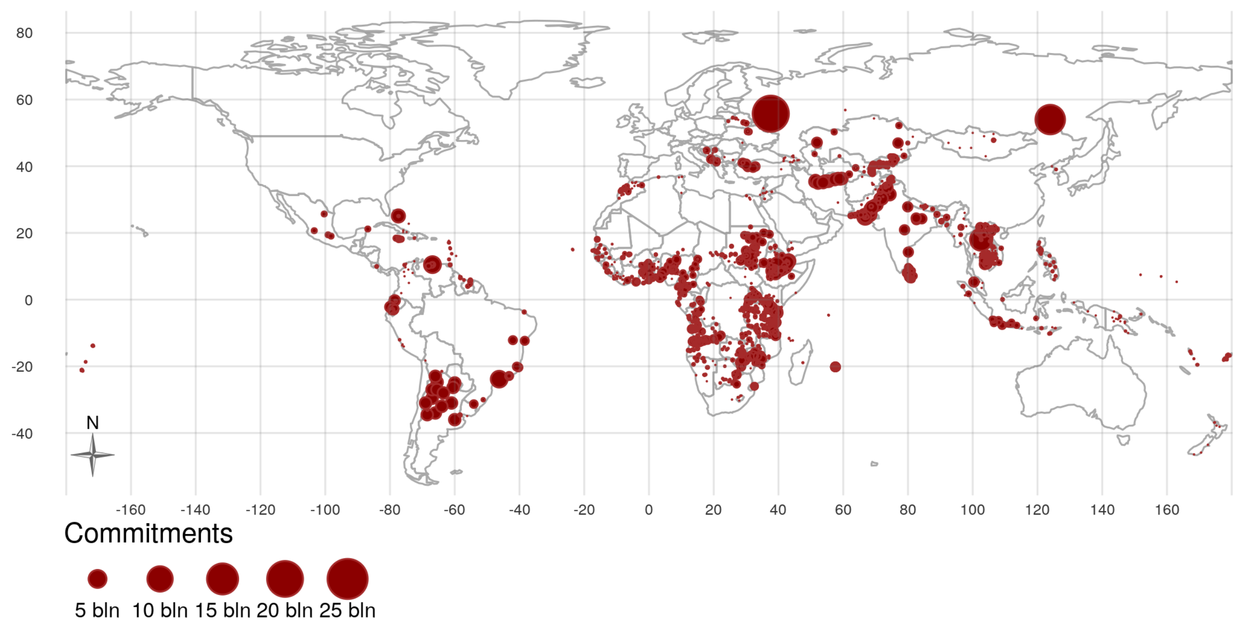
Figures and Tables

Figure 1: Locations of Chinese Government-Financed Projects, 2000-2014



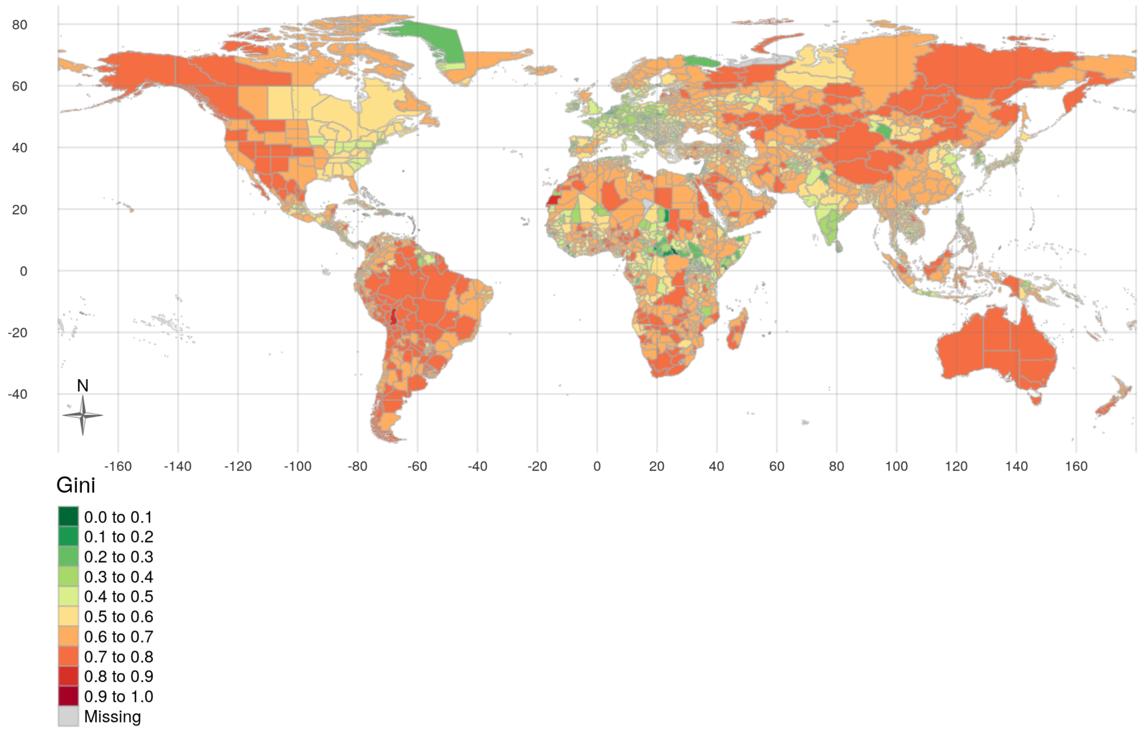
Notes: The figure shows all georeferenced Chinese Government-financed projects that reached the implementation or completion stage over the period 2000 to 2014.

Figure 2: Financial Size of Chinese Government-Financed Projects (in constant 2014 US$), 2000-2014



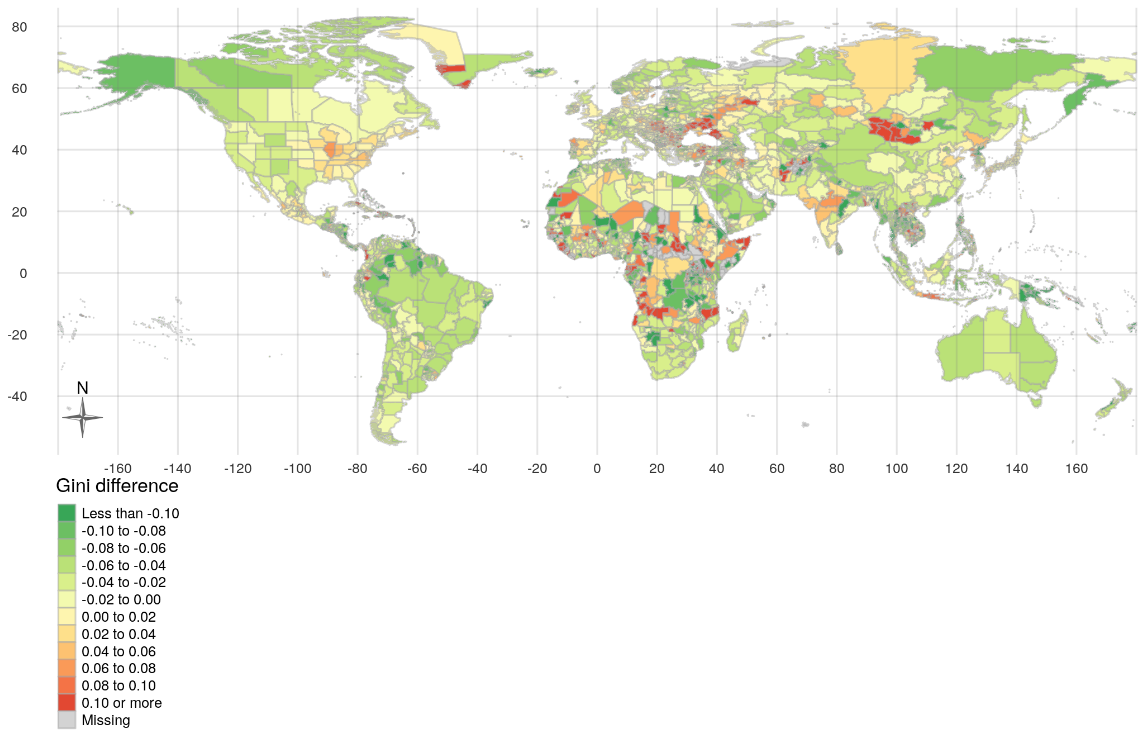
Notes: The figure shows all georeferenced Chinese Government-financed projects that reached the implementation or completion stage over the period 2000 to 2014. The total financial size of each project has been divided by the number of locations where each project was active.

Figure 3: Nighttime Light Inequality within ADM1 regions, average 2000-2013



Notes: The figure shows the average Gini coefficient of light per km^2 within ADM1 regions over the period 2000 to 2013. Spatial inequality is on average more pronounced in larger regions and regions with lower levels of population density. Conversely, smaller and more densely populated regions generally exhibit lower level of spatial inequality. Note that we do not use this cross-sectional variation in our analysis but instead net out these fixed differences (region size, geography, etc.) and focus on changes over time.

Figure 4: Changes in Nighttime Light Inequality within ADM1 regions between 2000 and 2013



Notes: The figure shows the change in the Gini coefficient of light per km^2 within ADM1 regions between 2000 and 2013. During this period of time, South America and the Middle East experienced widespread reductions in spatial inequality, while large parts of Africa, Asia, and Eastern and Central Europe experienced both increases and reductions in spatial inequality.

Table 1: Chinese aid and within-region inequality, ADM1, 2002-2013, OLS & 2SLS

	Sector of projects			
	(1)	(2)	(3)	(4)
	All	ODA	OOF	Transport
	Panel a) OLS estimates – Dependent variable: $Gini$			
$ChnAid_{t-2}$	-0.0008	-0.0018	-0.0013	-0.0112***
	(0.0017)	(0.0020)	(0.0021)	(0.0040)
Log population	-0.0198	-0.0198	-0.0198	-0.0199
	(0.0144)	(0.0144)	(0.0144)	(0.0144)
	Panel b) Reduced form estimates – Dependent variable: $Gini$			
$Steel_{t-3} \times \bar{p}$	-0.0267***	-0.0313***	-0.0371**	-0.0847***
	(0.0090)	(0.0109)	(0.0164)	(0.0240)
Log population	-0.0181	-0.0180	-0.0191	-0.0193
	(0.0141)	(0.0139)	(0.0144)	(0.0143)
	Panel c) 2SLS estimates – Dependent variable: $Gini$			
$ChnAid_{t-2}$	-0.0706***	-0.0977***	-0.0417**	-0.1038***
	(0.0249)	(0.0367)	(0.0189)	(0.0302)
Log population	-0.0180	-0.0178	-0.0190	-0.0203
	(0.0145)	(0.0139)	(0.0146)	(0.0145)
	Panel d) First-stage estimates – Dependent variable: $ChnAid_{t-2}$			
$Steel_{t-3} \times \bar{p}$	0.3783***	0.3200***	0.8897***	0.8158***
	(0.0594)	(0.0620)	(0.0697)	(0.1095)
Log population	0.0021	0.0024	0.0021	-0.0104
	(0.0288)	(0.0199)	(0.0198)	(0.0123)
Kleibergen-Paap F-statistic	40.60	26.66	162.90	55.52
Observations	29,881	29,881	29,881	29,881
Regions	2,674	2,674	2,674	2,674
Countries	158	158	158	158

Notes: The table reports OLS and 2SLS regression results at the regional (ADM1) level. The dependent variable is the Gini coefficient of light per km^2 within ADM1 regions in panels a-c and a binary indicator for the presence of Chinese aid projects in panel d. All specifications include ADM1-level fixed effects and country-year fixed effects. Standard errors clustered at the country level are in parentheses. $ChnAid_{t-2}$ refers to Chinese aid projects in the sector(s) indicated in the column header. The regional probability of receiving aid, $\bar{p}$, is also sector-specific and computed according the type indicated in the column title. Significant at: *** p<0.01, ** p<0.05, * p<0.1.

Table 2: Chinese aid and within-region inequality, tests for robustness, ADM1, 2002-2013, OLS

	Sector of projects							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	Transport	All amounts	Transport amounts	All	Transport	All completed	Transport completed
$ChnAid_{t+1}$	-0.0006	-0.0037						
	(0.0027)	(0.0052)						
$ChnAid_{t}$	-0.0009	-0.0064						
	(0.0021)	(0.0042)						
$ChnAid_{t-1}$	-0.0007	-0.0127*						
	(0.0023)	(0.0075)						
$ChnAid_{t-2}$	0.0002	-0.0091**	-0.0000	-0.0006**	-0.0012	-0.0107***	-0.0012	-0.0106*
	(0.0021)	(0.0043)	(0.0001)	(0.0002)	(0.0017)	(0.0035)	(0.0020)	(0.0055)
$ChnAid_{t-3}$	0.0023	-0.0041						
	(0.0021)	(0.0041)						
Log population	-0.0189	-0.0189	-0.0198	-0.0198	-0.0177	-0.0178	-0.0198	-0.0200
	(0.0186)	(0.0186)	(0.0144)	(0.0144)	(0.0127)	(0.0127)	(0.0144)	(0.0144)
$Gini_{t-1}$					0.1431***	0.1429***		
					(0.0208)	(0.0207)		
Estimation method	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Observations	24,649	24,649	29,881	29,881	29,558	29,558	29,881	29,881
Countries	157	157	158	158	158	158	158	158

Notes: The table reports OLS regression results at the regional (ADM1) level. The dependent variable is the Gini coefficient of light per km^2 within ADM1 regions. All specifications include ADM1-level fixed effects and country-year fixed effects. Standard errors clustered at the country level are in parentheses. $ChnAid_x$ refers to Chinese aid projects in the sector(s) indicated in the column header with x indicating a particular lead or lag of the starting date. Significant at: *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Chinese aid and within-region inequality, tests for robustness, ADM1, 2002-2013, 2SLS

	Sector of projects								
	(1) All amounts	(2) Transport amounts	(3) All	(4) Transport	(5) All completed	(6) Transport completed	(7) Transport	(8) Transport	(9) Transport
$ChnAid_{t-2}$	-0.0072***	-0.0065***	-0.0649***	-0.1011***	-0.0799***	-0.1948***	-0.0687*	-0.0827**	-0.0460
	(0.0025)	(0.0018)	(0.0225)	(0.0276)	(0.0290)	(0.0676)	(0.0359)	(0.0340)	(0.0320)
Log population	-0.0168	-0.0200	-0.0160	-0.0181	-0.0187	-0.0226	-0.0189	-0.0196	-0.0176
	(0.0149)	(0.0145)	(0.0127)	(0.0127)	(0.0146)	(0.0150)	(0.0143)	(0.0143)	(0.0143)
$Gini_{t-1}$			0.1422***	0.1406***					
			(0.0202)	(0.0199)					
$t \times \bar{p}$							-0.0028		
							(0.0018)		
$FDI_{t-2} \times \bar{p}$								-0.0049	
								(0.0045)	
$Trade_{t-2} \times \bar{p}$									-0.0148**
									(0.0069)
Estimation method	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Kleibergen-Paap F-statistic	17.71	50.77	40.39	53.60	33.74	21.74	45.87	49.52	46.71
Observations	29,881	29,881	29,558	29,558	29,881	29,881	29,798	29,881	28,873
Countries	158	158	158	158	158	158	158	158	146

Notes: The table reports 2SLS regression results at the regional (ADM1) level. The dependent variable is the Gini coefficient of light per km^2 within ADM1 regions. All specifications include ADM1-level fixed effects and country-year fixed effects. Standard errors clustered at the country level are in parentheses. $ChnAid_{t-2}$ refers to Chinese aid projects in the sector(s) indicated in the column header. The regional probability of receiving aid, $\bar{p}$, used for the interactions in columns 7-9 is the probability of receiving any Chinese-financed project (not the sector-specific probability, this avoids near perfect multicollinearity as described in the text). Significant at: *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Chinese aid and within-region inequality, sectoral complementarities, ADM1, 2002-2013, OLS & 2SLS

	Sector of projects			
	(1) Transport	(2) Transport	(3) Transport	(4) Transport
$ChnAid_{t-2}$	-0.0110***	-0.0109***	-0.1113***	-0.0526*
	(0.0038)	(0.0037)	(0.0406)	(0.0270)
$Production_{t-2}$	-0.0017		-0.0478	
	(0.0041)		(0.0925)	
$ChnAid_{t-2} \times Production_{t-2}$	-0.0063		0.3474	
	(0.0199)		(0.8509)	
$Education_{t-2}$		-0.0196		-0.0257
		(0.0144)		(0.0359)
$ChnAid_{t-2} \times Education_{t-2}$		-0.0098**		-0.2456*
		(0.0039)		(0.1417)
Log population	-0.0210	0.0020	-0.0190	-0.0183
	(0.0143)	(0.0112)	(0.0146)	(0.0147)
Estimation method	OLS	OLS	2SLS	2SLS
Kleibergen-Paap F-statistic	-	-	0.457	6.707
Observations	29,881	29,881	29,881	29,881
Countries	158	158	158	158

Notes: The table reports OLS and 2SLS regression results at the regional (ADM1) level. The dependent variable is the Gini coefficient of light per km^2 within ADM1 regions. All specifications include ADM1-level fixed effects and country-year fixed effects. $ChnAid_{t-2}$ refers to Chinese aid projects in the sector(s) indicated in the column header. Standard errors clustered at the country level are in parentheses. Significant at: *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Chinese aid and within-region inequality, ADM2, 2002-2013, OLS & 2SLS

	Sector of projects							
	(1) All	(2) Transport	(3) All	(4) Transport	(5) Transport	(6) Transport	(7) Transport	(8) Transport
$ChnAid_{t-2}$	-0.0038*	-0.0070	-0.0765***	-0.0875*	-0.0075*	-0.0070	-0.1387*	-0.0616
	(0.0019)	(0.0043)	(0.0189)	(0.0452)	(0.0041)	(0.0046)	(0.0820)	(0.0440)
$Production_{t-2}$					0.0047		-0.0271	
					(0.0061)		(0.0997)	
$ChnAid_{t-2} \times Production_{t-2}$					0.0539		3.5209	
					(0.0378)		(6.9638)	
$Education_{t-2}$						-0.0096**		-0.0999*
						(0.0040)		(0.0533)
$ChnAid_{t-2} \times Education_{t-2}$						0.0056		-0.1473
						(0.0096)		(0.2423)
Log population	-0.0058	-0.0058	-0.0057	-0.0060	-0.0058	-0.0058	-0.0063	-0.0058
	(0.0042)	(0.0042)	(0.0042)	(0.0043)	(0.0042)	(0.0042)	(0.0044)	(0.0042)
Estimation method	OLS	OLS	2SLS	2SLS	OLS	OLS	2SLS	2SLS
Kleibergen-Paap F-statistic	-	-	53.32	20.43	-	-	0.107	0.720
Observations	355,897	355,897	355,897	355,897	355,897	355,897	355,897	355,897
Countries	129	129	129	129	129	129	129	129

Notes: The table reports OLS and 2SLS regression results at the regional (ADM2) level. The dependent variable is the Gini coefficient of light per km^2 within ADM2 regions. All specifications include ADM2-level fixed effects and country-year fixed effects. $ChnAid_{t-2}$ refers to Chinese aid projects in the sector(s) indicated in the column header. Standard errors clustered at the country level are in parentheses. Significant at: *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Chinese aid and between-region inequality, ADM0 & ADM1, 2002-2013, OLS & 2SLS

	Sector of projects											
	(1) All	(2) Transport	(3) All	(4) Transport	(5) Transport	(6) Transport	(7) All	(8) Transport	(9) All	(10) Transport	(11) Transport	(12) Transport
	Country level (ADM0)						*Regional level (ADM1)*					
$ChnAid_{t-2}$	-0.0022	-0.0052	-0.0707	-0.0833*	0.0062	-0.0718	-0.0001	-0.0046	-0.0670*	-0.0965	-0.252**	-0.0497
	(0.0020)	(0.0043)	(0.0623)	(0.0449)	(0.0601)	(0.0558)	(0.0033)	(0.0057)	(0.0361)	(0.0614)	(0.1223)	(0.0606)
$Production_{t-2}$					0.0463						-0.6856	
					(0.0713)						(0.5008)	
$ChnAid_{t-2} \times Production_{t-2}$					-0.302***						4.8404	
					(0.0824)						(4.1439)	
$Education_{t-2}$						0.0422						0.0225
						(0.0340)						(0.0712)
$ChnAid_{t-2} \times Education_{t-2}$						-0.0682						-0.4032
						(0.1025)						(0.2821)
Log population	-0.146***	-0.146***	-0.117**	-0.122**	-0.1200**	-0.118**	-0.0270	-0.0270	-0.0253	-0.0277	-0.0012	-0.0253
	(0.0504)	(0.0505)	(0.0536)	(0.0503)	(0.0473)	(0.0519)	(0.0292)	(0.0292)	(0.0290)	(0.0291)	(0.0442)	(0.0296)
Method	OLS	OLS	2SLS	2SLS	2SLS	2SLS	OLS	OLS	2SLS	2SLS	2SLS	2SLS
Kleibergen-Paap F-statistic	-	-	15.68	43.21	1.028	5.139	-	-	35.77	47.70	0.411	1.884
Observations	1,789	1,789	1,789	1,789	1,789	1,789	23,731	23,731	23,731	23,731	23,731	23,731
Countries	159	159	159	159	159	159	126	126	126	126	126	126

Notes: The table reports OLS and 2SLS regression results at the country (ADM0) and regional (ADM1) level. The dependent variable is the Gini coefficient of light per km^2 between ADM1 regions in columns 1-6 and the Gini coefficient of light per km^2 between ADM2 regions in column 7-12. Columns 1-6 are estimated at the country level and include country fixed effects and year fixed effects. Columns 7-12 are estimated at the regional level and include ADM1-level fixed effects and country-year fixed effects. $ChnAid_{t-2}$ refers to Chinese aid projects in the sector(s) indicated in the column header. Standard errors clustered at the country level are in parentheses. Significant at: *** p<0.01, ** p<0.05, * p<0.1.

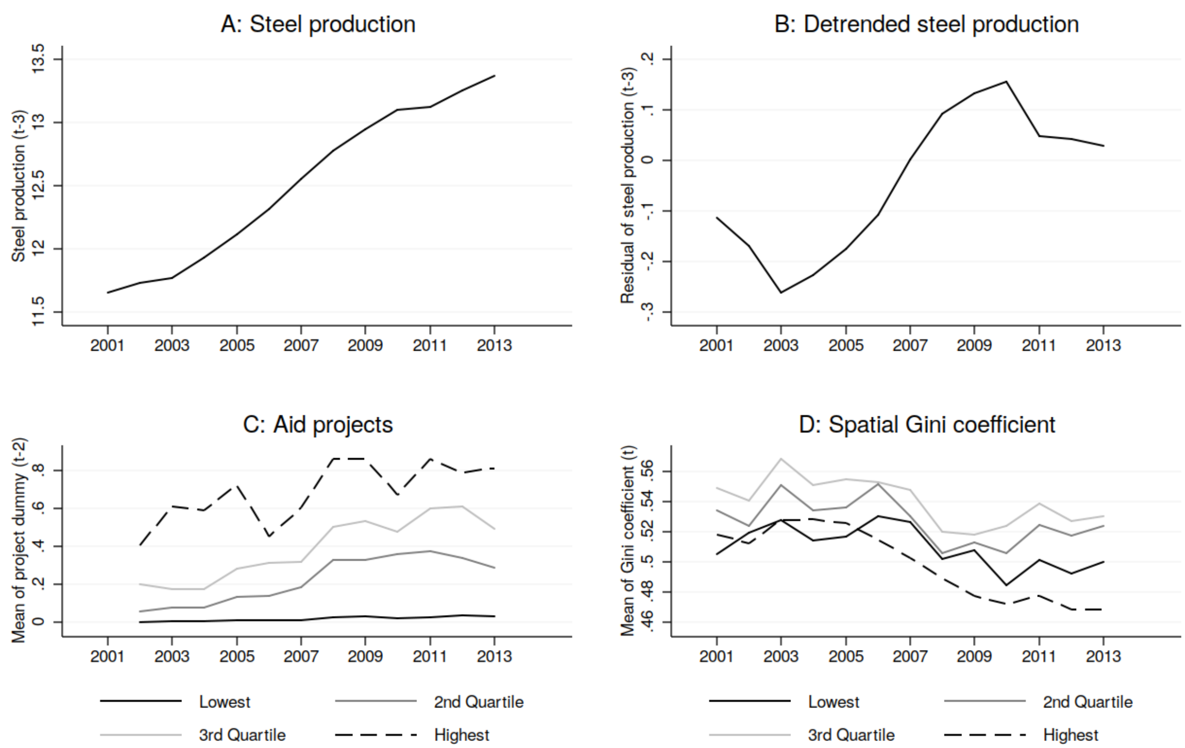
Table 7: World Bank aid and within-region inequality, ADM1 & ADM2, 2002-2013, OLS & 2SLS

	Sector of projects							
	(1) All	(2) Transport	(3) All	(4) Transport	(5) Transport	(6) Transport	(7) Transport	(8) Transport
	Panel a) Regional level estimates (ADM1)							
$WBAid_{t-2}$	0.0001	0.0012	-0.1441	-0.0615	0.0021	0.0003	-0.0183	-0.0657
	(0.0015)	(0.0022)	(0.1126)	(0.0450)	(0.0028)	(0.0022)	(0.1889)	(0.0463)
$WBProduction_{t-2}$					0.0009		0.2588	
					(0.0025)		(0.6450)	
$WBAid_{t-2} \times WBProduction_{t-2}$					-0.0032		-0.1591	
					(0.0040)		(0.5630)	
$WBEducation_{t-2}$						0.0007		-0.0391
						(0.0028)		(0.1526)
$WBAid_{t-2} \times WBEducation_{t-2}$						0.0038		0.2581
						(0.0036)		(0.3962)
Kleibergen-Paap F-statistic	-	-	2.821	7.243	-	-	0.0742	0.284
Observations	29,881	29,881	29,881	29,881	29,881	29,881	29,881	29,881
	Panel b) Regional level estimates (ADM2)							
$WBAid_{t-2}$	0.0000	-0.0004	-0.1938	-0.2281	0.0003	-0.0003	-0.1842	-0.1289
	(0.0009)	(0.0013)	(0.2372)	(0.2997)	(0.0013)	(0.0014)	(0.2344)	(0.2626)
$WBProduction_{t-2}$					-0.0012		-0.0360	
					(0.0016)		(0.2598)	
$WBAid_{t-2} \times WBProduction_{t-2}$					-0.0015		0.4755	
					(0.0022)		(0.4685)	
$WBEducation_{t-2}$						-0.0014		-0.2045
						(0.0023)		(0.3753)
$WBAid_{t-2} \times WBEducation_{i-2}$						0.0004		0.5074
						(0.0039)		(0.7527)
Estimation method (both panels)	OLS	OLS	2SLS	2SLS	OLS	OLS	2SLS	2SLS
Kleibergen-Paap F-statistic	-	-	0.845	0.644	-	-	0.197	0.165
Observations	355,897	355,897	355,897	355,897	355,897	355,897	355,897	355,897

Notes: The table reports OLS and 2SLS regression results at the regional (ADM1 and ADM2) level. The dependent variable is the Gini coefficient of light per km^2 within ADM1 or ADM2 regions. All specifications include the log of population, regional (ADM1 or ADM2) fixed effects, and country-year fixed effects. $WBAid_{t-2}$ refers to World Bank aid projects in the sector(s) indicated in the column header. Standard errors clustered at the country level are in parentheses. Significant at: *** p<0.01, ** p<0.05, * p<0.1.

Appendices

Appendix A1: Parallel Trends



Notes: The figures show the time series of Chinese steel production, in logs and lagged by three periods (panel a), linearly detrended Chinese steel production (panel b), the average incidence of Chinese aid projects in recipient regions grouped by quartiles of their probability to receive aid (panel c), and the average spatial Gini coefficient grouped by quartiles of their probability to receive aid (panel d).

Appendix A2: Countries included in the sample (Column 1 of Table 1)

Afghanistan	Georgia	Panama
Albania	Ghana	Papua New Guinea
Algeria	Grenada	Paraguay
American Samoa	Guatemala	Peru
Angola	Guinea	Philippines
Antigua and Barbuda	Guinea-Bissau	Poland
Argentina	Guyana	Romania
Armenia	Haiti	Russian Federation
Azerbaijan	Honduras	Rwanda
Bangladesh	Hungary	Samoa
Barbados	India	Saudi Arabia
Belarus	Indonesia	Senegal
Belize	Iran, Islamic Rep.	Serbia
Benin	Iraq	Seychelles
Bhutan	Jamaica	Sierra Leone
Bolivia	Jordan	Slovak Republic
Bosnia and Herzegovina	Kazakhstan	Solomon Islands
Botswana	Kenya	Somalia
Brazil	Korea, Dem. Rep.	South Africa
British Virgin Islands	Kyrgyz Republic	South Sudan
Bulgaria	Lao PDR	Sri Lanka
Burkina Faso	Latvia	St. Kitts and Nevis
Burundi	Lebanon	St. Lucia
Cabo Verde	Lesotho	St. Vincent and the Grenadines
Cambodia	Liberia	Sudan
Cameroon	Libya	Suriname
Central African Republic	Lithuania	Swaziland
Chad	Macedonia, FYR	Syrian Arab Republic
Chile	Madagascar	São Tomé and Principe
Colombia	Malawi	Tajikistan
Comoros	Malaysia	Tanzania
Congo, Dem. Rep.	Mali	Thailand
Congo, Rep.	Mauritania	Timor-Leste
Costa Rica	Mauritius	Togo
Croatia	Mexico	Tonga
Cuba	Micronesia, Fed. Sts.	Trinidad and Tobago
Czech Republic	Moldova	Tunisia
Côte d'Ivoire	Mongolia	Turkey
Djibouti	Montenegro	Turkmenistan
Dominica	Morocco	Turks and Caicos Islands
Dominican Republic	Mozambique	Uganda
Ecuador	Myanmar	Ukraine
Egypt, Arab Rep.	Namibia	Uruguay
El Salvador	Nepal	Uzbekistan
Equatorial Guinea	Nicaragua	Vanuatu
Eritrea	Niger	Venezuela, RB
Estonia	Nigeria	Vietnam
Ethiopia	Northern Mariana Islands	Yemen, Rep.
Fiji	Oman	Zambia
Gabon	Pakistan	Zimbabwe
Gambia, The	Palau	

Appendix A3: Definitions and Sources

Variable name	Description	Source
Gini of light per km^2	Gini coefficient of the sum of light per km^2 (light intensity) among lit 10 km^2 cells, weighted by land area in km^2.	Stable lights from NOAA, own calculation.
Gini of light per km^2, between	Gini coefficient of the sum of light per km^2 (light intensity) among lit ADM2 regions at ADM1 level or ADM1 regions at the country level, weighted by land area in km^2.	Stable lights from NOAA, own calculation.
Chinese aid project	Binary variable indicating the presence of at least one Chinese development (i.e., ODA-like and OOF-like) finance project in a (ADM1 or ADM2) region.	Dreher et al. (2017), own geocoding.
Chinese ODA project	Binary variable indicating the presence of at least one ODA-like finance project in a (ADM1 or ADM2) region. Includes only projects that are in implementation or completed.	Dreher et al. (2017), own geocoding.
Chinese OOF project	Binary variable indicating the presence of at least one Chinese OOF finance project in a (ADM1 or ADM2) region. Includes only projects that are in implementation or completed.	Dreher et al. (2017), own geocoding.
Log Chinese aid amounts	Chinese development finance (i.e., ODA-like and OOF-like) commitments in a (ADM1 or ADM2) region in constant 2014 USD. Includes only projects that are in implementation or completed.	Dreher et al. (2017), own geocoding.
Log Chinese aid amounts, transport	Chinese development finance (i.e., ODA-like and OOF-like) commitments for the transport sector in a (ADM1 or ADM2) region in constant 2014 USD. Includes only projects that are in implementation or completed.	Dreher et al. (2017), own geocoding.
Chinese aid project, transport	Binary variable indicating the presence of at least one Chinese project in the transport sector in a (ADM1 or ADM2) region. Includes only projects that are in implementation or completed.	Dreher et al. (2017), own geocoding.

Chinese aid project, social	Binary variable indicating the presence of at least one Chinese project in the social sector in a (ADM1 or ADM2) region. Includes only projects that are in implementation or completed. “Social Infrastructure & Services” includes health, education, governance, and water supply and sanitation projects.	Dreher et al. (2017), own geocoding.
Chinese aid project, economic	Binary variable indicating the presence of at least one Chinese project in the economic sector in a (ADM1 or ADM2) region. Includes only projects that are in implementation or completed. “Economic Infrastructure & Services” category includes transportation infrastructure projects (e.g., roads, railways, and airports), energy production and distribution projects, and information and communication technology (ICT) projects (e.g., broadband internet and mobile phone infrastructure).	Dreher et al. (2017), own geocoding.
Chinese aid project, production	Binary variable indicating the presence of at least one Chinese project in the production sector in a (ADM1 or ADM2) region. Includes only projects that are in implementation or completed. “Production Sector” includes agriculture, fishing, forestry, mining, industry, trade, and tourism projects.	Dreher et al. (2017), own geocoding.
Chinese aid project, energy	Binary variable indicating the presence of at least one Chinese project in the energy sector in a (ADM1 or ADM2) region. Includes only projects that are in implementation or completed.	Dreher et al. (2017), own geocoding.
Chinese aid project, education	Binary variable indicating the presence of at least one Chinese project in the education sector in a (ADM1 or ADM2) region. Includes only projects that are in implementation or completed.	Dreher et al. (2017), own geocoding.
Chinese aid project, health	Binary variable indicating the presence of at least one Chinese project in the health sector in a (ADM1 or ADM2) region. Includes only projects that are in implementation or completed.	Dreher et al. (2017), own geocoding.
Chinese aid project, water	Binary variable indicating the presence of at least one Chinese project in the water sector in a (ADM1 or ADM2) region. Includes only projects that are in implementation or completed.	Dreher et al. (2017), own geocoding.
Chinese aid project, completed	Binary variable indicating the presence of at least one Chinese development finance project in a (ADM1 or ADM2) region. Includes only projects that are completed.	Dreher et al. (2017), own geocoding.

Chinese transport project, completed	Binary variable indicating the presence of at least one Chinese project in the transport sector in a (ADM1 or ADM2) region. Includes only projects that are completed.	Dreher et al. (2017), own geocoding.
Log steel production	China's (log) production of crude steel in thousand tons.	World Steel Association (2000, 2010, 2016).
IBRD equity-to-loan ratio	"Equity" is defined as the sum of usable paid-in capital, general reserves, special reserves, and cumulative translation adjustments. It does not include the "callable capital" that the IBRD's shareholders are legally obligated to provide if and when it is needed. "Loans" are defined as the sum of loans outstanding and the present value of guarantees.	IBRD's annual financial statements, various years.
Probability to receive aid, all	Measures the share of years in the sample in which a (ADM1 or ADM2) region received at least one Chinese development finance project.	Own calculation.
Probability to receive aid, transport	Measures the share of years in the sample in which a (ADM1 or ADM2) region received at least one Chinese transport project.	Own calculation.
Probability to receive WB aid, all	Measures the share of years in the sample in which a (ADM1 or ADM2) region received at least one World Bank project.	Own calculation.
Probability to receive WB aid, transport	Measures the share of years in the sample in which a (ADM1 or ADM2) region received at least one World Bank transport project.	Own calculation.
Log population	Log of population in administrative region (different levels).	Global Human Settlement Layer (GHSL) from Joint Research Centre (JRC) at the European Commission, own calculation.

Appendix A4: Descriptive statistics (estimation samples)

First-order regions (ADM1)	Observations	Mean	St. dev.	Min	Max
Gini of light per km^2	29881	0.51	0.18	0.00000	0.85
Gini of light per km^2, between	23744	0.45	0.20	0.00003	0.98
Chinese aid project	29881	0.06	0.24	0	1
Chinese ODA project	29881	0.05	0.21	0	1
Chinese OOF project	29881	0.02	0.16	0	1
Chinese aid amounts	29881	0.72	3.39	0	23.74
Chinese aid amounts, transport	29881	0.22	1.98	0	21.66
Chinese aid project, transport	29881	0.01	0.12	0	1
Chinese aid project, social	29881	0.03	0.18	0	1
Chinese aid project, economic	29881	0.02	0.15	0	1
Chinese aid project, production	29881	0.01	0.08	0	1
Chinese aid project, energy	29881	0.01	0.08	0	1
Chinese aid project, education	29881	0.01	0.10	0	1
Chinese aid project, health	29881	0.02	0.12	0	1
Chinese aid project, water	29881	0.00	0.05	0	1
Chinese aid project, completed	29881	0.05	0.21	0	1
Chinese transport project, completed	29881	0.01	0.09	0	1
Log steel production	29881	13.00	0.47	12.11	13.62
IBRD equity-to-loan ration	29881	30.15	4.05	22.9	37.62
Probability to receive aid, all	29881	0.06	0.13	0	1
Probability to receive aid, transport	29881	0.01	0.04	0	0.50
Probability to receive WB aid, all	29881	0.27	0.25	0	1
Probability to receive WB aid, transport	29881	0.10	0.13	0	0.71
Log population	29881	12.92	1.84	1.42	19.17

(Continues on next page…)

Appendix A4 (continued)

Second-order regions (ADM2)					
Gini of light per km^2	355897	0.36	0.20	0	0.91
Chinese aid project	355897	0.01	0.07	0	1
Chinese ODA project	355897	0.00	0.06	0	1
Chinese OOF project	355897	0.00	0.05	0	1
Chinese aid amounts	355897	0.06	0.99	0	23.74
Chinese aid amounts, transport	355897	0.02	0.61	0	21.66
Chinese aid project, transport	355897	0.00	0.04	0	1
Chinese aid project, social	355897	0.00	0.05	0	1
Chinese aid project, economic	355897	0.00	0.05	0	1
Chinese aid project, production	355897	0.00	0.02	0	1
Chinese aid project, energy	355897	0.00	0.02	0	1
Chinese aid project, education	355897	0.00	0.03	0	1
Chinese aid project, health	355897	0.00	0.03	0	1
Chinese aid project, water	355897	0.00	0.01	0	1
Chinese aid project, completed	355897	0.00	0.06	0	1
Chinese transport project, completed	355897	0.00	0.03	0	1
Log steel production	355897	12.99	0.46	12.11	13.62
IBRD equity-to-loan ration	355897	30.16	4.05	22.90	37.62
Probability to receive aid, all	355897	0.00	0.03	0	0.93
Probability to receive aid, transport	355897	0.00	0.01	0	0.5
Probability to receive WB aid, all	355897	0.04	0.09	0	0.86
Probability to receive WB aid, transport	355897	0.02	0.05	0	0.71
Log population	355897	10.25	1.69	-1.01	16.79
Country level (ADM0)					
Gini of light per km^2, between	1789	0.53	0.21	0.02	0.94
Chinese aid project	1789	0.43	0.49	0	1
Chinese aid project, transport	1789	0.09	0.29	0	1
Log steel production	1789	12.99	0.47	12.11	13.62
Probability to receive aid, all	1789	0.39	0.32	0	1
Probability to receive aid, transport	1789	0.09	0.13	0	0.64
Log population	1789	15.40	2.24	8.37	20.97

Appendix A5: Chinese aid and within-region inequality, ADM1, 2002-2013, 2SLS

	Sector of projects								
	(1) All	(2) Transport	(3) Social	(4) Economic	(5) Production	(6) Energy	(7) Education	(8) Health	(9) Water
$ChnAid_{t-2}$	-0.0706***	-0.1038***	-0.0789***	-0.0713**	-0.0444	-0.0311	-0.1037***	-0.0660**	-0.4437
	(0.0249)	(0.0302)	(0.0227)	(0.0290)	(0.0576)	(0.0670)	(0.0289)	(0.0276)	(1.6293)
Log population	-0.0180	-0.0203	-0.0164	-0.0216	-0.0191	-0.0204	-0.0172	-0.0182	-0.0149
	(0.0145)	(0.0145)	(0.0143)	(0.0149)	(0.0146)	(0.0151)	(0.0144)	(0.0139)	(0.0243)
Estimation method	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Kleibergen-Paap F-statistic	40.60	55.52	53.87	56.40	14.11	17.63	73.84	39.68	0.05
Observations	29,881	29,881	29,881	29,881	29,881	29,881	29,881	29,881	29,881
Countries	158	158	158	158	158	158	158	158	158

Notes: The table reports 2SLS regression results at the regional (ADM1) level. The dependent variable is the Gini coefficient of light per km^2 within ADM1 regions. All specifications include ADM1-level fixed effects and country-year fixed effects. Standard errors clustered at the country level are in parentheses. $ChnAid_{t-2}$ refers to Chinese aid projects in the sector(s) indicated in the column header. Significant at: *** p<0.01, ** p<0.05, * p<0.1.

Appendix A6: Chinese aid and within-region inequality, ADM2, 2002-2013, 2SLS

	Sector of projects								
	(1) All	(2) Transport	(3) Social	(4) Economic	(5) Production	(6) Energy	(7) Education	(8) Health	(9) Water
$ChnAid_{t-2}$	-0.0765***	-0.0875*	-0.0850***	-0.0724**	0.0131	-0.0260	-0.1338***	-0.0888***	1.6593
	(0.0189)	(0.0452)	(0.0205)	(0.0286)	(0.1332)	(0.0697)	(0.0383)	(0.0308)	(12.2775)
Log population	-0.0057	-0.0060	-0.0055	-0.0060	-0.0058	-0.0058	-0.0057	-0.0057	-0.0064
	(0.0042)	(0.0043)	(0.0042)	(0.0043)	(0.0043)	(0.0042)	(0.0042)	(0.0042)	(0.0060)
Estimation method	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Kleibergen-Paap F-statistic	53.32	20.43	48.77	29.61	13.04	11.55	59.70	21.31	0.017
Observations	355,897	355,897	355,897	355,897	355,897	355,897	355,897	355,897	355,897
Countries	129	129	129	129	129	129	129	129	129

Notes: The table reports 2SLS regression results at the regional (ADM2) level. The dependent variable is the Gini coefficient of light per km^2 within ADM2 regions. All specifications include ADM2-level fixed effects and country-year fixed effects. Standard errors clustered at the country level are in parentheses. $ChnAid_{t-2}$ refers to Chinese aid projects in the sector(s) indicated in the column header. Significant at: *** p<0.01, ** p<0.05, * p<0.1.