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Does India Use Development Finance to Compete with China? A Subnational Analysis

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Abstract: China and India increasingly provide aid and credit to developing countries. This paper explores whether India uses these financial instruments to compete for geopolitical and commercial influence with China (and vice versa). To do so, we build a new geocoded dataset of Indian government-financed projects abroad between 2007 and 2014 and combine it with data on Chinese government-financed projects. Our regression results for 2,333 provinces within 123 countries demonstrate that India's Exim Bank is significantly more likely to locate a project in a given jurisdiction if China provided government financing there in the previous year. Since this effect is more pronounced in countries where China has made public opinion gains relative to India and where both lenders have a similar export structure, we interpret this as evidence of India competing with China. By contrast, we do not find evidence that China uses official aid or credit to compete with India through co-located projects.

Keywords: development finance, foreign aid, official development assistance, official credits, new donors, China, India, geospatial analysis

JEL classification: F34, F35, F59, H77, H81, O19, O22, P33, R58

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1 Introduction

China and India—the world's two most populated countries—committed almost US$155 billion in aid and credit to 132 developing countries between 2007 and 2014 alone.[1] Casual observation suggests that China and India may be using their financial resources to compete for geostrategic and commercial advantages around the globe. Since 2013, China has engaged in an unprecedented effort to build a "Belt" of roads, rails, ports, and pipelines from China to Central Asia and Europe and a "Maritime Silk Road" consisting of deep-water ports along the littoral areas of the Indian Ocean.[2] India is one of the few countries in the Asia-Pacific region that formally opposes China's Belt and Road Initiative (BRI) (Pant, 2017). It also refuses to accept bilateral aid from China. According to Agrawal (2007, p.7), Delhi competes with Beijing over "diplomatic influence, oil reserves, and markets for goods." Journalistic reports and case studies also suggest that India is sensitive to any real or perceived attempts by China to encroach upon its existing spheres of influence or otherwise engage in expansionary efforts.[3] During our own interviews with decision makers in Delhi (September 8-9, 2014), one official from India's Exim Bank indicated that countering Chinese influence is a consideration when the government decides on loan and export credit approvals. However, other interviewees claimed that India was "not benchmarking China at all" and such claims are a "media myth."

The existing literature is largely silent on the issue of whether and how emerging powers use aid and credit as tools of strategic rivalry. We seek to close this evidence gap by conducting a rigorous analysis of whether and how India and China use development finance instruments to compete with each other around the globe. We first determine if the Indian government allocates aid and credit across developing countries and their subnational localities in response to the receipt of Chinese government financing. We then evaluate whether India's behavior is consistent with the notion that it is seeking to compete with China.

[1] We introduce the Indian official financing data in Section 3. Data on Chinese official financing are from Dreher et al. (2021) and Bluhm et al. (2020). Dollar values are in constant 2014 US dollars. For comparison, the United States provided US$242 billion in official development assistance over the same time period (OECD, 2020).

[2] As explained by Brewster (2015, p.49-59), "China's strategic vulnerability in the Indian Ocean is principally a function of geography. The Indian Ocean is a largely enclosed ocean, with few entry points and vast distances between. The east-west sea lanes across the ocean, over which much of the world's energy is carried, are highly vulnerable to interdiction. This creates a strategic premium for those powers that are able to control the so-called 'chokepoints' and deny their rivals access to key ports. [...] In contrast to India's position, China currently has no ability to exert control over any of these chokepoints and nor has it any regular naval presence in any of the ports between." China's purported strategy to address this bottleneck is to "bind countries in the Bay of Bengal and the Indian Ocean closer to the Chinese economy as well as to build trade routes from China through their territory to the Indian Ocean" (Mullen and Poplin, 2015).

[3] For example, Ramachandran (2015) notes that "Indian aid intensified in 2007 in response to China's mounting interest in the Maldives." Likewise, Bhogal (2016) asserts that "[i]n order to check China's growing footprints in South Asia, India has expedited its own plans to establish links with Chabahar port in Iran via Afghanistan."

Those who assert that Delhi and Beijing use official financial instruments to compete with each other rarely articulate falsifiable hypotheses about government motivations. We follow Steinwand (2015, p.451) by defining "competition" as the provision of government financing "to counteract the influence gained by other donors." Therefore, if the Indian government responds to a new Chinese government-financed project by increasing its financial footprint in the same country or subnational locality, we consider this to be potential evidence of India seeking to compete with China. By increasing its presence in these jurisdictions, Delhi may be able to constrain or even undermine Beijing's influence in relative terms—either at the country level or subnationally with respect to regional governments or local firms. However, to more directly test whether Delhi seeks to counteract actual influence gains achieved by China, we leverage public opinion data to determine if Delhi assigns special priority to jurisdictions where popular sentiment has recently become more favorable towards China than India. We also differentiate between competition for commercial reasons (e.g., to secure export markets) and competition for geopolitical reasons (e.g., to strengthen ties with regional partner countries).[4]

Existing research on the competitive use of development finance focuses on rivalry between traditional providers of development finance (Mascarenhas and Sandler, 2006, Barthel et al., 2014, Fuchs et al., 2015, Davies and Klasen, 2019) and rivalry between established and emerging powers (Bueno de Mesquita and Smith, 2016, Hernandez, 2017, Humphrey and Michaelowa, 2019, Zeitz, 2020). However, to the best of our knowledge, rigorous studies of emerging-power competition that cover a large set of developing countries are non-existent. One reason is the absence of comprehensive and reliable data. To better understand whether and how India and China use official financial instruments to compete with each other in developing countries, we construct a new dataset that contains information on 1,194 Indian government-financed projects in 4,308 locations within 93 countries from 2007 to 2014. This dataset captures official development assistance, concessional and non-concessional loans, export credits, and other state-sponsored financial flows from India's two most important sources of development finance: the Ministry of External Affairs (MEA) and the Export-Import (Exim) Bank of India.[5] We combine these data with geocoded Chinese official financing data from Bluhm et al. (2020), covering 3,485 projects in 6,184 subnational locations within 138 countries.

We then compare the timing and location of Indian projects with those financed by China. Specifically, we run regressions on a sample covering 2,333 provinces within 123 countries and estimate the effect of Chinese government-financed projects on the allocation of Indian official financing using a linear probability model with province- and

[4]On this point, see Barthel et al. (2014) and Fuchs et al. (2015).

[5]Apart from AidData's Geocoded Global Chinese Official Finance dataset (Bluhm et al., 2020), the dataset introduced in this article is the only comprehensive geocoded project-level aid dataset of a bilateral donor that covers a significant period of time.

country-year-fixed effects.[6] Our results show that India's Exim Bank is more likely to allocate a credit-financed project to a subnational locality if the Chinese government provided financing there in the previous year. We observe weaker effects also at the national level. By contrast, development aid provided by India's MEA does not follow China's development activities in the average recipient country. We only find that the MEA allocates significantly more development aid in response to Chinese projects where it arguably matters most for geostrategic competition: in India's neighborhood. Since our main finding is more robust for India's Exim Bank, which primarily follows commercial objectives, we conclude that India is engaging primarily in commercial rather than geopolitical competition with China.

Our main analysis focuses on whether the distribution of funding from the Chinese government influences the aid and credit allocation decisions of the Indian government—rather than the reverse relationship. India is the more likely follower given that Beijing's oversees a substantially larger portfolio of overseas development projects (Asmus et al., 2020).[7] Nevertheless, we also test whether China competes with India, and consistent with our expectation, we find no evidence that Indian projects attract Chinese projects to the same localities.

A major empirical challenge is disentangling competition from other factors that may lead to a positive association between Indian and Chinese government financing. Chief among these alternative explanations are selectivity and imitation. Selectivity refers to the possibility that China and India follow similar financial allocation criteria. For example, both countries might favor jurisdictions with lower levels of economic development or higher-quality policies and institutions. We account for selectivity in our regression models by controlling for the various allocation determinants identified in the literature either directly or indirectly through the inclusion of fixed effects.

Imitation refers to the possibility that foreign donors and lenders—operating in unfamiliar settings with imperfect access to information—take cues from their peers with more local experience and tacit knowledge. We run several tests to disentangle competition from imitation. First, in recognition of the fact that imitation most likely occurs within sectors but competition can occur across sectors, we run sectoral regressions to test whether "crowding-in" takes place within the same sectors. When China provides aid or credit to a particular sector within a particular subnational locality, we find no evidence that India is more likely to approve aid or credit for the same jurisdiction and sector in the following year. This finding is inconsistent with the alternative explanation

[6] In our study, we define 'province' as the first subnational administrative (ADM1) region according to the GADM database (version 2.8).

[7] During our own interviews with decision makers in Delhi (September 8-9, 2014), an expert on Indian aid noted that "India is much slower than China" when it comes to planning and implementation. The expert referred to the Indian-financed Afghani parliament building as a case in point. The project was initiated by the Indian government in 2007 and inaugurated in 2015.

of imitation. Second, in order to test whether India is motivated by a desire for greater influence vis-à-vis China, we leverage data from Gallup World Poll. We find that Delhi is more likely to increase its financial footprint in jurisdictions where it has recently become less popular relative to China. This is a pattern that is difficult to reconcile with any explanation other than competition with China. Since the crowding-in effect is also more pronounced in countries where both lenders have a similar export structure, it appears that both emerging economies compete over commercial influence. Therefore, the weight of the evidence suggests that India is competing with China rather than simply imitating it or following a similar set of allocation criteria.

This article contributes to the literature in several ways. First and foremost, it is the first to analyze China-India competition in developing countries in a quantitative analysis. Second, to the best of our knowledge, we provide the first study of local competition using geocoded development finance data for two bilateral donors. Third, by including Exim Bank loans in our analysis, our study contributes to a relatively small body of evidence on South-South official financing flows to developing countries other than official development assistance (Werker et al., 2009, Hernandez and Vadlamannati, 2017, Horn et al., 2019, Kaya et al., 2021). Less concessional and more commercially-oriented projects make up a substantial proportion of the official financing that Southern providers of development finance provide to their peers each year, yet they largely represent largely a blind spot in the empirical literature.

This paper has four remaining sections. Section 2 provides an overview of the motivations that might guide the allocation of Indian and Chinese official finance and the conditions under which one would expect these emerging powers to compete with each other through the use of government financing instruments. In Section 3, we introduce a new geocoded, project-level dataset on Indian government-financed projects around the globe and provide descriptive statistics. Section 4 introduces our empirical model and explains how we distinguish between "competition" and other potential linkages between Indian and Chinese government financing in developing countries. Section 5 presents our empirical results and we conclude in Section 6.

2 The Argument

Established powers use aid and credit to secure policy concessions and curry favor with governing elites and the general public in recipient countries (Morgenthau, 1962, Alesina and Dollar, 2000, Kuziemko and Werker, 2006, Bueno de Mesquita and Smith, 2009, Faye and Niehaus, 2012, Kersting and Kilby, 2016, among many others). However, these motivations are not unique to established powers (Dreher et al., 2011, 2013, Budjan and Fuchs, 2021). Emerging powers—such as China and India—also use aid and credit to influence the policies of recipient countries and strengthen their relationships with the governments and citizens of foreign countries (Fuchs and Vadlamannati, 2013, Dreher et al., 2018, 2019, Anaxagorou et al., 2020). Therefore, as more official donors and creditors enter the international development finance market, competition for overseas influence is expected to intensify. Recipient countries may also be in a better position to exploit the competitive motivations of donors by strategically negotiating more generous financial packages and less stringent policy conditions (e.g., Greenhill et al., 2016, Hernandez, 2017).

Geostrategic Motivations. Geostrategic competition with China appears to play an important role in the way the Indian government thinks about its overseas development cooperation activities (Sridharan, 2014, Mullen and Poplin, 2015). Mukherjee (2015, p.180-182) identifies competition with China even as one of the primary motivations for the creation of India's foreign assistance program. According to Kragelund (2010, p.9), India began targeting African countries as early as in the 1960s "as a direct consequence of the competition with China." Shortly after India lost the Sino-Indian War of 1962, the MEA decided that it needed to expand India's influence in South and Southeast Asia (Kragelund, 2010). Its creation of the Indian Technical and Economic Cooperation (ITEC) program in 1964 was reportedly born out of the desire to counter China's growing influence (Mukherjee, 2015).

There are indications that competition with China has continued to guide India's grant giving and lending strategies during the 21^{st} century. Consider the case of Sri Lanka. India initially refused to provide Sri Lanka with any offensive weapons during its most recent civil conflict (2006–2009). However, during the Sri Lankan government's hour of need, China stepped forward as an alternative supplier of arms. Beijing's decision led to hand-wringing among strategists in Delhi, with India's National Security Adviser declaring that "[w]e are the big power in this region. [...] [L]et us make that very clear. We strongly believe that whatever requirements the Sri Lankan government have, they should come to us and we will give them what we think is necessary. We do not [favor] them going to China [...] or any other country" (Chennai Online, 2007). Then, after China dramatically increased the provision of aid and credit to Sri Lanka, Delhi decided to take action (ICG, 2011). As Campbell et al. (2012) explain, "[w]ith China and others challenging India's influence, Delhi [...] showered Sri Lanka and its leaders with increased aid and attention. India [...] offered more than [US]$1.5 billion in humanitarian and development assistance since 2008, a dramatic increase over previous years."

Sri Lanka does not appear to be an isolated theater in which India uses aid and credit to compete with China. Sridharan (2014) argues that "[Indian] aid is clearly influenced by the need to keep countries, other than Pakistan, from drifting further into China's strategic and economic orbit." Mullen and Poplin (2015) note that "[f]or Indian strategists, it doesn't seem far-fetched that China would use its increased maritime capability to create a zone of naval exclusion that stretches from the South China Sea to the Persian Gulf" and "India hopes to use its [overseas development] funding [...] to maintain and expand its leverage over the Indian Ocean Rim states to preclude a more permanent Chinese presence in those waters." Mukherjee (2015, p.179) claims that "[i]n Nepal, one of the first Indian projects was the construction of an airport in Kathmandu, which was built with a runway that was too short for [Chinese] airplanes [...] to land on." Similarly, DN (1988, p.1263) notes that "in the case of Bhutan, road-building has been concentrated on the north-south road linking Bhutan with India and enabling the Indian military to outflank Chinese positions." Aid from India is also considered to be "a means of obtaining a permanent seat in the UN Security Council" (Kragelund, 2008, p.574), i.e., to counter Chinese opposition to any such reform within the international body.[8] Zhang and Shivakumar (2017, p.265) echo this point, noting that China's and India's aid programs in the Pacific are both guided by a desire to influence "voting [in] multilateral fora especially the UN." China-India competition is also visible in commerce. Khare (2013) cites the former Mozambican minister Joaquim Tobias Dai: "We have China and India fighting for resources in Africa. [...] The Chinese want to go for gas, but Indians want to go for gas as well. This kind of competition is good for us."

In order for India to compete for influence with China through the provision of government financing, it would need to respond to China's aid and credit allocation decisions. Consequently, we hypothesize that if a developing country receives a new financial commitment from the Chinese government, it becomes more likely that the Indian government provides funding to the same recipient country (*Hypothesis 1*).

Commercial versus Geopolitical Competition. To disentangle commercial from geopolitical competition, we differentiate between two major sources of Indian official financing: MEA aid and Exim Bank loans. The Delhi-based MEA is responsible for the lion's share of India's development aid activities. According to an ECOSOC (2008) report, 80% of the total aid disbursed by India comes in the form of grants. The remaining 20% consists of highly concessional loans (with an estimated grant element of 53–57%). MEA projects are generally consistent with the OECD's criteria for official development assistance (ODA).[9] MEA's flagship program ITEC is perceived as "one of the essential functions of an integrated and imaginative foreign policy" and is expected to "have generated immense goodwill and substantive cooperation among the developing

[8] Hart and Jones (2010, p.73) note that "[i]n the run-up to the 2005 World Summit, [...] China used its financial influence to press many African states into siding against India's bid for a UN Security Council seat."

[9] The OECD defined ODA during our sample period as "[g]rants or loans to [developing] countries and territories [...] and to multilateral agencies which are: (a) undertaken by the official sector; (b) with promotion of economic development and welfare as the main objective; (c) at concessional financial terms (if a loan, having a grant element of at least 25 per cent). In addition to financial flows, technical co-operation is included in aid" (OECD DAC glossary).

countries."[10]

The Mumbai-based Exim Bank of India provides non-concessional and semi-concessional loans and export credits to developing countries and it is overseen by India's Ministry of Finance. Although some of its overseas lending activities meet the OECD's standard of concessionality for ODA (a grant element of at least 25%), most of its lending is focused on export promotion (Sinha and Hubbard, 2011). The Exim Bank's official mandate is "providing financial assistance to exporters and importers, and [...] functioning as the principal financial institution for coordinating the working of institutions engaged in financing export and import of goods and services with a view to promoting the country's international trade [...]."[11] Consequently, most of its loans and export credits are consistent with the OECD's definition of other official flows (OOF) rather than ODA.[12]

We expect that these different types of financial flows are guided by different motivations. Whereas ODA is largely used to advance foreign policy objectives, OOF is guided by commercial objectives (Dreher et al., 2018). The concessional nature of ODA is the key criterion that differentiates it from other financing instruments at the disposal of the Indian government. As Delhi increases the concessionality (i.e., the grant element) of its financial commitments to a given country, the value of the foreign policy concessions that it can reasonably expect to secure in exchange should increase (Dreher et al., 2008). Conversely, less concessional forms of official financing (e.g., loans and export credits from India's Exim Bank) should provide fewer opportunities for "aid-for-policy deals" (Bueno de Mesquita and Smith, 2009, 2016).

Existing research on the distribution of less concessional and more commercially-oriented types of government financing (e.g., export credits and market-rate loans) also suggests that governments tend to use these flows to pursue their commercial objectives.[13] Therefore, consistent with Dreher et al. (2018), we expect OOF from India's Exim Bank to be more responsive to commercial considerations than ODA from the MEA.[14] If India's

[10]See ITEC website available at `https://www.itecgoi.in/about` (accessed 17 February 2021).

[11]See the Exim Bank's website at `https://www.eximbankindia.in/objectives` (accessed 3 April 2018).

[12]OOF is categorized as "[t]ransactions by the official sector with [developing] countries [...] which do not meet the conditions for eligibility as [ODA], either because they are not primarily aimed at development, or because they have a grant element of less than 25 per cent" (OECD DAC glossary). For simplicity, we will use the terms OOF and credit interchangeably when we refer to official financing from the Exim Bank of India. The same holds for ODA and aid when we refer to official financing from the MEA.

[13]Capital-rich countries have traditionally used sovereign lending instruments to earn attractive financial returns in capital-poor countries (Eichengreen, 1989, Evrensel, 2004). Trade finance instruments also increase business opportunities for domestic firms in overseas markets by providing other countries with the financial means to buy goods and services from firms in the creditor country (Moravcsik, 1989, Kobayashi, 2008).

[14]This is confirmed by simple conditional correlations of Indian government finance with measures of India's geopolitical and commercial interests in recipient countries. We show these results in the next section after we have introduced our data.

response to China's official financing activities operates through ODA, its motivation for competition is more likely of a geopolitical nature. However, if India's response to China's official financing activities operates through OOF, its motivation for competition is probably of a commercial nature.

Currying Favor with the General Public. International public opinion can expand or constrain a foreign power's ability to achieve its strategic foreign policy objectives (Goldsmith and Horiuchi, 2012). Favorable public sentiment can also help countries to improve trade ties, ease access for investors, and avoid the costs from consumer boycotts (Disdier and Mayer, 2007, Guiso et al., 2009, Pandya and Leblang, 2017, Rose, 2019). Consequently, foreign powers bankroll projects that they think will help them win the "hearts and minds" of citizens in host countries (Brazys and Dukalskis, 2019, Eichenauer et al., 2021), and they employ various tools—including signage at project sites, ribbon-cutting ceremonies, traditional and social media coverage, and investments in telecommunication systems—to broadcast messages about their generosity and the purported benefits of their projects (Wellner et al., 2021). Foreign powers engage in these activities because they believe that more favorable public sentiment can "filter up and influence elite policy to be more amenable to [their own] interests" (Brazys and Dukalskis, 2019, p.567). They also do so because they know that their strategic rivals are pursuing a competing set of interests and seeking to create a public opinion environment that will favor those interests.[15]

Indeed, foreign powers often publicly contrast their activities and approaches with those followed by their rivals. In Sri Lanka, many Chinese government-financed projects undertaken between 2005 and 2014 were plagued by accusations of corruption and political bias, which later became a reputational liability for Beijing. Public support for China steadily eroded over the course of the Rajapaska administration, and against this backdrop of rising populist antipathy towards China, an opposition politician named Maithripala Sirisena decided to challenge Rajapaksa in the 2015 presidential election. He ran on an anti-China platform and used corruption and political bias in Chinese government-funded projects in the country's Southern Province to mobilize "his voters" in the Northern and Eastern Provinces. Recognizing that China was on its back foot, India saw a strategic window of opportunity and responded by green-lighting a raft of new development projects. Shortly thereafter, the Indian MEA published a report that called for a more forceful government response to the BRI: "It is time that India should accelerate its own connectivity projects under various initiatives such as 'Act East Policy,' 'Neighbourhood First policy,' 'Go West' Strategy, 'Spice Route,' etc. as a counter to the narrative of BRI which seems to have gained some currency in our neighborhood and

[15] Governments often refer to these policies and programs as "public diplomacy" efforts (Custer et al., 2018, 2019).

elsewhere. It is high time to showcase a more just, more equitable and more user friendly developmental assistance model to the countries who have fallen for the lure of BRI without realizing its far reaching deleterious consequences" (MEA, 2018). However, in other settings, it appears that the Indian government has taken defensive measures in response to public opinion gains achieved by the Chinese government. Nepal is a case in point. As Parashar (2016) has explained, "[t]he problem for India [...] is China's increasing involvement in landmark infrastructure projects [...] is helping it win the battle of perception."[16]

Recall that, at the outset of this study, we defined donor competition as settings in which "aid provisions [by one donor] are used to counteract the influence gained by other donors" (Steinwand, 2015, p.451). If this type of competition is at work, one might expect a foreign power to increase its spending in jurisdictions where it has recently suffered losses of influence at the expense of another foreign power. Therefore, in Section 4, we will test whether the probability of a new Indian financial commitment increase in response to new Chinese development projects when popular opinion in the recipient country becomes relatively more favorable towards China than India.

Local Competition. It is also possible that India distributes projects *within* recipient countries in ways that it thinks will allow it to effectively challenge and constrain China's influence (and vice versa). First, there is a demand-side channel for competitive co-location of projects. If government officials in recipient countries seek to preferentially channel aid to specific localities and they know that two strategic rivals are competing for influence, they may seek to pit those foreign donors against each other and promote a "bidding war" for specific projects in the same localities.[17]

A case in point is the Ithari-Dhalkewar road project that the Nepalese government pitched to both Chinese and Indian authorities shortly after the 1962 Sino-Indian War. China agreed to fund the project in April 1964. However, twelve months later, the Nepalese authorities asked Beijing to suspend work on the project and announced that the Indian government would instead finance the construction of the 170 kilometer road (Ispahani, 1989, p.177). A more contemporary example is Sri Lanka's seaport in Hambantota. During his tenure as president from 2005 to 2015, Mahinda Rajapaksa attempted to transform his home district Hambantota into an international shipping hub and a major urban center. To do so, he pitched several flagship infrastructure projects to India and China, including a deep seaport, an airport, and a road from the seaport to the airport.[18] The China Exim Bank agreed to bankroll all of these projects. However, in a

[16]On the political economy of aid within Nepal, see also Eichenauer et al. (2020).

[17]A large body of empirical research demonstrates that host-country politicians disproportionately channel incoming aid and credit to politically relevant jurisdictions (Jablonski, 2014, Masaki, 2018, Bommer et al., 2019, Dreher et al., 2019, Anaxagorou et al., 2020).

[18]According to Peebles (2015, p.22), "Hambantota was to be transformed from a sleepy Muslim

2010 interview, President Rajapaksa explained that “[the Hambantota port project] was offered to India first. I was desperate for development work. But ultimately the Chinese agreed to build it” (Velloor, 2010).

Another potential demand-side explanation is that host-country politicians favor specific localities for economic reasons and encourage competition between their foreign suitors in these localities. For example, right around the time that the Ethiopian government secured a loan from India Exim Bank for the Tendaho sugar factory in the Afar Region, it also received a China Exim Bank loan for a sugar factory (the Kessem Sugar Factory) in the same Ethiopian region. Indeed, resources that are exposed to competition among commercial powers are often location-specific.

There are also supply-side reasons for competitive co-location of Indian projects in the same subnational jurisdictions as China. Previous research demonstrates that the public opinion benefits of Chinese government-financed projects accrue to the subnational jurisdictions where they take place (Brazys and Dukalskis, 2019, Wellner et al., 2021). Therefore, one might expect the efforts of a rival that is seeking to counter Chinese influence to focus on the “frontlines” of the “battle for hearts and minds.” Geographical co-location might help a foreign power like India make the advantages of its own projects and the disadvantages of projects financed by China more salient in the perception of host-country leaders and citizens. Mullen and Poplin (2015) provide an example from northern Myanmar. They note that “[t]he [Chinese-constructed] Kyaukphyu Port became the cornerstone of Beijing’s strategy in [Myanmar], as it provides valuable land-based access to the Indian Ocean,” but “anti-China protests in the north of the country have [provided an] opportunity [for] India [. . .] to reinvigorate its own [grant-financed] transport project at Kaladan.”

Another supply-side rationale for competitive co-location is the fact that a foreign power may seek to constrain or undermine the influence of a competitor by rescuing or rehabilitating its troubled projects. That is to say, if “white elephant” projects create reputational risks for the donors and creditors that fund them, they may also create unique vulnerabilities that rivals can exploit and parlay into reputational gains. To illustrate the way that India might seek to gain a reputational advantage over China by rehabilitating or rescuing a troubled project, consider the China Exim Bank-financed construction of the Mattala Rajapaksa International Airport in Sri Lanka. When this project was initially approved in 2009, the Rajapaksa administration envisioned a 12,000

town to a second capital.” President Rajapaksa’s push to transform this remote part of the country into a “second capital” was part of a broader effort by the president to cement his domestic political support by implementing highly visible infrastructure projects in the country’s southern region, which is predominantly Sinhalese (Chowdhury, 2015). Athukorala and Jayasuriya (2013, p.20) refer to the southern (Sinhala) region of Sri Lanka as “the heartland of the electoral support base of the Rajapaksa family.” In a 2009 cable dispatch, the US Embassy in Colombo also characterized “the Hambantota [port] project [as] a huge deliverable to the President’s home region and his electoral base” (Fowler, 2009).

square meter terminal building supporting as many as one million travelers per year. However, within a few years of the airport becoming fully operational, it became known as "the world's emptiest international airport" (Larmer, 2017) and was also running an annual financial loss of US$18 million (Shepard, 2016). Consequently, the project became a focal point for public scorn and political opposition (Shepard, 2016). In recognition of this unique window of opportunity, an Indian state-owned company offered to rescue the distressed asset through a debt-for-equity deal in which it would effectively repay Sri Lanka's outstanding debt to China Exim Bank in exchange for a 40-year lease to run the airport (Wade, 2017).

Based on the logic of these demand- and supply-side arguments for competitive co-location, we hypothesize that provinces which receive Chinese government financing will become favored destinations for aid and credit from the Indian government. More specifically, we hypothesize that if a subnational locality receives new financial support from the Chinese government, it becomes more likely that the Indian government provides funding to the same subnational locality (*Hypothesis 2*).

3 Data

A comprehensive database with project-level information on India's overseas official financing activities over a longer period of time was not available prior to this study.[19] While data on the activities of OECD member states are readily available on the organization's website, official financing flows from most emerging powers, such as India and China, are considerably less transparent (Dreher et al., 2013, Asmus et al., 2020).[20]

In this section, we introduce a new dataset that captures Indian government-financed projects in the developing world. We first describe the process of assembling and geocoding the dataset and then explain how the project-level dataset that we assembled is aggregated to national and subnational units of analysis. We then contrast the allocation of Indian ODA with its OOF and compare the allocation of official financing from India with that from China.

[19] AidData released an earlier iteration of this project-level dataset in 2011 (Tierney et al., 2011), which covers only the 2008–2010 period in a comprehensive manner. This database enabled cross-country regression analysis only (Fuchs and Vadlamannati, 2013). The Indian Development Cooperation Research (IDCR) project has published a series of helpful aggregated data and case studies but has not released a project-level dataset (e.g., Mullen, 2014).

[20] There are at least two reasons for this lack of comprehensive data. First, given that emerging powers have only recently become major players in the global development finance business, they generally have not yet developed robust internal reporting systems to track their own overseas activities. Second, many emerging powers still have very large numbers of poor people living within their own borders, so there are weak political incentives to publicly disclose detailed information about programs that are at least nominally designed to improve living conditions in other developing countries. Indeed, previous empirical studies demonstrate that per capita income is positively associated with public support for foreign aid (Chong and Gradstein, 2008, Paxton and Knack, 2012, Cheng and Smyth, 2016). In democratic countries, the same relationship holds for a government's decision to introduce a development aid program (Budjan and Fuchs, 2021).

3.1 A New Dataset: India's Official Finance at the Project Level

In collaboration with AidData, a research lab at the College of William & Mary, we collected project-level information on the two major Indian agencies that provide official financing to other developing countries: the MEA and the Exim Bank. The first step of the data collection process was to retrieve project-level information from official government documents. We obtained information on MEA aid projects from the ministry's Outcome Budgets documents.[21] Our primary source for Exim Bank credit-financed projects were the bank's press releases announcing new lines of credit. We assembled information from these documents for all MEA and Exim Bank-financed projects about the project titles and descriptions, the commitment year, the recipient country, the financing type, and the commitment amount.[22] The resulting database consists of 1,194 projects in 93 countries from 2007 to 2014. In a second step, we allocated all projects to (sub)sectors according to the OECD-DAC definitions, ranging from "Education" to "Humanitarian Assistance" (see Appendix Figure A-1 for a comparison).

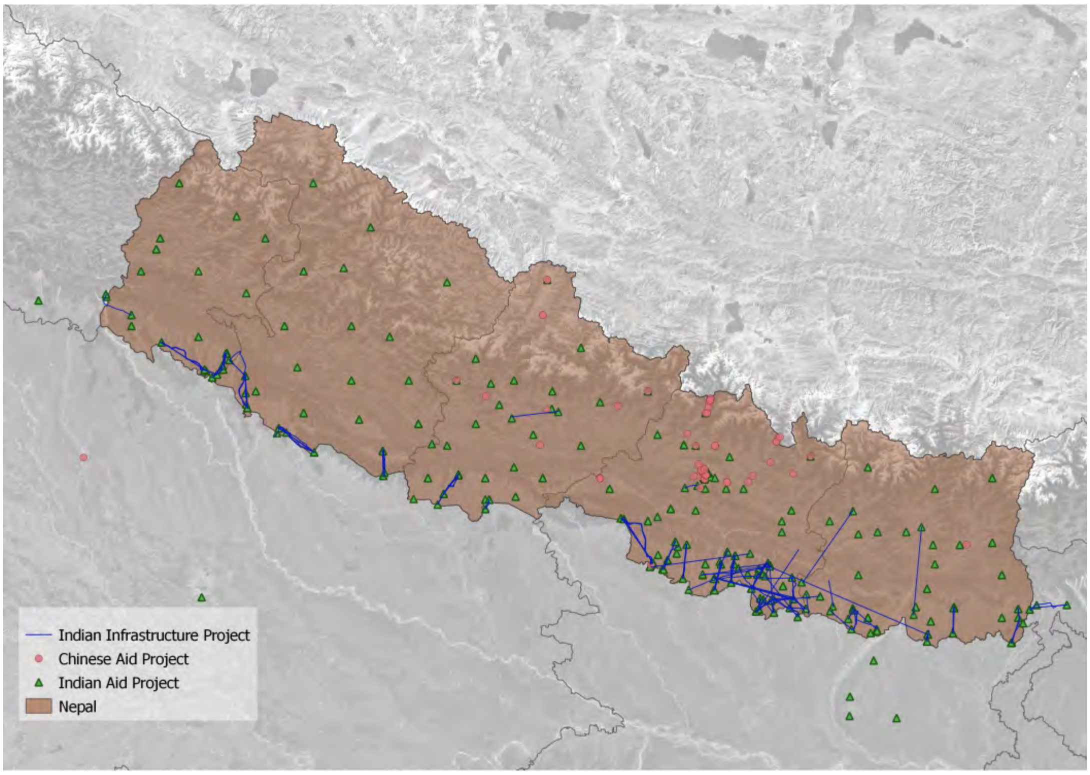
In a third step, we geocoded all of the projects in this database. For 50% of the projects, we applied AidData's "double blind" geocoding methodology (AidData, 2017). Two of our nine research assistants independently extracted relevant geographic information from the documents, searched the web for secondary information on the project locations, and created two separate entries and sets of spatial coordinates for each project. The authors then reviewed all double entries. Whenever the location information provided by the two research assistants differed for a project, the project was re-evaluated in an arbitration process. All research assistants have been constantly trained based on the insights gained from this arbitration process. Once the quality of the geocoding had been assured through the double coding, arbitration, and subsequent training, the remaining projects were coded by a single research assistant and have been quality-assured by the authors. The resulting dataset shows that the 1,194 projects are located at 4,308 project intervention sites at various administrative levels.

Our dataset accounts for the varying levels of geographic precision and coverage of Indian projects. While for some projects it is possible to find exact geographic coordinates, other projects are more difficult to localize. For instance, the MEA supported the project "[sending] English Teachers in Laos, Philippines, Vietnam" in 2010. Here, it was neither reasonable to expect nor feasible to find any information on subnational locations and we therefore geocoded the project to the three countries at the national level. In other cases, the location information that we gathered spans multiple provinces. To give an example, the large "Terai Road" project connects the Nepalese capital with the southern Terai region near the Indian border.[23] As illustrated in Figure 1 for the

[21]See MEA website at `https://mea.gov.in/budget.htm?59/Budget` (last accessed 7 February 2021).
[22]For a subset of projects, we also have information on commitment date and disbursement amount.
[23]The Terai region is a lowland region in southern Nepal and northern India.

Nepalese case, we created line features on the map that follow the projected course of infrastructure projects such as roads and railways to identify all regions that were affected by such infrastructure projects. For our empirical analysis below, we then extracted all first administrative units through which a line feature cuts.

Figure 1 – Geocoded Indian and Chinese development projects in Nepal (2000/07–2014)



Source: India: Authors' data, China: Bluhm et al. (2020)

Aggregating the project-level data to the level of world regions, panel A of Figure 2 shows that India prioritizes Africa and Asia. Few projects and less financing go to the Americas, Central and Eastern Europe, and Oceania. The African countries receiving most projects are Liberia, Ghana, Malawi, Mauritius, and Mozambique.[24] In Asia, India gives priority to its neighbors with the obvious exception of Pakistan. Nepal, Afghanistan, Myanmar, Bhutan, and Sri Lanka top the list of India's Asian recipients. Panel A of Figure 2 also shows that the MEA initiates more projects than the Exim Bank, while the Exim Bank commits larger amounts of official financing. In terms of financial values, 64% of India's financing commitments in our dataset are from the Exim Bank, while only 36% come from the MEA. In contrast, the MEA dominates with 88% in terms of the number of projects and is represented in almost three times more subnational locations.

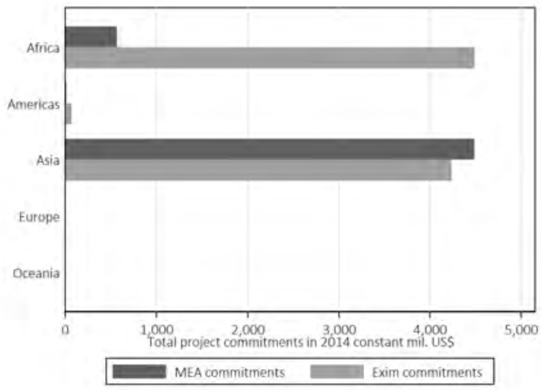
The largest projects recorded in our dataset are typically lines of credit (LOCs) and export credits extended by the Exim Bank to support large infrastructure projects.

[24] Appendix Table A-1 lists the top 10 recipient countries of official finance projects from India and China.

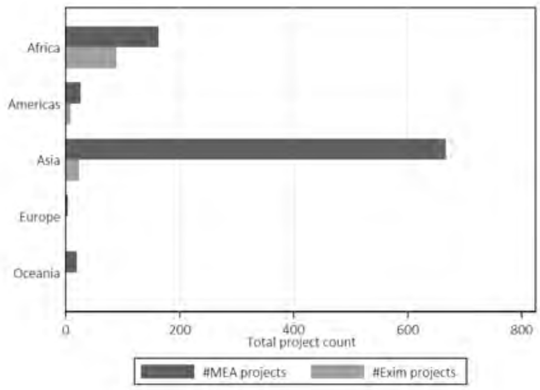
Figure 2 – Comparing Indian and Chinese official finance by world region (2007–2014)

Panel A—India

(a) Amount

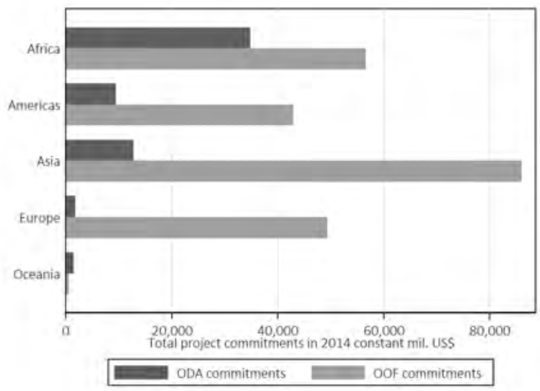


(b) Count

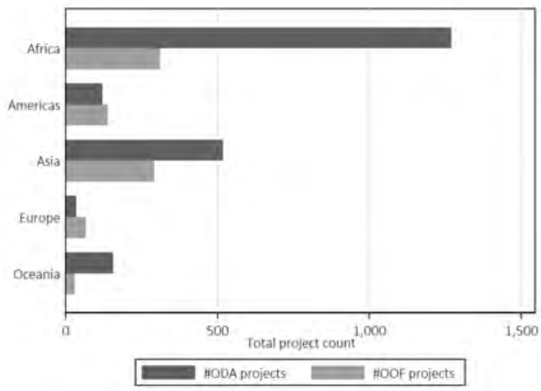


Panel B—China

(c) Amount



(d) Count



Source: India: Authors' data, China: Dreher et al. (2021).

For example, a LOC of US$921 million was extended to the Government of Nepal in 2014 in order to finance hydropower, irrigation, and infrastructure development projects. In Ethiopia, the Exim Bank extended a LOC of US$280 million in 2013 at the behest of the Indian government to finance a railway line from Asaita to Tadjoura in neighboring Djibouti. The MEA is also involved in large infrastructure projects, like the reconstruction and completion of the Salma Dam Power Project in the Herat province of Afghanistan, which was supported with US$218 million in 2010.[25]

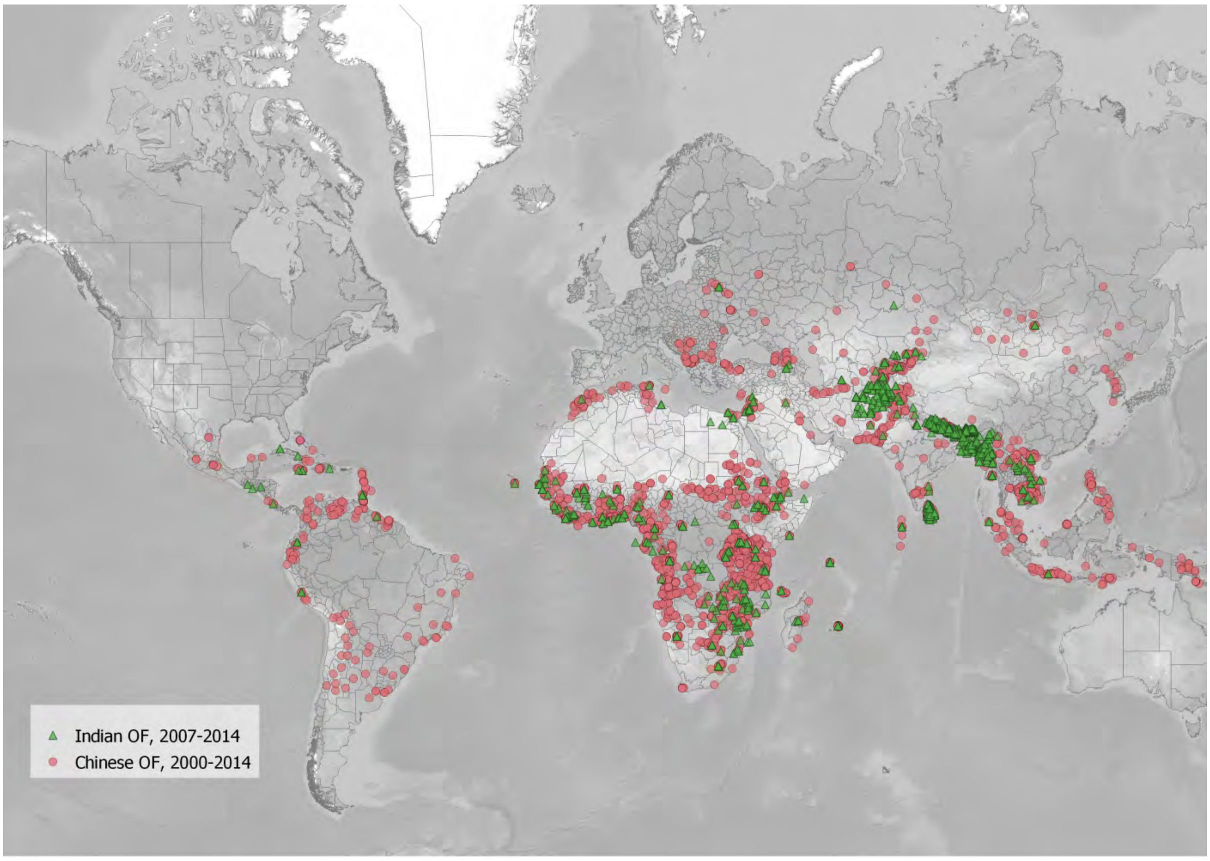
The spatial precision with which we can track project locations differs. To make this transparent, we assign a precision code to each project location.[26] This allows aggregating

[25]Appendix Tables A-2 and A-3 list the 10 largest Exim Bank and MEA projects, respectively.

[26]Following AidData's geocoding methodology (AidData, 2017), we assigned precision codes ranging from 1 to 7 to each project, where coordinates identify the following with decreasing precision: 1: an exact location (such as a building or a populated place), 2: a location within a 25 km radius, 3: a second-order administrative (ADM2) region (such as a district or municipality), 4: a province (i.e., an ADM1 region), 5: a larger region or topographical feature (e.g., when a project is described to be along

the data to the level of spatial aggregation required for the respective analysis. In our study, the main analysis will be carried out at the level of provinces.[27] The spatial precision of 599 projects is sufficient so that we can assign 2,174 project locations to their respective province. Figure 3 presents these project locations in a world map. In addition, we allocate monetary amounts to each province. As monetary commitments are observed at the project level, we divided the total project amount by the number of project locations before constructing the aggregates at the provincial level (see Dreher and Lohmann, 2015, Dreher et al., 2019, for similar approaches).

Figure 3 – World map of Indian and Chinese government-financed project locations (2000/07–2014)



Source: India: Authors' data, China: Bluhm et al. (2020).

3.2 Comparing Indian ODA and OOF

This new dataset allows us to test whether our expectation raised above that MEA aid is mainly driven by geopolitical interests and Exim Bank loans follow primarily commercial interests are reflected in the data. On the one hand, Exim Bank loans (OOF) should

a river or between populated places), 6: a project that is dispersed locally but can only be related to an independent political entity, and 7: an unclear location.

[27]Consequently, we drop all projects with a precision code above 4 for the purpose of this study.

primarily follow commercial interests, i.e., we expect commercial variables, such as the size of Indian exports to a recipient country and the recipient's creditworthiness, to play a larger role than for MEA's allocation. On the other hand, MEA aid (ODA) allocation should primarily follow geopolitical variables, such as recipient country's voting alignment with India in international organizations.

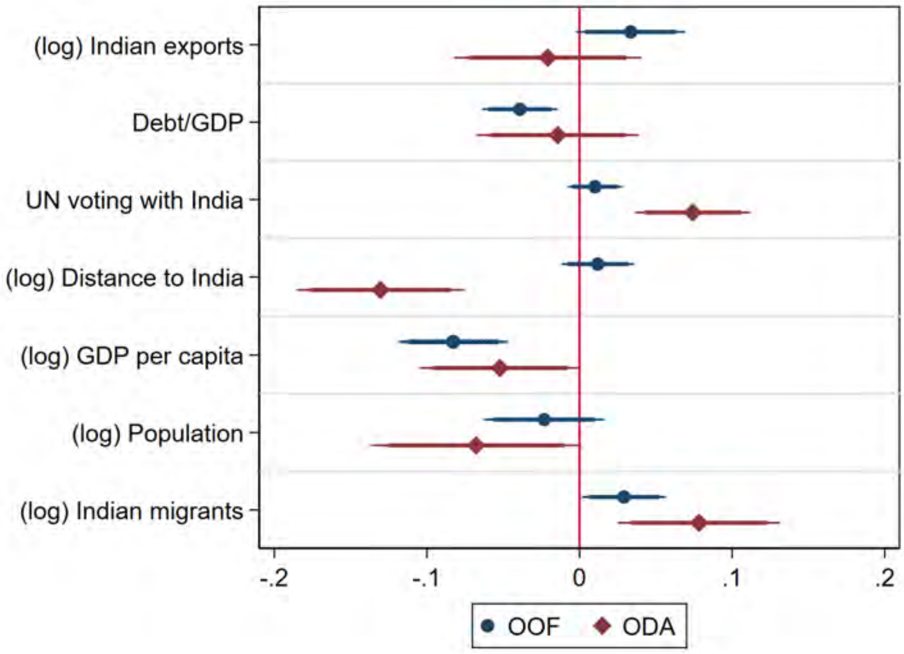
We run a simple set of cross-country allocation regressions. The dependent variable is the logged financial support from either the MEA or the Exim Bank to a recipient country in a given year between 2007 and 2014. We broadly follow Fuchs and Vadlamannati (2013) in our selection of explanatory variables. The geopolitical importance of the recipient country to India is tested with (logged) geographic distance (Mayer and Zignago, 2011) and the (lagged) voting alignment in the UN General Assembly (Bailey et al., 2017). India's economic interests are captured through (lagged and logged) Indian exports to the respective recipient country (IMF, 2016), and the recipient's (lagged) debt-to-GDP ratio to account for its creditworthiness (Kose et al., 2017). Furthermore, we control for economic need using (lagged and logged) GDP per capita (World Bank, 2017), (lagged and logged) population size (World Bank, 2017), and networks using a variable that measures the (logged) number of Indians living in the recipient country in 2000 (World Bank, 2017). Finally, we add binary variables for each year in our sample to account for changes in India's development finance budgets.

Figure 4 shows the results of a one-standard-deviation change in each of the explanatory variables on the logged monetary amount of Indian OOF and ODA, respectively. In line with expectations, commercial variables enter significantly in OOF but not in ODA regressions. Specifically, larger Exim Bank funds (OOF) are given to countries to which India exports more, which is in line with the institution's mandate. Moreover, smaller amounts of loans flow to more indebted countries, which likely follows from concerns about the ability of these countries to repay their debt. By contrast, MEA's aid allocation (ODA) reflects its geopolitical interests. More precisely, India's voting alignment in the UN General Assembly is significantly correlated with MEA aid. MEA aid is also more targeted towards countries in India's neighborhood, which are arguably of larger strategic interest to India. Both political variables do not turn out to be significant predictors of Exim Bank loans.[28] Based on these results and our theoretical considerations above, we will interpret India's MEA response to China's official financing activities as evidence of geopolitical competition. Conversely, we will interpret India's response to China's official financing activities through India's Exim Bank as evidence of

[28]The control variables are mostly significant and have the expected signs. Poorer countries receive both more Exim Bank credit and MEA aid. Larger countries in terms of population size receive fewer MEA aid, which mimics similar results for Chinese aid reported in Dreher and Fuchs (2015). This small-country bias could reflect the ease to buy foreign-policy concessions (Bueno de Mesquita and Smith, 2009). Finally, countries that host more Indian migrants receive significantly more Exim Bank credit and MEA aid.

commercial competition.

Figure 4 – Marginal effects of potential determinants of India's allocation of Exim Bank loans (OOF) and MEA aid (ODA) (standardized coefficients, OLS, 2007–2014)



Notes: The figure shows the results of least-squares regressions of India's country allocation of Exim Bank loans (in blue) and MEA aid (in red) over eight years (2007–2014). The dots represent a one-standard-deviation change in the respective explanatory variable on the logged monetary amount of Indian OOF and ODA, respectively (together with 90% and 95% confidence intervals). All regressions include year dummies. Standard errors are clustered by country. The number of observations is 887 in 119 country clusters. The R-squared takes values of 9.4% (Exim Bank) and 32.8% (MEA), respectively. Source: Authors' calculations.

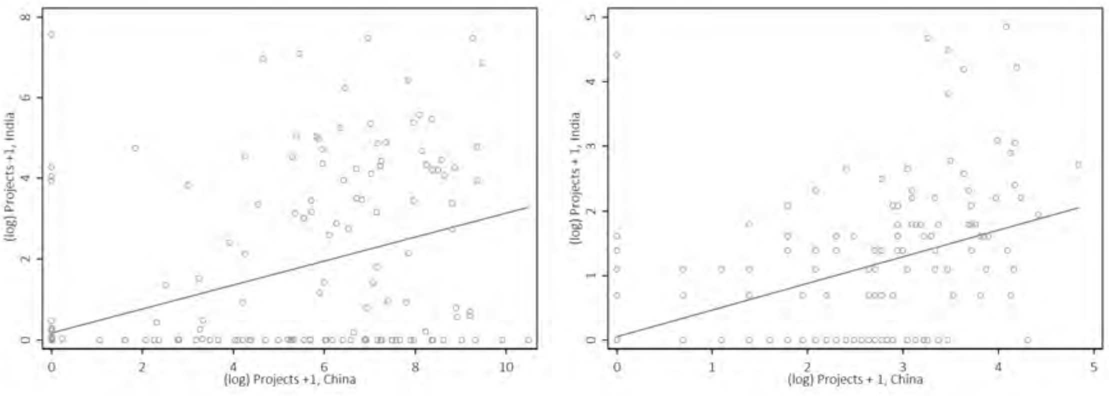
3.3 Chinese and Indian Official Finance in Comparison

We examine India's competitive behavior towards China using a project-level dataset of Chinese official financing flows covering the 2000–2014 period (Dreher et al., 2021). This dataset consists of 4,368 projects in 140 countries representing official financing of approximately US$362 billion. It covers both ODA and OOF projects that have been committed between 2000 and 2014. The dataset was assembled using AidData's Tracking Underreported Financial Flows (TUFF) methodology (Strange et al., 2017, Dreher et al., 2021). All projects that have reached the implementation or completion stage have been geocoded and can thus be included in our analysis below (Bluhm et al., 2020).

As panel B of Figure 2 demonstrates, China (like India) focuses its official financing efforts on Asia and Africa. However, while India allocates more ODA projects to neighboring countries, African countries benefit from more Chinese ODA projects. Similar to India, China initiates more ODA (74%) projects than OOF projects (26%).

Figure 5 – India's versus China's official finance projects by recipient country (2007–2014)

(a) Monetary amount **(b)** Project count



Source: India: Authors' data, China: Dreher et al. (2021).

In financial terms, ODA represents a relatively modest fraction (21%) of total official financing flows from China. Cambodia, Zimbabwe, Pakistan, Tanzania, and Sri Lanka are the largest recipients of Chinese official finance in terms of project numbers (see also Appendix Table A-1).

Figure 5 presents scatter plots of Indian and Chinese official finance. It demonstrates that, at the recipient-country level, the volume of financial support (left panel) and the number of projects (right panel) provided by these two emerging powers are positively correlated. A first look at the distribution of Chinese and Indian project locations in the world also suggests some geographical clustering of Chinese and Indian projects within countries (see again Figure 3).[29]

4 Empirical Strategy

We use the geocoded information about the provincial location of Indian and Chinese official projects to analyze whether and how India locates projects in the same jurisdictions as China's official financing activities in the 2007–2014 period.[30] First, we test whether India is more likely to commit a development project to a province if China finances a new project to the same country in which the province is located (*Hypothesis 1*). Second, we test whether India is more likely to commit a development project to a province if China finances a new project to the same province (*Hypothesis 2*). To estimate our hypotheses about the allocation of Indian official finance across provinces, we use a linear probability model with province- and country-year-fixed effects. Formally, we run the following regression model:

[29] See also world map of Chinese and Indian projects at the country level in Appendix Figure A-2.

[30] Below, we also examine the inverse relationship, i.e., the effect of Indian official financing activities on Chinese project locations.

$$IndiaOF_{ijt} = \alpha ChinaOF_{jt-1} + \beta ChinaOF_{ijt-1} + \mathbf{c'}_{ijt-1}\gamma + \xi_{ij} + \psi_t + \epsilon_{ijt}, \quad (1)$$

where $IndiaOF_{ijt}$ is a binary variable that takes the value one if India launches either a new Exim Bank loan or MEA aid project in province i of country j in year t; $ChinaOF_{jt-1}$ is a binary variable for a Chinese project in the same country in the previous year $t-1$; $ChinaOF_{ijt-1}$ is a binary variable for a Chinese project in the same province in the previous year $t-1$; and $\mathbf{c}_{ijt-1}$ is the vector of lagged time-variant controls at the province level.

While we use a binary dependent variable, $IndiaOF_{ijt}$, and binary variables of interest, $ChinaOF_{jt-1}$ and $ChinaOF_{ijt-1}$ in our baseline specification, we replace them by continuous variables that measure the logged financial value of official finance commitments in robustness tests. The latter comes with the obvious advantage that it accounts for the size of projects. However, one important caveat is that 39 percent of the Chinese projects lack information on their financial value (Dreher et al., 2021). Moreover, given that only 4.2% of province-years in our sample are "treated" with Indian and 7.7% with Chinese projects, the use of monetary amounts is more likely to be biased by outliers. Therefore, our preferred measure is the project dummy variable.

We include the following control variables that vary across provinces and time and are lagged by one year: the logarithm of average nighttime light to proxy the provincial level of development (Elvidge et al., 2017, Goodman et al., 2019); the logarithm of average precipitation (Willmott and Matsuura, 2001, Goodman et al., 2019), and the number of conflict fatalities (Gleditsch et al., 2002, Allansson et al., 2017) to control for temporary shocks; and the logged population level (CIESIN, 2016, Goodman et al., 2019) as a larger population might increase the probability of receiving a project. Province-fixed effects ξ_{ij} account for (time-invariant) country- and province-specific characteristics such as access to the sea, geographic distance to India, or a recipient's historical ties with India.[31] Year-fixed effects ψ_t absorb year-specific factors such as India's budget for overseas official finance or changes in the Indian government. Standard errors are cluster-robust at the country level. Appendix Table A-4 provides detailed definitions and sources and Appendix Table A-5 provides descriptive statistics of each variable included in our analysis.

In our preferred specification, we absorb variation at the recipient-country level over time with country-year-fixed effects. This allows us to account for unobserved time-varying country-specific characteristics. The equation becomes

[31] These fixed effects also account for a Chinese or Indian development presence prior to 2007, the beginning of our sample period. We therefore do not worry that a "stock" effect biases our results.

$$IndiaOF_{ijt} = \beta ChinaOF_{ijt-1} + \mathbf{c'}_{ijt-1}\gamma + \xi_{ij} + \zeta_{jt} + \epsilon_{ijt}, \tag{2}$$

where country-year-fixed effects are denoted by ζ_{jt}. In addition to the other fixed effects, they account for common shocks to all provinces within a given country in a given year (such as international sanctions, changing national-level government policies, and a recipient country's current political and economic relations with India). In these regressions, we thus identify the effect of $ChinaOF$ on $IndiaOF$ only through variation *within* provinces over time, controlled for all factors that affect the entire country in a given year. In contrast to the typical cross-country allocation studies in the foreign aid literature, the country-year-fixed effects applied here can absorb time-variant country-level drivers of project allocation that might affect the allocation of Chinese and Indian official finance in similar ways. For example, both China and India might seek to curry favor with a new government after its election (Rommel and Schaudt, 2019).[32] However, Equation (2) has the downside that we cannot test Hypothesis 1 as the commitment of Chinese development projects at the country level in a year is fully captured by the country-year-fixed effects. We thus run regressions based on both estimation equations to test our hypotheses.

A major challenge of our empirical approach is to separate competition from other explanations that may lead to a positive association between Indian and Chinese official financing. Chief among these rival explanations are selectivity and imitation.[33] Selectivity refers to the possibility that China and India follow similar financial allocation criteria. For example, both funders might favor jurisdictions with lower levels of economic development or higher-quality policies and institutions. We account for typical selectivity criteria in our regression models by controlling for the various allocation determinants identified in the literature—either directly or indirectly through various fixed effects.

Imitation refers to the possibility that foreign donors and lenders—operating in unfamiliar settings with imperfect access to information—take cues from their peers with more local experience and tacit knowledge. As Davies and Klasen (2019, p.244) note, a lack of information about the distribution of local needs and opportunities could lead governments to "base their expectations in part on the choices made by other governments, leading to herding whereby one donor's aid follows that of others due to the presumed information their donations convey." We run several tests to distinguish

[32]We acknowledge that we cannot control for unobserved province-specific variables that change over time. These could include province-year-specific need factors such as natural disasters that affect only parts of the country under analysis, events that increase a province's international importance in a given year (e.g., international summit, trade fair), and the time-varying domestic political relevance of a province (for example driven by provincial or municipal elections). This prevents us from interpreting our estimates as causal estimates.

[33]Aid provision occurs in mutual agreement between donor and recipient (Carnegie and Dolan, 2020). Recipients can prohibit donors to provide aid in a given province which would, if anything, lead to an underestimation of competition.

competition from imitation. First, we recognize that imitation most likely occurs within the same sectors but competition can occur across sectors. We run regressions at the sector level to test whether the "crowding-in" of projects is inter- or cross-sectoral. Second, we argue that if Delhi cares about China's growing influence, India's development finance is more responsive in countries where China's relative popularity increases. It would be hard to reconcile evidence that India provides significantly more projects to jurisdictions in countries where it has become less popular relative to China with explanations other than competition with China. Specifically, we use Gallup World Poll data to test whether the crowding-in effect is larger in countries where China's popularity increased relative to India (Gallup, 2018). We then add an interaction term of $ChinaOF$ with China's relative popularity vis-à-vis India (and control for the level of support for India itself). We interpret a positive coefficient on the interaction term as evidence suggesting competitive behavior of India towards China through development finance. Third, we would expect that India's response is stronger in geopolitically and commercially important jurisdictions. If interactions with such variables are significant, this would further support the idea that competition is driving the positive association between Indian and Chinese official finance.

5 Results

5.1 Credit Allocation by the Exim Bank of India

We start by analyzing India's response to new Chinese development projects with Exim Bank loans to test for commercial competition and then analyze geopolitical competition with MEA aid in the next subsection. The first three columns in Table 1 test Hypotheses 1 and 2 and are based on Equation (1). In column 1, the coefficient on $ChinaOF_{ijt-1}$ is positive and statistically significant at the ten-percent level. Quantitatively, the likelihood of an Indian Exim Bank project in a province increases by 0.8 percentage points in the year after China has launched a project in the same province. The effect is sizable in light of the average likelihood of a new Indian Exim Bank project being set up in a province in a given year (0.5 percent). Thus, the commitment of a new Chinese project more than doubles the probability of a province becoming a recipient of credit from India's Exim Bank. However, India does not appear to respond to new Chinese projects elsewhere in the same country, as the coefficient on $ChinaOF_{jt-1}$ is close to zero and statistically insignificant. These results are consistent with the idea of localized competition between India and China (Hypothesis 2).

Column 2 considers the contemporaneous values at the country level, $ChinaOF_{jt}$, and the province level, $ChinaOF_{ijt}$, to allow for an immediate response. As we use data on official commitments rather than disbursements, it would not be surprising to observe an effect already in the same year. We also consider longer lags of Chinese official

Table 1 – India's Exim Bank loans and Chinese official finance (2007–14)

	Baseline (1)	Timing (2)	Placebo (3)	Baseline (4)	Timing (5)	Placebo (6)
$ChinaOF_{ijt+1}$			-0.001			-0.001
			(0.005)			(0.005)
$ChinaOF_{ijt}$		0.009**	0.010**		0.008*	0.008*
		(0.004)	(0.004)		(0.004)	(0.004)
$ChinaOF_{ijt-1}$	0.008*	0.010*	0.011**	0.008**	0.009**	0.010**
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)
$ChinaOF_{ijt-2}$		0.005	0.008		-0.001	0.001
		(0.008)	(0.009)		(0.005)	(0.005)
$ChinaOF_{ijt-3}$		-0.001	0.003		0.002	0.004
		(0.004)	(0.005)		(0.003)	(0.004)
$ChinaOF_{jt+1}$			0.003			
			(0.002)			
$ChinaOF_{jt}$		0.003**	0.005***			
		(0.001)	(0.002)			
$ChinaOF_{jt-1}$	-0.001	-0.001	0.000			
	(0.002)	(0.002)	(0.002)			
$ChinaOF_{jt-2}$		0.001	0.001			
		(0.002)	(0.002)			
$ChinaOF_{jt-3}$		0.002	0.002			
		(0.002)	(0.003)			
Controls	✓	✓	✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Country-year FE				✓	✓	✓
Observations	18,673	18,673	16,338	18,657	18,657	16,324
Adjusted R-squared	0.039	0.040	0.045	0.265	0.266	0.276

Notes: The unit of observation is the province (ADM1 region). Dependent and explanatory variables are binary with 1 indicating if at least one Indian (respectively Chinese) project is committed to a province. All specifications control for log nighttime light (t-1), log precipitation (t-1), log population (t-1), and log conflict-related deaths (t-1). Columns 4–6 include country-year-fixed effects in addition to province- and year-fixed effects. Robust standard errors clustered at the country level are presented in parentheses. Significant at: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

finance to allow for more flexibility in the timing of India's response to Chinese projects. Specifically, we add the second and third lag at both the country level, $ChinaOF_{jt-2}$ and $ChinaOF_{jt-3}$, and the provincial level, $ChinaOF_{ijt-2}$ and $ChinaOF_{ijt-3}$. We continue to find an economically and statistically significant effect of $ChinaOF_{ijt-1}$ on $IndiaOF_{ijt}$. The results also suggest that India's Exim Bank is a very fast mover: the likelihood of a loan already increases in the same year in which a new Chinese project is announced. Specifically, we observe an contemporaneous effect at both the province and country level as shown by the economically and statistically significant coefficients of $ChinaOF_{ijt}$ and $ChinaOF_{jt}$.[34] The effect appears to be much stronger with respect to the province

[34]Note that the positive coefficients on $ChinaOF_{jt}$ and $ChinaOF_{ijt}$ could also be the result of reverse causality, which is why we did not include them in our baseline specification. We test the inverse relationship below and find no robust evidence that *China* responds to India. We conclude that it is

of interest with a cumulative effect over four years of 2.3 percentage points compared to the entire country with 0.5 percentage points only. As such, the results confirm a stronger inclination toward localized competition between India and China (Hypothesis 2) and only provide weak evidence for countrywide competition between both emerging economies (Hypothesis 1). Finally, there is no evidence of a delayed Indian response to China either at the country or the province level as all longer lags do not reach significance at conventional levels.

An alternative interpretation of the results in columns 1 and 2 is that there might be unobserved time-variant factors at the country or provincial level that attract both Chinese and Indian projects. To address this concern, column 3 shows a "placebo test" for the timing of new projects. Specifically, we include the one-year leads $ChinaOF_{jt+1}$ and $ChinaOF_{ijt+1}$. A significant coefficient on the lead variable would raise concerns on the interpretation of our results as an Indian response to Chinese activities. Column 3 provides no evidence for any "anticipation" effects and our model thus passes the placebo test. This raises the confidence in our interpretation of a positive crowding-in of Indian Exim Bank loan projects in response to Chinese development projects.

Columns 4–6 of Table 1 include country-year-fixed effects, as specified in Equation (2). This allows us to test Hypothesis 2 in a more rigorous setting. Country-year-fixed effects absorb unobserved time-variant factors at the country level, such as changes in government. Our preferred specification in column 4 confirms our main result of a crowding-in of Indian Exim Bank loans following new Chinese projects at the province level. The coefficient on $ChinaOF_{ijt-1}$ is of similar size and now statistically significant at the five-percent level. We explore the response time of India's Exim Bank in column 5 and repeat the placebo exercise in column 6. The results are quantitatively similar to the previous regressions without country-year-fixed effects and confirm the earlier interpretation of our findings.

Table 2 provides a number of sensitivity analyses. In column 1, we examine whether our coefficient of interest is robust to omitting all control variables. This way, we check for a "bad controls" bias, as discussed in Angrist and Pischke (2009, p.64). The results are virtually unaffected. Column 2 uses logged financial commitments in constant 2014 US dollars for both the dependent variable and the variable of interest rather than binary variables. This allows us to analyze the intensive margin of development finance commitments in addition to the extensive margin. We find that India's Exim Bank increases the financial size of its loan commitments by 0.013 percent in response to a one-percent increase of Chinese official financing committed to a particular province.[35] We thus again find a positive crowding-in effect. Although marginally insignificant (p-value:

unlikely that reverse causality is of major concern.

[35] This appears small in quantitative size. However, note that the financial value of the median Indian OOF project is only 38% of the median Chinese OOF project.

0.103), we come to the same qualitative conclusion when we look at logged project counts in column 3.[36]

Table 2 – Sensitivity analysis for Table 1

		Projects in		Response to	
	No controls	(log) \$ amounts	(log) Count	Chinese OOF	Chinese ODA
	(1)	(2)	(3)	(4)	(5)
$ChinaOF_{ijt-1}$	0.007**	0.013**	0.006	0.012*	0.003
	(0.004)	(0.005)	(0.004)	(0.007)	(0.006)
Controls		✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Country-year FE	✓	✓	✓	✓	✓
Observations	19,568	18,657	18,657	18,657	18,657
Adjusted R-squared	0.265	0.249	0.243	0.266	0.265

Notes: The unit of observation is the province (ADM1 region). Dependent and explanatory variables are binary with 1 indicating if at least one Indian (respectively Chinese) project is committed to a province in column 1, in logged US\$ amounts in column 2, and in logged project counts in column 3, respectively. Columns 4 and 5 document how India's Exim Bank loan commitments react toward Chinese OOF and ODA projects, respectively. Except for column 1, all specifications control for log nighttime light (t-1), log precipitation (t-1), log population (t-1), and log conflict-related deaths (t-1). Robust standard errors clustered at the country level are presented in parentheses. Significant at: $^{***}: p < 0.01$; $^{**}: p < 0.05$; $^{*}: p < 0.1$.

Next, we explore whether India's Exim Bank is more likely to commit a loan project in response to more similar Chinese OOF lending than to Chinese ODA projects. We use the baseline regression from column 4 of Table 1 and replace our variable of interest with a binary variable for any Chinese lending project (OOF) in column 4, and with a binary variable for any Chinese aid project (ODA) in column 5. In line with the commercial competition explanation, the coefficients of interest show that India's Exim Bank reacts to the more directly competing market-oriented flows from China (column 4), while Chinese aid projects do not appear to trigger a significant response by India's Exim Bank. This supports our interpretation of commercial competition since China's Exim Bank, a leading provider of Chinese OOF, is a direct competitor of India's Exim Bank.

Summing up our results so far, it thus appears that India's Exim Bank responds quickly to China's development activities in a given province. We find robust evidence for Hypothesis 2: New Chinese activities, and Chinese OOF projects in particular, increase the likelihood that the Indian Exim Bank provides a loan to a given province. However, we observe only weak evidence of such a response to China's development activities elsewhere in the country (Hypothesis 1). As the actor at play is the Mumbai-based Exim Bank that is tasked with commercial goals, we treat this as first suggestive evidence of commercial competition between the two emerging powers. However, since the crowding-in effect

[36]Note that we add one to all project counts and US dollar values before we take logarithms.

could be equally the result of imitation, we will return to this question in Section 5.3, where we offer several tests to separate competition from alternative explanations.

5.2 Aid Allocation by India's Ministry of External Affairs

Table 3 replicates the analysis of Table 1 for Indian MEA aid. The Delhi-based ministry does not only manage India's foreign policy but is also India's leading aid agency. It provides highly concessional loan and grant projects. As the regression table shows, the MEA does not provide more aid projects in provinces and countries that obtained a new Chinese project in the previous year. The coefficients on $ChinaOF_{ijt-1}$ and $ChinaOF_{jt-1}$ are very small and statistically insignificant. While at first it appears that there exists a delayed crowding-in of MEA aid at the provincial level after three years (columns 2 and 3), the corresponding coefficient becomes insignificant once we add country-year-fixed effects to the province-fixed effects (columns 5 and 6). Again, there is no evidence of any "anticipation" effect in our placebo regressions, which would be inconsistent with our crowding-in interpretation (columns 3 and 6). We thus conclude that there is no robust evidence that the Indian MEA uses aid—at the province or national level—to compete with China.

In Table 4, we deepen the analysis in the same manner as in Table 2. Our conclusion of a lack of robust crowding-in effects of Indian MEA aid holds when we omit control variables (column 1), or use logged monetary amounts (column 2) or logged project counts (column 3) for both the dependent variable and the independent variables of interest instead of project dummies. We also find no evidence that our estimates for all Chinese projects conceal significant responses of India's MEA to Chinese OOF (column 4) or Chinese ODA flows (column 5) when considered separately.

These results suggest that India does not time the provision of its aid to strengthen its geopolitical ties with other countries at those moments when China engages more intensively with specific countries and provinces via ODA-financed projects. However, this finding may only hold true for the average recipient country. A different picture might emerge if we look at countries where India has particularly strong interests. Therefore, we now turn to an analysis of heterogeneous effects.

5.3 Disentangling Competition from Alternative Explanations

Sectoral Decomposition. As a first attempt to disentangle competition from imitation, we analyze whether the crowding-in of Indian projects occurs in the same sectors or across sectors. One would expect to see crowding-in within the same sectors because foreign financiers often design and implement development projects in unfamiliar settings and with limited access to information, which gives them an incentive to follow cues from other donors and creditors with more local experience and tacit knowledge.

Table 3 – India's MEA aid and Chinese official finance (2007–14)

	Baseline (1)	Timing (2)	Placebo (3)	Baseline (4)	Timing (5)	Placebo (6)
$ChinaOF_{ijt+1}$			0.009			0.001
			(0.009)			(0.009)
$ChinaOF_{ijt}$		0.001	0.008		-0.006	-0.008
		(0.007)	(0.009)		(0.007)	(0.008)
$ChinaOF_{ijt-1}$	0.014	0.016	0.012	0.003	0.002	0.000
	(0.013)	(0.014)	(0.011)	(0.008)	(0.009)	(0.009)
$ChinaOF_{ijt-2}$		0.010	0.012		-0.001	-0.001
		(0.009)	(0.012)		(0.008)	(0.009)
$ChinaOF_{ijt-3}$		0.025*	0.019*		0.010	0.009
		(0.014)	(0.010)		(0.009)	(0.011)
$ChinaOF_{jt+1}$			-0.002			
			(0.004)			
$ChinaOF_{jt}$		0.004	0.002			
		(0.004)	(0.004)			
$ChinaOF_{jt-1}$	-0.005	-0.004	-0.006			
	(0.003)	(0.003)	(0.004)			
$ChinaOF_{jt-2}$		0.002	0.002			
		(0.004)	(0.004)			
$ChinaOF_{jt-3}$		0.002	0.001			
		(0.004)	(0.004)			
Controls	✓	✓	✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Country-year FE				✓	✓	✓
Observations	18,673	18,673	16,338	18,657	18,657	16,324
Adjusted R-squared	0.453	0.454	0.446	0.607	0.607	0.600

Notes: The unit of observation is the province (ADM1 region). Dependent and explanatory variables are binary with 1 indicating if at least one Indian (respectively Chinese) project is committed to a province. All specifications control for log nighttime light (t-1), log precipitation (t-1), log population (t-1), and log conflict-related deaths (t-1). Columns 4–6 include country-year-fixed effects in addition to province- and year-fixed effects. Robust standard errors clustered at the country level are presented in parentheses. Significant at: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Indeed, Davies and Klasen (2019, p.244) note that a lack of information about the distribution of local needs and opportunities can prompt governments to "base their expectations in part on the choices made by other governments, leading to herding whereby one donor's aid follows that of others due to the presumed information [that] their donations convey." Competition, on the other hand, is equally likely to occur within or across sectors. If India wants to counteract the influence of China, it can seek to differentiate itself by pursuing projects in sectors where it has a comparative advantage vis-à-vis China, or it can seek to design and implement projects in the same sectors but in more efficient, effective, or sustainable ways. Therefore, we will seek to determine if the relationship between the receipt of Chinese government financing and Indian government finance is primarily driven by *within-sector* crowding-in because this would provide strong

Table 4 – Sensitivity analysis for Table 3

		Projects in		Response to	
	No controls	(log) $ amounts	(log) Count	Chinese OOF	Chinese ODA
	(1)	(2)	(3)	(4)	(5)
$ChinaOF_{ijt-1}$	0.002	-0.010	-0.006	0.011	-0.001
	(0.008)	(0.007)	(0.006)	(0.013)	(0.011)
Controls		✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Country-year FE	✓	✓	✓	✓	✓
Observations	19,568	18,657	18,657	18,657	18,657
Adjusted R-squared	0.599	0.640	0.753	0.607	0.607

Notes: The unit of observation is the province (ADM1 region). Dependent and explanatory variables are binary with 1 indicating if at least one Indian (respectively Chinese) project is committed to a province in column 1, in logged US$ amounts in column 2, and in logged project counts in column 3, respectively. Columns 4 and 5 document how India's MEA aid commitments react toward Chinese OOF and ODA projects, respectively. Except for column 1, all specifications control for log nighttime light (t-1), log precipitation (t-1), log population (t-1), and log conflict-related deaths (t-1). Robust standard errors clustered at the country level are presented in parentheses. Significant at: $^{***}: p < 0.01$; $^{**}: p < 0.05$; $^{*}: p < 0.1$.

grounds to question our interpretation of the results as competition.

To test these expectations, we regress Indian projects in a specific sector on Chinese projects in the same sector. Specifically, we look into the three broad development finance sectors defined by the OECD—Social Infrastructure & Services, Economic Infrastructure & Services, and Production Sectors—as well as the three largest narrow sectors in our Indian development finance dataset (in terms of project numbers), which are Energy Generation & Supply, Health, and Transport & Storage. Panel A of Table 5 documents coefficients for Exim Bank loans, and panel B reports results for MEA aid. We find no evidence of India being more likely to provide an Exim Bank loan or MEA aid project to the same region and of the same sector as China in the previous year.

Overall, the crowding-in of Indian projects does not occur within the same sector. Our results are thus driven by projects committed in the same province but in different sectors. It appears unlikely that the crowding-in effect is mainly driven by imitation of specific activities. Rather this evidence is in line with our competition interpretation. However, with the sectoral decomposition, we cannot fully rule out that imitation drives the positive association between India's and China's loan allocation. This is why we proceed with more direct tests of our competition interpretation.

Public Opinion. As a more direct test of our competition interpretation of the crowding-in effect, we analyze whether India is particularly responsive to new Chinese development projects in jurisdictions where India has recently suffered public opinion losses vis-à-vis China. There are good reasons both for why India might prioritize jurisdictions in which it is unpopular (e.g., to improve its public image) or popular

Table 5 – Sectoral decomposition

	Social (1)	Economic (2)	Production (3)	Energy (4)	Health (5)	Transport (6)
	Panel A: Indian Exim Bank loans					
$ChinaOF_{ijt-1}$	0.000	0.005	-0.001	0.007	-0.003	0.002
	(0.000)	(0.004)	(0.003)	(0.007)	(0.002)	(0.005)
	Panel B: Indian MEA aid					
$ChinaOF_{ijt-1}$	-0.003	-0.010**	-0.008	-0.001	0.000	-0.005*
	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)	(0.003)
Controls	✓	✓	✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Country-year FE	✓	✓	✓	✓	✓	✓
Observations (A)	18,657	18,657	18,657	18,657	18,657	18,657
Observations (B)	18,657	18,657	18,657	18,657	18,657	18,657
Adjusted R-squared (A)	0.226	0.136	0.147	0.161	0.733	0.102
Adjusted R-squared (B)	0.495	0.565	0.171	0.633	0.585	0.797

Notes: The unit of observation is the province (ADM1 region). Dependent and explanatory variables are binary with 1 indicating if at least one Indian (respectively Chinese) project is committed to a province. The column labels indicate the sector within which the project has been allocated. Panel A reports estimates for Exim Bank loans, panel B reports estimates for MEA aid. All specifications control for log nighttime light (t-1), log precipitation (t-1), log population (t-1), and log conflict-related deaths (t-1). All columns include country-year-fixed effects in addition to province- and year-fixed effects. Robust standard errors clustered at the country level are presented in parentheses. Significant at: *** : $p < 0.01$; ** : $p < 0.05$; * : $p < 0.1$.

(e.g., fewer obstacles to project implementation). However, it would be hard to reconcile evidence that India provides more projects to jurisdictions where it has become less popular *relative* to China with explanations other than India competing with China.

One way to proxy for the relative levels of influence enjoyed by two donor governments is public opinion about these donor governments in recipient countries. Most donor governments have policies and programs in place to win the "hearts and minds" of citizens in host countries (e.g., Dietrich et al., 2018, Blair et al., 2019, Eichenauer et al., 2021). They understand that public perceptions can "filter up and influence elite policy to be more amenable to [their own] interests," and that their strategic rivals are seeking to create a more favorable public opinion environment to promote their interests (Brazys and Dukalskis, 2019, p.567). Therefore, if one can consistently measure levels of public approval for two governments over space and time, one can effectively proxy for the relative gains and losses that one government is experiencing vis-à-vis another government in specific jurisdictions. The Gallup World Poll provides such data (Gallup, 2018). Each year, the survey is conducted in more than 160 countries worldwide. Gallup interviews at least 1,000 individuals in each country and weights them in a manner that ensures the final survey results are nationally representative. We use the Gallup World Poll question "Do you approve or disapprove of the job performance of the leadership of [country]?", where [country] is either China or India.[37] This allows us to generate a measure of the distance in public approval rates between the two countries.

Table 6 – Interactions with public opinion

	Exim Bank loans				MEA aid
	(1)	(2)	(3)	(4)	(5)
$ChinaOF_{ijt-1}$	0.014*	0.013	0.015	0.020	-0.018
	(0.008)	(0.008)	(0.020)	(0.017)	(0.023)
$ChinaOF_{ijt-1}$ × Approval Distance 1	0.091**		0.086*	0.083*	-0.150
	(0.044)		(0.048)	(0.043)	(0.118)
$ChinaOF_{ijt-1}$ × Approval Distance 2		0.091*			
		(0.053)			
$ChinaOF_{jt-1}$ × Approve India			0.013		
			(0.038)		
$ChinaOF_{jt-1}$ × Disapprove India				-0.021	
				(0.033)	
$ChinaOF_{jt-1}$ × Nationalist Sentiment			-0.013	-0.001	
			(0.026)	(0.039)	
Controls	✓	✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Country-year FE	✓	✓	✓	✓	✓
Observations	5,560	5,560	5,560	5,560	5,560
Adjusted R-squared	0.239	0.238	0.238	0.238	0.613

Notes: The unit of observation is the province (ADM1 region). Dependent and explanatory variables are binary with 1 indicating if at least one Indian (respectively Chinese) project is committed to a province. Columns 1–4 report estimates for Exim Bank loans; column 5 reports estimates for MEA aid. Approval Distance 1 excludes 'don't know' and 'refuse to answer' replies, while Approval Distance 2 includes both. The variables subtract the approval rate for the Chinese government from the approval rate of the Indian government. All specifications control for log nighttime light (t-1), log precipitation (t-1), log population (t-1), and log conflict-related deaths (t-1). All columns include country-year-fixed effects in addition to province- and year-fixed effects. Robust standard errors clustered at the country level are presented in parentheses. Significant at: $^{***}: p < 0.01$; $^{**}: p < 0.05$; $^{*}: p < 0.1$.

More specifically, we augment our regression equation with an interaction between $ChinaOF_{ijt-1}$ and the difference between the approval rates of the Chinese government and the Indian government in the recipient country. In column 1 of Table 6, we compute the approval rates only for those respondents that provided an answer to the question. Column 2 includes respondents that refused to answer or replied with "don't know" and treat these observations as absence of approval. According to both columns, the coefficients on the interaction term are positive and statistically significant at conventional levels. This implies that the increase in the probability of a new Indian Exim Bank loan in response to new Chinese development projects is more pronounced when popular opinion in the recipient country becomes relatively more favorable about China than about India.[38] As the insignificant coefficients on India's approval and disapproval rates

[37] Note that data on public opinion about India are available for 2006–2010 only.

[38] We plot the corresponding marginal effects plots in Appendix Figure A-3.

in columns 3 and 4 show, this finding is driven by the *relative* difference in public sentiment towards India and China rather than by the absolute levels of public support for India in these countries. It also holds when we control for nationalist sentiment.[39] These interaction results are difficult to reconcile with any explanation other than donor competition between the two Asian powers. Replicating the analysis for the Indian MEA, we again find no evidence of a crowding-in effect after the commitment of new Chinese projects—not even in areas that develop a more positive view of China relative to India (column 5).

Commercial and Geopolitical Interests. Improved public opinion ultimately serves the goal of advancing a donor country's interests. As a final test of our competition interpretation, we directly test whether commercial and geopolitical interests are associated with the crowding-in effect. Specifically, we consider commercial and geopolitical factors that have been suggested as "fueling" or intensifying competition. If competition is indeed the driver of the crowding-in effect, the effect should be more pronounced in the countries that matter most to Delhi. Conversely, it is unlikely that these factors matter if the crowding-in effect is driven by imitation or selectivity. Empirically, we separately add an interaction of one of two 'competition-intensifying' variables with our variable of interest to our baseline specification.

First, with respect to commercial competition, we expect that India will be more sensitive to the receipt of Chinese aid and credit in countries to which China and India export similar goods. To test this expectation, we calculate an export similarity index (ESI). We follow the seminal contribution of Finger and Kreinin (1979) and proxy the similarity of the sectoral export structure between India and China in a given country as $\sum_{s=1}^{n} Min(X_s^{India,j}; X_s^{China,j})$, where X represents the respective donor country's exports to recipient country j in the product division s as a share of the donor's total exports to recipient country j.[40] To mitigate concerns about reverse causality, we use trade values from 2007, i.e., the first year of our estimation sample. The resulting index ranges from zero to one, with higher values indicating more similar export structures. In our sample, India and China on average have the most similar export structure in Gambia (0.65), followed by Zambia (0.64), and the index indicates least room for commercial competition in Eritrea (0.03), followed by Somalia (0.09).

Second, concerning geopolitical competition, we expect that the Delhi-based MEA is more responsive to Chinese activities in its neighborhood, as India's geostrategic stakes are much higher in South Asia than elsewhere. If the effects in India's neighborhood

[39]We construct a control variable for nationalist sentiment by adding a variable that captures the approval towards foreign governments more generally. Specifically, we take the mean of leadership approval of the USA, Russia, and the European Union.

[40]Note that s indicates 2-digit codes of the Standard International Trade Classification (Growth Lab, 2019). Fuchs et al. (2015) use this index to analyze aid competition among Western donors.

are stronger, this would support our competition interpretation of the crowding-in effect. We interact our variable of interest with a binary variable that takes a value of one if the recipient country is part of the multilateral organization of the region, Bay of Bengal Initiative for Multi-Sectoral Technical and Economic Cooperation (BIMSTEC).[41] We prefer this variable over a simple geography-based neighborhood dummy because of the long-standing conflict between India and neighboring Pakistan. As Shrivastava (2005, p.973) notes, "[f]or India, membership of BIMSTEC implies closer ties with its eastern neighbours, offsetting the influence of China in the region, sidelining Pakistan, access to [the Association of Southeast Asian Nations], security, economic prosperity due to [the free trade agreement] and clout in regional and international affairs."

Table 7 – Interactions with commercial and geopolitical variables

	Exim Bank loans		MEA aid	
	ESI	BIMSTEC	ESI	BIMSTEC
	(1)	(2)	(3)	(4)
$ChinaOF_{ijt-1}$	-0.021*	0.007*	-0.016	-0.000
	(0.011)	(0.004)	(0.029)	(0.008)
$ChinaOF_{ijt-1}$ × ESI	0.073**		0.045	
	(0.033)		(0.076)	
$ChinaOF_{ijt-1}$ × BIMSTEC		0.017		0.047**
		(0.020)		(0.022)
Controls	✓	✓	✓	✓
Province FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Country-year FE	✓	✓	✓	✓
Observations	18,577	18,657	18,577	18,657
Adjusted R-squared	0.266	0.266	0.610	0.608

Notes: The unit of observation is the province (ADM1 region). Dependent and explanatory variables are binary with 1 indicating if at least one Indian (respectively Chinese) project is committed to a province. Columns 1–2 report estimates for Exim Bank loans; columns 3–4 report estimates for MEA aid. All specifications control for log nighttime light (t-1), log precipitation (t-1), log population (t-1), log conflict-related deaths (t-1). All columns include country-year-fixed effects in addition to province- and year-fixed effects. Robust standard errors clustered at the country level are presented in parentheses. Significant at: $^{***}: p < 0.01$; $^{**}: p < 0.05$; $^{*}: p < 0.1$.

Table 7 presents the results. As expected, we find that India's Exim Bank is more likely to co-locate a project in response to a Chinese project in a given province if India and China have a similar export structure in the respective country (column 1). In quantitative terms, the likelihood of an Exim Bank response is 7.3 percentage points larger in a country where India and China have the same export structure compared to a country where India's and China's exports show no sectoral overlap. The likelihood

[41]The BIMSTEC member states are Bangladesh, Bhutan, India, Myanmar, Nepal, Sri Lanka, and Thailand.

of an Exim Bank loan increases in response to Chinese activities in a given province if the export similarity exceeds 0.4 percent (see also graphical visualization in Appendix Figure A-4). This is further evidence for commercial competition of India with China.[42] By contrast, we find no evidence that India's Exim Bank is more responsive to China's engagement in its neighborhood than elsewhere (column 2).

We repeat the analysis for India's MEA, which is arguably guided to a larger extent by geopolitical motives than the country's Exim Bank. Column 3 shows that India's MEA is not more (or less) likely to respond to a new Chinese project if this is located in a recipient country where both emerging economies have a similar export pattern. This is not surprising given that we have seen above that India's MEA primarily follows geopolitical interests. By contrast, Chinese development projects lead to a crowding-in of Indian MEA aid in India's neighborhood, the BIMSTEC countries (column 4). In quantitative terms, a new Chinese development project in the previous year increases the likelihood of an Indian MEA aid project commitment by 4.7 percentage points if the recipient country is part of this group of strategic importance to India. To sum up, while development aid provided by India's MEA does not follow China's development activities in the average recipient country, the MEA does allocate its development aid to compete with China where it arguably matters most: in India's neighborhood.

5.4 Does China Compete with India?

Competition between actors can be one-sided with only one party reacting to the other but it might also be reciprocal. It is thus an obvious next step to evaluate whether China steps up its development activities when India launches new projects in countries and provinces. Cheru and Obi (2011, p.91) characterize India's strategy vis-à-vis China as one of "playing 'catch up.'" Compared to China's activities, India's development funds are much smaller, the implementation of projects is much slower, and its projects are less visible (Sato et al., 2011). Therefore, China is the likely leader and India is the likely follower and we might not necessarily expect Chinese financing to follow Indian-financed projects. Indeed, China may very well consider its primary competitors to be larger and more established sources of official funds, such as the United States and the World Bank (Humphrey and Michaelowa, 2019, Zeitz, 2020). On the other hand, with its much larger official finance envelope, China might still react to India. For example, China could follow a tit-for-tat strategy when it comes to new projects to send "preemptive" signals.

Tables 8 (OOF) and 9 (ODA) consequently analyze whether China reacts to new Indian official finance projects with new project commitments, i.e., we test the opposite

[42] We replicated the regression with import similarity rather than export similarity. The corresponding interaction did not reach statistical significance at conventional levels. The same is true for interactions with measures of the size of Indian diaspora communities at either the provincial or national level (data from MEA, 2001). Results are shown in Appendix A-6.

Table 8 – China's OOF and Indian official finance (2008–14)

	Baseline (1)	Timing (2)	Placebo (3)	Baseline (4)	Timing (5)	Placebo (6)
$IndiaOF_{ijt+1}$			0.015			0.035
			(0.028)			(0.031)
$IndiaOF_{ijt}$		-0.037*	-0.013		-0.037	-0.032
		(0.019)	(0.022)		(0.025)	(0.030)
$IndiaOF_{ijt-1}$	-0.002	0.000	0.009	-0.014	0.008	0.020
	(0.017)	(0.021)	(0.030)	(0.018)	(0.022)	(0.029)
$IndiaOF_{ijt-2}$		-0.004	0.003		0.013	0.025
		(0.025)	(0.030)		(0.019)	(0.025)
$IndiaOF_{ijt-3}$		-0.024	0.004		-0.017	0.002
		(0.021)	(0.024)		(0.020)	(0.027)
$IndiaOF_{jt+1}$			-0.015			
			(0.009)			
$IndiaOF_{jt}$		-0.001	-0.008			
		(0.009)	(0.008)			
$IndiaOF_{jt-1}$	-0.008	-0.009	-0.014			
	(0.007)	(0.009)	(0.011)			
$IndiaOF_{jt-2}$		0.013	0.019			
		(0.011)	(0.014)			
$IndiaOF_{jt-3}$		0.005	0.011			
		(0.011)	(0.012)			
Controls	✓	✓	✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Country-year FE				✓	✓	✓
Observations	16,339	11,671	9,336	16,325	11,661	9,328
Adjusted R-squared	0.125	0.134	0.151	0.255	0.255	0.246

Notes: The unit of observation is the province (ADM1 region). Dependent and explanatory variables are binary with 1 indicating if at least one Chinese OOF (respectively Indian official finance) project is committed to a province. All specifications control for log nighttime light (t-1), log precipitation (t-1), log population (t-1), and log conflict-related deaths (t-1). Columns 4–6 include country-year-fixed effects in addition to province- and year-fixed effects. Robust standard errors clustered at the country level are presented in parentheses. Significant at: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

direction of our main argument using the same empirical strategy. The tables replicate the results from Table 1 and Table 3 but switch the dependent variable and the main variables of interest. Overall, there is no evidence of a crowding-in of Chinese development projects—neither for aid in the strict sense nor for more commercially-oriented flows—in response to new Indian project commitments. It does not appear that China uses development finance as a tool of competition with India in a systematic manner.[43] This also holds when we look at monetary amounts and project counts rather than project dummies, or break down Indian official finance into Exim Bank loans and MEA aid (see Appendix Tables A-7 and A-8 for details). These non-findings suggest that while India

[43]In column 2, the coefficient on $IndiaOF_{ijt}$ is even negative but the coefficient is very small, only weakly significant, and not robust as can be seen in column 3, for example.

competes with China with development finance, the opposite does not appear to be the case. Furthermore, these results mitigate concerns that this paper's main finding of a positive crowding-in of Indian projects in response to Chinese projects is driven by reverse causality.

Table 9 – China's ODA and Indian official finance (2008–14)

	Baseline (1)	Timing (2)	Placebo (3)	Baseline (4)	Timing (5)	Placebo (6)
$IndiaOF_{jt+1}$			0.023			0.013
			(0.027)			(0.025)
$IndiaOF_{jt}$		-0.000	0.004		0.027	0.017
		(0.025)	(0.028)		(0.024)	(0.030)
$IndiaOF_{jt-1}$	0.004	0.008	-0.004	0.016	0.034	0.030
	(0.018)	(0.028)	(0.042)	(0.025)	(0.026)	(0.033)
$IndiaOF_{jt-2}$		-0.022	-0.044		0.014	-0.012
		(0.029)	(0.035)		(0.038)	(0.041)
$IndiaOF_{jt-3}$		0.019	0.021		0.033	0.038
		(0.029)	(0.035)		(0.033)	(0.040)
$IndiaOF_{jt+1}$			-0.006			
			(0.014)			
$IndiaOF_{jt}$		0.016	0.022			
		(0.013)	(0.016)			
$IndiaOF_{jt-1}$	0.002	-0.001	-0.001			
	(0.008)	(0.012)	(0.013)			
$IndiaOF_{jt-2}$		0.006	0.007			
		(0.016)	(0.019)			
$IndiaOF_{jt-3}$		-0.005	-0.006			
		(0.011)	(0.012)			
Controls	✓	✓	✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Country-year FE				✓	✓	✓
Observations	16,339	11,671	9,336	16,325	11,661	9,328
Adjusted R-squared	0.277	0.283	0.291	0.380	0.390	0.393

Notes: The unit of observation is the province (ADM1 region). Dependent and explanatory variables are binary with 1 indicating if at least one Chinese ODA (respectively Indian official finance) project is committed to a province. All specifications control for log precipitation (t-1), log population (t-1), and log conflict-related deaths (t-1). Columns 4–6 include country-year-fixed effects in addition to province- and year-fixed effects. Robust standard errors clustered at the country level are presented in parentheses. Significant at: $^{***}: p < 0.01$; $^{**}: p < 0.05$; $^{*}: p < 0.1$.

6 Concluding Remarks

Does India compete with China in developing countries using development finance? To tackle this research question, we constructed a new dataset on Indian development finance that covers 1,194 projects at 4,308 project intervention sites in 93 countries on all continents and then tested whether India increases its development footprint in response to new Chinese project commitments in the previous years.

Our regression results on a sample covering 2,333 provinces within 123 countries confirm that India's Exim Bank is more likely to allocate a credit-financed project to a subnational locality if the Chinese government provided financing there in the previous year. We observe weaker effects also at the national level. Since our effect is more pronounced in countries where China has made public opinion gains relative to India and where both lenders have a similar export structure, we interpret this as evidence of India competing with China. By contrast, development aid provided by India's MEA does not follow China's development activities in the average recipient country. We only find that the MEA allocates its development aid to compete with China where it arguably matters most: in India's neighborhood. Since we find only robust evidence of competition for India's Exim Bank, which primarily follows commercial objectives, we conclude that India is engaging primarily in commercial rather than geopolitical competition with China. Finally, analyzing China's possible response to Indian development activities, we find no evidence that Indian projects crowd in Chinese projects in the same localities.

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A Appendix

Table A-1 – Top 10 recipient countries of Indian and Chinese OF projects (2007–2014)

Rank	India	China
1	Nepal (127)	Cambodia (125)
2	Afghanistan (106)	Zimbabwe (82)
3	Myanmar (88)	Pakistan (73)
4	Bhutan (82)	Tanzania (68)
5	Sri Lanka (67)	Sri Lanka (65)
6	Bangladesh (65)	Liberia (64)
7	Maldives (44)	Ethiopia (64)
8	Laos (21)	Cameroon (63)
9	Liberia (20)	Kenya (61)
10	Ghana (17)	Ghana (61)

Note: We report the total number of projects committed during the 2007–2014 period in parentheses.
Source: India: Authors' data, China: Dreher et al. (2021).

Table A-2 – The 10 largest Indian Export-Import Bank projects, in terms of committed amounts in million constant 2014 US$ (2007–2014)

Rank	Recipient	Year	Title (shortened)	Commitment
1	Nepal	2014	Extension of Goi Supported Line of Credit	921.1
2	Myanmar	2012	Line of Credit for Myanmar Foreign Trade Bank	474.9
3	Sri Lanka	2009	Track laying	432.0
4	Sri Lanka	2010	Line of Credit to the government of Sri Lanka	382.4
5	Sri Lanka	2012	Line of Credit for financing various projects	363.2
6	Nepal	2012	Line of Credit for financing infrastructure projects	237.4
7	Ethiopia	2010	Line of Credit to the government of Ethiopia	213.3
8	Myanmar	2013	Two Lines of Credit to Myanmar Foreign Trade Bank (MFTB)	186.2
9	Tanzania	2012	Line of Credit for water supply schemes in Dar-es-Salaam and Chalinzi	169.2
10	Ethiopia	2008	Development of Sugar industry	168.4

Source: India: Authors' data.

Table A-3 – The 10 largest Indian Ministry of External Affairs projects, in terms of committed amounts in million constant 2014 US$ (2007–2014)

Rank	Recipient	Year	Title (shortened)	Commitment
1	Afghanistan	2010	Salma Dam Project	218.7
2	Bhutan	2013	Punatsangchu-II Hydroelectric Project	143.8
3	Bhutan	2013	Mangdechhu Hydroelectric Project	141.4
4	Bhutan	2013	Punatsangchu-I Hydroelectric Project	117.4
5	Bhutan	2013	Project-Tied Assistance (PTA)	95.8
6	Bangladesh	2013	Grant assistance	87.9
7	Bhutan	2014	Project Tied Assistance	79.7
8	Bhutan	2011	Punatsangchhu-I Hydroelectric Project	72.7
9	Bhutan	2008	Project Tied Assistance	69.8
10	Sri Lanka	2013	Reconstruction and Repair of houses for Internally Displaced Persons (IDPs)	69.2

Source: India: Authors' data.

Table A-4 – Data Sources

Variable	Description	Source
	Indian official financing	
Indian OF project	1 if at least one Indian Ministry of External Affairs (MEA) or Exim Bank project is committed to ADM1	Authors' data
Indian Exim Bank project	1 if at least one Exim Bank project is committed to ADM1	Authors' data
Indian MEA project	1 if at least one MEA project is committed to ADM1	Authors' data
Indian OF projects (count)	Number of Indian MEA or Exim Bank projects committed to ADM1, logarithm, 1 is added before taking the logarithm	Authors' data
Indian Exim Bank projects (count)	Number of Indian Exim Bank projects committed to ADM1, logarithm, 1 is added before taking the logarithm	Authors' data
Indian MEA projects (count)	Number of Indian MEA projects committed to ADM1, logarithm, 1 is added before taking the logarithm	Authors' data
Indian OF amount	Amount of Indian MEA and Exim Bank commitments to ADM1 in constant 2014 US$, logarithm, 1 is added before taking the logarithm	Authors' data
Indian Exim Bank amount	Amount of Indian Exim Bank commitments to ADM1 in constant 2014 US$, logarithm, 1 is added before taking the logarithm	Authors' data
Indian MEA amount	Amount of Indian MEA commitments to ADM1 in constant 2014 US$, logarithm, 1 is added before taking the logarithm	Authors' data
Indian OF project, country level	1 if at least one Indian OF project is committed to the recipient country (ADM0) in any of its ADM1 regions	Authors' data
	Chinese official financing	
Chinese OF project	1 if at least one Chinese ODA-like, OOF-like or Vague (Official Finance) project is committed to ADM1, one-year lag	Bluhm et al. (2020)
Chinese ODA project	1 if at least one Chinese ODA-like project is committed to ADM1, one-year lag	Bluhm et al. (2020)

Table A-4 Data Sources, Continued

Variable	Description	Source
Chinese OOF project	1 if at least one Chinese OOF-like or Vague (Official Finance) project is committed to ADM1, one-year lag	Bluhm et al. (2020)
Chinese OF projects (count)	Number of Chinese ODA-like, OOF-like and Vague (Official Finance) projects to ADM1 in constant 2014 US$, one-year lag, logarithm, 1 is added before taking the logarithm	Bluhm et al. (2020)
Chinese OF amount	Amount of Chinese ODA-like, OOF-like and Vague (Official Finance) commitments to ADM1 in constant 2014 US$, one-year lag, logarithm, 1 is added before taking the logarithm	Bluhm et al. (2020)
Chinese OF project, country level	1 if at least one Chinese ODA-like, OOF-like or Vague (Official Finance) project is committed to the recipient country (ADM0) in any of its ADM1 regions, one-year lag	Dreher et al. (2021)
	Cross-country correlates	
Distance to India	Distance from recipient country to India, logarithm, 1 is added before taking the logarithm	Mayer and Zignago (2011)
UN voting with India	Voting alignment between recipient country and India in the UN General Assembly, one-year lag	Bailey et al. (2017)
Indian exports	Indian exports to the recipient country, one-year lag, logarithm, 1 is added before taking the logarithm	IMF (2016)
Debt/GDP	Recipient's debt-to-GDP ratio, one-year lag	Kose et al. (2017)
GDP per capita	GDP per capita of the recipient country, one-year lag, logarithm	World Bank (2017)
Population	Population count, one-year lag, logarithm	World Bank (2017)
Indian migrants	Number of Indians living in the recipient country in 2000, logarithm, 1 is added before taking the logarithm	World Bank (2017)
	Control Variables	
Nighttime light	Mean value of light pixel in ADM1, one-year lag, logarithm, 1 is added before taking the logarithm	Elvidge et al. (2017), Goodman et al. (2019)

Table A-4 Data Sources, Continued

Variable	**Description**	**Source**
Conflict-related deaths	Number of conflict-related fatalities in ADM1, one-year lag, logarithm, 1 is added before taking the logarithm	Gleditsch et al. (2002), Allansson et al. (2017)
Precipitation	Average annual precipitation in centimeter in ADM1, on year lag, logarithm, 1 is added before taking the logarithm	Willmott and Matsuura (2001), Goodman et al. (2019)
Distance to capital	Simple distance from ADM1 province centroid to capital city, in km, logarithm	Authors' calculations
Population	Number of inhabitants in ADM1, one-year lag, logarithm, 1 is added before taking the logarithm	CIESIN (2016), Goodman et al. (2019)
Approve India [China]	1 if the answer to the survey question "Do you approve or disapprove of the job performance of the leadership of India [China]?" is approve and 0 otherwise. Possible answers are: approve, disapprove, don't know, refused to answer, one-year lag	Gallup (2018)
Disapprove India [China]	1 if the answer to the survey question "Do you approve or disapprove of the job performance of the leadership of India [China]?" is disapprove and 0 otherwise, one-year lag	Gallup (2018)
Approval distance 1	Difference between approval value for China and approval value of India, including "don't know" and "refuse to answer", one-year lag	Gallup (2018)
Approval distance 2	Difference between approval value for China and approval value of India, excluding "don't know" and "refuse to answer", one-year lag	Gallup (2018)
Nationalist sentiment	Mean of leadership approvals of the USA, Russia, and the European Union. Values based on the survey question about the respective country as stated for the variable *Approve India*, one-year lag	Gallup (2018)

Table A-4 Data Sources, Continued

Variable	Description	Source
ESI	Export similarity index computed as $\sum_{s=1}^{n} Min(X_s^{India,j}; X_s^{China,j})$, with X representing a donor country's (Chinese or Indian) exports to recipient country j in the product division s as a share of the donor's total exports to recipient country j in 2007. Note that s indicates 2-digit codes of the Standard International Trade Classification (Growth Lab, 2019)	Authors' calculations with data from Growth Lab (2019)
ISI	Import similarity index computed as $\sum_{s=1}^{n} Min(M_s^{India,j}; M_s^{China,j})$, with M representing a donor country's (Chinese or Indian) imports from recipient country j in the product division s as a share of the donor's total imports to recipient country j in 2007. Note that s indicates 2-digit codes of the Standard International Trade Classification (Growth Lab, 2019)	Authors' calculations with data from Growth Lab (2019)
BIMSTEC	1 for member countries of the Bay of Bengal Initiative for Multi-Sectoral Technical and Economic Cooperation (BIMSTEC): member states are Bangladesh, Bhutan, India, Myanmar, Nepal, Sri Lanka, and Thailand	Own coding
Indian diaspora (national)	1 if the recipient country has a (contemporaneous or historic) Indian diaspora community, 2001	MEA (2001)
Indian diaspora (subnational)	1 if there is Indian diaspora in ADM1, 2001	MEA (2001)

Table A-5 – Descriptive statistics

Variable	Count	Mean	SD	Min	Max
Indian offical financing					
Indian OF project	18673	0.04	0.20	0.00	1.00
Indian Exim Bank project	18673	0.01	0.07	0.00	1.00
Indian MEA project	18673	0.04	0.19	0.00	1.00
Indian OF projects (count)	18673	0.04	0.20	0.00	1.00
Indian Exim Bank projects (count)	18673	0.01	0.11	0.00	4.00
Indian MEA projects (count)	18673	0.10	1.00	0.00	48.00
Indian OF amount (million US$)	18673	0.49	6.89	0.00	288.82
Indian Exim Bank amount (million US$)	18673	0.30	5.81	0.00	271.67
Indian MEA amount (million US$) n	18673	0.19	3.61	0.00	288.82
Indian OF project, country level	18673	0.26	0.44	0.00	1.00
Indian OF projects (count), country level	18673	0.85	2.75	0.00	35.00
Indian OF amount (thousand US$), country level	18673	0.01	0.05	0.00	0.99
Indian Exim Bank project: Social Infrastructure & Services	18673	0.00	0.01	0.00	1.00
Indian Exim Bank project: Economic Infrastructure & Services	18673	0.00	0.05	0.00	1.00
Indian Exim Bank project: Production Sectors	18673	0.00	0.03	0.00	1.00
Indian Exim Bank project: Energy Generation & Supply	18673	0.00	0.04	0.00	1.00
Indian Exim Bank project: Transport & Storage	18673	0.00	0.03	0.00	1.00
Indian Exim Bank project: Health	18673	0.00	0.03	0.00	1.00
Indian MEA project: Social Infrastructure & Services	18673	0.00	0.06	0.00	1.00
Indian MEA project: Economic Infrastructure & Services	18673	0.01	0.11	0.00	1.00
Indian MEA project: Production Sectors	18673	0.00	0.05	0.00	1.00
Indian MEA project: Energy Generation & Supply	18673	0.00	0.06	0.00	1.00
Indian MEA project: Transport & Storage	18673	0.00	0.06	0.00	1.00
Indian MEA project: Health	18673	0.00	0.06	0.00	1.00

Table A-5 Descriptive statistics, Continued

Variable	**Count**	**Mean**	SD	**Min**	**Max**
Chinese official financing					
Chinese OF project	18673	0.08	0.27	0.00	1.00
Chinese OOF project	18673	0.03	0.17	0.00	1.00
Chinese ODA project	18673	0.05	0.23	0.00	1.00
Chinese OF amount (million US$)	18673	7.81	176.54	0.00	20356.48
Chinese OF projects (count)	18673	0.16	0.73	0.00	22.00
Chinese OF project, country level	18673	0.66	0.47	0.00	1.00
Chinese OF projects (count), country level	18673	2.52	3.39	0.00	35.00
Chinese OF amount (million US$), country level	18673	403.30	2454.80	0.00	35465.06
Chinese OF project: Social Infrastructure & Services	18673	0.04	0.19	0.00	1.00
Chinese OF project: Economic Infrastructure & Services	18673	0.03	0.18	0.00	1.00
Chinese OF project: Production Sectors	18673	0.01	0.09	0.00	1.00
Chinese OF project: Energy Generation & Supply	18673	0.01	0.09	0.00	1.00
Chinese OF project: Transport & Storage	18673	0.02	0.14	0.00	1.00
Chinese OF project: Health	18673	0.02	0.14	0.00	1.00
Control variables					
Nighttime light	16338	3.87	7.38	0.00	63.00
Precipitation	18668	97.59	73.48	0.04	537.62
Population (million)	18673	1.37	3.55	0.00001	101.61
Conflict-related deaths	18673	15.50	145.72	0.00	7331.44
Interaction variables					
Approve India	5739	0.30	0.16	0.07	0.79
Disapprove India	5739	0.27	0.14	0.04	0.73
Approval distance 1	5739	-0.11	0.12	-0.61	0.34
Approval distance 2	5739	-0.11	0.10	-0.57	0.17
Nationalist sentiment	14090	0.39	0.17	0.05	0.88
ESI	18593	0.38	0.11	0.04	0.65
BIMSTEC	18673	0.06	0.24	0.00	1.00
ISI	18593	0.37	0.28	0.00	1.00
Indian diaspora (national)	18673	0.47	0.50	0.00	1.00
Indian diaspora (subnational)	18673	0.08	0.27	0.00	1.00

Table A-6 – Interactions with additional variables (see footnote 42)

	Indian Exim Bank loans			Indian MEA aid		
	(1)	(2)	(3)	(4)	(5)	(6)
$ChinaOF_{ijt-1}$	0.002	0.006	0.007*	0.011	0.009	0.005
	(0.006)	(0.006)	(0.004)	(0.015)	(0.013)	(0.008)
$ChinaOF_{ijt-1}$ × ISI	0.016			-0.026		
	(0.015)			(0.029)		
$ChinaOF_{ijt-1}$ × Indian diaspora (national)		0.003			-0.014	
		(0.008)			(0.016)	
$ChinaOF_{ijt-1}$ × Indian diaspora (subnational)			0.006			-0.012
			(0.013)			(0.035)
Controls	✓	✓	✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Country-year FE	✓	✓	✓	✓	✓	✓
Observations	18,577	18,657	18,657	18,577	18,657	18,657
Adjusted R-squared	0.266	0.265	0.265	0.610	0.607	0.607

Notes: The unit of observation is the province (ADM1 region). Dependent and explanatory variables are binary with 1 indicating if at least one Chinese (respectively Indian) project is committed to an ADM1 region. Columns 1–3 report estimates for the subset of Indian Exim Bank loans, while columns 4–6 document estimates for the subset of Indian MEA aid. All specifications control for log nighttime light (t-1), log precipitation (t-1), log population (t-1), log conflict related deaths (t-1). Robust standard errors clustered at the country level are presented in parentheses. Significant at: $^{***}: p < 0.01$; $^{**}: p < 0.05$; $^{*}: p < 0.1$.

Table A-7 – Sensitivity analysis for Table 8: China's OOF and Indian official finance

		Projects in		Response to	
	No controls	(log) \$ amounts	(log) Count	Indian Exim Bank loans	Indian MEA aid
	(1)	(2)	(3)	(4)	(5)
$IndiaOF_{jt-1}$	-0.013	-0.018	-0.021	-0.035	-0.012
	(0.018)	(0.022)	(0.025)	(0.031)	(0.021)
Controls		✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Country-year FE	✓	✓	✓	✓	✓
Observations	17,122	16,325	16,325	16,325	16,325
Adjusted R-squared	0.250	0.243	0.284	0.255	0.255

Notes: The unit of observation is the province (ADM1 region). Dependent and explanatory variables are binary in column 1, with 1 indicating if at least one Chinese OOF (respectively Indian official finance) project is committed to a province, in logged US\$ amounts in column 2, and in logged project counts in column 3, respectively. Columns 4 and 5 document how Chinese OOF commitments react toward Indian Exim Bank loans and MEA aid projects, respectively. Except for column 1, all specifications control for log nighttime light (t-1), log precipitation (t-1), log population (t-1), and log conflict-related deaths (t-1). Robust standard errors clustered at the country level are presented in parentheses. Significant at: $^{***}: p < 0.01$; $^{**}: p < 0.05$; $^{*}: p < 0.1$.

Table A-8 – Sensitivity analysis for Table 9: China's ODA and Indian official finance

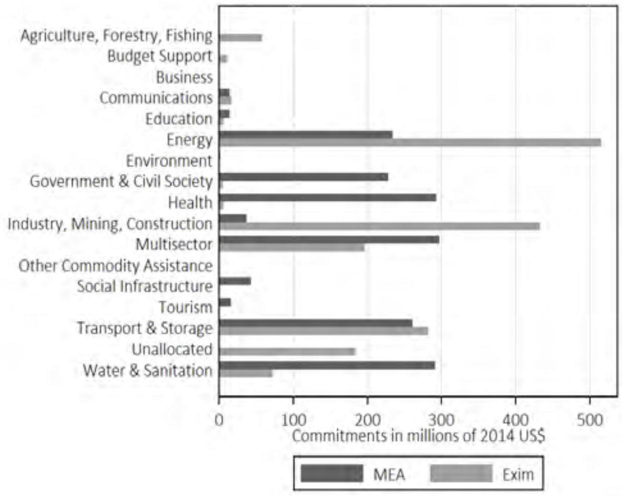
		Projects in		Response to	
	No controls	(log) $ amounts	(log) Count	Indian Exim Bank loans	Indian MEA aid
	(1)	(2)	(3)	(4)	(5)
$IndiaOF_{jt-1}$	0.014	-0.025	-0.010	-0.016	0.024
	(0.025)	(0.022)	(0.037)	(0.046)	(0.028)
Controls		✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Country-year FE	✓	✓	✓	✓	✓
Observations	17,122	16,325	16,325	16,325	16,325
Adjusted R-squared	0.383	0.306	0.411	0.380	0.380

Notes: The unit of observation is the province (ADM1 region). Dependent and explanatory variables are binary in column 1, with 1 indicating if at least one Chinese ODA (respectively Indian official finance) project is committed to a province, in logged US$ amounts in column 2, and in logged project counts in column 3, respectively. Columns 4 and 5 document how Chinese ODA commitments react toward Indian Exim Bank loans and MEA aid projects, respectively. Except for column 1, all specifications control for log nighttime light (t-1), log precipitation (t-1), log population (t-1), and log conflict-related deaths (t-1). Robust standard errors clustered at the country level are presented in parentheses. Significant at: $^{***}: p < 0.01$; $^{**}: p < 0.05$; $^{*}: p < 0.1$.

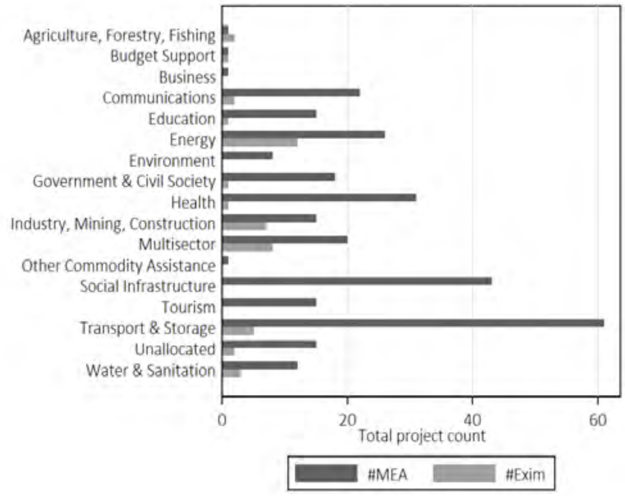
Figure A-1 – Comparing Indian and Chinese official finance by sector (2007–2014)

Panel A—India

(a) Amount

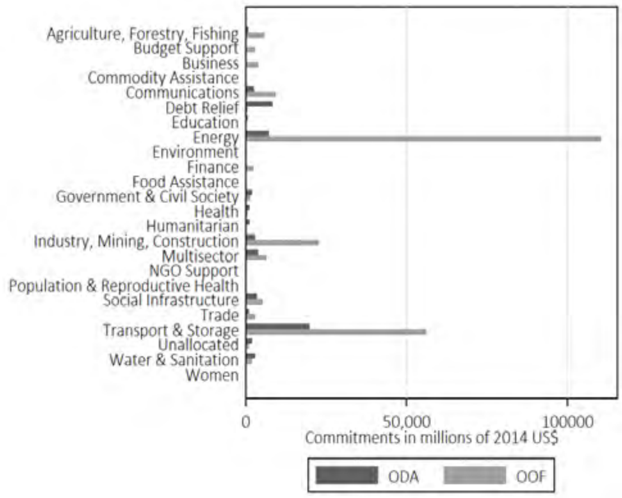


(b) Count

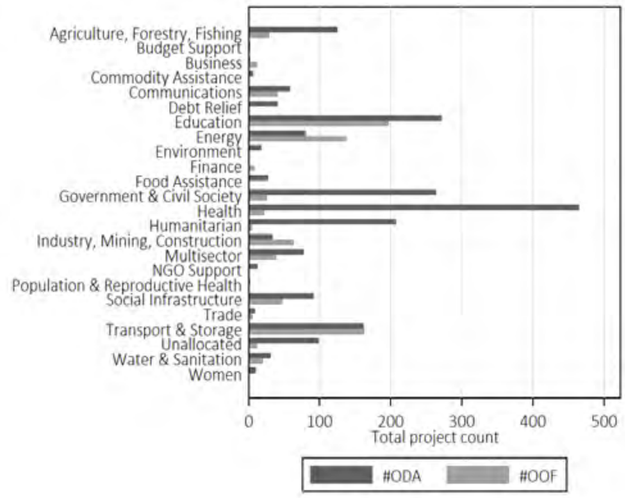


Panel B—China

(c) Amount



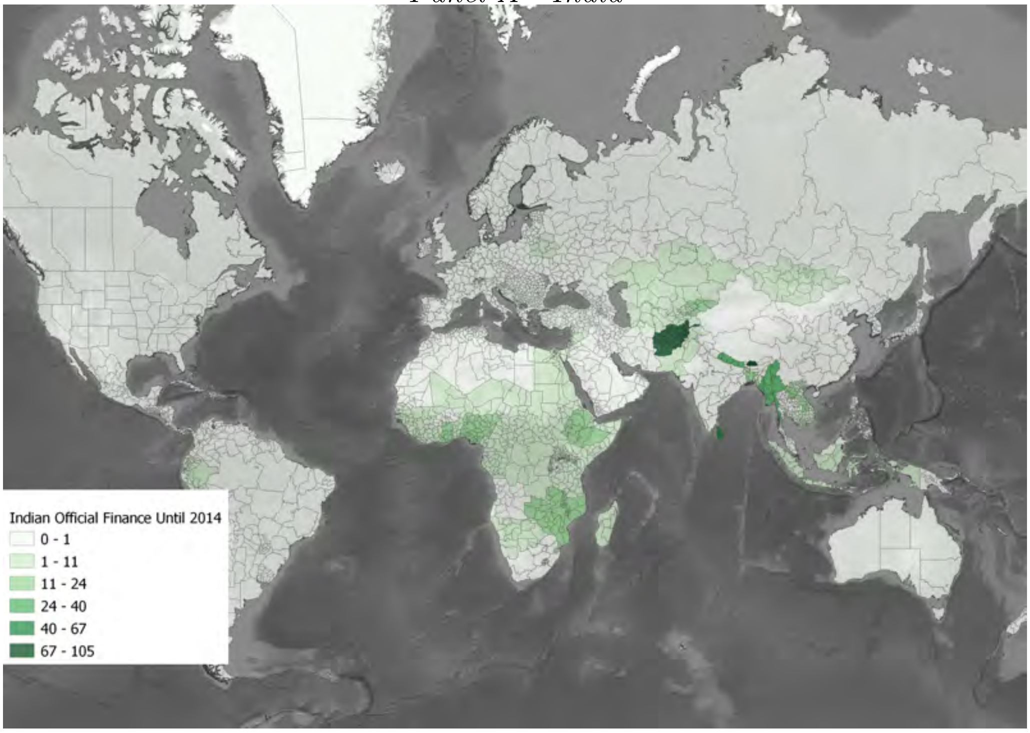
(d) Count



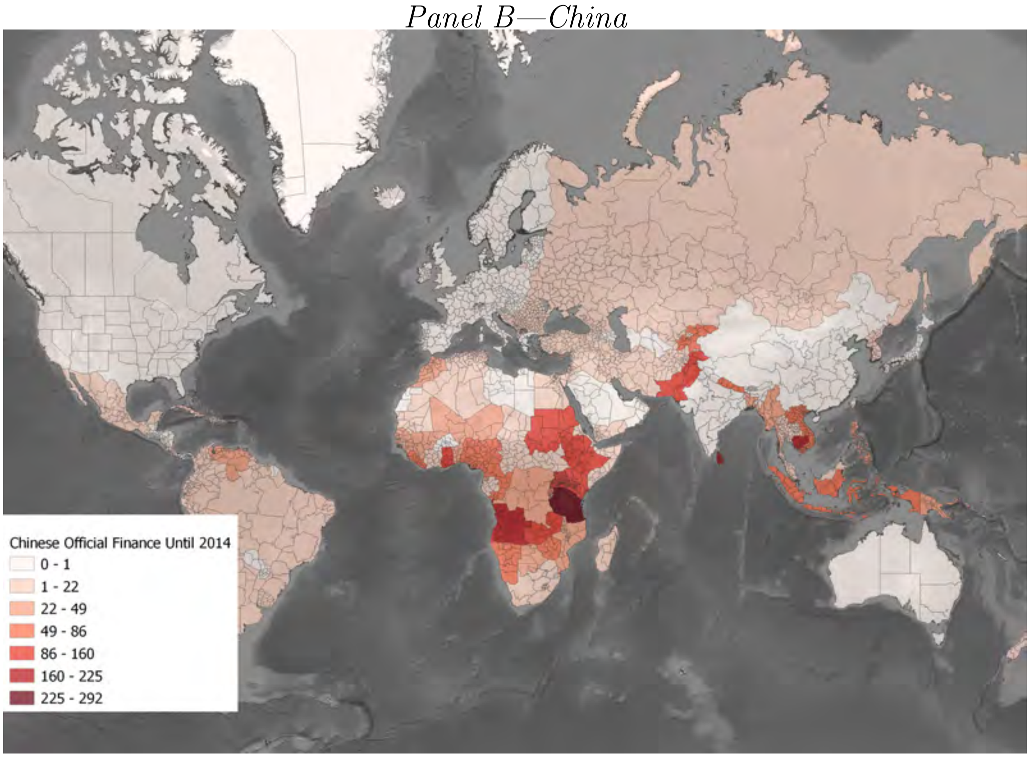
Notes: Panel A displays the number of India's official finance (OF) projects by sector (source: Authors' data). Panel B displays the number of China's official finance (OF) projects by sector (source: Dreher et al. 2021). We used OECD-DAC Creditor Reporting System (CRS) sector codes to categorize the projects.

Figure A-2 – Number of India's and China's official finance projects by recipient country (2007–2014)

Panel A—India

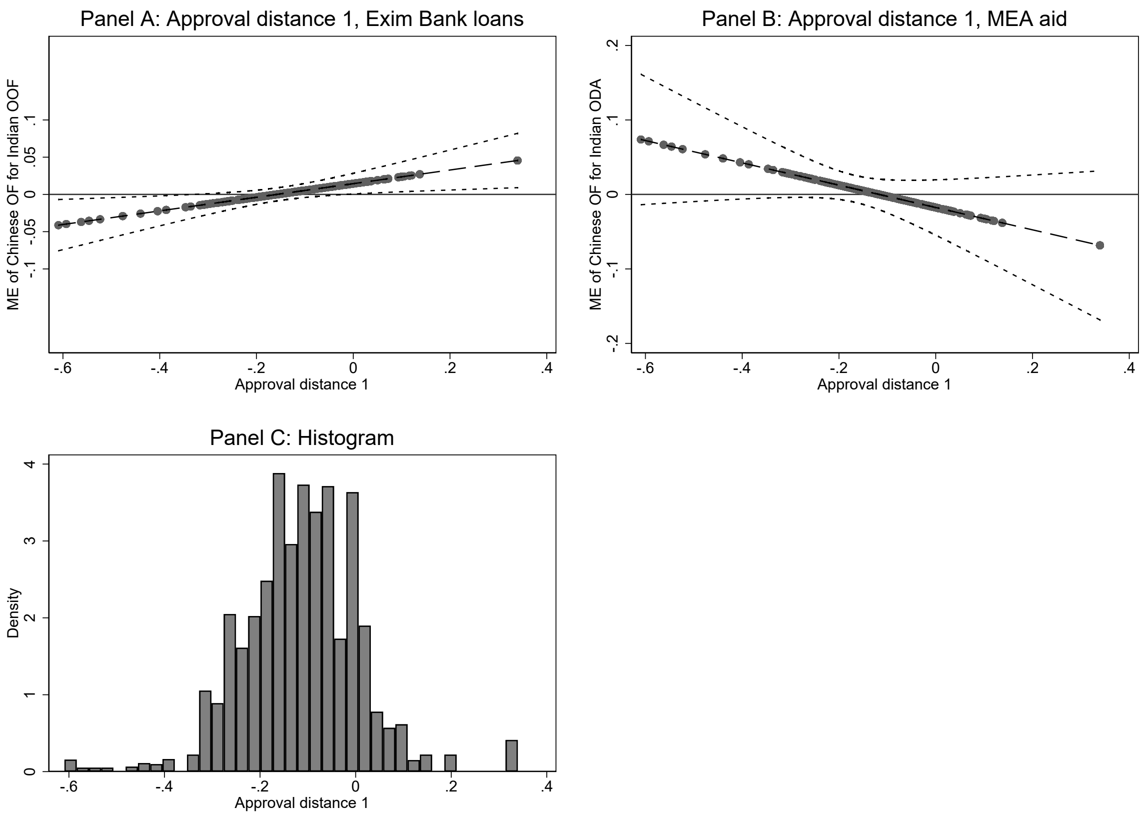


Panel B—China



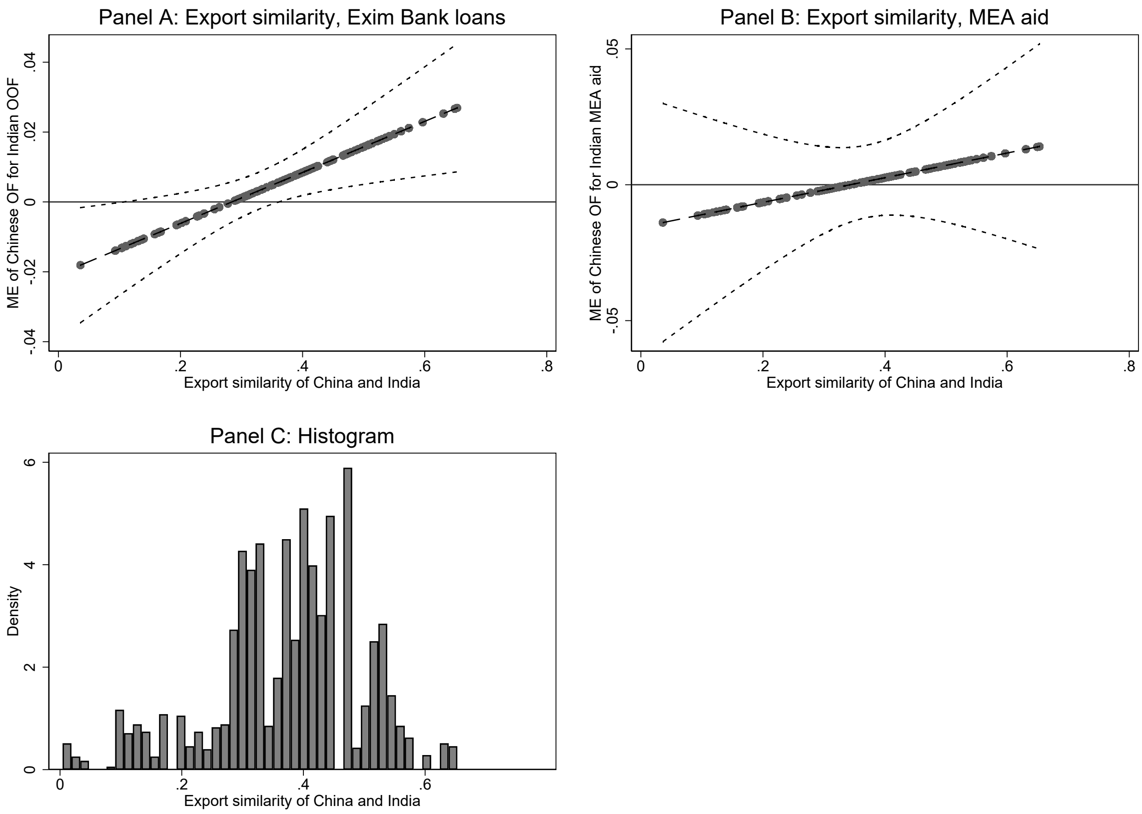
Notes: Panel A displays the number of India's official finance (OF) projects by recipient country (source: Authors' data). Panel B displays the number of China's official finance (OF) projects by recipient country (source: Dreher et al. 2021).

Figure A-3 – Marginal effects: Approval distance 1



Notes: Panel A shows the marginal effects for the Exim Bank loans model of column 1 in Table 6 and the corresponding 90%-confidence interval. Panel B shows the marginal effects for the MEA aid model of column 5 in 6 and the corresponding 90%-confidence interval. Panel C shows the distribution of this approval distance variable in our sample.

Figure A-4 – Marginal effects: Export Similarity Index



Notes: Panel A shows the marginal effects for the Exim Bank loans model of column 1 in Table 7 and the corresponding 90%-confidence interval. Panel B shows the marginal effects for the MEA aid model of column 3 in 7 and the corresponding 90%-confidence interval. Panel C shows the distribution of the export similarity index in our sample.