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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 article explores whether India uses these financial instruments to compete for geopolitical and commercial influence with China. We build a new geocoded dataset of Indian government-financed projects in the Global South 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 India is more popular relative to China 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.

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development finance, foreign aid, official development assistance, official credits, South-South cooperation, China, India, geostrategic competition, geospatial analysis

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 (Brewster 2015; Mullen and Poplin 2015). 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, 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.[2] During our own interviews with decision makers in Delhi, 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."[3]

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. Specifically, 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*) and same subnational locality (*Hypothesis 2*). We then evaluate whether India's behavior is consistent with the notion that it is seeking to compete with China.[4]

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, 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 is more or less favorable towards India than China. 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).

Existing research on the competitive use of development finance focuses on rivalry between traditional providers of development finance (Davies and Klasen 2019; Fuchs, Öhler, and Nunnenkamp 2015; Mascarenhas and Sandler 2006) and rivalry between established and emerging powers (Bueno de Mesquita and Smith 2016; Hernandez 2017; Humphrey and Michaelowa 2019; Zeitz 2021). 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 1,196 Indian government-financed projects in 4,308 locations within 93 countries from 2007 to 2014.[5] In sum, the monetary value of these projects amounts to US$14.58 billion (in constant 2014 values). The 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. 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 country-province- and 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 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 oversees a substantially larger portfolio of overseas development projects (Asmus, Fuchs, and Müller 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 (Davies and Klasen 2019). 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. 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 selectivity and imitation. First, we partially 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. Second, 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. It is thus unlikely that India is simply responding (more slowly) to the same allocation criteria than China. In recognition of the fact that imitation most likely occurs within sectors but competition can occur across sectors, this sectoral finding is also inconsistent with the alternative explanation of imitation. Third, in order to test whether India is motivated by a desire for greater influence vis-à-vis China, we leverage data from the Gallup World Poll. We find that India's Exim Bank is more likely to increase its financial footprint in jurisdictions where it is more 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 (Bunte 2019; Horn, Reinhart, and Trebesch 2021; Kaya, Kilby, and Kay 2021; Werker, Ahmed, and Cohen 2009). Less concessional and more commercially-oriented projects make up a substantial proportion of the official financing that Southern providers of development finance commit to their peers each year, yet they largely represent a blind spot in the empirical literature.

A New Dataset: Indian Development Finance at the Project Level

In collaboration with AidData, a research lab at 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 (see Appendix C for details on the data collection process). The first step of the data collection process was to retrieve project-level information from official government documents. The resulting database consists of 1,196 projects in 93 countries from 2007 to 2014. In sum, the monetary value of these projects amounts to US$14.58 billion (in constant 2014 values), of which US$9.56 billion were committed by the Exim Bank and US$5.02 billion originate from the MEA. In a second step, we allocated all projects to (sub)sectors according to the OECD-DAC definitions, ranging from "Education" to "Humanitarian Assistance."

In a third step, we geocoded all of the projects in this database. Our 1,196 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. As illustrated in Figure 1 for the 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 infrastructure projects. For our empirical analysis below, we then extracted all first administrative units through which a line feature cuts. The spatial precision of 599 projects is sufficient so that we can assign 2,166 project locations to their respective province. Figure 2 presents these project locations in a world map.

Aggregating the project-level data to the level of world regions, we observe that India prioritizes Africa and Asia. The African countries receiving most projects are Liberia, Ghana, Malawi, Mauritius, and Mozambique. Nepal, Afghanistan, Myanmar, Bhutan, and Sri Lanka top the list of India's Asian recipients. We also observe 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 percent of India's financing commitments in our dataset are from the Exim Bank, while only 36 percent come from the MEA. In contrast, the MEA dominates with 88 percent in terms of the number of projects and is represented in almost three times more subnational locations.

This new dataset allows us to test whether our expectation (explained in more detail in Appendix B) that MEA aid is mainly driven by geopolitical interests and Exim Bank loans follow primarily commercial interests are reflected in the data. Figure 3 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.[8] 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

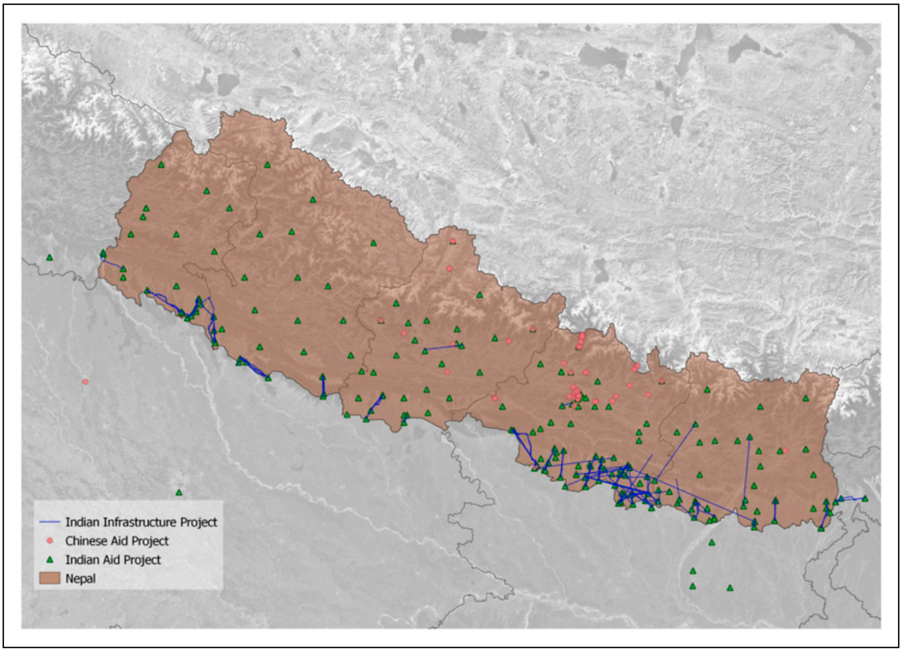

Figure 1. Geocoded Indian and Chinese development projects in Nepal (2000/07–2014).
Notes. This figure illustrates the locations of development projects in Nepal. The green triangles represent the locations of Indian development projects (2007–2014). The blue lines represent line features of Indian development projects, including the Terai Road project. The red circles represent the locations of Chinese development projects (2000–2014). Source: India: Authors' data, China: Bluhm et al. (2020).

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, UN voting and geographic distance, do not turn out to be significant predictors of Exim Bank loans. Based on these results and our theoretical considerations (Appendix B), 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 commercial competition.

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

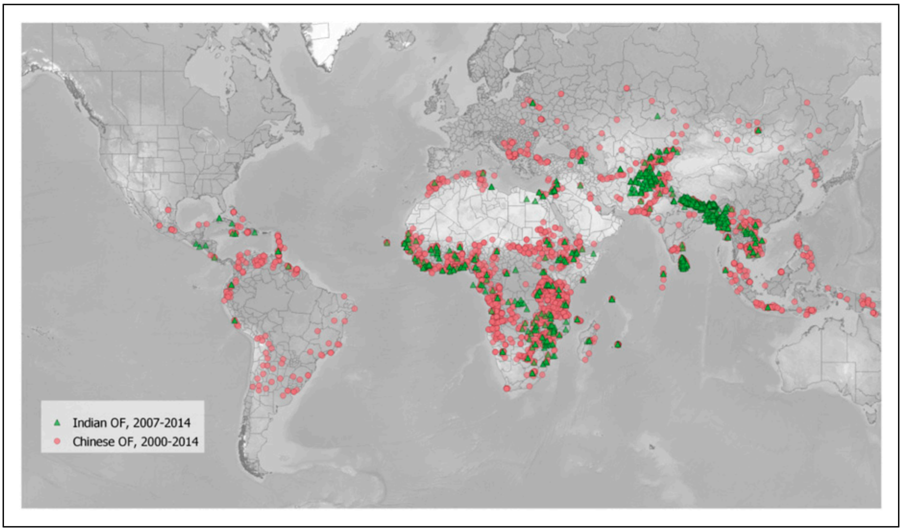

Figure 2. World map of Indian and Chinese government-financed project locations (2000/07–2014).
Notes. Source: India: Authors' data, China: Bluhm et al. (2020).

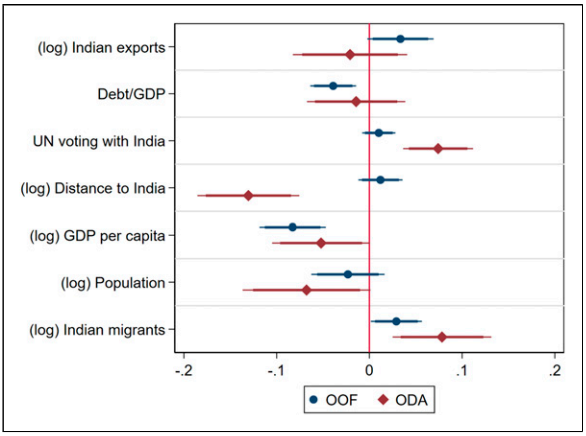

Figure 3. Marginal effects of potential determinants of India's allocation of Exim Bank loans (OOF) and MEA aid (ODA) (standardized coefficients, OLS, 2007–2014).
Notes. The figure shows the results of least-squares regressions of India's country allocation of Exim Bank loans (in blue) and MEA aid (in red) over 8 years (2007–2014). The dots represent a one-standard-deviation change in the respective explanatory variable on the logged monetary amount of countrywide Indian OOF and ODA, respectively (together with 90 percent and 95 percent 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 percent (Exim Bank) and 32.8 percent (MEA), respectively. Source: Authors' calculations.

jurisdictions as China's official financing activities in the 2007–2014 period. First, we test whether India is more likely to commit a development project to a province if China finances a new project in 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 in the same province (*Hypothesis 2*). To test our hypotheses about the allocation of Indian official finance across provinces, we use a linear probability model with country-province- and year-fixed effects. Formally, we run the following regression model

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

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 new Chinese project in the same country in the previous year $t-1$; $ChinaOF_{ijt-1}$ is a binary variable for a new 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 monetary 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 Chinese projects lack information on their monetary value (Dreher et al. 2021, 2022). Moreover, given that only 4.2 percent of province-years in our sample are "treated" with Indian and 7.7 percent with Chinese projects, the use of monetary amounts is more likely to be biased by outliers. Therefore, our preferred measure is the binary project variable.

We include the following control variables that vary across provinces and time and are lagged by 1 year: the logarithm of average nighttime light to proxy the provincial level of development; the logarithm of average precipitation and the number of conflict fatalities to control for temporary shocks; the logged population level as a larger population might increase the probability of receiving a project; and a binary variable for projects extended by the World Bank to account for the regional dynamics of one of the most important providers of development finance. For the latter, we use loan projects extended by the World Bank's International Bank for Reconstruction and Development (IBRD) in Exim Bank loan regressions and International Development Association (IDA) aid projects in MEA aid regressions. Country-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).[9] 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 C-4 provides detailed definitions and sources and Appendix Table C-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

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

where country-year-fixed effects are denoted by ζ_{jt}. In addition to the other fixed effects, they account for shocks common 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 (unobserved) 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).[10] 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 two main 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.[11] 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. To provide an example, controlling for (IBRD or IDA) World Bank projects can partially account for the selectivity if both China and the World Bank favor provinces with lower levels of economic development.

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, 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 competition from selectivity and imitation. First, we run regressions at the sector level to test whether the co-location of projects is visible within sectors. We do so because imitation and selectivity most likely occur within the same sectors but competition can occur across sectors. Second, if Delhi wants to constrain or challenge Beijing's growing influence, one would expect it to increase spending in jurisdictions where it has a public opinion advantage over China but its competitive (incumbent) advantage is under threat. Specifically, we use Gallup World Poll data to test whether the crowding-in effect is stronger in countries where the gap between public support for India and public support for China is larger (Gallup 2018). We add an interaction term of *ChinaOF* with India's relative popularity vis-à-vis China (and, in one specification, control for the level of support for India itself). We interpret a positive coefficient on the interaction term as evidence of India trying to compete with China via development finance. Third, one would expect India's response to be stronger in geopolitically and commercially important countries, so if interactions with such variables are significant, this evidentiary pattern would support the idea that competition is driving the positive association between Indian and Chinese development finance.

Results

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).[12] In column 1, the coefficient on $ChinaOF_{ijt-1}$ is positive and statistically significant at the 10 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 committed a project to 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 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 fast

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 (0.005)			−0.001 (0.004)
$ChinaOF_{ijt}$		0.009 (0.004)**	0.010 (0.004)**		0.008 (0.004)*	0.008 (0.004)*
$ChinaOF_{ijt-1}$	0.008 (0.005)*	0.010 (0.005)*	0.011 (0.005)**	0.008 (0.004)**	0.009 (0.004)**	0.010 (0.005)**
$ChinaOF_{ijt-2}$		0.005 (0.008)	0.008 (0.009)		−0.001 (0.005)	−0.000 (0.005)
$ChinaOF_{ijt-3}$		−0.001 (0.004)	0.002 (0.004)		0.002 (0.003)	0.004 (0.004)
$ChinaOF_{jt+1}$			0.003 (0.002)			
$ChinaOF_{jt}$		0.003 (0.001)**	0.005 (0.002)***			
$ChinaOF_{jt-1}$	−0.001 (0.002)	−0.001 (0.002)	0.000 (0.003)			
$ChinaOF_{jt-2}$		0.001 (0.002)	0.001 (0.002)			
$ChinaOF_{jt-3}$		0.002 (0.002)	0.002 (0.003)			
Controls	✓	✓	✓	✓	✓	✓
Country-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	0.275

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 the presence of World Bank IBRD projects (t-1), 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 country-province- and year-fixed effects. Robust standard errors clustered at the country level are presented in parentheses. Significant at: ***: $p < .01$; **: $p < .05$; *: $p < .1$.

mover: the likelihood of a loan already increases in the same year in which a new Chinese project is announced. Specifically, we observe a contemporaneous effect at both the province and country level as shown by the economically and statistically significant coefficients of $ChinaOF_{ijt}$ and $ChinaOF_{jt}$.[13] There is no evidence of a delayed Indian response to China either at the country or province level as all longer lags do not reach statistical significance at conventional levels. The overall effect appears to be much stronger with respect to the province of interest with a cumulative effect over 4 years of 2.3 percentage points compared to the entire country with only 0.5 percentage points. As such, the results confirm a stronger inclination toward localized competition of India towards China (Hypothesis 2) and only provide weak evidence for countrywide competition (Hypothesis 1).

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 1-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. Appendix Table E-1 confirms the absence of anticipation effects when we perform a placebo test that controls for 2-year leads in addition to 1-year leads. Taken together, 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 5 percent level. We explore the response time of India's Exim Bank in column 5 and repeat the placebo exercise in column 6 (and Appendix Table E-1). 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, 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 instead of 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 1 percent increase of Chinese official financing committed to a particular province.[14] We thus again find a positive crowding-in effect. We come to the same qualitative

Table 2. Sensitivity Analysis for Table 1.

		Projects in		Response to		
	No controls	(log) $ amounts	(log) Count	Chinese OOF	Chinese ODA	Top recipients
	(1)	(2)	(3)	(4)	(5)	(6)
$ChinaOF_{ijt-1}$	0.007 (0.004)**	0.013 (0.005)**	0.006 (0.004)	0.012 (0.007)*	0.003 (0.006)	0.021 (0.011)*
Controls		✓	✓	✓	✓	✓
Country-province FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Country-year FE	✓	✓	✓	✓	✓	✓
Observations	19,568	18,657	18,657	18,657	18,657	3240
Adjusted R-squared	0.265	0.249	0.243	0.266	0.265	0.226

Notes. The unit of observation is the province (ADM1 region). Dependent and explanatory variables are binary with 1 indicating if at least one Indian Exim Bank (respectively Chinese) project is committed to a province in columns 1 and 6, 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 aid commitments react toward Chinese OOF and ODA projects, respectively. Column 6 includes the quartile of countries that receive most financing from the Exim Bank. Except for column 1, all specifications control for the presence of World Bank IBRD projects (t-1), 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: ***: $p < .01$; **: $p < .05$; *: $p < .1$.

conclusion when we look at logged project counts in column 3 with a marginally insignificant coefficient (p-value: .107).

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 development finance flows from China (column 4), while Chinese aid projects do not appear to trigger a significant response by India's Exim Bank (column 5). This supports our interpretation of one-sided commercial competition since China's Exim Bank, a leading provider of Chinese OOF, is a direct competitor of India's Exim Bank.

Given that India's budget is significantly smaller than China's, one would expect that India is more likely to respond to China in countries where it has a significant development footprint. In other parts of the world, it should be less likely to try to keep up with Beijing. To test this portfolio size argument, we repeat the analysis for the top quartile of countries that receive Exim Bank financing in column 6. Indeed, we observe larger effects that almost triple in size.

In the Online Appendix, we also test the robustness of our results to outliers. In Appendix Table E-2, we show that our results are virtually unchanged when we winsorize dollar amounts and project counts at the 99.9^{th} percentile of the respective distribution, i.e., we replace the largest values of these variables by their values at the 99.9^{th} percentile, while the bottom values of these variables remain unchanged. In Figures E-1, E-2, and E-3, we also show that our main results are not driven by single recipient countries as they are robust to the exclusion of any individual recipient country.

Summing up our results so far, it 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 could equally be the result of selectivity and imitation, we will return to this question below, where we offer several tests to separate competition from alternative explanations.

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 not only manages 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. Again, there is no evidence of any anticipation effect in our placebo regressions, which would be inconsistent with our crowding-in interpretation. We thus preliminarily 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) and 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. Focusing on the MEA's top 25 percent of aid recipient countries in column 6 also leaves our qualitative conclusions unaltered. The results are robust when we winsorize dollar

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 (0.008)			0.001 (0.009)
$ChinaOF_{ijt}$		0.001 (0.007)	0.008 (0.009)		−0.006 (0.007)	−0.008 (0.008)
$ChinaOF_{ijt-1}$	0.013 (0.013)	0.016 (0.014)	0.012 (0.011)	0.003 (0.008)	0.003 (0.009)	0.000 (0.009)
$ChinaOF_{ijt-2}$		0.008 (0.009)	0.010 (0.011)		−0.001 (0.008)	−0.001 (0.009)
$ChinaOF_{ijt-3}$		0.023 (0.014)	0.016 (0.010)		0.010 (0.009)	0.009 (0.011)
$ChinaOF_{jt+1}$			−0.004 (0.003)			
$ChinaOF_{jt}$		0.002 (0.004)	−0.002 (0.004)			
$ChinaOF_{jt-1}$	−0.005 (0.003)	−0.005 (0.004)	−0.007 (0.004)*			
$ChinaOF_{jt-2}$		0.002 (0.003)	0.003 (0.004)			
$ChinaOF_{jt-3}$		0.003 (0.004)	0.002 (0.004)			
Controls	✓	✓	✓	✓	✓	✓
Country-province FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Country-year FE				✓	✓	✓
Observations	18,673	18,673	16,338	18,657	18,657	16,324
Adjusted R-squared	0.454	0.457	0.451	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 the presence of World Bank IDA projects (t-1), 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 country-province- and year-fixed effects. Robust standard errors clustered at the country level are presented in parentheses. Significant at: ***: $p < .01$; **: $p < .05$; *: $p < .1$.

Table 4. Sensitivity Analysis for Table 3.

		Projects in		Response to		
	No controls	(log) $ amounts	(log) Count	Chinese OOF	Chinese ODA	Top recipients
	(1)	(2)	(3)	(4)	(5)	(6)
$ChinaOF_{ijt-1}$	0.002	−0.010	−0.006	0.011	−0.000	0.002
	(0.008)	(0.007)	(0.006)	(0.013)	(0.011)	(0.011)
Controls		✓	✓	✓	✓	✓
Country-province FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Country-year FE	✓	✓	✓	✓	✓	✓
Observations	19,568	18,657	18,657	18,657	18,657	10,065
Adjusted R-squared	0.599	0.640	0.753	0.607	0.607	0.591

Notes. The unit of observation is the province (ADM1 region). Dependent and explanatory variables are binary with 1 indicating if at least one Indian MEA (respectively Chinese) project is committed to a province in columns 1 and 6, 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. Column 6 includes the quartile of countries that receive most finance from MEA. Except for column 1, all specifications control for the presence of World Bank IDA projects (t-1), 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: ***: $p < .01$; **: $p < .05$; *: $p < .1$.

amounts and project counts at the 99.9th percentile of the respective distribution (see Appendix Table E-3).

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.

Disentangling Competition from Alternative Explanations

Sectoral Decomposition. As a first attempt to disentangle competition from selectivity and imitation, we analyze whether the crowding-in of Indian projects occurs in the same sectors or across sectors. Imitation should be visible as co-location of projects 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. Indeed, Davies and Klasen (2019, 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." Likewise, if the co-location of projects was the mere outcome of selectivity, i.e., both donors following the same allocation criteria, one would expect co-location to occur in the same sectors. For example, a natural disaster would typically lead to Indian and Chinese aid in the same sector of humanitarian assistance if imitation or selectivity was at play. 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* co-location because this would provide strong grounds to question our interpretation of the results as competition.

To test this, 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 to the same sector as China in the previous year. All same-sector effects are smaller than the significant positive aggregate effects for Exim Bank loans in Table 1 (0.008).

Overall, the co-location 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 or both donors following the same allocation criteria. Instead, this evidence is in line with our competition interpretation. However, with the sectoral decomposition, we cannot fully rule out that selectivity and imitation drive 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 the gap between public opinion towards India and public opinion vis-à-vis China is large. If Delhi is using its international development finance program to constrain or challenge Beijing's growing influence, one might expect it to focus on any jurisdiction where China has established a local presence and could make a competitive gain at its expense.[15] However, given that

Table 5. Sectoral Decomposition.

	Social	Economic	Production	Energy	Health	Transport
	(1)	(2)	(3)	(4)	(5)	(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	✓	✓	✓	✓	✓	✓
Country-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 the presence of World Bank IBRD (panel A) or IDA (panel B) projects (t-1), 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 country-province- and year-fixed effects. Robust standard errors clustered at the country level are presented in parentheses. Significant at: ***: $p < .01$; **: $p < .05$; *: $p < .1$.

Indian policymakers have scarce resources and must make risk-adjusted reward calculations, we expect Delhi to practice strategic entry deterrence, i.e., to increase spending in jurisdictions where it has a public opinion advantage over Beijing but its competitive (incumbent) advantage is under threat.

One way to proxy for the relative levels of influence enjoyed by two (potentially competing) 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., Blair, Marty, and Roessler 2022; Dietrich, Mahmud, and Winters 2018; Eichenauer, Fuchs, and Brückner 2021; Wellner et al., 2024). 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, 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.[16] This allows us to generate a measure of the distance in public approval rates between the two countries.

More specifically, we augment our regression equation with an interaction between $ChinaOF_{ijt-1}$ and the difference between the approval rates of the Indian government and the Chinese government in the recipient country. In column 1 of Table 6, we compute the approval rates only for those respondents who provided an answer to the question. Column 2 includes respondents that refused to answer or replied with "don't know" and treats 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 is relatively more favorable about India than about China.[17] As the insignificant coefficients on India's and China's approval and disapproval rates in Appendix Table E-4 show, this finding is driven by the 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.[18] 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 hold a more positive view of India relative to China (columns 3 and 4 of Table 6).

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

Table 6. Interactions With Public Opinion, Commercial, and Geopolitical Variables.

	Public Opinion				Commerce and Geopolitics			
	Exim Bank Loans		MEA Aid		Exim Bank Loans		MEA Aid	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ChinaOF_{ijt-1}$	0.014 (0.008)*	0.013 (0.008)	−0.017 (0.023)	−0.020 (0.021)	−0.021 (0.011)*	0.007 (0.004)*	−0.016 (0.029)	−0.000 (0.008)
$ChinaOF_{ijt-1}$ × Approval distance 1	0.091 (0.044)**		−0.151 (0.117)					
$ChinaOF_{ijt-1}$ × Approval distance 2		0.091 (0.053)*		−0.191 (0.117)				
$ChinaOF_{ijt-1}$ × ESI					0.073 (0.033)**		0.046 (0.076)	
$ChinaOF_{ijt-1}$ × BIMSTEC						0.017 (0.020)		0.047 (0.022)**
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Country-year FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	5,560	5,560	5,560	5,560	18,577	18,657	18,577	18,657
Adjusted R-squared	0.238	0.238	0.613	0.613	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 1–4 explore interactions with the Approval Distance 1 or Approval Distance 2, respectively. The variable subtracts the approval rate for the Chinese government from the approval rate of the Indian government. Columns 1 and 2 report estimates for Exim Bank loans; columns 3 and 4 report estimates for MEA aid. Columns 5–8 explore interactions with the export similarity index (ESI) and an indicator for countries being part of the geopolitical alliance Bay of Bengal Initiative for Multi-Sectoral Technical and Economic Cooperation (BIMSTEC). Columns 5 and 6 report estimates for Exim Bank loans; columns 7 and 8 report estimates for MEA aid. All specifications control for the presence of World Bank IBRD (Exim Bank loans) or IDA (MEA aid) projects (t-1), 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 country-province- and year-fixed effects. Robust standard errors clustered at the country level are presented in parentheses. Significant at: ***: $p < .01$; **: $p < .05$; *: $p < .1$.

(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.[19] 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 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).[20] 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, 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 6 presents the results.[21] 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 5). 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 overlap. The likelihood of an Exim Bank loan increases in response to Chinese activities in a given province if the export similarity exceeds 0.4 (see also graphical visualization in Appendix Figure E-6).[22] This is further evidence for commercial competition of India with China.[23] By contrast, we find no evidence that India's Exim Bank is more responsive to China's engagement in its neighborhood than elsewhere (column 6).

We repeat the analysis for India's MEA, which is, as we explained and tested above, guided to a larger extent by geopolitical motives than the country's Exim Bank. Column 7 shows that India's MEA is not more (or less) likely to respond to a new Chinese project if it 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 8). 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. The effect is sizeable in light of the average likelihood of a new MEA aid project being set up in a province in a given year (3.7 percent). 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 allocates its development aid to compete with China where it arguably matters most: in India's neighborhood.

Further Checks. A critical reader might be concerned that the observed co-location of Indian Exim Bank projects relative to Chinese projects is driven by a boost in local demand generated by Chinese projects rather than competition.[24] While this is unlikely to be the main driver of co-location in light of the above-documented links with India's relative popularity and India-China export similarity, we cannot rule out such an effect. To test whether our observed pattern might indeed be driven by an economic boom created by Chinese projects, we repeat our baseline regression and add an interaction of our variable of interest *IndiaOF* with a 1-year lead of nighttime lights to proxy for local growth. If an economic boom was driving our results, we should observe a positive significant coefficient on the interaction term. Since this is not the case (see Appendix Table E-6), this further adds to our confidence in the competition explanation of the co-location of projects.

Next, we estimate a spatial Durbin model (see Appendix E-5) to account for spatial dependence. More specifically, we allow for the possibility that a new Chinese project in neighboring provinces in the previous year affects the allocation of Indian projects. Reassuringly, our main finding is robust to accounting for potential spatial dependence. The insignificant coefficients on Wx suggest that there are no neighborhood effects of Chinese projects on India's project allocation. In other words, there is no evidence that a new Chinese project in the neighboring provinces attracts a new Indian Exim Bank loan or, alternatively, a MEA project.

Finally, competition between actors can be one-sided with only one party reacting to the other but it might also be reciprocal. In a final step, we, therefore, seek to evaluate whether China steps up its development activities when India launches new projects in countries or specific provinces. The non-findings reported in Appendix F suggest that while India competes with China through development finance, the opposite does not appear to be the case. This is in line with the characterization of Cheru and Obi (2011, 91) that India's strategy vis-à-vis China is one of "playing 'catch up.'"

Concluding Remarks

Our regression results based on a joint 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 to the province in the previous year. We also observe co-location effects at the national level, albeit to a lesser extent. Since our effect is more pronounced in countries where India is more popular relative to China and where both lenders have a similar export structure, we interpret this as evidence of India competing with China. It is thus unlikely that India allocates projects (more slowly) to the same province as China simply because it follows the same allocation criteria as 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 robust evidence of competition only 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. Nevertheless, our finding about India using aid to compete with China in its neighborhood is also of high relevance since 36 percent of Indian aid remains in its own world region. Finally, analyzing China's possible response to Indian development activities, we find no evidence that China competes with India in the same localities.

At first sight, rivalry does not need to be detrimental from a development perspective. Rivalries can lead to more aid activities and this is to be welcomed if aid is effective.[25] They can also create policy space for developing countries, allowing them to choose the most competent partner country. Competition can also be beneficial if it leads donors to strive for the best development solutions and more effective projects and programs. However, research has shown that strategically motivated aid is less effective according to country growth rates and project evaluations (Dreher et al. 2013, 2018; Kilby and Dreher 2010). There are thus reasons to be concerned about adverse effects of the rivalries documented in this article.

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Data Availability Statement

The data that support the findings of this study are available in the supporting information of this article. We make the Indian Development Finance Dataset, which has been introduced in this article, publicly available at https://indiandevelopmentfinance.net.

Supplemental Material

Supplemental material for this article is available online.

Notes

1. We introduce the Indian official financing data in the Empirical Strategy section. Data on Chinese official financing are from Dreher et al. (2021a), Dreher et al. (2022), 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. 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."
3. Authors' interviews were carried out with Indian ministries, public institutions, think tanks, and non-governmental organizations on September 8–9, 2014 in Delhi.
4. Appendix B outlines our argument in detail. It 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.
5. The dataset is publicly available at https://www.indiandevelopmentfinance.net.
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.
8. We provide details on the variables used in Appendix C.
9. 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.
10. 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.

11. Aid provision occurs in mutual agreement between donor and recipient (Carnegie and Dolan 2021). Recipients can prohibit donors to provide aid in a given province which would, if anything, lead to an underestimation of competition.
12. While we do not show the coefficients of control variables in the main paper to save space, we report them in additional tables in Online Appendix D.
13. 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 unlikely that reverse causality is of major concern.
14. This appears small in quantitative size. However, note that the financial value of the median Indian OOF project is only 38 percent of the median Chinese OOF project.
15. There are good reasons for India to prioritize either jurisdictions in which it is unpopular (e.g., to improve its public image) or popular (e.g., to face fewer obstacles to project implementation). However, it would be hard to reconcile evidence that relative levels of public sentiment matter with explanations other than India competing with China (as we control for absolute levels in opinion about the two Asian countries).
16. Note that data on public opinion about India are available for 2006–2010 only.
17. We show the corresponding marginal effects plot in Appendix Figure E-4. To mitigate the possibility of misspecification bias, we also run an alternative specification in the spirit of Hainmueller, Mummolo, and Xu (2019) where we divide the range of approval distance into three equally frequent groups. As can be seen from Appendix Figure E-5, we come to the same conclusion.
18. 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.
19. Note that *s* indicates 2-digit codes of the Standard International Trade Classification. Fuchs, Öhler, and Nunnenkamp (2015) use this index to analyze aid competition among Western donors.
20. The BIMSTEC member states are Bangladesh, Bhutan, India, Myanmar, Nepal, Sri Lanka, and Thailand. In our sample, Exim Bank and MEA allocated 18 percent and 36 percent of their development projects to BIMSTEC members, respectively.
21. We show the corresponding marginal effects plot in Appendix Figure E-6 and an alternative specification where we divide the range of the Export Similarity Index into three equally frequent groups in Appendix Figure E-7.
22. The likelihood of an Exim Bank loan even *decreases* in response to Chinese activities in a given province if the export similarity is close to zero. It seems that India withdraws from countries where it has no commercial interests as gaining ground in its competition to China may appear too costly in light of a new Chinese project.
23. 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. Results are shown in Appendix Table E-7.

24. An increase in demand appears likely since previous research finds that Chinese development projects boost growth at the level of recipient countries and subnational regions targeted. See Dreher et al. (2021a, 2021b). We thank an anonymous reviewer for raising this issue.
25. A case in point is China's and India's "vaccine diplomacy" during the coronavirus pandemic, which led to very high vaccination rates in Bhutan already in spring 2020.

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