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The Great Equalizer: Effects of Chinese Official Finance on Economic Complexity across Recipient Countries

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ABSTRACT

THE GREAT EQUALIZER: EFFECTS OF CHINESE OFFICIAL FINANCE ON ECONOMIC COMPLEXITY ACROSS RECIPIENT COUNTRIES

Jan Denninger, Lennart Kaplan

This paper analyzes whether Chinese aid and other forms of official finance affect structural transformation in low- and-middle income countries. Specifically, we employ an instrumental variables (IV) approach to causally analyze the effect on the Economic Complexity Index of 98 recipient countries over the 2002-2016 period. Economic complexity is defined as the diversity and sophistication of the goods an economy produces. The results reveal that Chinese official financing (OF) does not have statistically significant effects at the aggregate level; however, its effectiveness varies across sectors and recipients. A sectoral perspective shows that Chinese OF to recipients' production sectors has a significantly negative effect on their economic complexity. These effects are most pronounced for high-complexity recipients, suggesting that China primarily targets industries below existing levels of complexity, thereby impeding potential structural transformation. In contrast, low-complexity recipients experience positive complexity effects from Chinese social sector projects, especially from those related to education. Given that China is known for its demand-driven approach of lending, recipients should push for an adjustment in the composition and allocation of Chinese OF to render structural transformation more likely.

Keywords: Aid, China, Trade, Economic Complexity, Structural Change

JEL classification: P45, F14, F35, O11, O35

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1. Introduction

China, once a developing country, today dominates world exports and has become a technological leader. Simultaneously, Beijing has transitioned from being a net recipient of foreign aid to a lender that, in many areas, surpasses the influence of Western-led international financial institutions such as the World Bank and the International Monetary Fund (IMF) (Horn et al., 2021; Dreher et al. 2022). Against this background, some political observers and researchers have voiced positive expectations that 'China's rise' could help to promote the Chinese economic model in other low- and middle-income countries. For example, Klaus Schwab – economist and founder of the World Economic Forum – stated that *"the Chinese model is certainly a very attractive model for quite a number of countries"* (Billingsley, 2022). In this context, former Kenyan President Uhuru Kenyatta remarked on cooperation with China in 2022 as follows: *"Our partnership with China is not a partnership based on China telling us what to do. It is a partnership of friends, working together to meet Kenya's socio-economic agenda* […] *We do not need lectures about what we need, we need partners to help us achieve what we require"* (Kardon and Leutert, 2023). Particularly, China places a special emphasis on infrastructure development, which is praised as a catalyst for economic development, reducing transportation costs, promoting trade, attracting foreign direct investment (FDI), and fostering economic diversification and productivity (Calderon and Servén, 2004; Dreher et al., 2018b; Bluhm et al., 2025; Horigoshi et al., 2022). Indeed, it has been shown that Chinese development projects increase connectivity and thus productivity in recipient countries. At the same time, China has been facing recurring allegations that its development projects are economically inefficient 'white elephants' (Financial Times, 2016; The Economist, 2017). In this respect, the Carnegie Endowment voiced concerns, stating that "*China and Latin America must confront the legacy of past deals gone wrong and attempt to move beyond commodity-based trade"* (Ferchen, 2018). According to Hausmann (2019), *"Chinese development finance* […] *delivers a corruption-filled sugar high to the economy, followed by a nasty financial (and sometimes political) hangover."*

Against this background, this paper seeks to assess whether Chinese official financing (OF), composed of foreign aid (official development assistance; ODA) and other forms of development finance (other official flows; OOF),[1] helps or hinders economic development.

[1] ODA and OOF correspond to the definitions established by the Organisation for Economic Co-operation and Development (OECD). However, note that these definitions exclude official investments. The sum of ODA and OOF flows, along with flows that lack clear categorization ('vague'), constitutes China's total official financing (OF).

Building on previous literature, we specifically examine the effects of Chinese OF on technological sophistication, using the concept of economic complexity as a framework. Economic complexity is defined as the diversity and sophistication of the goods a society produces. Due to data availability, economic complexity is oftentimes proxied by the composition of countries' export baskets, as is the case in our paper. Previous research indicates that economic complexity is positively associated to economic growth (Hausmann et al., 2013) and reduces cross-country inequality (Hartmann et al., 2017) and carbon intensity (Romero and Gramkow, 2021). To measure economic complexity, a country's export basket is used to derive an Economic Complexity Index (ECI) (Hidalgo and Hausmann, 2009; Hausmann et al., 2013). We couple temporal variation in countries' economic complexity with comprehensive data on Chinese ODA and OOF projects (Dreher et al., 2022) to test our main hypothesis in a panel of 98 recipient countries over the 2002-2016 period. As Chinese OF is often characterized as economically self-interested (Dreher and Fuchs, 2015), endogenous allocation poses a significant challenge when evaluating the effectiveness of Chinese development finance. To address this concern, we employ a Bartik (1991)-style shift-share instrumental variable approach to examine the causal effect of Chinese ODA and OOF. Historically, China's official financing has been driven by domestic oversupplies in industrial production (Bluhm et al., 2025; Dreher et al., 2021). Thus, we construct our instrumental variable as the interaction of Chinese domestic oversupplies (shift) with the probability of receiving aid (cross-sectional shares). Given the richness of current literature on shift-share instruments, we thoroughly assess the robustness of our approach (e.g., Borusyak et al., 2022).

While we do not find any evidence on an average effect of Chinese ODA and OOF on economic complexity, our analysis reveals relevant differences across aid sectors and sub-samples. In particular, we find positive effects for low complexity countries and negative effects for high complexity countries. The *complexity-increasing effects* seem to be driven by Chinese ODA in the social sector (e.g., health and education), whereas *complexity-reducing effects* are induced by non-concessional finance (OOF) in the production sector.

Our paper contributes to the aid effectiveness literature by examining the mechanisms through which development finance and foreign aid affect structural change and economic sophistication. This is particularly important as, *"What you export matters"* for economic development (Hausmann et al., 2007). Furthermore, we bring greater nuance to the polarized literature on Chinese development finance by providing further insights into the conditions under which Chinese aid acts as either a catalyst or an impediment to economic development.

Thus, our findings provide valuable guidance to recipient governments regarding which modalities (concessional versus non-concessional) and domestic conditions (economic complexity status) are related to positive or negative outcomes of Chinese OF. This is especially relevant given China's demand-driven approach to lending, which allows recipients a degree of influence over allocation decisions.

The remainder of this paper proceeds as follows: Section 2 links theoretical and empirical findings on economic complexity and Chinese OF, culminating in the formulation of hypotheses. Section 3 presents the data in detail and establishes the empirical strategy to estimate the effects of Chinese ODA and OOF on recipients' economic complexity. Section 4 presents the corresponding results. Section 5 concludes.

2. Linking Economic Complexity and Chinese Official Finance

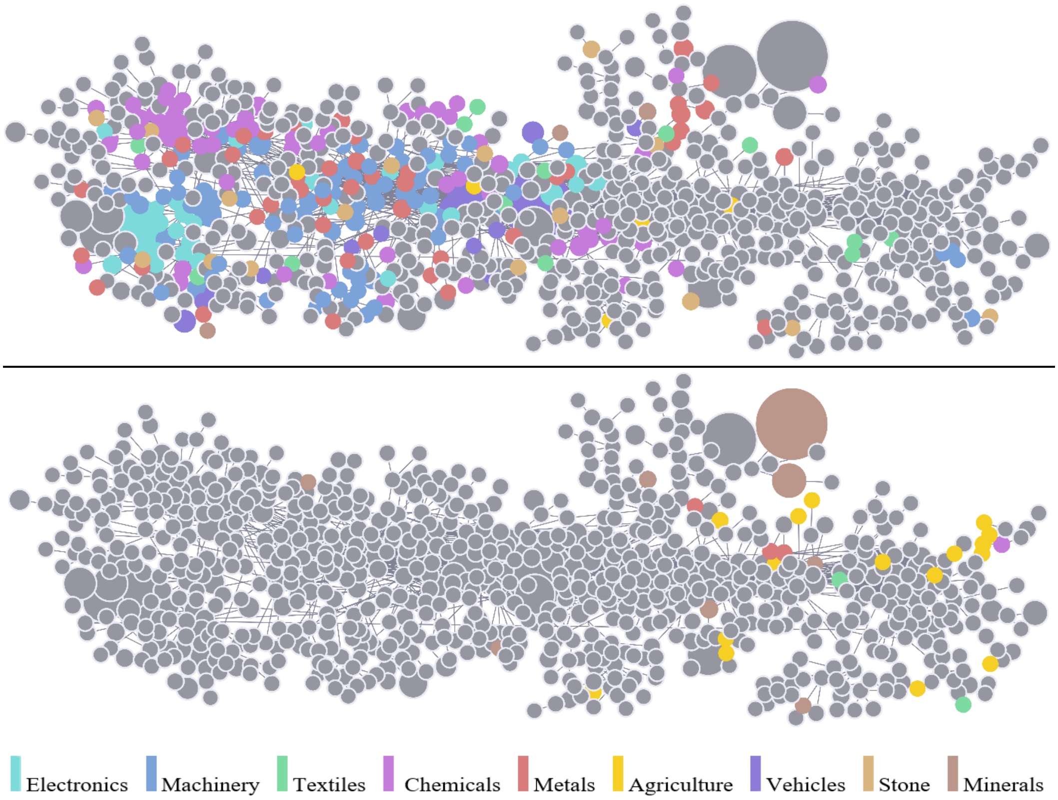
2.1 The Concept of Economic Complexity

2.1.1 The Product Space

Manufacturing requires knowledge, yet the resulting productive knowledge is mostly tacit and non-fungible, as it is embedded in a society's collective know-how (Jaffe et al., 1993; Hidalgo, 2021). This explains the different capabilities of countries to produce certain products, as they cannot manufacture products that require productive knowledge they do not possess (Hausmann and Hidalgo, 2011; Hidalgo, 2015: 128). Consequently, there is a 'nestedness' of the least common industries in the most diversified locations, while simpler industries are more widespread globally due to their lower productive knowledge requirements (Bustos et al., 2012; Balland and Rigby, 2017). The concept of 'relatedness' between products captures the ease with which a given country could enter the production of product B if it already produces product A. To measure the similarity of products, economic complexity theory assumes that a country exports a particular product if it has a revealed comparative advantage (RCA) in that product.[2] This framework underpins the construction of the Product Space (PS), which organizes products into communities, with each product represented by a node (Hidalgo et al., 2007). Products within the same community share similar capabilities, making them more closely related and thus more likely to be co-exported (Hidalgo et al., 2007; Hausmann et al., 2013).

[2] According to Balassa's (1986) definition, this is the case when a country exports more of a certain good as a share of its total exports than the product's share in total world trade (RCA > 1).

In theory, countries engage in a diffusion process within the PS transitioning from products they already export with a RCA to related or proximate products. However, the pace of diffusion is determined by the heterogeneous structure of the PS (Hausmann and Klinger, 2006; Hidalgo et al., 2007). Densely connected regions of the PS indicate that neighboring products differ only slightly in their required capabilities, while sparsely connected regions suggest that neighboring products require different capabilities (Hausmann and Klinger, 2006; Hidalgo et al., 2007). Therefore, fostering structural transformation by moving to neighboring products is more challenging in sparsely connected parts of the PS. Interestingly, the different parts manifest themselves in a core-periphery structure. The dense core comprises relatively complex product communities, such as engineering, while the sparse periphery consists of simple product communities, such as cereals. A large part of the global South's production structures is concentrated in the periphery of the PS. To illustrate how production structures between the core and periphery may differ, Figure 1 compares the country with the highest economic complexity index value in 2016 (Japan: 2.21) to the country with the lowest (Nigeria: -1.29) (The Growth Lab at Harvard University, 2019).[3]



[3] Nodes are color-coded based on the intensity of production factors and divided into different communities (Leamer, 1984). Their size reflects the corresponding product's weight in world trade (Hausmann et al., 2013). 2016 was chosen as reference year since it is the last year of the study period. The ranking has changed little since then.

Figure 1. Product Spaces of Japan (above) and Nigeria (below) in 2016

Source: The Growth Lab at Harvard University (2019)

Products that the respective country exports with RCA appear in color. Japan's PS is more colorful because its exports are more diversified than Nigeria's. While Japan mainly exports products from within highly complex industries, such as semiconductors, Nigeria's exports are concentrated on low-complexity sectors, such as crude oil. In turn, as mentioned above, the heterogeneous structure of the PS makes structural transformation more difficult for Nigeria. Simply put, low-complexity countries like Nigeria face a tradeoff between diversifying into achievable but unappealing industries (due to their low complexity) and pursuing highly complex industries, which are attractive but difficult to develop due to their low relatedness (Hidalgo, 2023: 20).[4] This dynamic perpetuates underdevelopment as a self-reinforcing condition.

2.1.2 The Economic Complexity Index

In economic complexity theory, fostering economic development necessitates the acquisition of productive knowledge and its use in increasingly diverse and more complex industries (Hidalgo and Hausmann, 2009; Hausmann et al., 2013). Economic complexity thus manifests itself in the productive knowledge of a society, expressed in the diversity and sophistication of the goods it exports.[5] To measure economic complexity, a country's export basket is used to derive the Economic Complexity Index (ECI). The more diversified and the less ubiquitous a country's exports are, the more complex its economy is. Yet, an important distinction must be made regarding ubiquity. Non-ubiquitous products can be divided into those characterized by advanced technology and those that are rare in nature (Gala et al., 2018b). While the former require special capabilities, the latter are inherently non-ubiquitous (Hidalgo and Hausmann, 2009). For example, the Democratic Republic of the Congo (DR Congo) is the leading exporter of the rare metal cobalt (Calvão et al., 2021). Although cobalt is a non-ubiquitous good, the DR Congo's export structure is far less diversified than those of other cobalt exporters such as Australia. The DR Congo's exports can therefore be considered non-ubiquitous but not complex. In contrast, diversified and sophisticated economies like South Korea rank high on

[4] There is mixed evidence on whether countries should approach highly related industries or leap into less related but more complex industries (Boschma and Capone, 2015; Lee and Malerba, 2017; Alshamsi et al., 2018).

[5] In principle, economic complexity techniques are not necessarily tied to export data. It has also been applied to data on, e.g., industries (Fritz and Manduca, 2021), patents (Balland and Rigby, 2017), and employment (Wohl, 2020).

the ECI, since they export many low ubiquity goods that are also produced by other highly diversified economies. In other words, economic complexity arises from the combination of non-ubiquity in the technological sense (i.e. not based on natural endowments), along with diversity.

In addressing this phenomenon, Hausmann et al. (2013: 24) and Hidalgo and Hausmann (2009: 10571) highlight the importance of using the information on diversity and ubiquity to adjust these two components for each other.[6] To illustrate this on a global scale, Figure 2 visualizes the mean ECI values over the 2002-2016 period for most economies.[7] It becomes evident that the world exhibits a nuanced dichotomy in terms of economic complexity, characterized by a complex core (green levels) and a less complex periphery (yellow/orange/red). The core is concentrated in high-income countries, whereas the countries in the periphery are mainly located in low- and middle-income countries, especially on the African continent.

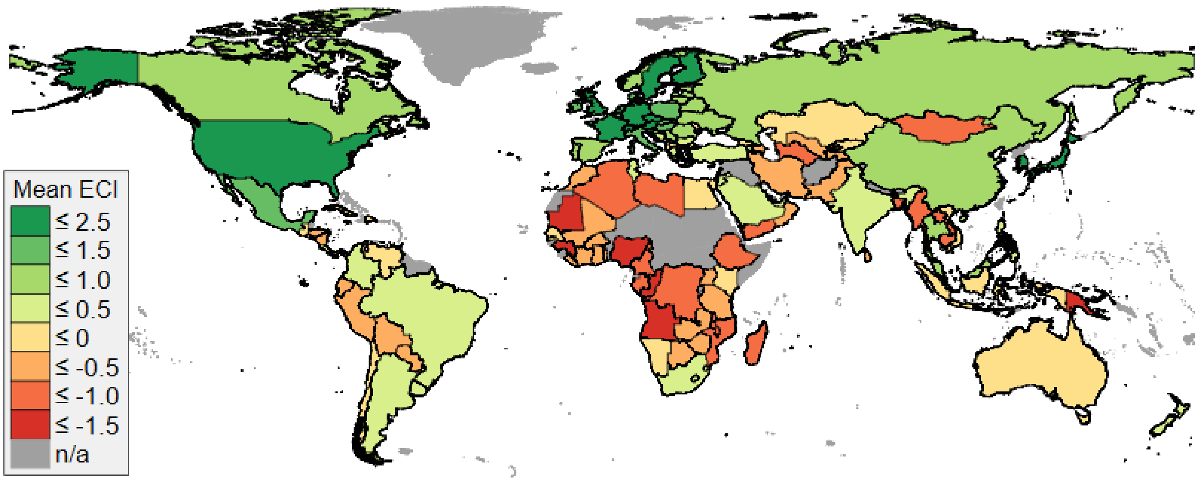


Figure 2. World Map of the Economic Complexity Index (2002-2016)

Source: Author's illustration based on data taken from The Growth Lab at Harvard University (2019)

2.2 The Determinants and Implications of Economic Complexity

As Hidalgo (2021: 1) notes, the concepts of relatedness (Section 2.1.1) and economic complexity (Section 2.1.2) do not make specific assumptions about the underlying determinants but rather estimate the combined presence of economic activities in a certain location. Hence, they ought to serve as a guiding principle for development strategies rather than a direct tool

[6] See Appendix C for the derivation of the ECI.

[7] The ECI does not cover countries with a population of less than 1.2 million inhabitants, a yearly trade volume of less than US$1 billion, and with data that is unreliable or not adequately classified (Hausmann et al., 2013: 69).

for governmental intervention (Hidalgo, 2023: 13). However, recent studies attempt to examine the factors that may contribute to spurring economic complexity, as outlined below.

First, regarding the infrastructural determinant, Gao et al. (2017) show that not only cross-industry learning but also interregional spillover effects driven by improved connectivity were pivotal for China's own structural transformation.[8] Accordingly, the development of a solid digital and transport infrastructure can make a significant contribution to export diversification and sophistication (Rehman and Sohag, 2022). However, fostering economic growth and complexity requires more than just the "hardware" of infrastructure. , Institutions play a crucial role in bringing infrastructure to life by strengthening incentives for innovative entrepreneurship and human capital accumulation (e.g., Dollar and Kraay, 2003; Glaeser et al., 2004; Acemoglu et al., 2005). Moreover, as Sweet and Maggio (2015) argue, stronger intellectual property rights are associated with higher levels of economic complexity – but only in countries that are already at above-average levels of complexity. Further, entrepreneurs in developing countries often lack access to adequate financing due to underdeveloped financial sectors (Chu, 2020; Njangang et al., 2021). This represents one of the fundamental bottlenecks many developing countries face, namely the ability to create adequate employment opportunities in complex industries and service sectors for broad segments of society (Gala et al., 2018a). Accordingly, a country would benefit complexity-wise if its labor markets were capable of and its institutions willing to absorb a diverse set of workers, including ethnic and sexual minorities (Bahar et al., 2022; Vu, 2022a). This insight stems from the knowledge theory that underlies ECI's methodology (Hidalgo, 2015).

The implications of economic complexity have likely been studied as extensively as its determinants. The ECI is able to explain 78 percent of the variance in income across countries where natural resource exports account for less than 10 percent of their gross domestic product (GDP) (Hausmann et al., 2013: 27). Beyond economic growth, Hartmann et al. (2017) and Hidalgo (2021: 14) show that, at the international level, socioeconomically comparable regions exhibit lower income inequality when they are more economically complex. In contrast, Zhu et al. (2020) and Bandeira Morais et al. (2021) show that in China and Brazil, economic complexity does not reduce income inequality at the subnational level, except in urban areas. This finding underscores the tacit nature of (complex) knowledge, which in turn limits the share of the population that benefits from higher economic complexity. In summary, economic

[8] Specifically, Gao et al. (2017) and Banerjee et al. (2020) argue that industries in provinces that are connected by transportation networks are able to increase productivity and achieve higher GDP per capita levels.

complexity is by no means a panacea for the structural problems of many (developing) countries. Nevertheless, the complexity of production and export structures is associated with considerable advantages across diverse economic outcomes. Therefore, if Chinese development finance is indeed aimed at the socioeconomic development of recipient countries, the promotion of structural transformation should be one of the benchmarks for its effectiveness.

The 21st century witnessed a significant shift in the global development landscape with China's transition from being a net recipient of foreign aid to a major player in providing development finance. As early as 2009, China overtook the US as the largest bilateral donor of foreign aid (Horigoshi et al., 2022: 20). As an 'emerging' donor, China is committed to use ODA and OOF in assisting developing nations in achieving economic progress and alleviating poverty (State Council, 2021). Many low- and middle-income countries' governments see the Chinese approach of structural transformation as a role model for economic development. For this reason, we will evaluate the effects of Chinese foreign aid (ODA) and development finance (OOF) on economic complexity and complement existing studies on the general relationship between aid and the ECI (Kamguia et al., 2022). The following subsection will summarize the status quo of empirical evidence on this topic.

2.3 The Perils and Promises of Chinese Development Finance

China's marked departure from the traditional Western-led aid model has been sparking heated public debate and intense academic discourse about the implications for recipient countries' development trajectories. Critics frequently accuse China of prioritizing speed over quality (Doig, 2019) and creating 'white elephant' projects that fail to achieve their intended economic outcomes (The Economist, 2017). With respect to governance outcomes in recipients, Chinese OF is not officially tied to specific economic policies or governance reforms (Dreher and Fuchs, 2015). However, Chinese OF has been shown to disrupt democratic governance and impede economic reforms by undermining the conditionality targets of traditional donors (Li, 2017; Brazys and Vadlamannati, 2021).[9] At the same time, China is often praised for its quick implementation. Former Senegalese President Abdoulaye Wade remarked on China's pace compared to that of Western donors, stating: *"I have found that a contract that would take five years to discuss, negotiate and sign with the World Bank takes three months when we have*

[9] Abstention from interfering in the internal affairs of another country has been a fundamental tenet in China's foreign policy since 1955 and is maintained despite the country's growing economic and political might (Li, 2019).

dealt with Chinese authorities." (Wade, 2008). While the direction of the effects of Chinese OF on the ECI is unclear ex ante, we hypothesize that there is a significant relationship.

H1: *Chinese foreign aid significantly affects recipients' economic complexity.*

Considering the portfolio of Chinese aid, while the bulk of project funding flows into the economic and production sectors (which are primarily on OOF-like terms), the majority of projects are directed toward the social sector (which is primarily on ODA-like terms). Dreher et al. (2021a) find that ODA-like commitments have larger (positive) growth effects compared to OOF-like commitments on short-term growth across all sectors. Thus, we hypothesize that ODA-like commitments are related to more significant effects.

H2: *ODA-like commitments show a larger (positive) effect than OOF-like commitments.*

One of the key differences between Western donors and the Chinese development model is China's holistic approach to official financing covering multiple sectors at once. First, China has been increasingly supporting social infrastructure (e.g., health clinics, schools) via ODA. As for the 'social' sector, educational aid has been shown to increase enrollment rates, thereby building human capital (Riddell and Niño-Zarazúa, 2016), which Zhu and Li (2017) argue is associated with higher economic complexity. Particularly, higher human capital is an important long-term determinant of productive knowledge and know-how (Hartmann et al., 2017). We expect Chinese development financing in the 'social' sector to have a significantly positive effect on economic complexity, mainly driven by improved education.

Second, regarding the 'economic' sector, we base our strongly positive expectations on the above argumentation, as China's infrastructural projects have been shown to increase connectivity in recipient countries (Bluhm et al., 2025; Dreher et al., 2021), thereby likely improving their economic complexity (Gao et al., 2017; Rehman and Sohag, 2022).

Third, we do not expect significant results of Chinese foreign aid directed toward the 'production' sector. For one, as Kamguia et al. (2022) argue, agricultural aid is very unlikely to promote economic complexity, as agriculture itself is minimally complex and offers limited opportunities for diversification to more complex products. On the other hand, the effect of Chinese aid directed toward industry, mining, and construction likely depends on the complexity of the specific industries. For instance, financing to extractive sectors without corresponding investment in processing industries is unlikely to foster economic complexity due to Dutch disease effects (Camargo and Gala, 2017). Thus, we hypothesize that the impact depends on the existing complexity level of recipients and is likely to cancel out when examined at the aggregate level.[10]

H3: Chinese aid will have heterogeneous effects across sectors depending on the initial economic complexity in recipient countries and their respective needs.

3. Data and Empirical Strategy

3.1 Dependent Variable

The main dependent variable (DV) used in our estimates is the ECI (The Growth Lab at Harvard University, 2019). Excluding high-income countries and restricting the sample to recipients of Chinese OF for which ECI data are available (87 countries),[11] the ECI is below zero for approximately 70 percent of the sample (see Appendix Figure A1). Thus, the export structures of most recipients are relatively undiversified and simple, since ECI values below zero indicate countries whose economic complexity is lower than that of the average country in the dataset, and vice versa (Hidalgo, 2021). Among the recipients of Chinese OF, those with the highest mean ECI during 2002-2016 are concentrated in high and upper middle-income countries, whereas seven of the bottom ten countries are located in Africa (see Appendix Table A2).

3.2 Main Explanatory Variable

Turning to the main variable(s) of interest on Chinese OF (ODA and OOF, respectively), China does not publish official project-level data on its international lending activities, unlike the Creditor Reporting System of OECD-DAC donors (Horn et a., 2021). Therefore, we rely on AidData's Global Chinese Development Finance Dataset (version 2.0) (Dreher et al., 2022), which includes 9,766 Chinese development projects worth approximately US$ 1,124 billion across 165 countries over the 2000-2014 period, making it the most comprehensive dataset on Chinese foreign aid.[12]

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[10] As the 'other' sector captures many heterogeneous aid projects, it is challenging to make assumptions on its effectiveness. Therefore, we exclude all those sectoral flows from our main analysis whose potential effects on economic complexity have scant theoretical basis, e.g., the 'other', the humanitarian, and the unspecified sectors. The 'other' sector covers about 27.7 percent of total Chinese OF. While we expect results to be insignificant due to the sectoral heterogeneity, we test them for completeness. The humanitarian sector covers about 0.2 percent of total Chinese OF amounts, whereas the unspecified sector accounts for roughly 3.2 percent.

[11] See Appendix Table A1 for a list of Chinese OF recipients that are not covered by the ECI and are thus excluded from the analysis. The list contains 45 countries and territories amounting to 2,587 projects.

[12] While the original dataset covers the 2000-2017 period (13,427 projects), we restrict the sample period to 2000-2014 in order to derive a sufficiently strong instrument (see Section 3.4 for details). We restrict the second version (2000-2017) of the dataset instead of using the first version of the dataset (2000-2014 period) (Dreher et al., 2021a), since it includes about twice the number of projects: 9,766 compared to 4,373.

Excluding regional recipients (102 projects) and canceled or suspended projects (80 projects) from the analysis, about 68 percent of the remaining 9,584 projects reached the completion stage between 2000 and 2014. We also exclude projects that were only pledged and not officially committed, reducing the dataset to 8,809 projects in 138 countries. The dataset categorizes projects into three funding types: 'ODA-like' projects (concessional financing[13] to support socioeconomic development), 'OOF-like' projects (not primarily development-focused or not concessional enough to be 'ODA-like'), and 'Vague (OF)' projects (insufficient information for classification). The term 'official financing' (OF) includes all three categories. Most projects between 2000 and 2014 (about 76 percent) were based on ODA-like terms (see Appendix Figure A2). However, when considering the size of projects – measured as their financial value in constant 2017 US$ – ODA-like projects accounted for only about 21 percent of total Chinese aid during this period (see Appendix Figure A3 for the yearly distribution).[14]

Figure 3 shows the distribution of Chinese ODA and OOF by the total number of projects (panels A and B) and their financial value in constant 2017 US$ (panels C and D). Chinese OF exhibits a dual nature, with ODA-funded social projects predominantly directed towards poorer (low-complexity) recipients, and OOF-funded productive sector projects primarily targeting richer (high-complexity) recipients. This finding underpins our later analysis, where we will separately examine the effects of ODA and OOF while accounting for heterogeneities across low- and high-complexity recipients.

3.3 Control Variables

To strengthen our estimates of the relationship between Chinese ODA/OOF and economic complexity, and reduce the risk of omitted variable bias, our baseline estimates include a subset of controls that have been shown to be relevant for economic complexity (Lapatinas et al., 2019; Kamguia et al., 2022; Yalta and Yalta, 2021). These are (i) individuals using the Internet (% of population), (ii) total natural resource rents (% of GDP), and (iii) trade (% of GDP), all sourced from the World Bank (2023). For robustness tests, we include additional controls that might also have an impact on economic complexity in recipient countries (Zhu and Fu, 2013; Javorcik et al., 2018; Khan et al., 2020; Lee and Vu, 2020; Saadi, 2020; Vu, 2022a). These are (i) net

[13] Accordingly, ODA is granted on preferential terms. This means that the terms of financial assistance, such as interest rates and repayment periods, should be more favorable than those of commercial loans. For a financial flow to qualify as ODA, it must have a grant element of at least 25 percent.
[14] In addition, grants are mainly awarded under ODA-like conditions, while OOF-like conditions are mainly used for loans, export buyer's and export seller's credits. Appendix A provides a more detailed discussion on Chinese allocation by funding type in our sample.

inflows of FDI (% of GDP), (ii) net ODA received (% of GNI), (iii) remittances received (% of GDP), and (iv) research and development expenditure (% of GDP), all taken from World Bank (2023). In addition, we also control for the sum of public and private investment in a country (IMF, 2021), the state of democracy as a proxy for institutional quality (Marshall et al., 2019), as well as for country-level shocks, namely conflict (Sundberg and Melander, 2013; Davies et al., 2023) and natural disasters (EM-DAT, 2022).

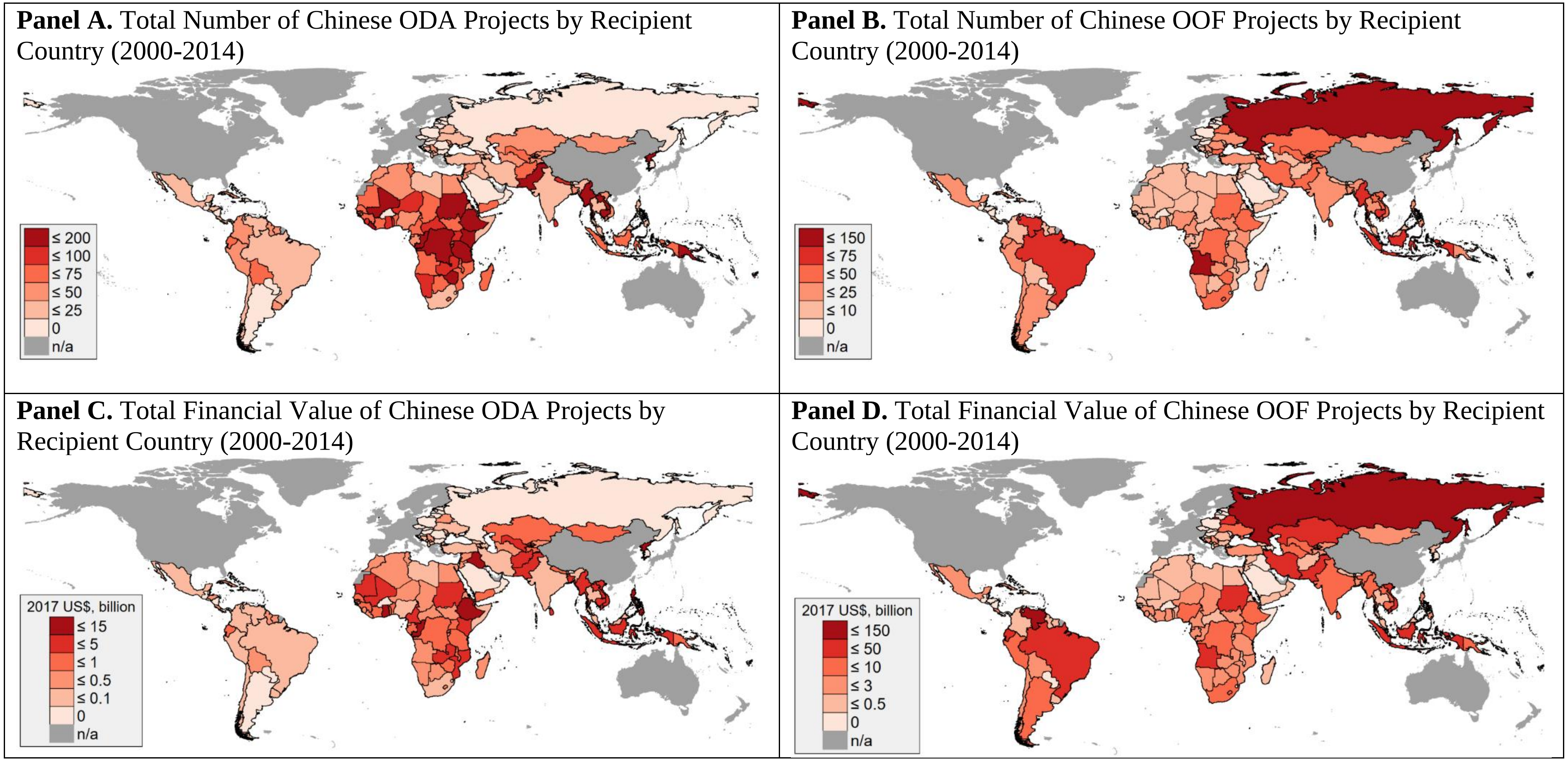

Figure 3. World Maps of Chinese ODA and OOF Projects (2002-2014)

Source: Authors' illustration based on data taken from Dreher et al. (2021a)

3.4. Empirical Strategy

To test the relationship between economic complexity and Chinese OF, we rely on the following model to be estimated:

$$ECI_{i,t} = \alpha + \beta_1 OF_{CHN,i,t-2} + \beta_2 X_{i,t} + \eta_i + \mu_t + \varepsilon_{i,t} \quad (1)$$

where $ECI_{i,t}$ is the ECI of country i in year t. $OF_{CHN,i,t-2}$ refers to Chinese ODA-like and OOF-like commitments, respectively. In line with previous research on Chinese aid (Dreher et al. 2021a; Gehring et al., 2022), the main specification lags $OF_{CHN,i}$ by two years to ensure sufficient time for commitments to materialize. As China is known for its quick project implementation, a two-year period is a realistic timeframe for commitments to affect economic outcomes. Nevertheless, we re-run our baseline estimates for different lags as a robustness check (see Section 4.2). Furthermore, we use two measures of $OF_{CHN,i,t-2}$, namely the number of Chinese development projects and their logged financial amounts.[15] Using financial amounts has the merit of considering the size of projects, yet about 38 percent of the projects lack financial information. Therefore, our preferred estimations rely on the number of projects. $X_{i,t}$ is the set of control variables presented in Section 3.3. η_i and μ_t represent country- and year-fixed effects, respectively. $\varepsilon_{i,t}$ is the error term.[16]

It should be noted that a standard regression framework would be prone to issues of endogeneity. One potential cause is reverse causality in which the economic complexity of recipients influences their probability of receiving Chinese development projects. On the one hand, China could direct more OF to countries with lower complexity as China – contrary to the claims of its critics – behaves in an altruistic manner to support low complexity countries (Guillon and Mathonat, 2020). On the other hand, China might tend to direct more OF to countries with higher complexity if this appears more profitable for commercial reasons (Dreher and Fuchs, 2015; Dreher et al., 2018). Moreover, time-varying omitted variables (e.g., political linkages) that are both correlated with economic complexity and OF could confound

[15] Dreher et al. (2021a) add a value of one before taking logs – a common practice to keep zero-valued observations since ln (0) is undefined. Since the dataset does not contain a single observation with zero value for the financial amount (but many missing observations), we follow their approach of adding a value of one before taking logs.

[16] Using a two-step System Generalized Method of Moments (GMM) approach, Kamguia et al. (2022) also include the lagged value of the ECI, as an independent variable to account for path-dependencies in economic complexity. However, we do not include it as a further control since country fixed effects should be sufficient in that regard.

the relationship between the explanatory and dependent variable. Finally, measurement error in the explanatory variable could induce further endogeneity bias.

To address potential endogeneity, we adopt an IV approach that is used in Dreher et al. (2021a). Its basic intuition stems from the relation between China's development finance and domestic oversupply in terms of industrial production ($Materials$) (Bluhm et al., 2025; Dreher et al., 2021). China's rapid economic growth over the past decades has fueled massive investments in infrastructure and construction projects. To meet the soaring demand for materials such as aluminum and steel, the country has significantly expanded its production capacity. Government policies, eager to promote economic growth and employment, led to excessive investment and overcapacity in these sectors (Guo, 2009), wherein surplus production created redundant production facilities. In response, the Chinese government has sought to address this issue by trying to reduce domestic supply and increase foreign demand. In addition to lowering domestic supply, the Chinese government has relocated production facilities abroad (Kenderdine and Ling, 2018; Stone et al., 2022). To boost foreign demand, China often obliges the recipients of its loans, grants, or export credits to import the construction materials they need from China's excess stocks – an approach that particularly gained traction in the wake of the Belt and Road Initiative (BRI) (Mattlin and Nojonen, 2015; Ghossein et al., 2018, 2021). These multifaceted tactics to offset overproduction lead us to expect a strong and positive relationship between China's industrial production and OF, particularly in the countries that previously already received Chinese OF. This rationale applies across sectors, as many Chinese development projects, even those not focused on infrastructure, often include construction elements (e.g., hospitals and schools for health and education projects) (Mattlin and Nojonen, 2015; Ghossein et al., 2018, 2021). To capture this, $Materials$ is composed of the annual production volumes of six major Chinese industrial inputs needed for the fulfilment of many Chinese development projects: aluminum, cement, glass, iron, steel, and timber.[17] Since they exhibit temporal trends, we detrend them. We use factor analysis to capture the joint variability of these logged and detrended materials.

This results in the estimation of the following first-stage regression.[18]

[17] For our IV estimates, we draw on data from (i) the National Bureau of Statistics of China (NBSC, 2021) and the United States Geological Survey (USGS, 2021) for yearly Chinese production volumes of aluminum, cement, glass, iron, steel, and timber.

[18] This IV approach was also applied by, e.g., Bluhm et al. (2025), Gehring et al. (2022), and Wellner et al. (2022).

$$OF_{CHN,i,t-2} = \gamma_1 Materials_{t-3} \times p_{CHN,i} + \gamma_2 \eta_i + \gamma_3 \mu_t + \epsilon_{i,t-2} \quad (2)$$

where $OF_{CHN,i,t-2}$ refers to Chinese ODA-like and OOF-like commitments, respectively, $Materials_{t-3}$ represents the time-varying part of the IV, and $p_{CHN,i}$ the probability of receiving Chinese aid during 2000-2014, which varies across recipients.[19] Like Dreher et al. (2021a), we opt for a one-year lag of $Materials$ as China is known to provide its aid quickly, partly due to the need to offload its domestic oversupply (Swedlund, 2017). η_i and μ_t refer to country- and year-fixed effects, respectively. $\epsilon_{i,t-2}$ is the error term.

We restrict the sample to the 2000-2014 period, even though the dataset includes Chinese development project data up until 2017. This is because both $Materials$ and $Reserves$ (and their corresponding domestic oversupplies) became less relevant in explaining Chinese OF allocation after 2014.[20] Turning to panels A-D of Appendix Figure A6 and comparing them with data on the number of Chinese projects over time, this is not surprising. Stagnant industrial output[21] and sharply declining foreign-exchange reserves from 2015 onward[22], coupled with a further expansion of Chinese OF projects (recall Appendix Figure A2Figure), results in an opposing effect post-2015 and weakens the IV's strength. Rather than speculating about alternative drivers or motivational forces of China's increased development finance after 2014, we follow the literature and shorten the sample by three years, thereby losing 232 observations but enhancing the relevance of the IV employed.

One possible concern is that the IV may violate the exclusion restriction, particularly if it directly impacts the economic complexity in recipient countries. Recent studies are concerned with issues arising from Bartik (1991)-style shift-share IVs, such as the IV chosen here (e.g., Christian and Barrett, 2017; Adão et al., 2019; Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022). In general, shift-share IV designs represent methodological specifications aimed at

[19] Appendix Figure A5 shows each country's probability of receiving Chinese ODA (panel A) and OOF (panel B) projects between 2000 and 2014.

[20] We also ran regressions for the 2000-2017 period. While the overall results are similar, $Materials$ become insignificant in the fixed-effects framework. Therefore, $Materials$ loses relevance for explaining Chinese OF allocation after 2014.

[21] While the production of the six industrial goods included in Materials largely stagnated from 2015 (see panel A of Appendix Figure A6) causing the detrended first factor to decline (see panel B), this does not per se explain whether China's domestic oversupply was solved, thereby reducing its motivation to further expand its development finance engagement. While closer examining this issue is beyond the scope of this study, we assume that China's government has been able to curb the problem at least partially through consolidation measures and the expansion of domestic infrastructure and housing investments. The consequences of the latter (often inefficient measures) can currently be seen in China's housing vacancy crisis (Wan and Qiu, 2023).

[22] China's reserves (incl. gold) reached a peak of about US$3.9 trillion in 2014 and decreased thereafter to roughly US$3.2 trillion in 2017. Since then, they largely stabilized and amounted to about US$3.3 trillion in 2022.

estimating the impact of shocks ('shifters'; here: $Materials$) on units affected by these shocks to varying degrees ('shares'; here: $p_{CHN,i}$) (Adão et al., 2019). Borusyak et al. (2022) argue that under certain assumptions, the estimator's consistency may be rooted in the shocks. However, when controlling for year-fixed effects, $Materials$ does not and cannot exhibit correlation with the error term, making it (conditionally) exogenous to Chinese OF. Goldsmith-Pinkham et al. (2020), by contrast, claim that the exogeneity condition should be interpreted in terms of shares, provided that the research design can be described as reflecting differential exogenous exposure to common shocks. Therefore, it is crucial to control for the endogenous probability of receiving Chinese ODA/OOF by including country-fixed effects. In turn, the interaction of the probability of receiving Chinese aid with an exogenous variable yields an exogenous instrument, assuming parallel trends (Goldsmith-Pinkham et al., 2020). Echoing Dreher et al. (2021a), this approach relies on a differences-in-differences setting to examine differential effects of $Materials$ on the amount of Chinese aid directed to countries with an above- (regular recipients) and a below-median (irregular recipients) probability of receiving development projects from China. While controlling for country- and year-fixed effects, the core assumption guiding these estimations is that changes in $Materials$ do not differentially affect the economic complexity of countries in both groups, apart from the effect of Chinese development projects. Simply put, following Dreher et al. (2021a), we draw on parallel pre-trends for both regular and irregular recipients in the variables of interest and a (conditionally) exogenous treatment. We discuss the validity of this assumption in Appendix D.

4. Results

4.1 Aggregate Economic Complexity Effects of Chinese Development Finance - Baseline Results

Table 1 presents the results of the main specification on the effects of Chinese ODA/OOF on recipients' economic complexity over the 2002-2016 period.[23] For the reader's convenience, we only show results regarding the variable of interest, Chinese OF (t-2), and the corresponding results for the IV. However, all estimates include controls for Internet usage (% of population), total natural resources rents (% of GDP), and trade (% of GDP), as well as country- and year-fixed effects.[24] In columns 1 and 2, the number of Chinese development projects – measured as

[23] Recall that we measure Chinese aid yearly over the 2000-2014 period and lag it by two years. See Table Appendix Table A5 and Appendix Table A6 for descriptive statistics and a list of countries, respectively.
[24] In what follows, all estimates use these controls and country- and year-fixed effects unless indicated otherwise.

ODA and OOF projects, respectively – are the variables of interest, whereas in columns 3 and 4, these are replaced by the respective logged financial amounts.

In panel A, we show results using Ordinary Least Squares (OLS) estimation. As presented in column 1, the number of Chinese ODA projects does not affect recipients' economic complexity at conventional levels of statistical significance. The same applies to projects that are carried out on less concessional (OOF-like) terms (column 2). Further, the results remain insignificant looking at financial amounts rather than project numbers (columns 3 and 4). Given the potential endogeneity issues – such as reverse causality, omitted variables, and measurement error – that could bias the OLS results, we apply the IV approach presented in Section 3.4. The respective results are shown in panels B-D.

Panel B illustrates estimates in reduced form, wherein the instrument ($Materials_{t-3} \times p_{CHN,i}$) substitutes the respective Chinese aid variables. Results consistently show no statistically significant effects of $Materials$ on recipients' ECI at conventional levels.

Panel C shows first-stage estimates using 2SLS, while panel D presents the respective second-stage results. In all first-stage regressions, the instrument shows the expected positive sign and is statistically significant at the 1 percent level. This underscores the relevance of the instrument, i.e., a rise in $Materials$ in year t leads to increases in Chinese ODA/OOF project numbers and financial amounts (especially OOF-like) one year later ($t + 1$) for countries that regularly receive Chinese OF. Based on the 90 percent confidence interval in column 1 of panel D, a one standard deviation increase in $Materials$ is associated with about 1.55-2.36 additional Chinese OF projects, on average (c.p.).

Table 1. Economic Complexity Effects of Chinese OF, Baseline Results (2002-2016)

	ODA Projects (1)	OOF Projects (2)	(log) ODA Amounts (3)	(log) OOF Amounts (4)
Panel A. OLS estimates – DV: ECI				
Chinese OF (t-2)	0.003 (0.003)	-0.001 (0.006)	-0.000 (0.001)	-0.001 (0.001)
Panel B. Reduced-form estimates – DV: ECI				
Materials (t-3) x Probability	-0.003 (0.040)	-0.039 (0.060)	0.008 (0.045)	-0.051 (0.061)
Panel C. First-stage estimates – DV: Chinese OF (t-2)				
Materials (t-3) x Probability	1.215*** (0.164)	1.529*** (0.343)	1.207*** (0.386)	4.332*** (1.271)
Panel D. 2SLS estimates – DV: ECI				

Chinese OF (t-2)	-0.002 (0.033)	-0.025 (0.039)	0.006 (0.037)	-0.012 (0.014)
Observations	1,309	1,309	1,309	1,309
Number of Countries	98	98	98	98
Kleibergen-Paap F-statistic	54.63	19.89	9.76	11.62

Notes: Each column per panel corresponds to one regression. In panels A-C, the DV is the recipient ECI in year t. The variable of interest, *Chinese OF* (*t*-2), refers to China's ODA/OOF projects with a lag of two years and is measured as project numbers in columns 1 and 2 and logged financial amounts in columns 3 and 4. Columns 1 and 3 refer to ODA and columns 2 and 4 refer to OOF projects. All regressions include Internet usage (% of population), total natural resources rents (% of GDP), and trade (% of GDP) as control variables, as well as country- and year-fixed effects. Standard errors are in parentheses. p<0.1; **p<0.05; ***p<0.01.

As the bottom of Table 1 shows, the Kleibergen-Paap F-statistic is well above ten (the rule-of-thumb value) for the regressions that focus on project numbers (columns 1 and 2). Thus, the instrument is sufficiently strong for these settings. However, for regressions that focus on financial amounts of ODA (columns 3), the F-statistic falls slightly below ten. Moving to our primary findings, panel C presents the second-stage results of the 2SLS estimates. In line with the OLS findings in panel A, the 2SLS results are statistically insignificant at conventional levels throughout. These results are thus in contrast to our first hypothesis (see Section 2.4) and the aggregate null effect is remarkably robust as we show in Appendix E. Therefore, overall, Chinese OF does not significantly affect the economic complexity of recipients, regardless of whether one considers ODA-like projects or OOF-like projects. Apart from the insignificance of the results, it is worth noting that unlike the OLS estimates, the 2SLS results show a negative sign even for ODA projects. Hence, contrary to our second hypothesis (see Section 2.3), the financing terms of Chinese development projects do not play a pivotal role in explaining the aggregate insignificance of our results.

Although in principle a precisely estimated zero effect is preferable to an imprecisely estimated significant effect (Dreher and Langlotz, 2020: 1178), the overall ineffectiveness of Chinese ODA/OOF in complexity terms is at least questionable given the positive short-run growth effects found by Dreher et al. (2021a) and the positive effects on connectivity discovered by Bluhm et al. (2025). This is compounded by the sheer size of Chinese support: the average recipient country within the sample receives about 4.9 projects worth around US$640 million per year. Motivated by our hypothesis on sectoral and country-level difference, we delve deeper into potential heterogeneities and mechanisms in Section 4.2 (and in Appendix F).

4.2 Heterogeneities and Mechanisms

To achieve a more nuanced understanding of the forces at play, we examine potential heterogeneity in our results. As discussed in Section 2.3, China follows a multifaceted approach to OF, covering a wide range of different sectors. China focuses on the social sector in terms of the number of projects, while directing the lion's share of its commitments in terms of financial value to non-social sectors. In turn, the effects of Chinese ODA/OOF on recipients' economic complexity likely differ across sectors. Therefore, we re-run our baseline estimates across different (broadly defined) sectors, namely the social, economic, and production sectors. We present the corresponding results in Table 2.[25] The F-statistics easily cross the rule-of-thumb value of ten, suggesting that the interaction of $Materials$ and the probability to receive aid is also a sufficiently strong IV for sectoral analyses. Therefore, we interpret the effects presented below as causal.

Starting with the social sector, we find positive yet insignificant results across all flow classes (see panel A of Table 2). As for the economic sector, the results are equally insignificant throughout but show negative coefficients for OOF-like projects (see panel B). These results are somewhat surprising, since economic sector projects should be primarily responsible for the connectivity-enhancing results of Chinese development finance found by Bluhm et al. (2025).[26] This is due to the economic sector's focus on the construction of transport, energy, and communications infrastructures, thereby reducing travel times[27] and improving the access to electricity and the Internet. All these factors have been found to increase knowledge sharing, thereby fostering productive capabilities and ultimately economic complexity as mentioned previously in our article. However, the null results provide suggestive evidence that potential progress in connectivity does not necessarily boost knowledge transfer in recipients, which is crucial in achieving economic complexity (Hidalgo, 2015; Gao et al., 2017; Hidalgo, 2021).

Turning to panel C, the results show that OOF projects targeted toward the production sector negatively affect recipient countries' economic complexity at the 10 percent and the 5 percent level of statistical significance, respectively. In general, a country's ECI decreases if it exports fewer diverse products and/or if its exports shift towards products of lower complexity compared to its previous complexity level (Hidalgo, 2023). However, due to the ECI's

[25] For these estimations, we use sectoral probabilities and thus construct sector-specific instruments.

[26] Bluhm et al. (2025), however, examine economic effects at the *subnational level*. These might dissipate at the *country level* and may explain the null effects in our study.

[27] For instance, a 2009-2012 highway project in Kenya, linking Nairobi to Thika (roughly 50km apart) increased travel speed and reduced travel times significantly from 2-3 hours to 30/45 minutes (Dreher et al., 2022: 192-193).

measurement, it is challenging to identify those industries into which Chinese production sector financing mainly flows and whose exports thus cause recipients' ECI to fall.[28] Nonetheless, given that the bulk of Chinese production sector projects are concentrated on industry, mining, and construction (about 26.6 percent of the total financial value during 2000-2014), we assume that production sector financing flows mainly to industries of rather low complexity, shrinking recipients' ECI and thus limiting their potential for structural transformation.

Table 2. Economic Complexity Effects of Chinese OF across Sectors (2002-2016)

	Coef.	Countries	Obs.	Kl.-Paap *F*-Stat.
Panel A. Social Sector				
ODA Projects	0.034	98	1,309	86.64
	(0.046)			
OOF Projects	0.096	98	1,309	22.75
	(0.123)			
Panel B. Economic Sector				
ODA Projects	0.039	98	1,309	11.14
	(0.152)			
OOF Projects	-0.047	98	1,309	14.32
	(0.061)			
Panel C. Production Sector				
ODA Projects	-0.215	98	1,309	12.84
	(0.248)			
OOF Projects	-0.279**	98	1,309	22.52
	(0.125)			

Notes: Shows separate results for different sectors as indicated in the panel headers. Each row per panel corresponds to one regression. The DV is the recipient ECI in year t. The variable of interest, *Chinese OF* (*t*-2), refers to China's ODA/OOF projects with a lag of two years and is measured as project numbers. In separate rows of each panel, we show discrete results for ODA and OOF projects. All regressions include Internet usage (% of population), total natural resources rents (% of GDP), and trade (% of GDP) as control variables, as well as country- and year-fixed effects. Standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Next, we explore some of the potential underlying drivers that might explain these sectoral differences and perform a sample split for recipient countries that exhibit above-median (high-complexity; see Appendix Table A7Table A7) and below-median ECI levels (low-complexity;

[28] Nevertheless, we also examined the effects of Chinese aid on the exports of recipients in important low-complexity industries (coal, crude oil, natural gas, ores, petroleum products, and wood) with data from UN Comtrade (2022). While increases in the exports of these products are likely associated with a reduction in economic complexity due to their low-complexity nature, the results are mostly insignificant. For brevity, we do not report the results in tables.

see Appendix Table A8) in a given year, respectively.[29] With F-statistics above ten for most regressions, we find negative coefficients for high-complexity recipients in the aggregate and across all sectors, no matter the type of financing. Focusing on statistically significant effects, the OOF-dominated sectors (economic and production) prevail (see panels C and D). These negative effects are strong enough to cause statistically significant negative effects on the ECI of high-complexity countries in the aggregate as well (see panel A). Although negative signs are observed for the social sector (see panel B), the results are insignificant. In sum, the economic complexity of high-complexity recipients is significantly negatively affected by Chinese development projects, especially through the production sector.

Turning to low-complexity recipients, the results generally point to a different, slightly more promising picture in terms of economic complexity. The coefficients exhibit positive values, except for OOF-like projects in the production sector (see panel D). Yet, statistically significant effects boil down to the social sector (see panel B). Low-complexity recipients thus benefit from Chinese projects targeting their social sector: an additional social ODA-like project is associated with an increase of a recipient's ECI by about 0.11 units two years later, on average (c.p.). The rapid onset of effects may seem surprising, given that aid to the education sector (arguably the most crucial part of the social sector for reasons of complexity) is known to lead to quantifiable socioeconomic effects in recipient countries only in the longer term, if at all (Clemens et al. 2012). To strengthen the results for the social sector, we therefore repeat the social sector regressions using different lags for both high-complexity (see Appendix Table A10) and low-complexity recipients (see Appendix Table A11Table A11). For the former, the negative but insignificant effects are confirmed across all lags ($t - 1$ to $t - 6$). For the latter, however, Chinese development finance (ODA, and OOF, respectively) creates persistent positive and statistically significant effects. Yet for $t - 6$, the effects become insignificant which could also be due to shrinking sample sizes at larger lags.

To further corroborate these results, we perform another sample split regarding the level of educational attainment. In doing so, we split our sample into an above- and a below-median group in terms of the average years of schooling during the 2002-2015 period (see Appendix

[29] This is motivated by the fact that the mean ECI values of individual world regions differ strongly: in the regional analysis, the leaders in terms of complexity are North and South American countries (-0.194 between 2002 and 2016), followed by Asia (-0.433) and Africa (-0.871). Albeit not covered in our regional analysis due to data constraints, the actual frontrunners are European countries (0.371). Middle Eastern countries (-0.362) are ranked between American and Asian countries. Oceania yields a mean ECI value of -1.624. However, Papua New Guinea is the only Oceanian country covered by the ECI.

Table A12Table).[30] Given that the average years of schooling are higher for high-complexity countries (8.88 years) than for low-complexity countries (6.22 years), educational attainment is a likely covariate of economic complexity and therefore the results mirror those for the complexity sample split.[31] More precisely, we find negative yet insignificant results of Chinese social sector projects for above-median schooling recipients (see panel A) and statistically significant positive effects for recipients with below-median levels of schooling (see panel B).

Taken together, the different results according to recipient's level of complexity (and some of its covariates) are counterintuitive upon first glance. While high-complexity recipients should find it easier to gain in complexity due to path-dependencies, as explained in Section 2.2, we find negative effects for this sub-group. In contrast, the results reinforce the finding that low-complexity recipients benefit primarily from Chinese social sector projects. Nevertheless, these positive effects do not seem to be sufficient to allow low-complexity countries to benefit significantly in the aggregate and are hence unlikely to foster structural transformation in these countries. The differential impact is likely due to the nature of Chinese development projects themselves. Recalling the descriptive statistics from Section 3.2 (and especially Figure 3), poorer (low-complexity) countries receive more projects, but less financial amounts in the aggregate. This applies vice versa for richer (high-complexity) countries. Given a reallocation in China's aid portfolio during the COVID pandemic (Fuchs et al., 2022), these effects may have changed in more recent years.

5. Conclusion

Economic growth in recipient countries is arguably the most common subject of study in the aid-effectiveness literature, although results vary across different donors (Burnside and Dollar, 2000; Dalgaard et al., 2004; Rajan and Subramanian, 2008; Clemens et al., 2012; Galiani et al., 2017; Dreher and Langlotz, 2020). Since the onset of the 21st century, China has established itself as one of the most important players in foreign aid and development finance. As reliable data on Chinese finance increasingly become available (e.g., Dreher et al., 2021), this paper aims to understand how Chinese official finance (OF) affects the fundamentals of economic

[30] Specifically, we take data from Barro and Lee's (2013) educational attainment dataset, which covers the 1950-2015 period at five-year intervals. To fill up the missing years, we perform a linear interpolation.

[31] Although we cannot completely rule it out, we do not assume that education is a main driver of the heterogeneity observed for complexity. True, education is a key determinant of complexity (Zhu and Li, 2017). Accordingly, positive results for the social sector should theoretically also be observed for high-complexity recipients. Instead, they are negative and insignificant across all lags. So, we assume that these results are rather due to China's different approaches depending on the region to which their development projects are directed.

development by considering its effects on economic complexity. This measures the diversification and complexity of a country's exports, offering insights into the potential of structural transformation and thus possible longer-term growth effects (Hidalgo and Hausmann, 2009; Hausmann et al., 2013; Zhu and Li, 2017).

Our results show that Chinese development finance (in terms of ODA and OOF, respectively) has no statistically significant effects on the economic complexity of recipient countries in aggregate terms and is thus unlikely to foster structural transformation. These baseline results hold for various lags and are robust even after the incorporation of various controls, the omission of potential outliers, the formulation of different definitions for the independent variables, and the use of alternative IVs. However, because of China's multifaceted approach, we consider heterogeneities across sectors and variation depending on the initial complexity levels of recipients. For high-complexity recipients, the aggregate shows significant negative effects on complexity caused mainly by sectors that are primarily based on OOF-like terms (economic and production). These countries experience a detrimental export performance, which may hinder overall structural change (Hartmann et al., 2017). For low-complexity recipients, particularly in Africa, the effects of Chinese development projects are slightly more promising. These countries benefit from development projects that target their social sector (e.g., health and education projects) and are financed primarily on ODA-like terms. While these effects appear too weak to prevail in the aggregate, they are in line with the significant growth effects that Dreher et al. (2021b) show in an African sub-sample. In sum, our findings add more nuance to the largely negative portrayal of Chinese aid. As Chinese OF reduces the performance of high-complexity countries and tends to benefit low-complexity countries, it could be seen as an *equalizer* of economic complexity among low- and middle-income countries. Thus, more selective allocation of financing could unleash the potential of Chinese aid as a *promoter* of structural transformation. As China pursues a demand-driven approach of aid allocation, recipients have the chance to take more agency (Brazys and Vadlamannati, 2021). Nonetheless, in order to enable a more informed demand for projects and financial terms, greater empirical efforts are needed to understand China's development financing.

In that respect, our findings leave ample room to investigate the underlying mechanisms. First, a more granular approach could help to understand why production sector projects negatively affect high-complexity recipients' level of complexity. It would be helpful to identify the specific industries into which Chinese aid flows. This is also related to the ECI itself, whose intertwined methodology does not allow for conclusions on the concrete impact of single industries. The ECI measure used here restricts a country's complexity to its exports. This does not reflect the geography of other complexity-driving activities such as research and innovation (Hidalgo, 2023). For this reason, recent multidimensional approaches, which add publication and patent data (e.g., Pugliese et al., 2019; Catalán et al., 2022), would allow for a more adequate picture of complexity effects if these datasets become more comprehensive.

Second, China has significantly expanded its engagement since the announcement of the BRI in 2013. If the BRI's emphasis is more on connectivity in order to enhance mobility, along with knowledge transfers and productivity, this could positively affect economic complexity in recipient countries and particularly in specific regions. To do so, a subnational analysis could provide more clarity on whether increased connectivity (Bluhm et al., 2025) indeed translates into higher economic complexity, provided that the available data support such an endeavor.[32]

Third, little is known about the underlying terms of China's funding, apart from the different use of ODA-like and OOF-like projects across sectors and regions. For instance, different interest rates and maturities, as well as the size of the grant element, could influence the effect of Chinese development projects on recipients' economic complexity. These determinants directly affect recipients' ability to repay their debt and thus their fiscal space to foster structural transformation. In this context, it would be worthwhile to investigate to what extent the underlying terms drive the heterogeneous effects of ODA- and OOF-like finance in our paper (Horn et al., 2023a). This would also be of interest to other international financial institutions adapting to the modalities of China, not to become yet another complexity equalizer, but to push the global financial portfolio towards more growth-promoting terms.

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Appendix A: Data

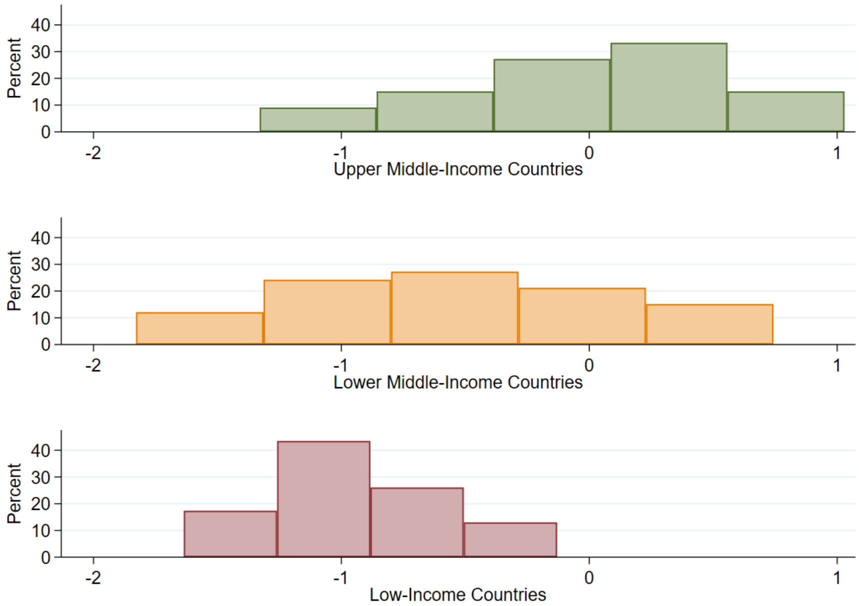
Further Details on Explanatory Variables

AidData collected these data based on the so-called Tracking Underreported Financial Flows methodology, which standardizes a vast amount of non-structured but publicly available project-level information (Custer et al., 2021). The dataset includes information on project status, funding type, and the sector to which funds are directed.

Figure 3 shows the distribution of Chinese ODA and OOF by the total number of projects (panels A and B) and their financial value in constant 2017 US$ (panels C and D). The largest share of Chinese ODA projects was directed to African countries (54 percent), followed by Asian (22.1 percent) and Latin American countries (9.6 percent), while Asian countries received the largest share of OOF projects (32.9 percent), followed by African (29.9 percent) and Latin American countries (18.7 percent) (see Appendix Table A3). In financial terms, African countries received 45.4 percent of total ODA project amounts, while Asian countries received 38.7 percent and Latin American countries only 4.2 percent. However, in terms of OOF project amounts, African countries received only 17.8 percent, while 21.2 percent went to Asian countries and the largest share, 35.6 percent, to Latin American countries (see Appendix Table A3). Accordingly, African countries are underrepresented in the largest projects funded by China in terms of financial amounts. Only Angola is among the countries that received the largest 20 OF projects (see Appendix Table A4). Interestingly, the largest Chinese projects are mainly directed to infrastructure development and extractive sectors, which exacerbates the resource curse and thus likely entrenches low-complexity path dependencies (Camargo and Gala, 2017).

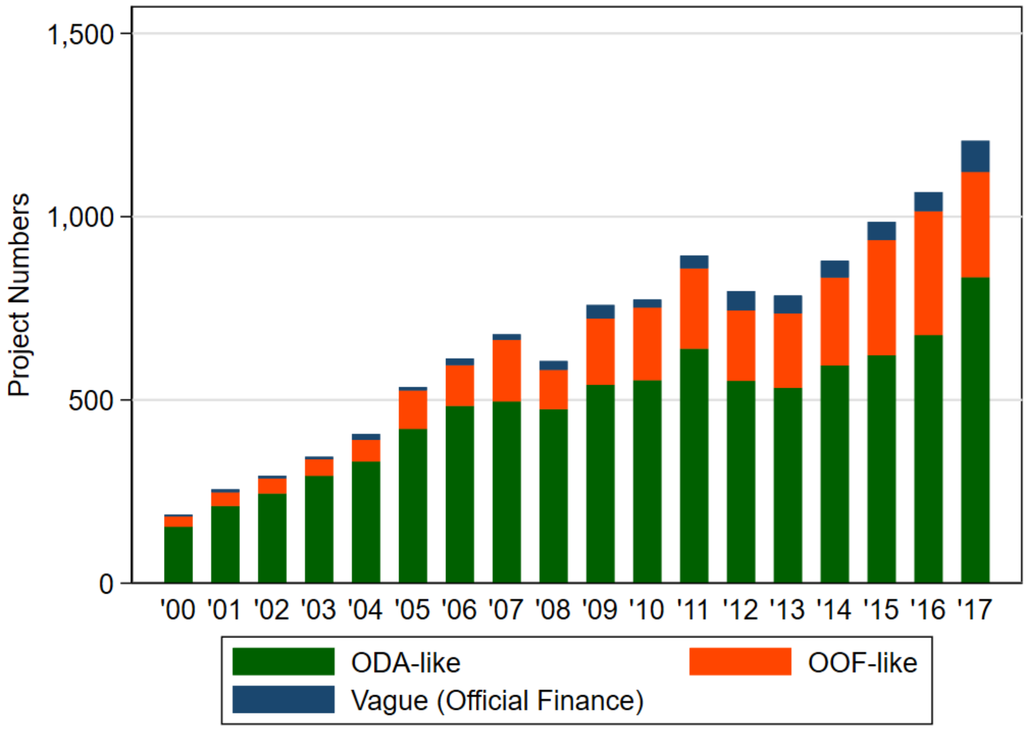
While about 52 percent of all projects focused on social sectors, only about 31 percent went to economic and production sectors. In contrast, about 65 percent of the total financial value was concentrated in the latter sectors, whereas the social sectors received less than 5 percent (see Appendix Figure A4). This shows that while the smaller social sector projects are typically ODA-like, China tends to use OOF-like commitments for larger economic and production sector projects (Dreher et al., 2018b, 2021).

Figure A1. ECI Distribution for Recipients of Chinese OF by Income Group (2002-2016)



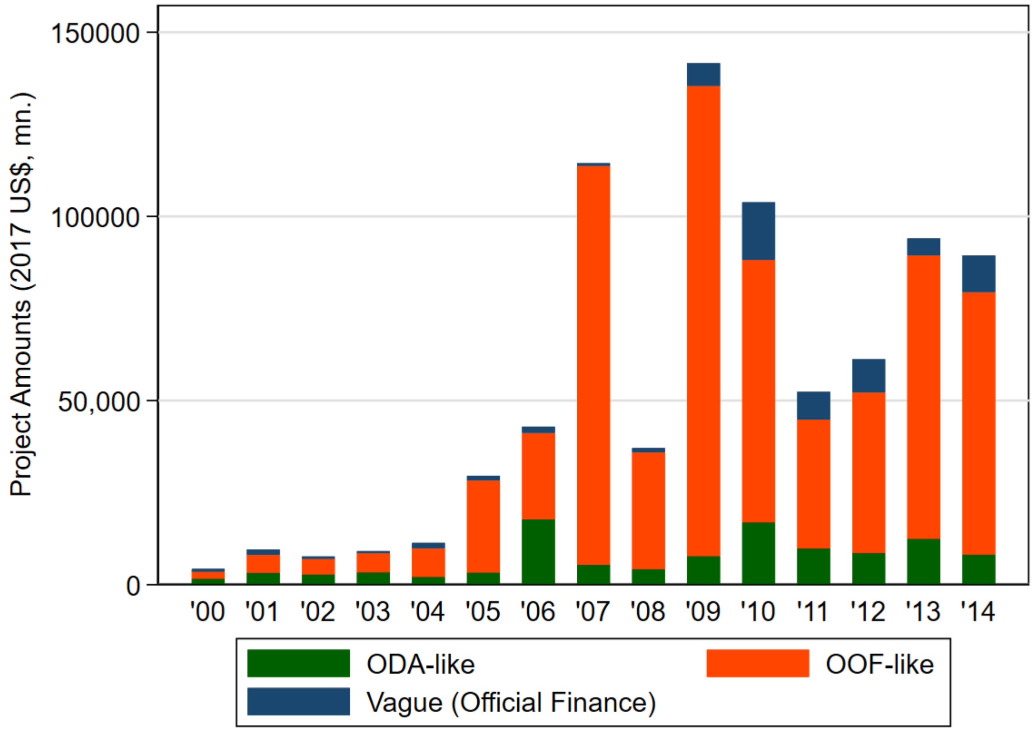
Source: Authors' illustration; data taken from Dreher et al. (2022) for Chinese development finance, The Growth Lab at Harvard University (2019) for the ECI, and World Bank (2022) for income classifications.
Notes: Since the income status of some countries changed during the 2002-2016 period, we assigned countries to the income status they exhibited most often during the period. ECI values below zero indicate countries whose economic complexity is lower than that of the average country in the dataset, and vice versa (Hidalgo, 2021).

Figure A2. Total Number of Chinese OF Projects by Flow Class (2000-2017)



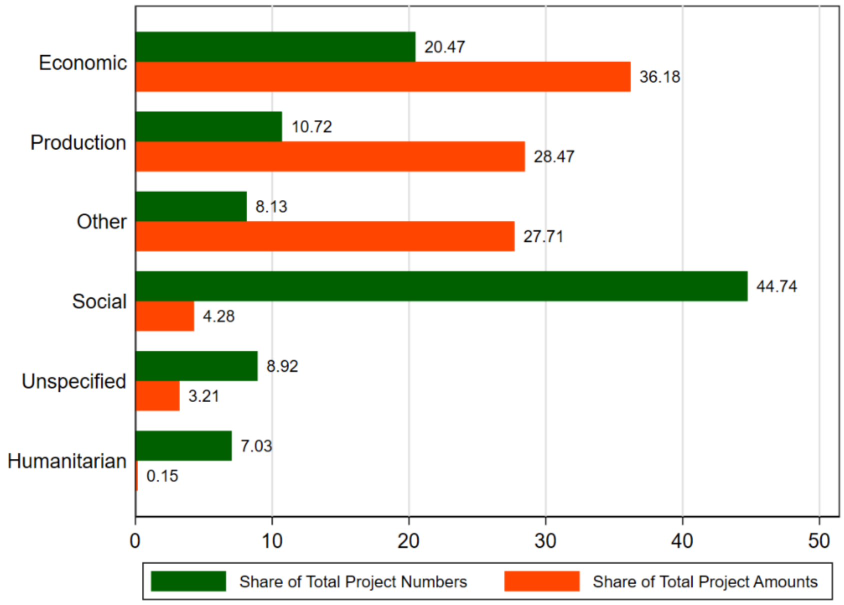
Source: Authors' illustration; data taken from Dreher et al. (2022).
Notes: Exceptionally also includes 2015-2017 to support the argument regarding the restriction of the sample period (see Section 3).

Figure A3. Total Amount of Chinese OF Projects by Flow Class (2000-2014)



Source: Authors' illustration; data taken from Dreher et al. (2022).

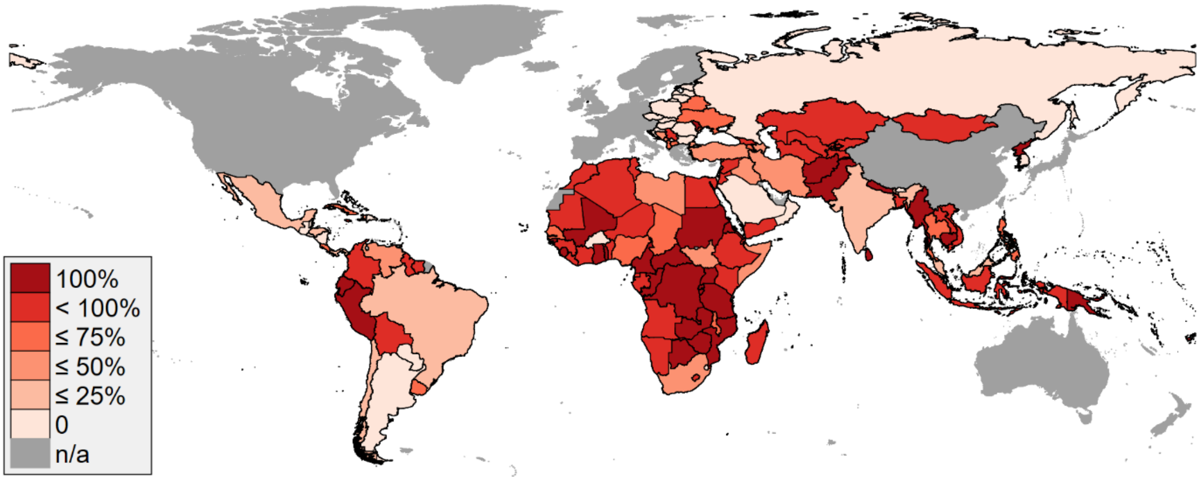
Figure A4. Proportion of Chinese OF Projects across Broad Sectors (2000-2014)



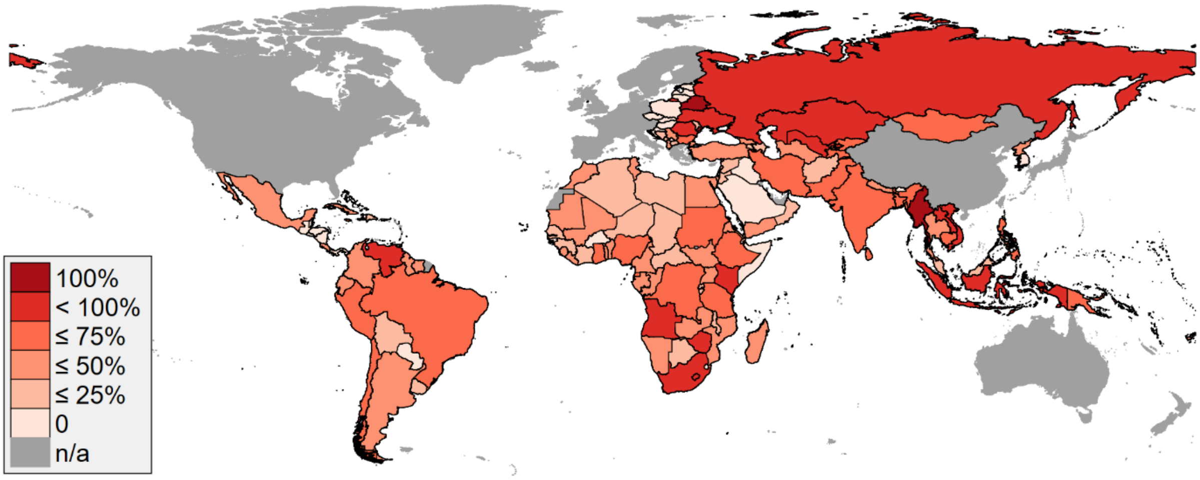
Source: Authors' illustration; data taken from Dreher et al. (2022).

Figure A5. Probability of Receiving Chinese ODA/OOF Projects by Recipient (2000-2014)

Panel A. Probability of Receiving Chinese ODA Projects by Recipient (2000-2014)



Panel B. Probability of Receiving Chinese OOF Projects by Recipient Country (2000-2014)



Source: Authors' illustration; data taken from Dreher et al. (2022).

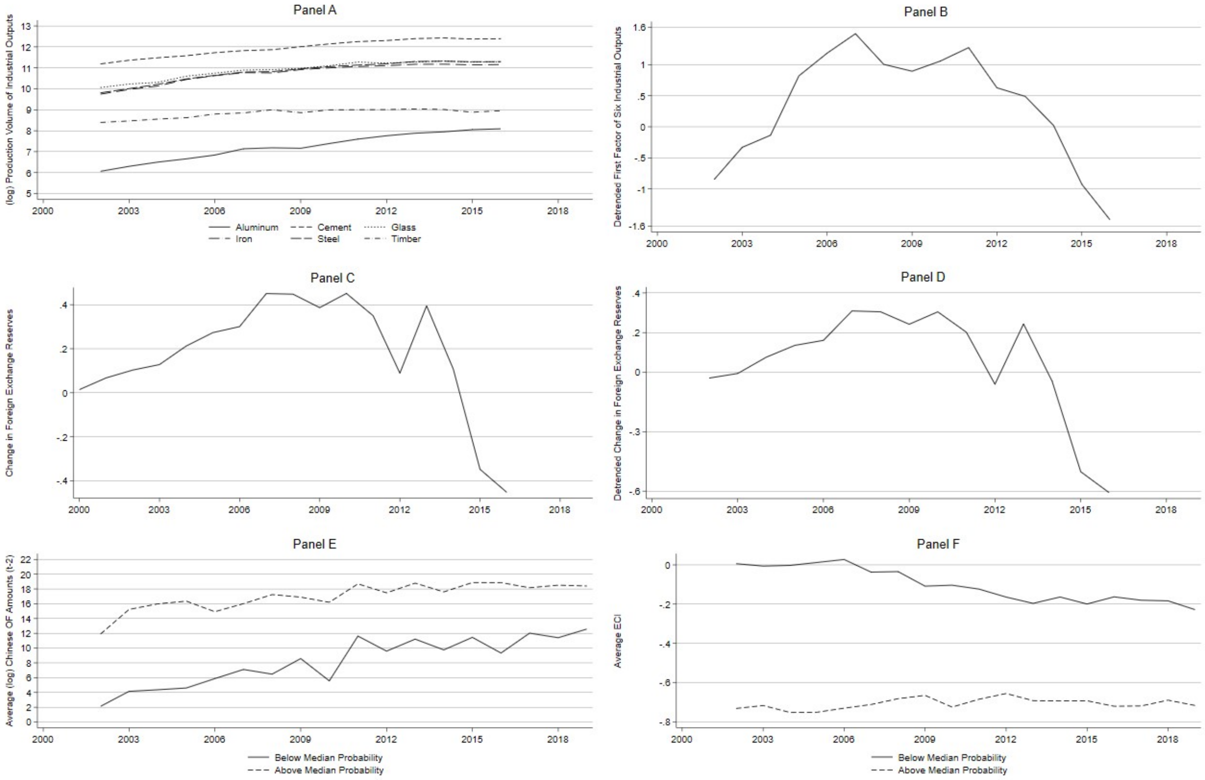


Figure A6. Chinese Development Finance and Its Components (2000-2019)

Notes: Panel A shows China's logged production of aluminum, cement, iron, and steel (all in 10,000 tons), glass (in 10,000 weight cases), and timber (in 10,000 cubic meters) over time. Panel B shows the detrended first factor of these materials using factor analysis. Panel C reports the change in net foreign exchange reserves (in trillions of constant 2017 US$) and panel D its detrended version. Panel E shows average logged Chinese OF amounts for an above- and below-median group in terms of their probability to receive Chinese OF. Panel F shows the average ECI for both groups over time. For the derivation of the medians, we use the sample of column 1 in Table 1.

Table A1. Low- and Middle-Income Chinese OF Recipients not Covered by the ECI

Afghanistan (75)	Djibouti (75)	Marshall Islands (17)	Somalia (18)
Antigua and Barbuda (26)	Dominica (60)	Micronesia (100)	South Sudan (71)
Barbados (6)	Equatorial Guinea (15)	Montenegro (12)	Sudan (237)
Benin (80)	Eritrea (46)	Nauru (12)	Suriname (40)
Burundi (91)	Fiji (105)	Nepal (90)	Syria (36)
Cabo Verde (53)	Grenada (69)	Niger (86)	Timor-Leste (56)
Central African Republic (83)	Guinea-Bissau (54)	Niue (20)	Tonga (76)
Chad (64)	Guyana (52)	Rwanda (75)	Vanuatu (72)
Comoros (46)	Haiti (22)	Saint Lucia (11)	West Bank and Gaza (12)
Cook Islands (24)	Iraq (9)	Samoa (75)	
Curacao (1)	Lesotho (77)	Seychelles (77)	
DPR Korea (110)	Maldives (46)	Sierra Leone (105)	

Source: Authors' illustration; data taken from Dreher et al. (2022).
Note: Covers the 2000-2014 period. Cancelled and suspended Chinese development projects as well as informal pledges are excluded. Chinese OF project numbers in parentheses.

Table A2. Top 10 and Bottom 10 by Mean ECI (2002-2016)

Rank	Recipient	Region	Mean ECI
1	Hungary	Europe	1.269
2	Slovakia	Europe	1.239
3	Mexico	America	1.030
4	Poland	Europe	0.992
5	Belarus	Europe	0.919
6	Malaysia	Asia	0.861
7	Thailand	Asia	0.743
8	Russia	Europe	0.735
9	Croatia	Europe	0.675
10	Romania	Europe	0.674
…	…	…	…
86	Yemen	Middle East	-1.250
87	Gabon	Africa	-1.313
88	DR Congo	Africa	-1.389
89	Myanmar	Asia	-1.466
90	Congo	Africa	-1.468
91	Mauritania	Africa	-1.571
92	Guinea	Africa	-1.591
93	Angola	Africa	-1.628
94	Papua New Guinea	Oceania	-1.739
95	Nigeria	Africa	-1.841

Source: Authors' illustration; data taken from Dreher et al. (2022) for the recipients of Chinese OF and The Growth Lab at Harvard University (2019) for the ECI
Note: Covers all recipients of Chinese OF for which ECI data is available as used in the sample of Table 1.

Table A3. Regional Distribution of Chinese OF (2000-2014)

Region	ODA-like		OOF-like	
	Numbers	Amounts	Numbers	Amounts
Africa	3,522 (54.0%)	49,127 (45.4%)	578 (29.9%)	113,477 (17.8%)
Asia	1,440 (22.1%)	41,864 (38.7%)	636 (32.9%)	136,659 (21.2%)
America	628 (9.6%)	4,590 (4.2%)	362 (18.7%)	227,515 (35.6%)
Oceania	555 (2.4%)	2,523 (2.3%)	62 (3.2%)	6,144 (1.0%)
Europe	158 (2.4%)	908 (0.8%)	237 (12.2%)	137,494 (21.5%)
Middle East	205 (3.1%)	9,214 (8.5%)	58 (3.0%)	18,523 (2.9%)

Multi-Region	17 (0.3%)	41 (0.0%)	2 (0.1%)	0 (0%)
Total	**100%**	**100%**	**100%**	**100%**

Source: Authors' illustration; data taken from Dreher et al. (2022).
Notes: Amounts are in millions of constant 2017 US$; respective shares are in parentheses (rounded).

Table A4. Largest Chinese OF Projects (2000-2014)

Rank	Recipient	Year	Flow Class	Flow Type	Short Description	Amount (const. 2017 US$, mn.)
1	Venezuela	2007	OOF-like	Loan	China-Venezuela Joint Fund	78,072
2	Russia	2013	OOF-like	Loan	CNPC disburses loan – via oil prepayment facility – to Rosneft	32,065
3	Russia	2009	OOF-like	Loan	CDB provides loan to Rosneft for East Siberia-Pacific Ocean Oil Pipelin Project	19,556
4	Brazil	2009	OOF-like	Loan	CDB provides line of credit for oil exploration in the Snatos Basin	13,037
5	Russia	2009	OOF-like	Loan	CDB provides loan to Transneft for East Siberia-Pacific Ocean Oil Pipeline Project	13,037
6	Venezuela	2010	OOF-like	Loan	China-Venezuela Joint Fund	12,499
7	Argentina	2010	Vague (OF)	Loan	China signs railway investment agreement	12,086
8	Venezuela	2010	OOF-like	Loan	China-Venezuela Joint Fund	12,086
9	Russia	2005	OOF-like	Loan	CDB and CEIB provide loan for the acquisition of Baikalfinansgrup and Yuganskneftegaz	11,301
10	Philippines	2006	ODA-like	Loan	CEIB offers concessional loan for infrastructure projects	10,581
11	Kazakhstan	2008	OOF-like	Loan	CDB and Bank of China provide syndicated loan for the Kazakhstani section of the Turkmenistan-China Gas Pipeline	9,927
12	Brazil	2009	OOF-like	Loan	CDB provides line of credit for oil exploration in the Santos Basin	9,126
13	Iraq	2010	ODA-like	DF	Chinese government cancels part of Iraq's outstanding debt obligations	8,098
14	Angola	2009	OOF-like	EBC	CEIB extends master loan facility agreement	7,822
15	Belarus	2009	OOF-like	EBC	China commits credit line to Belarus for investment projects	7,431
16	Russia	2006	OOF-like	Loan	Bank of China provides loan to Taihu Limited for the purchase of Udmurtneft	6,348
17	Venezuela	2007	OOF-like	Loan	China-Venzuela Joint Fund	6,246
18	Brazil	2010	OOF-like	Loan	CEIB provides loan to Petrobras	6,043
19	Peru	2014	OOF-like	Loan	CDB, CEIB, ICBC, and Bank of China provide syndicated loan to repay debts of Las Bambas Copper Project	5,771
20	Venezuela	2009	OOF-like	Loan	China-Venezuela Joint Fund	5,215

Source: Author's illustration; data taken from Dreher et al. (2022).
Notes: CDB – China Development Bank; CEIB – Export-Import Bank of China; CNPC – China National Petroleum Corporation; DF – Debt Forgiveness; EBC – Export Buyer's Credit; ICBC – Industrial and Commercial Bank of China.

Table A5. Descriptive Statistics (Estimation Sample)

Variable	Obs	Mean	Std. Dev.	Min	Max
Economic Complexity Index	1,309	-.37	.73	-3.11	1.4
Number of OF projects (t-2)	1,309	4.08	4.9	0	39
Number of ODA projects (t-2)	1,309	2.77	3.52	0	33
Number of OOF projects (t-2)	1,309	1.11	2.45	0	34
(log) OF amounts (t-2)	1,309	12.95	8.37	0	25.16
(log) ODA amounts (t-2)	1,309	10.2	8.15	0	23.08
(log) OOF amounts (t-2)	1,309	6.8	9.3	0	25.16
Individuals using the Internet (% of population)	1,309	19.7	18.57	.06	78.79
Total natural resources rents (% of GDP)	1,309	8.64	11.07	0	66.06
Trade (% of GDP)	1,309	77.42	31.72	11.86	210.37

Note: This table provides descriptive statistics for the estimation sample used in column 1 of Table 1.

Table A6. List of Countries (Estimation Sample)

Albania	Ecuador	Lithuania	Russia
Algeria	Egypt	Madagascar	Saudi Arabia
Angola	El Salvador	Malayisa	Senegal
Argentina	Estonia	Mali	Serbia
Armenia	Eswatini	Mauritania	Slovak Republic
Azerbaijan	Ethiopia	Mauritius	South Africa
Bangladesh	Gabon	Mexico	Sri Lanka
Belarus	Georgia	Moldova	Tajikistan
Bolivia	Ghana	Mongolia	Tanzania
Bosnia and Herzegovina	Guatemala	Morocco	Thailand
Botswana	Guinea	Mozambique	Togo
Brazil	Honduras	Myanmar	Tunisia
Bulgaria	Hungary	Namibia	Turkey
Burkina Faso	India	Nicaragua	Turkmenistan
Cambodia	Indonesia	Nigeria	Uganda
Cameroon	Iran	North Macedonia	Ukraine
Chile	Jamaica	Oman	Uruguay
Colombia	Jordan	Pakistan	Uzbekistan
Congo	Kazakhstan	Panama	Venezuela
Costa Rica	Kenya	Papua New Guinea	Viet Nam
Côte d'Ivoire	Kyrgyz Republic	Paraguay	Yemen
Croatia	Lao PDR	Peru	Zambia
Cuba	Latvia	Philippines	Zimbabwe
DR Congo	Lebanon	Poland	
Dominican Republic	Libya	Romania	

Note: This country list refers to the estimation sample used in column 1 of Table 1. N=98.

Appendix B: Further Results

Table A7. Complexity Effects of Chinese OF, High-Complexity Recipients (2002-2016)

	Coef.	Countries	Obs.	Kl.-Paap *F*-Stat.
	Panel A. Overall			
ODA Projects	-0.088 (0.093)	60	663	11.47
OOF Projects	-0.084* (0.045)	60	663	8.40
	Panel B. Social Sector			
ODA Projects	-0.069 (0.091)	60	663	23.20
OOF Projects	-0.139 (0.147)	60	663	8.61
	Panel C. Economic Sector			
ODA Projects	-0.648 (0.663)	60	663	4.10
OOF Projects	-0.160* (0.086)	60	663	8.65
	Panel D. Production Sector			
ODA Projects	-0.613* (0.318)	60	663	9.12
OOF Projects	-0.275*** (0.095)	60	663	25.76

Notes: Shows overall and discrete results for different sectors, as indicated in the panel headers, for recipients of above-median complexity. Each row per panel corresponds to one regression. The DV is the recipient ECI in year t. The variable of interest, *Chinese OF* (t-2), refers to China's development finance projects with a lag of two years and is measured as project numbers. In separate rows of each panel, we show discrete results for ODA and OOF projects. All regressions include Internet usage (% of population), total natural resources rents (% of GDP), and trade (% of GDP) as control variables, as well as country- and year-fixed effects. Standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table A8. Complexity Effects of Chinese OF, Low-Complexity Recipients (2002-2016)

	Coef.	Countries	Obs.	Kl.-Paap *F*-Stat.
Panel A. Overall				
ODA Projects	0.049	56	637	45.00
	(0.039)			
OOF Projects	0.067	56	637	6.77
	(0.054)			
Panel B. Social Sector				
ODA Projects	0.114*	56	637	54.62
	(0.063)			
OOF Projects	0.371**	56	637	10.33
	(0.156)			
Panel C. Economic Sector				
ODA Projects	0.241	56	637	4.93
	(0.244)			
OOF Projects	0.107	56	637	5.33
	(0.075)			
Panel D. Production Sector				
ODA Projects	0.085	56	637	4.65
	(0.271)			
OOF Projects	-0.044	56	637	3.71
	(0.285)			

Notes: Shows overall and discrete results for different sectors, as indicated in the panel headers, for recipients of below-median complexity. Each row per panel corresponds to one regression. The DV is the recipient ECI in year t. The variable of interest, *Chinese OF* (t-2), refers to China's development finance projects with a lag of two years and is measured as project numbers. In separate rows of each panel, we show discrete results for, ODA and OOF projects. All regressions include Internet usage (% of population), total natural resources rents (% of GDP), and trade (% of GDP) as control variables, as well as country- and year-fixed effects. Standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table A10. Timing of Social Sector Effects, High-Complexity Recipients (2002-2016)

	Coef.	Countries	Obs.	Kl.-Paap *F*-Stat.
	Panel A. Chinese OF (t-1)			
ODA Projects	-0.045	60	708	30.56
	(0.082)			
OOF Projects	-0.141	60	708	8.79
	(0.120)			
	Panel B. Chinese OF (t-3)			
ODA Projects	-0.080	59	617	19.42
	(0.084)			
OOF Projects	-0.110	59	617	8.16
	(0.142)			
	Panel C. Chinese OF (t-4)			
ODA Projects	-0.083	58	573	24.04
	(0.091)			
OOF Projects	-0.050	58	573	7.56
	(0.131)			
	Panel D. Chinese OF (t-5)			
ODA Projects	-0.053	57	529	17.01
	(0.062)			
OOF Projects	-0.015	57	529	7.53
	(0.126)			
	Panel E. Chinese OF (t-6)			
ODA Projects	-0.060	57	529	31.73
	(0.066)			
OOF Projects	0.021	57	529	4.94
	(0.140)			

Notes: Shows results for various lags of Chinese social sector aid, as indicated in the panel headers, for recipients of above-median complexity. Each row per panel corresponds to one regression. The DV is the recipient ECI in year t. The variable of interest, *Chinese OF* (t-2), refers to China's development finance projects with a lag of two years and is measured as project numbers. In separate rows of each panel, we show discrete results for ODA and OOF projects. All regressions include Internet usage (% of population), total natural resources rents (% of GDP), and trade (% of GDP) as control variables, as well as country- and year-fixed effects. Standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table A11. Timing of Social Sector Effects, Low-Complexity Recipients (2002-2016)

	Coef.	Countries	Obs.	Kl.-Paap *F*-Stat.
	Panel A. Chinese OF (t-1)			
ODA Projects	0.111*	56	683	54.42
	(0.062)			
OOF Projects	0.487**	56	683	13.00
	(0.196)			
	Panel B. Chinese OF (t-3)			
ODA Projects	0.137*	56	591	52.47
	(0.072)			
OOF Projects	0.375**	56	591	8.12
	(0.190)			
	Panel C. Chinese OF (t-4)			
ODA Projects	0.131*	55	545	56.70
	(0.072)			
OOF Projects	0.215*	55	545	7.09
	(0.123)			
	Panel D. Chinese OF (t-5)			
ODA Projects	0.138**	52	497	51.01
	(0.070)			
OOF Projects	0.231	52	497	11.06
	(0.165)			
	Panel E. Chinese OF (t-6)			
ODA Projects	0.135	52	454	27.00
	(0.084)			
OOF Projects	0.151	52	454	16.36
	(0.136)			

Notes: Shows results for various lags of Chinese social sector aid, as indicated in the panel headers, for recipients of below-median complexity. Each row per panel corresponds to one regression. The DV is the recipient ECI in year t. The variable of interest, *Chinese OF* (t-2), refers to China's development finance projects with a lag of two years and is measured as project numbers. In separate rows of each panel, we show discrete results for ODA and OOF projects. All regressions include Internet usage (% of population), total natural resources rents (% of GDP), and trade (% of GDP) as control variables, as well as country- and year-fixed effects. Standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table A12. Social Sector Complexity Effects by Years of Schooling (2002-2016)

	Coef.	Countries	Obs.	Kl.-Paap *F*-Stat.
Panel A. Above-Median Years of Schooling				
ODA Projects	-0.052	52	592	23.30
	(0.131)			
OOF Projects	-0.018	52	592	11.68
	(0.229)			
Panel B. Below-Median Years of Schooling				
ODA Projects	0.060**	37	426	54.46
	(0.029)			
OOF Projects	0.259**	37	426	6.19
	(0.131)			

Notes: Shows results for Chinese social sector aid for recipients of above-median years of schooling (panel A) and recipients of below-median years of schooling (panel B). Each row per panel corresponds to one regression. The DV is the recipient ECI in year t. The variable of interest, *Chinese OF* (t-2), refers to China's development finance projects with a lag of two years and is measured as project numbers. In separate rows of each panel, we show discrete results for ODA and OOF projects. All regressions include Internet usage (% of population), total natural resources rents (% of GDP), and trade (% of GDP) as control variables, as well as country- and year-fixed effects. Standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Appendix C: Derivation of the ECI

The lynchpin of ECI's measurement is the M_{cp} matrix where the rows capture different countries c and the columns capture different products p. An element of the matrix is equal to 1 if a country c exports a product p with RCA > 1, and 0 otherwise. Hausmann et al. (2013: 24) measure diversity and ubiquity by summing over the rows and the columns of that matrix, respectively.

Formally,

$$Diversity = k_{c,0} = \sum_{p} M_{cp} \tag{1}$$

$$Ubiquity = k_{p,0} = \sum_{c} M_{cp} \tag{2}$$

Accordingly, for countries, this results in an iterative process to calculate the mean ubiquity of the products they export and the mean diversity of countries also exporting those products etc. For products, in turn, this means including the mean diversity of countries exporting a particular product and the mean ubiquity of other products exported by those countries etc. This results in the 'Method of Reflections', which is defined as follows (Hausmann et al., 2013: 24):

$$k_{c,N} = \frac{1}{k_{c,0}} \sum_{p} M_{cp} \times k_{p,N-1} \tag{3}$$

$$k_{p,N} = \frac{1}{k_{p,0}} \sum_{c} M_{cp} \times k_{c,N-1} \tag{4}$$

When inserting (4) into (3), this yields

$$k_{c,N} = \frac{1}{k_{c,0}} \sum_{p} M_{cp} \frac{1}{k_{p,0}} \sum_{c'} M_{c'p} \times k_{c',N-2} \tag{5}$$

which can also be written as

$$k_{c,N} = \sum_{c'} k_{c',N-2} \sum \frac{M_{c'p} M_{cp}}{k_{c,0} k_{p,0}} \tag{6}$$

or, rewritten, as

$$k_{c,N} = \sum_{c'} k_{c',N-2} \widetilde{M}^{C}_{c,c'} \tag{7}$$

where the authors define

$$\widetilde{M}^{C}_{c,c'} = \sum_{p} \frac{M_{cp} M_{c'p}}{k_{c,0} k_{p,0}} \tag{8}$$

Hausmann et al. (2013: 24) note that (7) is fulfilled when $k_{c,N} = k_{c,N-2} = 1$. This reflects the eigenvector of $\widetilde{M}_{cc'}$ corresponding to the largest eigenvalue. However, since this eigenvector consists only of ones, it does not contain the information needed. Instead, Hausmann et al. (2013: 24) take the eigenvector corresponding to the second largest eigenvalue. Hence, if $\vec{k}_n$ to be the vector whose c^{th} element is $k_{c,N}$, then:

$$\vec{k}_n = \widetilde{M}^{C} \times \vec{k}_{n-2} \tag{9}$$

where $\widetilde{M}^{C}$ is the matrix whose (c, c') element is $\widetilde{M}^{C}_{c,c'}$.

If n is taken to infinity, this leads to a distribution which remains fixed up to a scalar factor:

$$\widetilde{M}^{C} \times \vec{k} = \lambda \vec{k} \tag{10}$$

Thus, $\vec{k}$ is an eigenvector of $\widetilde{M}^{C}$. As described above, Hausmann et al. (2013: 24) define the ECI as the eigenvector corresponding to the second largest eigenvalue of the $\widetilde{M}^{C}$ matrix, since this eigenvector covers the greatest amount of variance and is thus the preferred measure of economic complexity.

Taken together, the Economic Complexity Index is defined as:

$$ECI = \frac{\vec{K} - \langle \vec{K} \rangle}{std(\vec{K})} \tag{11}$$

where $\langle\ \rangle$ constitutes an average, std represents the standard deviation, and $\vec{K}$ stands for the eigenvector of $\widetilde{M}_{cc'}$ corresponding to the second largest eigenvalue.

Appendix D: Validity of Parallel Trends Assumption

Trends across regular and irregular recipients would have to align with yearly fluctuations in $Materials$ to affect our results. However, in the case of nonlinear nonparallel trends, running fixed-effects regressions may prove inadequate for isolating exogenous interannual variability and thus identifying causal effects (Christian and Barrett, 2017). Accordingly, one might capture a spurious correlation that biases causal inferences. We therefore follow Christian and Barrett (2017) and Dreher et al. (2021a) and show graphically (see Appendix Figure A6) the variation in $Materials$ (panel A) and its detrended version (panel B), along with variations in average logged Chinese OF amounts (t-2) (panel E) and the ECI (panel F) for both regular and irregular recipients. The probability-specific trends in both average logged Chinese OF amounts and economic complexity are mostly parallel for regular and irregular recipients. Additionally, there is no apparent nonlinear trend in regular recipients that resembles the trend observed in irregular recipients for both Chinese OF and economic complexity. It is therefore unlikely that the parallel trends assumption is violated. However, given the more pronounced decline of economic complexity for irregular recipients after 2006 (panel F), one could argue that the adverse effects of the 2007/2008 global financial crisis might affect our results. We address this issue in robustness checks (see Appendix E).

The exogeneity of our IV could be further violated if changes in detrended $Materials$ affect recipients' economic complexity differentially across regular and irregular recipients for reasons other than China's OF. Since regular recipients of China's OF are also more likely to receive exports and FDI from China (e.g., Dong and Fan, 2017; Morgan and Zheng, 2019), $Materials$ could also be correlated with Chinese exports and/or outward FDI. Thus, differential effects of Chinese aid on recipients' economic complexity could be tied to Chinese exports and/or outward FDI rather than Chinese aid itself. We also deal with this issue in robustness checks (see Appendix E).Besides physical project inputs, Dreher et al. (2021a), among others, use a second instrument for over-time variation in Chinese OF, namely the lagged and detrended net change in China's foreign-exchange reserves ($Reserves$). Similar to $Materials$, the authors' choice of $Reserves$ is motivated by China's domestic oversupply. Due to China's large trade surpluses, foreign-exchange reserves grew strongly from the 2000s onward. The World Bank (2023) reports that China's international reserves (including gold) surged from about US\$170 billion in 2000 to roughly US\$3.9 trillion in 2014. Thus, China's foreign-exchange reserves became excessive and ought to be gradually reduced to counter the risks of currency appreciation or inflation (Liu, 2023: 65). Consequently, China resorted to its foreign-exchange reserves to recapitalize the CDB and the CEIB – two state-owned banks primarily responsible for executing Chinese development finance (Liu, 2023: 70).[33] Further, to render its lending more profitable, China increased foreign currency-denominated loans on OOF-like rather than on more concessional ODA-like terms (Dreher et al., 2021a; Horn et al., 2021).[34] However, albeit promising, $Reserves$ turns out to be not useful when estimating complexity effects using a Two-Stage Least Squares (2SLS) approach. Therefore, we refrain from using it as an IV and focus on $Materials$ as the only time-varying part of our instrument. However, for robustness, we use alternative instruments, namely (i) $Reserves$ interacted with $p_{CHN,i}$ (see Appendix Table A14) and (ii) both $Materials$ and $Reserves$ interacted with $p_{CHN,i}$ as a two-fold IV (see Appendix Table A15Table A15Table A15).

[33] As Dreher et al. (2021a) note, referring to Kong and Gallagher (2016), this approach was initiated as early as 2008 through the so-called 'entrust loan' agreement. Here, China's Administration of Foreign Exchange (a sub-department of the People's Bank of China) acts as principal and provides foreign-exchange reserves to its agent, first and foremost the China Development Bank, which in turn uses them for its international lending activities.
[34] Indeed, the average annual growth rate of China's OOF-like projects was about 19.9 percent between 2000 and 2014, compared with about 10.9 percent for China's ODA-like projects.

Appendix E: Robustness Checks

Given that complexity effects could set in earlier or later than accounted for in our baseline estimates, Appendix Table A13 analyzes the timing of effects in more detail. To do so, we modify the lag configuration of Chinese ODA/OOF and adjust the lag structure of the instrument accordingly. For instance, when we lag Chinese OF by three years, the associated instrument is lagged by four years. Overall, the results remain broadly in line with the baseline results presented in Table 1 and, for convenience, again in the fourth row of Appendix Table A13. The coefficients are statistically insignificant at conventional levels for the various lag configurations and for both project numbers (columns 1-3) and financial amounts (columns 4-6). Focusing on OF project numbers (column 1), it is interesting to note that while the coefficients show a negative sign contemporaneously and up until three years after project commitments, the coefficient turns positive in the fourth and fifth year but remains statistically insignificant. When we use the same sample as for the fifth year but adjust the lag of Chinese OF from five to two years as in the baseline specification (last row), the results stay insignificant. Further, we conduct a placebo test by examining the influence of future Chinese OF on the current ECI of recipients (first row). The coefficients remain insignificant.

Additionally, although we do not show these results in tables, we also estimated specifications across sectors modifying the lag structure (from $(t-3)$ to $(t-6)$) to account for different timings, similar to Appendix Table A13 for various lags of our baseline results. The social sector results remain insignificant regardless of the lag chosen. For the economic sector, the coefficients change sign from negative to positive starting at $(t-4)$, indicating that complexity effects through higher connectivity might take some time to materialize. However, the results remain insignificant. The significant negative effects found for the production and the other sectors become insignificant as of $(t-4)$, pointing to rather medium-term negative complexity effects of Chinese aid targeted toward these sectors.

Moreover, we obtain equally insignificant results overall when applying alternative instruments to estimate complexity effects during the 2002-2016 period, namely (i) $Reserves$ alone (see Appendix Table A14) and (ii) $Materials$ and $Reserves$ combined (see Appendix Table A15). For the first case, similar to solely using $Materials$ (see Table 1), most of the first-stage estimates are strongly positive and statistically significant at the one percent level. Nevertheless, the F-statistics are lower than for the sole use of $Materials$. The same holds true to an even greater extent for the two-fold IV approach. While $Materials$ continues to provide strongly positive and statistically significant first-stage estimates, $Reserves$ no longer seems to have a statistically significant effect on Chinese OF one year later.[35] Again, this leads to much lower F-statistics. In sum, these results support the rationale of restricting the sample period and relying on $Materials$ as the sole IV.

To account for the possibility that detrended $Materials$ affect recipients' economic complexity for reasons other than China's aid (recall Section 3.4), we control for yearly Chinese exports and outward FDI to a country (see Appendix Table A16).[36] However, the results confirm the insignificance of our baseline estimates. We further perform various placebo tests (see Appendix Table A17). First, we explain Chinese foreign aid with future values of my IV, rather than using lags (panel A). The F-statistics are substantially lower, indicating that $Materials$ in $t+1$ do not adequately explain Chinese OF in t. The results thus consistently bolster the primary findings as presented in Table 1. Next, panel B shows a placebo test where the number of Chinese OF projects is substituted by the number of projects that should be barely related to $Materials$, including projects such as debt relief agreements and developmental food aid. If $Materials$ accurately captures the availability of tangible 'hardware' project inputs, it should have limited predictive power for projects that do not primarily rely on such inputs. Accordingly, panel B shows very low F-statistics. Additionally, panels C and D present results for specifications where we instrument Chinese exports and outward FDI, respectively, with $Materials$, still controlling for Chinese OF. While the export specification in panel C shows very low F-statistics, the specification involving FDI in panel D yields substantial but lower F-statistics than those observed in columns 1 and 2 of Table 1. Although data on bilateral Chinese FDI is limited to the 2003-2012 period, these results provide suggestive evidence that FDI is a complementary means for channeling $Materials$ (domestic oversupply) to countries that frequently receive Chinese OF projects.[37] However, given the higher F-statistics across all sectors when instrumenting Chinese development finance (instead of FDI) and the insignificant results throughout, we assume Chinese OF to be the primary method for China's government to offset its domestic oversupply of $Materials$.

[35] Interestingly, regardless of the specification used, both instruments, as well as their combination, are weak in explaining logged Chinese OF amounts, as indicated by insignificant first-stage results and low F-statistics.
[36] Bilateral Chinese FDI data are from UNCTAD (2022) and bilateral export data from UN Comtrade (2022).
[37] This contrasts with the results of Dreher et al. (2021a), who also find very weak F-statistics for the FDI specification. However, this could be explained by differences in the sample, as growth data cover a much broader range of countries compared with ECI data.

Theoretically, as argued by Dreher et al. (2021a), the adverse effects of the 2007/2008 global financial crisis could affect our results. Turning back to Appendix Figure A6 and looking at Panel A, it becomes evident that the logged production of $Materials$ remained steady from 2007 to 2008, while Panel F shows that the ECI declined less for the group that has a higher probability of receiving Chinese OF. However, our results barely change when we exclude 2007 and 2008 from the analysis (see Appendix Table A18Table A18). Moreover, our principal findings remain consistent when we control for other common determinants of economic complexity (see Appendix Table A19)[38] and country-level shocks, namely conflict and natural disasters (see Appendix Table A20Table A20).[39] In addition, we examine the impact of excluding potential outliers from the analysis. In doing so, we calculate a recipient country's respective share of total world trade for all products included in $Materials$ and exclude those countries that have an average share of more than one percent for at least one of the products over the sample period. The results are similar (see Appendix Table A21).[40] Next, we repeat our baseline results (that include committed, implemented, and completed projects) considering only projects that reached at least the implementation phase (see Appendix Table A23) or those that are already completed (see Appendix Table A24). One might expect stronger, possibly even significant effects on recipients' economic complexity as China's projects proceed, yet the results remain insignificant throughout. Finally, we test the effects on an alternative dependent variable, namely the Economic Fitness Index (EFI) (Cristelli et al., 2013; Tacchella et al., 2012). Showing significantly positive first-stage estimates and high F-statistics, the instrument is also strong in this case (see Appendix Table A25).[41] The results confirm the negative baseline coefficients even on conventional levels of statistical significance, at least for OF and OOF-like project numbers and for OOF-like project amounts (see panel C).[42]

[38] These are net FDI inflows (% of GDP), logged total public and private investment, the state of democracy, domestic credit to the private sector (% of GDP), net ODA received (% of GNI), remittances received (% of GDP), and research and development expenditure (% of GDP).

[39] Specifically, we control for conflict, measured as the logged number of battle deaths per country and year, and for natural disasters, measured as the logged number of people affected by a natural disaster per country and year.

[40] See Appendix Table A22Table A22 for an overview of which countries cross this threshold for each product included in $Materials$. To calculate the respective shares, we use UN Comtrade (2022) export data on aluminum (HS code 76), cement (2523), glass (70), iron and steel (72), and timber (44).

[41] See Appendix Table A26 and Appendix Table A27 for descriptive statistics and a list of countries, respectively.

[42] Although the two indices are similar in nature, they are defined differently, thereby potentially explaining the different results in terms of statistical significance. Broadly speaking, the ECI focuses on the overall complexity and diversification of a country's export basket (see Section 2.2), whereas the EFI focuses on a country's competitiveness in specific product markets and assesses its ability to produce and export goods efficiently and effectively (Cristelli et al., 2013; Tacchella et al., 2012). In addition, EFI's data coverage ends in 2015, thus limiting the sample period to 2002-2015.

Table A13. Complexity Effects of Chinese OF, Various Lags (2002-2016)

	ODA Projects (1)	OOF Projects (2)	(log) ODA Amounts (3)	(log) OOF Amounts (4)	Obs. (5)
Chinese OF (t+1)	-0.016 (0.041)	-0.054 (0.073)	-0.007 (0.027)	-0.009 (0.010)	1,574
Chinese OF (t)	-0.015 (0.037)	-0.064 (0.063)	-0.004 (0.033)	-0.016 (0.013)	1,498
Chinese OF (t-1)	-0.004 (0.035)	-0.033 (0.040)	0.005 (0.035)	-0.014 (0.014)	1,401
Chinese OF (t-2) (Baseline)	-0.002 (0.033)	-0.025 (0.039)	0.006 (0.037)	-0.012 (0.014)	1,309
Chinese OF (t-3)	0.003 (0.032)	-0.014 (0.040)	0.014 (0.038)	-0.007 (0.014)	1,216
Chinese OF (t-4)	0.010 (0.031)	0.004 (0.040)	0.022 (0.037)	-0.001 (0.014)	1,126
Chinese OF (t-5)	0.014 (0.028)	0.022 (0.039)	0.024 (0.035)	0.006 (0.016)	1,037
Chinese OF (t-2) (Reduced Sample)	0.024 (0.036)	-0.012 (0.051)	0.047 (0.061)	-0.006 (0.020)	1,033

Table 3. Complexity Effects of Chinese OF, Alternative Instruments I (2002-2016)

	ODA Projects (1)	OOF Projects (2)	(log) ODA Amounts (3)	(log) OOF Amounts (4)
Panel A. OLS estimates – DV: ECI				
Chinese OF (t-2)	0.003 (0.003)	-0.001 (0.006)	-0.000 (0.001)	-0.001 (0.001)
Panel B. Reduced-form estimates – DV: ECI				
Materials (t-3) x Probability	0.008 (0.223)	-0.157 (0.337)	0.072 (0.255)	-0.251 (0.336)
Panel C. 2SLS estimates – DV: ECI				
Chinese OF (t-2)	0.001 (0.033)	-0.020 (0.041)	0.012 (0.044)	-0.012 (0.016)
Panel D. First-stage estimates – DV: Chinese OF (t-2)				
Materials (t-3) x Probability	6.782*** (0.903)	8.050*** (1.891)	5.828*** (2.205)	21.351*** (6.537)
Observations	1,309	1,309	1,309	1,309
Number of Countries	98	98	98	98
Kleibergen-Paap *F*-statistic	56.36	18.13	6.99	10.67

Notes: Uses detrended changes in Chinese foreign-exchange reserves interacted with the probability of receiving Chinese aid during the 2000-2014 period as an IV. Each column per panel corresponds to one regression. In panels A-C, the DV is the recipient ECI in year t. The variable of interest, *Chinese OF* (*t*-2), refers to China's development finance projects with a lag of two years and is measured as project numbers in columns 1 and 2 and logged financial amounts in columns 3 and 4. Columns 1 and 3 refer to ODA and columns 2 and 4 refer to OOF projects. All regressions include Internet usage (% of population), total natural resources rents (% of GDP), and trade (% of GDP) as control variables, as well as country- and year-fixed effects. Standard errors are in parentheses. p<0.1; **p<0.05; ***p<0.01.

Table A15. Complexity Effects of Chinese OF, Alternative Instruments II (2002-2016)

	ODA Projects (1)	OOF Projects (2)	(log) ODA Amounts (3)	(log) OOF Amounts (4)
Panel A. OLS estimates – DV: ECI				
Chinese OF (t-2)	0.003	-0.001	-0.000	-0.001
	(0.003)	(0.006)	(0.001)	(0.001)
Panel B. Reduced-form estimates – DV: ECI				
Materials (t-3) x Probability	-0.016	-0.062	-0.009	-0.058
	(0.039)	(0.057)	(0.041)	(0.059)
Reserves (t-3) x Probability	0.090	0.165	0.121	0.047
	(0.151)	(0.222)	(0.157)	(0.230)
Panel C. 2SLS estimates – DV: ECI				
Chinese OF (t-2)	-0.002	-0.025	0.005	-0.012
	(0.032)	(0.039)	(0.036)	(0.014)
Panel D. First-stage estimates – DV: Chinese OF (t-2)				
Materials (t-3) x Probability	0.976***	1.446***	1.454***	4.770***
	(0.935)	(0.578)	(0.603)	(1.851)
Reserves (t-3) x Probability	1.685	0.587	-1.745	-3.065
	(1.981)	(3.000)	(3.340)	(7.965)
Observations	1,309	1,309	1,309	1,309
Number of Countries	98	98	98	98
Kleibergen-Paap *F*-statistic	30.25	10.18	5.06	5.83

Notes: Uses (i) the logged and detrended annual industrial output volumes of Materials and (ii) the detrended annual changes in Chinese foreign-exchange reserves, both interacted with the probability of receiving Chinese aid during the 2000-2014 period as a two-fold IV. Each column per panel corresponds to one regression. In panels A-C, the DV is the recipient ECI in year t. The variable of interest, *Chinese OF* (t-2), refers to China's development finance projects with a lag of two years and is measured as project numbers in columns 1 and 2 and logged financial amounts in columns 3 and 4. Columns 1 and 3 refer to ODA and columns 2 and 4 refer to OOF projects. All regressions include Internet usage (% of population), total natural resources rents (% of GDP), and trade (% of GDP) as control variables, as well as country- and year-fixed effects. Standard errors are in parentheses. p<0.1; **p<0.05; ***p<0.01.

Table A16. Complexity Effects of Chinese OF, Export & FDI Controls (2002-2016)

	Coef. OF	Coef. Control	Count.	Obs.	Kl.-Paap *F*-Stat.
Panel A. Chinese Exports Control					
ODA Projects	-0.019	-0.048	93	1,157	47.02
	(0.030)	(0.045)			
OOF Projects	-0.052	-0.045	93	1,157	16.65
	(0.037)	(0.044)			

Panel B. Chinese FDI Control

ODA Projects	0.016 (0.041)	-0.015* (0.008)	80	693	17.50
OOF Projects	-0.040 (0.060)	-0.008 (0.013)	80	693	12.35

Notes: Controls for Chinese recipient-country specific exports (panel A) and outward FDI flows (panel B). Each row per panel corresponds to one regression. The DV is the recipient ECI in year t. The variable of interest, *Chinese OF* (*t*-2), refers to China's development finance projects with a lag of two years and is measured as project numbers. In separate rows of each panel, we show results for ODA and OOF projects. All regressions include Internet usage (% of population), total natural resources rents (% of GDP), and trade (% of GDP) as control variables, as well as country- and year-fixed effects. Standard errors are in parentheses. p<0.1; **p<0.05; ***p<0.01.

Table A17. Complexity Effects of Chinese OF, Placebo Tests (2002-2016)

	Coef.	Countries	Obs.	Kl.-Paap *F*-Stat.
	Panel A. Future Values of IV			
ODA Projects	-0.020 (0.060)	97	1,293	4.91
OOF Projects	0.080 (0.061)	97	1,293	2.90
	Panel B. Sectors Not Relying on Physical Inputs			
ODA Projects	-0.030 (0.388)	98	1,309	3.95
OOF Projects	0.884 (1.734)	98	1,309	0.56
	Panel C. Chinese Exports as IV			
ODA Projects	-0.001 (0.004)	93	1,157	0.38
OOF Projects	-0.007 (0.014)	93	1,157	0.52
	Panel D. Chinese FDI as IV			
ODA Projects	-0.000 (0.003)	80	693	2.40
OOF Projects	0.001 (0.005)	80	693	22.24

Notes: Performs various placebo regressions as indicated in the panel headers. Each row per panel corresponds to one regression. The DV is the recipient ECI in year t. The variable of interest, *Chinese OF* (*t*-2), refers to China's development finance projects with a lag of two years and is measured as project numbers. In separate rows of each panel, we show results for ODA and OOF projects. All regressions include Internet usage (% of population), total natural resources rents (% of GDP), and trade (% of GDP) as control variables, as well as country- and year-fixed effects. Standard errors are in parentheses. p<0.1; **p<0.05; ***p<0.01.

Table A18. Complexity Effects of Chinese OF, without 2007/2008 (2002-2016)

	ODA Projects (1)	OOF Projects (2)	(log) ODA Amounts (3)	(log) OOF Amounts (4)
Panel A. OLS estimates – DV: ECI				
Chinese OF (t-2)	0.004	0.001	-0.000	-0.001
	(0.004)	(0.008)	(0.001)	(0.001)
Panel B. Reduced-form estimates – DV: ECI				
Materials (t-3) x Probability	-0.006	-0.030	0.005	-0.043
	(0.041)	(0.062)	(0.046)	(0.063)
Panel C. 2SLS estimates – DV: ECI				
Chinese OF (t-2)	-0.005	-0.019	-0.047	-0.009
	(0.034)	(0.038)	(0.150)	(0.014)
Panel D. First-stage estimates – DV: Chinese OF (t-2)				
Materials (t-3) x Probability	1.191***	1.598***	1.101***	4.550***
	(0169)	(0.362)	(0.403)	(1.257)
Observations	1,133	1,133	1,133	1,133
Number of Countries	98	98	98	98
Kleibergen-Paap *F*-statistic	49.53	19.47	7.45	13.11

Notes: Excludes the years of the global financial crisis (2007/2008). Each column per panel corresponds to one regression. In panels A-C, the DV is the recipient ECI in year t. The variable of interest, *Chinese OF* (t-2), refers to China's development finance projects with a lag of two years and is measured as project numbers in columns 1 and 2 and logged financial amounts in columns 3 and 4. Columns 1 and 3 refer to ODA and columns 2 and 4 refer to OOF projects. All regressions include Internet usage (% of population), total natural resources rents (% of GDP), and trade (% of GDP) as control variables, as well as country- and year-fixed effects. Standard errors are in parentheses. p<0.1; **p<0.05; ***p<0.01.

Table A19. Complexity Effects of Chinese OF, Additional Controls I (2002-2016)

	ODA Projects (1)	OOF Projects (2)	(log) ODA Amounts (3)	(log) OOF Amounts (4)
Panel A. OLS estimates – DV: ECI				
Chinese OF (t-2)	0.009	-0.018***	0.000	-0.002
	(0.006)	(0.007)	(0.001)	(0.001)
Panel B. Reduced-form estimates – DV: ECI				
Materials (t-3) x Probability	0.006	-0.126	-0.005	-0.134
	(0.060)	(0.083)	(0.060)	(0.084)
Panel C. 2SLS estimates – DV: ECI				
Chinese OF (t-2)	0.006	-0.084	-0.005	-0.025
	(0.060)	(0.055)	(0.056)	(0.018)
Panel D. First-stage estimates – DV: Chinese OF (t-2)				
Materials (t-3) x Probability	0.889***	1.490***	1.040*	5.283**
	(0.184)	(0.422)	(0.539)	(2.233)
Observations	1,133	1,133	1,133	1,133
Number of Countries	98	98	98	98
Kleibergen-Paap *F*-statistic	23.40	12.44	3.73	5.60

Notes: Each column per panel corresponds to one regression. In panels A-C, the DV is the recipient ECI in year t. The variable of interest, *Chinese OF* (t-2), refers to China's development finance projects with a lag of two years and is measured as project numbers in columns 1 and 2 and logged financial amounts in columns 3 and 4. Columns 1 and 3 refer to OF and columns 2 and 4 refer to OOF projects. All regressions include foreign direct investment (% of GDP), official development assistance received (% of GNI), remittances received (% of GDP), research & development expenditure (% of GDP), the (logged) sum of public and private investment), and the state of democracy (polity score) as control variables, as well as country- and year-fixed effects. Standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table A20. Complexity Effects of Chinese OF, Additional Controls II (2002-2016)

	ODA Projects (1)	OOF Projects (2)	(log) ODA Amounts (3)	(log) OOF Amounts (4)
Panel A. OLS estimates – DV: ECI				
Chinese OF (t-2)	0.005	-0.002	0.000	-0.001
	(0.003)	(0.006)	(0.001)	(0.001)
Panel B. Reduced-form estimates – DV: ECI				
Materials (t-3) x Probability	0.012	-0.028	0.021	-0.034
	(0.038)	(0.055)	(0.042)	(0.055)
Panel C. 2SLS estimates – DV: ECI				
Chinese OF (t-2)	0.008	-0.021	0.020	-0.009
	(0.026)	(0.038)	(0.040)	(0.014)
Panel D. First-stage estimates – DV: Chinese OF (t-2)				
Materials (t-3) x Probability	1.451***	1.417***	1.083*	4.005**
	(0.184)	(0.289)	(0.355)	(1.100)
Observations	1,403	1,403	1,403	1,403
Number of Countries	102	102	102	102
Kleibergen-Paap *F*-statistic	62.09	24.12	9.30	13.26

Notes: Each column per panel corresponds to one regression. In panels A-C, the DV is the recipient ECI in year t. The variable of interest, *Chinese OF* (*t*-2), refers to China's development finance projects with a lag of two years and is measured as project numbers in columns 1 and 2 and logged financial amounts in columns 3 and 4. Columns 1 and 3 refer to ODA and columns 2 and 4 refer to OOF projects. All regressions include the (logged) numbers of (i) battle deaths (as a measure of conflict) and (ii) people affected by a natural disaster per country and year as control variables, as well as country- and year-fixed effects. Standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table A21. Complexity Effects of Chinese OF, Excluding Main Exporters (2002-2016)

	ODA Projects (1)	OOF Projects (2)	(log) ODA Amounts (3)	(log) OOF Amounts (4)
Panel A. OLS estimates – DV: ECI				
Chinese OF (t-2)	0.005	0.008**	0.001	0.000
	(0.004)	(0.003)	(0.001)	(0.001)
Panel B. Reduced-form estimates – DV: ECI				
Materials (t-3) x Probability	-0.021	0.003	-0.011	-0.007
	(0.048)	(0.069)	(0.058)	(0.067)
Panel C. 2SLS estimates – DV: ECI				
Chinese OF (t-2)	-0.017	0.002	-0.011	-0.001
	(0.038)	(0.045)	(0.060)	(0.012)
Panel D. First-stage estimates – DV: Chinese OF (t-2)				

Materials (t-3) x Probability	1.270***	1.501***	0.946***	5.486***
	(0.179)	(0.335)	(0.366)	(1.405)
Observations	1,014	1,014	1,014	1,014
Number of Countries	75	75	75	75
Kleibergen-Paap F-statistic	50.38	20.06	6.69	15.24

Notes: Excludes the main exporters of the industrial products that a part of $Materials$. Each column per panel corresponds to one regression. In panels A-C, the DV is the recipient ECI in year t. The variable of interest, *Chinese OF* (*t*-2), refers to China's development finance projects with a lag of two years and is measured as project numbers in columns 1-3 and logged financial amounts in columns 4-6. Columns 1 and 4 refer to OF, columns 2 and 5 refer to ODA, and columns 3 and 6 refer to OOF projects. All regressions include Internet usage (% of population), total natural resources rents (% of GDP), and trade (% of GDP) as control variables, as well as country- and year-fixed effects. Standard errors are in parentheses. p<0.1; **p<0.05; ***p<0.01.

Table A22. The Main Exporters of Products Included in the Materials IV

Export Share	Aluminum (HS Code: 76)	Cement (HS Code: 2523)	Glass (HS Code: 70)	Iron & Steel (HS Code: 72)	Timber (HS Code: 44)
≥ 1%	Brazil, India, Malaysia, Russia, South Africa, Turkey	Egypt, India, Indonesia, Iran, Malaysia, Mexico, Pakistan, Russia, Senegal, Thailand, Togo, Turkey, Turkmenistan, Venezuela, Viet Nam	Malaysia, Mexico, Turkey	Brazil, India, Russia, South Africa, Turkey, Ukraine	Brazil, Chile, Indonesia, Malaysia, Romania, Russia, Thailand, Viet Nam

Notes: Shows the countries that are excluded in the regressions shown in Appendix Table A27 compared to the baseline estimates of Appendix Table 1.

Table A23. Complexity Effects of Chinese OF, Implemented Projects (2002-2016)

	ODA Projects (1)	OOF Projects (2)	(log) ODA Amounts (3)	(log) OOF Amounts (4)
Panel A. OLS estimates – DV: ECI				
Chinese OF (t-2)	0.004	-0.000	0.000	-0.001
	(0.003)	(0.005)	(0.001)	(0.001)
Panel B. Reduced-form estimates – DV: ECI				
Materials (t-3) x Probability	0.012	-0.036	0.012	-0.056
	(0.045)	(0.068)	(0.051)	(0.068)
Panel C. 2SLS estimates – DV: ECI				
Chinese OF (t-2)	0.010	-0.022	0.007	-0.009
	(0.036)	(0.041)	(0.031)	(0.011)
Panel D. First-stage estimates – DV: Chinese OF (t-2)				
Materials (t-3) x Probability	1.237***	1.640***	1.622***	6.146***
	(0.143)	(0.323)	(0.453)	(1.323)

Observations	1,309	1,309	1,309	1,309
Number of Countries	98	98	98	98
Kleibergen-Paap *F*-statistic	75.00	25.82	12.84	21.59

Notes: Includes only projects that have entered at least the implementation phase. Each column per panel corresponds to one regression. In panels A-C, the DV is the recipient ECI in year t. The variable of interest, *Chinese OF* (*t*-2), refers to China's development finance projects with a lag of two years and is measured as project numbers in columns 1 and 2 and logged financial amounts in columns 3 and 4. Columns 1 and 3 refer to ODA and columns 2 and 4 refer to OOF projects. All regressions include Internet usage (% of population), total natural resources rents (% of GDP), and trade (% of GDP) as control variables, as well as country- and year-fixed effects. Standard errors are in parentheses. p<0.1; **p<0.05; ***p<0.01.

Table A24. Complexity Effects of Chinese OF, Completed Projects (2002-2016)

	ODA Projects (1)	OOF Projects (2)	(log) ODA Amounts (3)	(log) OOF Amounts (4)
Panel A. OLS estimates – DV: ECI				
Chinese OF (t-2)	0.003	0.002	0.000	-0.000
	(0.003)	(0.005)	(0.001)	(0.001)
Panel B. Reduced-form estimates – DV: ECI				
Materials (t-3) x Probability	0.013	-0.021	0.014	-0.037
	(0.044)	(0.069)	(0.051)	(0.072)
Panel C. 2SLS estimates – DV: ECI				
Chinese OF (t-2)	0.011	-0.015	0.009	-0.006
	(0.036)	(0.049)	(0.031)	(0.011)
Panel D. First-stage estimates – DV: Chinese OF (t-2)				
Materials (t-3) x Probability	1.218***	1.387***	1.661***	6.382***
	(0.142)	(0.272)	(0.434)	(1.109)
Observations	1,309	1,309	1,309	1,309
Number of Countries	98	98	98	98
Kleibergen-Paap *F*-statistic	73.87	26.05	14.61	33.10

Notes: Includes only projects that have entered at least the completion phase. Each column per panel corresponds to one regression. In panels A-C, the DV is the recipient ECI in year t. The variable of interest, *Chinese OF* (*t*-2), refers to China's development finance projects with a lag of two years and is measured as project numbers in columns 1 and 2 and logged financial amounts in columns 3 and 4. Columns 1 and 3 refer to ODA and columns 2 and 4 refer to OOF projects. All regressions include Internet usage (% of population), total natural resources rents (% of GDP), and trade (% of GDP) as control variables, as well as country- and year-fixed effects. Standard errors are in parentheses. p<0.1; **p<0.05; ***p<0.01.

Table A25. Complexity Effects of Chinese OF, Alternative Measure (EFI) (2002-2015)

	ODA Projects (1)	OOF Projects (2)	(log) ODA Amounts (3)	(log) OOF Amounts (4)
Panel A. OLS estimates – DV: EFI				
Chinese OF (t-2)	-0.001	-0.005	-0.001*	-0.001
	(0.001)	(0.003)	(0.001)	(0.001)
Panel B. Reduced-form estimates – DV: EFI				
Materials (t-3) x Probability	-0.021	-0.068**	-0.016	-0.081**
	(0.025)	(0.031)	(0.024)	(0.033)

Panel C. 2SLS estimates – DV: EFI				
Chinese OF (t-2)	-0.016	-0.046**	-0.013	-0.020*
	(0.018)	(0.023)	(0.019)	(0.010)
Panel D. First-stage estimates – DV: Chinese OF (t-2)				
Materials (t-3) x Probability	1.336***	1.471***	1.249***	4.013***
	(0.167)	(0.333)	(0.398)	(1.232)
Observations	1,318	1,318	1,318	1,318
Number of Countries	107	107	107	107
Kleibergen-Paap *F*-statistic	63.63	19.54	9.84	10.62

Notes: Uses the Economic Fitness Index (EFI) as an alternative DV. Each column per panel corresponds to one regression. In panels A-C, the DV is the recipient EFI in year t. The variable of interest, *Chinese OF* (t-2), refers to China's development finance projects with a lag of two years and is measured as project numbers in columns 1 and 2 and logged financial amounts in columns 3 and 4. Columns 1 and 3 refer to ODA and columns 2 and 4 refer to OOF projects. All regressions include Internet usage (% of population), total natural resources rents (% of GDP), and trade (% of GDP) as control variables, as well as country- and year-fixed effects. Standard errors are in parentheses. p<0.1; **p<0.05; ***p<0.01.

Table A26. Descriptive Statistics (Estimation Sample / EFI) (2002-2015)

Variable	Obs	Mean	Std. Dev.	Min	Max
Economic Fitness Index	1,318	.53	.68	0	4.4
Number of OF projects (t-2)	1,318	3.86	4.7	0	39
Number of ODA projects (t-2)	1,318	2.75	3.51	0	33
Number of OOF projects (t-2)	1,318	.95	2.25	0	34
(log) OF amounts (t-2)	1,318	11.57	8.59	0	25.16
(log) ODA amounts (t-2)	1,318	9.46	8.29	0	23.08
(log) OOF amounts (t-2)	1,318	5.15	8.5	0	25.16
Individuals using the Internet (% of population)	1,318	16.64	17.7	.06	77
Total natural resources rents (% of GDP)	1,318	10.07	11.97	0	66.06
Trade (% of GDP)	1,318	73.83	31.67	11.86	210.37

Notes: Provides descriptive statistics for the estimation sample used in column 1 of Appendix Table A25.

Table A27. List of Countries (Estimation Sample / EFI) (2002-2015)

Albania	DR Congo	Lebanon	Rwanda
Algeria	Ecuador	Libya	Saudi Arabia
Angola	Egypt	Lithuania	Senegal
Argentina	El Salvador	Madagascar	Serbia
Armenia	Eritrea	Malaysia	Sierra Leone
Azerbaijan	Estonia	Mali	Slovak Republic
Bangladesh	Ethiopia	Mauritania	Somalia
Belarus	Gabon	Mexico	South Africa
Belize	Gambia	Mongolia	Sudan
Benin	Georgia	Montenegro	Suriname
Bhutan	Ghana	Morocco	Syria
Bolivia	Guatemala	Mozambique	Tajikistan
Bosnia and Herzegovina	Guinea	Myanmar	Tanzania
Brazil	Guinea-Bissau	Nepal	Thailand
Bulgaria	Guyana	Nicaragua	Togo
Burkina Faso	Honduras	Niger	Tunisia

Burundi	Hungary	Nigeria	Turkey
Cambodia	India	North Macedonia	Turkmenistan
Cameroon	Indonesia	Oman	Uganda
Central African Republic	Iran	Pakistan	Ukraine
Chad	Iraq	Panama	Uruguay
Chile	Jordan	Paraguay	Uzbekistan
Colombia	Kazakhstan	Peru	Venezuela
Congo	Kenya	Philippines	Yemen
Costa Rica	Kyrgyz Republic	Poland	Zambia
Côte d'Ivoire	Lao PDR	Romania	Zimbabwe
Croatia	Latvia	Russia	

Note: This country list refers to the estimation sample used in column 1 of Appendix Table A25. N=107.

Appendix F: Extended Heterogeneity Analysis

Since China's engagement spans globally but differs regionally in its financing terms and the primary sectors targeted (recall Figure 3), its economic complexity effects are likely more nuanced across regions than our primary findings suggest. Therefore, we show results for Africa, the Americas, and Asia overall and across sectors.[43]

In our regional analysis, our 2SLS results show rather low F-statistics due to smaller sample sizes. For this reason, we refrain from a causal interpretation of our findings. Starting with Africa, we find significantly positive effects of ODA-like projects overall and explicitly also for the social sector (see Appendix Table A28). Moving to Latin American countries, we find insignificant results for ODA-like projects both overall and across sectors (see Appendix Table A29). Yet, the remaining results paint a clearer picture. First, the coefficients of the OOF-like projects show negative effects on recipients' economic complexity, particularly for non-social sectors. This suggests that Latin American countries are extensively negatively affected by China's development projects. Perhaps most interesting is the result for OOF-like production sector projects: exhibiting F-statistics well above ten, the coefficient indicates that an additional Chinese production sector OOF-like project is associated with a decrease of about 0.55 units in a recipient's ECI two years later, on average (c.p.). For Asian recipients, we find exclusively insignificant results both in the aggregate and across sectors (see Appendix Table A30).

Moreover, the effectiveness of Chinese OF might be contingent upon the prevalent political institutions and economic governance within recipients (Burnside and Dollar, 2000; Denizer et al., 2013; Dreher et al., 2021b), as well as China's own strategic interests in favoring politically aligned countries (Dreher et al., 2018a). Therefore, we undertake an analysis that involves the

[43] Note that we exclude Europe, the Middle East, and Oceania from further investigation due to data constraints.

interaction of the number of Chinese projects with the following factors pertaining to recipients: (i) the state of democracy (Marshall et al., 2019), (ii) the soundness of economic policies (Burnside and Dollar, 2000), (iii) the extent of corruption (Kaufmann et al., 2011), and (iv) recipients' UNGA voting alignment with China (Bailey et al., 2017; Voeten et al., 2009). Following Dreher et al. (2021a), we use a Control Function framework, which leverages the residuals from the first-stage regressions presented in Table 1. The estimations incorporate bootstrapped standard errors, generating 500 replications to enhance robustness. This approach assumes that the degree of the bias remains consistent irrespective of the variable subjected to interaction with Chinese OF. The results reveal that the majority of interactions lacks statistical significance (see Appendix Table A31). Therefore, the effectiveness of Chinese ODA/OOF projects does not depend upon recipients' institutional quality, economic governance, and their level of corruption. However, there is one exception: we find that ODA-like projects are more effective when the recipient country's voting behavior in the UNGA aligns more closely with China's (see panel D). Nevertheless, when accounting for recipient countries' initial level of economic complexity (in 2002), these outcomes lose statistical significance (see panel E). For this reason, UNGA voting alignment with China is more likely to be a covariate of economic complexity, i.e., high-complexity recipients tend to be less aligned with China in their UNGA voting behavior, and vice versa.[44] Consequently, while we do not report these results in a table, a sample split between above- and below-median aligned recipient countries confirm those of the sample split between above- and below-median complex countries. While above-median aligned recipients benefit in terms of complexity only through Chinese OF to the social sector, below-median aligned countries are negatively affected by Chinese OF overall and especially through the production sector. This insight is confirmed by another covariate of economic complexity, namely total natural resources exports (% of GDP). Total natural resources exports of high-complexity recipients accounted for about 4.42% of GDP over the 2002-2016 period, far less than for low-complexity recipients (about 13.75% of GDP). Consequently, the results for a sample split between above-mean and below-median natural resources exporters are consistent with those for the complexity sample split. For the first group, we find significantly positive effects for the social sector (see Appendix Table A32), and for the second group, results are negative yet insignificant throughout (see Appendix Table A33).

[44] This is not surprising, given that high-complexity recipients are more likely to be economic competitors of China and hence less motivated to vote in tandem with China to preserve their own agenda. High-complexity recipient countries show an ideal point distance of their UNGA voting alignment with China that is nearly twice as high (0.756 during the 2002-2016 period) compared to low-complexity recipients (0.391).

Table A28. Complexity Effects of Chinese OF in Africa, 2SLS (2002-2016)

	Coef.	Countries	Obs.	Kl.-Paap *F*-Stat.
Panel A. Overall				
ODA Projects	0.272** (0.119)	30	439	7.29
OOF Projects	0.093 (0.102)	30	439	4.33
Panel B. Social Sector				
ODA Projects	0.406** (0.187)	30	439	6.92
OOF Projects	0.508 (0.322)	30	439	8.96
Panel C. Economic Sector				
ODA Projects	0.288 (0.351)	30	439	3.29
OOF Projects	0.131 (0.140)	30	439	3.80
Panel D. Production Sector				
ODA Projects	0.066 (0.461)	30	439	4.64
OOF Projects	-0.057 (0.266)	30	439	67.79

Notes: Shows overall and separate results for different sectors, as indicated in the panel headers, for African countries. Each row per panel corresponds to one 2SLS regression. The DV is the recipient ECI in year t. The variable of interest, *Chinese OF* (t-2), refers to China's development finance projects with a lag of two years and is measured as project numbers. In separate rows of each panel, we show discrete results for ODA and OOF projects. All regressions include Internet usage (% of population), total natural resources rents (% of GDP), and trade (% of GDP) as control variables, as well as country- and year-fixed effects. Standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table A29. Complexity Effects of Chinese OF in the Americas, 2SLS (2002-2016)

	Coef.	Countries	Obs.	Kl.-Paap *F*-Stat.
Panel A. Overall				
ODA Projects	0.003 (0.055)	19	270	23.33
OOF Projects	-0.146*** (0.052)	19	270	9.11
Panel B. Social Sector				
ODA Projects	0.038 (0.120)	19	270	9.76
OOF Projects	-0.442* (0.254)	19	270	11.21

	Coef.	Countries	Obs.	Kl.-Paap F-Stat.
Panel C. Economic Sector				
ODA Projects	0.510 (0.644)	19	270	0.45
OOF Projects	-0.261** (0.129)	19	270	5.49
Panel D. Production Sector				
ODA Projects	2.333 (4.819)	19	270	0.30
OOF Projects	-0.546*** (0.090)	19	270	225.34

Notes: Shows overall and separate results for different sectors, as indicated in the panel headers, for Latin American countries. Each row per panel corresponds to one 2SLS regression. The DV is the recipient ECI in year t. The variable of interest, *Chinese OF* (t-2), refers to China's development finance projects with a lag of two years and is measured as project numbers. In separate rows of each panel, we show discrete results for ODA and OOF projects. All regressions include Internet usage (% of population), total natural resources rents (% of GDP), and trade (% of GDP) as control variables, as well as country- and year-fixed effects. Standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table A30. Complexity Effects of Chinese OF in Asia, 2SLS (2002-2016)

	Coef.	Countries	Obs.	Kl.-Paap F-Stat.
Panel A. Overall				
ODA Projects	-0.079 (0.078)	21	294	12.55
OOF Projects	0.082 (0.086)	21	294	7.95
Panel B. Social Sector				
ODA Projects	-0.055 (0.135)	21	294	7.58
OOF Projects	0.245 (0.240)	21	294	5.53
Panel C. Economic Sector				
ODA Projects	0.010 (0.289)	21	294	6.83
OOF Projects	0.047 (0.093)	21	294	9.08
Panel D. Production Sector				
ODA Projects	-0.197 (0.347)	21	294	7.37
OOF Projects	0.279 (0.307)	21	294	2.75

Notes: Shows overall and separate results for different sectors, as indicated in the panel headers, for Asian countries. Each row per panel corresponds to one 2SLS regression. The DV is the recipient ECI in year t. The variable of interest, *Chinese OF* (t-2), refers to China's development finance projects with a lag of two years and is measured as project numbers. In separate rows of each panel, we show discrete results for ODA and OOF projects. All regressions include Internet usage (% of population), total natural resources rents (% of GDP), and trade (% of GDP) as control variables, as well as country- and year-fixed effects. Standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table A31. Complexity Effects of Chinese OF, Interactions (2002-2016)

	Coef. Chinese Aid	Coef. Interaction	Countries	Obs.	Kl.-Paap *F*-Stat.
		Panel A. State of Democracy			
ODA Projects	0.000	-0.000	96	1,271	32.26
	(0.032)	(0.001)			
OOF Projects	-0.025	-0.000	96	1,271	43.08
	(0.046)	(0.001)			
		Panel B. Economic Soundness			
ODA Projects	0.012	-0.002	61	856	36.59
	(0.023)	(0.003)			
OOF Projects	-0.086	0.005	61	856	27.74
	(0.056)	(0.005)			
		Panel C. Corruption			
ODA Projects	-0.006	-0.003	98	1,309	40.26
	(0.025)	(0.006)			
OOF Projects	-0.034	-0.009	98	1,309	46.81
	(0.042)	(0.011)			
		Panel D. UNGA Voting Alignment with China			
ODA Projects	0.007	0.020	96	1,289	40.17
	(0.030)	(0.013)			
OOF Projects	-0.014	0.024*	96	1,289	45.56
	(0.043)	(0.013)			
		Panel E. UNGA Voting Alignment with China (Controlling for Initial ECI)			
ODA Projects	-0.004	0.016	96	1,289	40.17
	(0.030)	(0.012)			
OOF Projects	-0.021	0.016	96	1,289	45.56
	(0.043)	(0.013)			

Notes: Includes Chinese aid variables in levels (Coef. Chinese Aid) as interactions with different potential mechanisms (Coef. Interaction), as indicated in the panel headers. Each row per panel corresponds to one regression. The DV is the recipient ECI in year t. The variable of interest, *Chinese OF* (t-2), refers to China's development finance projects with a lag of two years and is measured as project numbers. In separate rows of each panel, we show discrete results for ODA and OOF projects. All regressions include Internet usage (% of population), total natural resources rents (% of GDP), and trade (% of GDP) as control variables, as well as country- and year-fixed effects. Estimation using a Control Function approach that controls for the residuals of the respective first-stage regressions from Appendix Table A1. Bootstrapped standard errors with 500 replications are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table A32. Complexity Effects of Chinese OF, High-Resources Exporters (2002-2016)

	Coef.	Countries	Obs.	Kl.-Paap *F*-Stat.
	Panel A. Overall			
ODA Projects	0.088* (0.046)	62	695	33.61
OOF Projects	0.022 (0.061)	62	695	10.09
	Panel B. Social Sector			
ODA Projects	0.139* (0.075)	62	695	28.65
OOF Projects	0.198 (0.146)	62	695	23.87
	Panel C. Economic Sector			
ODA Projects	0.313 (0.216)	62	695	7.20
OOF Projects	0.032 (0.080)	62	695	8.18
	Panel D. Production Sector			
ODA Projects	0.187 (0.304)	62	695	7.28
OOF Projects	-0.305 (0.205)	62	695	9.41

Notes: Shows overall and discrete results for different sectors, as indicated in the panel headers, for recipients of above-median natural resources exports (% of GDP). Each row per panel corresponds to one regression. The DV is the recipient ECI in year t. The variable of interest, *Chinese OF* (t-2), refers to China's development finance projects with a lag of two years and is measured as project numbers. In separate rows of each panel, we show discrete results for ODA and OOF projects. All regressions include Internet usage (% of population), total natural resources rents (% of GDP), and trade (% of GDP) as control variables, as well as country- and year-fixed effects. Standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table A33. Complexity Effects of Chinese OF, Low-Resources Exporters (2002-2016)

	Coef.	Countries	Obs.	Kl.-Paap *F*-Stat.
	Panel A. Overall			
ODA Projects	-0.072 (0.054)	54	604	18.42
OOF Projects	-0.005 (0.064)	54	604	8.33
	Panel B. Social Sector			
ODA Projects	-0.033 (0.047)	54	604	44.76
OOF Projects	0.016 (0.168)	54	604	10.32
	Panel C. Economic Sector			

ODA Projects	-0.366 (0.368)	54	604	3.13
OOF Projects	-0.016 (0.098)	54	604	3.57
	Panel D. Production Sector			
ODA Projects	-0.616 (0.380)	54	604	6.19
OOF Projects	0.008 (0.240)	54	604	18.61

Notes: Shows overall and discrete results for different sectors, as indicated in the panel headers, for recipients of below-median natural resources exports (% of GDP). Each row per panel corresponds to one regression. The DV is the recipient ECI in year t. The variable of interest, *Chinese OF* (*t*-2), refers to China's development finance projects with a lag of two years and is measured as project numbers. In separate rows of each panel, we show discrete results for ODA and OOF projects. All regressions include Internet usage (% of population), total natural resources rents (% of GDP), and trade (% of GDP) as control variables, as well as country- and year-fixed effects. Standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Appendix G: Effects on GDP Components

Analogous to Dreher et al. (2021a), we explore the extent to which Chinese ODA/OOF affects recipients' GDP components. Specifically, we examine the impact of Chinese ODA/OOF on gross fixed capital formation (overall and private), FDI inflows, consumption expenditure (public, private, and the sum of both), and gross domestic savings. We measure these elements as changes in logged constant values. The results could help to gauge whether Chinese ODA/OOF is used to develop the domestic economy, thereby contributing to foster economic complexity (e.g., Javorcik et al., 2018; Khan et al., 2020). If funds from China are primarily spent on consumption, they may fuel short-term growth but might not spur longer-term diversification toward more complex industries. Conversely, investment should tend to have a positive effect on the economic complexity of an economy, at least if it serves to increase innovation and productive capabilities (Dreher et al., 2021a). Indeed, as presented in Appendix Table A7**Fehler! Verweisquelle konnte nicht gefunden werden.**, an ODA-like Chinese project contributes to an increase of 1.6 percent in gross fixed capital formation, while an OOF-like Chinese project is associated with a substantial 9.5 percent rise in FDI inflows, on average. However, a Chinese ODA-like project brings about a modest rise of 0.4 percent in overall consumption expenditure, on average, primarily attributed to an upswing in household consumption expenditure of 0.5 percent.

In sum, Chinese ODA/OOF boosts both consumption and investment in recipients, with the latter showing stronger effects. Dreher et al. (2021a) argue that these overall positive effects (especially those on investment) translate into positive short-run growth. However, recalling our insignificant baseline results, they do not seem to manifest in aggregate complexity gains, questioning their innovative potential.[45]

Table A7. Effects of Chinese OF on Determinants of Components of GDP (2002-2016)

	Coef.	Std. Err.	Count.	Obs.	Kl.-Paap *F*-Stat.
			Panel A. Gross Fixed Capital Formation		
ODA Projects	0.016**	0.008	133	1,730	82.70
OOF Projects	-0.005	0.019	133	1,730	22.35
			Panel B. Gross Fixed Private Capital Formation		
ODA Projects	0.045	0.046	77	857	71.03
OOF Projects	0.192	0.249	77	857	6.46
			Panel C. Foreign Direct Investment Inflows		
ODA Projects	0.010	0.043	148	1,913	76.72
OOF Projects	0.095*	0.055	148	1,913	20.91
			Panel D. Overall Final Consumption Expenditure		
ODA Projects	0.004*	0.003	122	1,560	76.79
OOF Projects	-0.005	0.005	122	1,560	20.98
			Panel E. General Government Final Consumption Expenditure		
ODA Projects	0.000	0.004	119	1,516	71.08
OOF Projects	-0.004	0.008	119	1,516	19.05
			Panel F. Household Final Consumption Expenditure		
ODA Projects	0.005*	0.003	121	1,531	71.61
OOF Projects	-0.005	0.006	121	1,531	19.26
			Panel G. Savings		
ODA Projects	-0.015	0.014	127	1,521	61.77
OOF Projects	-0.015	0.024	127	1,521	24.10

Notes: Each row corresponds to one regression. The respective DV is indicated in the panel headers and is measured in first differences of logged constant US$. The variable of interest, *Chinese OF* (*t*-2), refers to China's development finance projects with a lag of two years and is measured as project numbers. In separate rows of each panel, we show discrete results for ODA and OOF projects. All regressions include country- and year-fixed effects. Standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

[45] Although we do not capture these results in a table, we repeated these specifications for both high- and low-complexity recipients. All significant results presented in Appendix Table A8 become insignificant for both samples, except for the positive effects of Chinese ODA-like projects on gross capital formation in low-complexity recipients (effect size: +2.3 percent). In addition, OF projects appear to negatively affect gross fixed private capital formation in high-complexity recipients. This gives further support for our findings presented above.