Growth in the Shaded Sun: The Role of International Development Finance and Corruption

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Abstract

I study how developing-country governments decide the amount, sources, and sectoral allocation of development finance (DF) as China has emerged alongside traditional donors. Using project-level data from nearly 110 countries (2000–2021), I document systematic patterns in DF allocation across countries, sectors, and providers that vary with corruption and monitoring intensity. I develop a growth model in which governments allocate DF while choosing how much investment to divert under provider-specific monitoring and financing conditions. Calibrating the model to 108 countries shows heterogeneous welfare implications of Chinese DF: about 15% of countries gain while roughly 55% experience welfare losses.

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1 Introduction

Governments in developing countries finance public investment through multiple sources of official development finance (DF) that differ in borrowing terms and monitoring intensity. In recent years, these financing sources have become increasingly heterogeneous, most prominently through the coexistence of traditional providers in the Development Assistance Committee (DAC)—a group of advanced economies including the United States—and China, which has emerged over the past two decades as a major official provider (Horn et al., 2021). These provider groups differ systematically in financial terms and monitoring practices: Chinese DF is generally less concessional and closer to market-based borrowing in interest rates and associated costs, while its monitoring practices are often perceived to be less stringent relative to DAC finance. The expansion of Chinese lending has drawn substantial attention in academic research and policy discussions, reflecting both its role in filling financing gaps left by DAC providers and concerns about corruption in DF projects (e.g., Isaksson and Kotsadam (2018)). Yet despite this growing interest, a unified framework for analyzing how heterogeneous financing conditions interact with recipient-country corruption to shape DF allocation remains limited.

Two factors have constrained progress on this question. First, DF was historically dominated by DAC providers offering highly concessional, grant-based funding and was therefore often viewed as donor-driven aid rather than as a portfolio of financing options chosen by recipient governments. In practice, however, governments actively seek diverse forms of finance, including both loans and grants. The rise of China introduced meaningful heterogeneity in financing terms, elevating the importance of recipient-side allocation decisions. Second, systematic analysis has only recently become feasible with the availability of project-level data covering both DAC and Chinese DF across sectors and countries.

This paper develops a framework to study how developing governments' corruption incentives interact with heterogeneous DF providers to shape public investment and welfare. Governments face financing sources that differ in borrowing costs and monitoring intensity. Providers with stricter monitoring limit diversion but often offer cheaper financing, while those with weaker oversight allow greater diversion at higher borrowing costs. When governments value diversion, this trade-off distorts public investment decisions along multiple margins—including project size, project counts,

sectoral allocation, and the choice of financing source. As a result, the efficiency of public capital depends not only on domestic corruption but also on the international DF environment. To study these mechanisms, I combine newly assembled project-level data covering more than one million projects across nearly 110 developing countries with a growth model that embeds diversion incentives and heterogeneous monitoring across providers, and I quantify the resulting welfare consequences of Chinese DF through cross-country calibration.

I begin by documenting four stylized facts linking corruption to DF allocation using newly assembled project-level data covering more than one million projects across nearly 110 developing countries and 30 official providers from 2000 to 2021. Corruption—measured by the Corruption Perceptions Index—is systematically correlated with DF allocation across sources and sectors, extending existing evidence beyond aggregate flows to project- and cross-sector-level patterns. The corruption index should be interpreted as a reduced-form proxy for diversion incentives and institutional frictions affecting the use of public funds. While corruption measures may be correlated with broader institutional quality, the empirical analysis does not attempt to isolate the causal effect of corruption or diversion incentives. Instead, it documents systematic correlations between institutional environments and DF allocation patterns that serve as stylized facts motivating the mechanism developed in the theoretical model.

First, at the country level, more corrupt governments rely more heavily on Chinese DF: a one-standard-deviation increase in corruption is associated with a 7.9-percentage-point increase in the Chinese share of DF inflows. Second, Chinese project size increases with corruption, whereas DAC project size does not. Third, the number of DAC-financed projects decreases as corruption rises, while the number of Chinese-financed projects increases. Fourth, project size in hard-to-monitor sectors increases disproportionately with corruption, and this pattern remains statistically significant even for DAC-financed projects.

These correlations reflect equilibrium outcomes shaped by both supply and demand forces. However, the sectoral and project-level heterogeneity is consistent with a two-way interaction between corruption and DF inflows operating on the demand side, taking supply-side financing conditions as given. The model developed below formalizes this mechanism by distinguishing between two concepts of corruption. The first is fundamental corruption, captured by a parameter reflecting the government's

preference for diversion over household consumption. The second is actual diversion, which corresponds more closely to the survey-based corruption indices used in the empirical analysis. In this framework, higher fundamental corruption increases reliance on DF with weaker monitoring, while heterogeneous monitoring and borrowing terms shape equilibrium diversion and DF allocation, which in turn are reflected in measured corruption.

To formalize these mechanisms and conduct quantitative welfare analysis, I develop a parsimonious growth model in which a borrowing government chooses the amount, source, and sectoral allocation of DF in a two-provider environment. Financing conditions differ across providers and sectors and are summarized by interest rates, monitoring intensity, and fixed costs of accessing funds. These supply-side features are taken as given. The model does not attempt to explain the determination of provider-specific financing terms; instead, it studies recipient-side allocation decisions conditional on the observed financing environment. The government may divert part of public investment for its own benefit, with diversion determined endogenously given the financing environment and the underlying corruption parameter.

The model embeds this problem in a standard neoclassical framework with private and public capital. Public capital is constructed from differentiated projects across sectors, linking the model directly to the project-level data. Diversion generates a wedge between the book and effective value of public capital, allowing public-investment efficiency to emerge endogenously. Unlike existing models that treat DF as an exogenous transfer, the government optimally selects how much DF to use, from which provider, and in which sectors.

Heterogeneous monitoring and borrowing costs create a trade-off between DAC and Chinese DF. DAC financing features lower interest rates but stronger monitoring, whereas Chinese financing is less concessional but permits greater diversion. Accessing DF in each sector also entails provider-specific fixed costs that capture broader supply-side factors affecting financing conditions. These financing terms—interest rates, monitoring intensity, and fixed costs—are interpreted broadly to summarize contractual and institutional features of lending arrangements, including nonstandard provisions documented in recent work, such as collateralization, requirements regarding the use of provider-country inputs, or policy-related conditions. They may also reflect differential access or implicit rationing of certain recipients or sectors by providers. The model abstracts from detailed contract design and instead treats such

features as part of the financing environment faced by recipient governments.

Because these financing terms vary across providers and sectors, corruption distorts allocation along multiple demand-side margins—affecting project size, project counts, provider choice, and sectoral composition. These mechanisms jointly rationalize the stylized facts.

Beyond explaining the empirical patterns, the model yields broader implications. First, the efficiency of public capital emerges endogenously from the interaction between corruption incentives and heterogeneous financing conditions, providing a theoretical foundation for a parameter often treated as exogenous. Second, the welfare consequences of Chinese DF depend on both the level of underlying corruption and the sectoral distribution of financing. Chinese DF can expand investment opportunities where DAC financing is costly to secure—reflected in higher DAC fixed costs relative to Chinese fixed costs—but it may also amplify inefficiencies when monitoring differentials are large. Which force dominates depends on sector-specific financing terms, making the net welfare effect country-specific and ultimately a quantitative question.

Finally, I calibrate the model for 108 developing economies across 13 sectors. Provider- and sector-specific financing terms are estimated using project-level data. Relative to a counterfactual steady state without Chinese DF, about 15% of countries experience clear welfare gains, while 55% face potentially large welfare losses. Outcomes depend not only on corruption levels but also on which sectors receive Chinese financing.

Case studies illustrate this heterogeneity. When Chinese DF is allocated to sectors with monitoring standards close to those of DAC DF, or where DAC financing is difficult to secure, welfare gains are more likely. By contrast, when Chinese DF is concentrated in sectors with substantially weaker monitoring—especially when cheaper DAC financing is readily accessible—it tends to generate welfare losses. These findings suggest that coordination between DAC countries and China on lending practices, as well as clearer sectoral specialization in areas where the other provider is less active, could enhance citizen welfare in recipient countries.

Related Literature.—This paper contributes to several strands of research at the intersection of international macroeconomics and development.

First, it relates to the literature on global capital allocation, particularly the growing study of official capital flows. While much of the international macro literature

has traditionally focused on private capital, recent work emphasizes the comparable importance of official flows (Avdjiev et al., 2022). A related strand examines China's expanding role in global capital markets (Coppola et al., 2021; Horn et al., 2021; Clayton et al., 2026). The development of new datasets on Chinese DF (Dreher et al., 2021) has enabled empirical analyses of its allocation and effects (Isaksson and Kotsadam, 2018; Knutsen and Kotsadam, 2020). This paper contributes by establishing new stylized facts on DF allocation and introducing a macro-development framework that integrates Chinese DF, corruption, and public investment in a unified model.

Second, the paper connects to the literature on corruption and growth. Empirical work links institutional quality to long-run development (Mauro, 1995; Acemoglu et al., 2001), while theoretical studies provide microfoundations for rent-seeking and public investment distortions (Svensson, 2000; Robinson and Torvik, 2005) and embed political frictions in growth frameworks (Aguiar and Amador, 2011). I contribute by documenting project-level evidence that corruption shapes DF allocation decisions and by developing a multi-sector growth model in which corruption and external financing jointly determine public-investment efficiency and welfare.

Third, the paper relates to the literature on public capital and growth. Classic contributions incorporate public capital into growth models (Barro, 1990; Glomm and Ravikumar, 1994), and empirical work documents its importance for output (Aschauer, 1989; Bom and Ligthart, 2014). Subsequent research highlights that the effective value of public capital may fall short of its nominal value due to inefficiencies (Hulten, 1992; Dabla-Norris et al., 2012). Unlike models that treat public-investment inefficiency as exogenous or assume tax financing, I analyze an environment where governments rely on heterogeneous DF and endogenize public-capital efficiency through corruption-driven allocation choices across sectors and providers.

Finally, the paper contributes to the literature on foreign aid allocation and impact. Early work studies donor motives and the growth effects of aid (Alesina and Dollar, 2000; Boone, 1996; Burnside and Dollar, 2004), while more recent studies exploit quasi-experimental variation in aid flows (Galiani et al., 2017). Most theoretical models treat aid as an exogenous transfer (Chatterjee and Turnovsky, 2007). By contrast, I develop a framework in which DF use is endogenous and interacts with corruption across multiple sectors, linking project-level allocation patterns to aggregate growth and welfare outcomes.

Outline.—The paper proceeds as follows. Section 2 describes the institutional

background and data. Section 3 documents stylized facts on corruption and DF flows. Section 4 introduces a growth model motivated by these facts. Section 5 derives the model's theoretical implications. Section 6 calibrates the model, and Section 7 presents counterfactual analyses. Section 8 concludes.

2 Institutional Background & Data

2.1 Institutional Background

Development Finance (DF).—Development finance (DF) refers to cross-border resource flows intended to support development in recipient countries and is distinct from commercial lending. Two features distinguish DF from other forms of external finance. First, DF is typically contracted at the project level, with funds earmarked for specific investments. Second, it primarily consists of official flows between governments or multilateral institutions, with only a limited role for private lenders.[1]

Development Assistance Committee (DAC).—The Development Assistance Committee (DAC), established in the 1960s, coordinates development assistance among advanced economies. Historically, DAC members have supplied the majority of DF and have set many of the global norms governing development lending. DAC financing is typically highly concessional, featuring very low interest rates and large grant components, and is often accompanied by extensive monitoring and policy conditions. Members include major advanced economies such as the United States, Japan, Germany, and the United Kingdom.

Chinese Development Finance.—Over the past two decades, China has emerged as a major provider of DF. Chinese lending differs systematically from DAC financing. Most Chinese loans are extended at near-market interest rates and are largely non-concessional. Contracts often include provisions allowing lenders to cancel loans or demand immediate repayment under political or economic contingencies (Gelpern et al., 2021). Many agreements also contain confidentiality clauses that obscure contract details, in contrast to the transparency norms emphasized by DAC lenders. As a result, a substantial share of Chinese official lending is not reported to international statistical agencies (Horn et al., 2021).

[1] An example is in 2007, when the Australian government lent AUD 300 million (a zero-interest concessional loan) to Indonesian government under the Eastern Indonesia National Roads Improvement Project (EINRIP) to upgrade roads and bridges in eastern provinces.

Despite these features, Chinese DF remains attractive to many borrowing governments and has expanded rapidly across both countries and sectors (see Online Appendix 1.4)[2]. Several factors contribute to this pattern. First, concessional DAC financing can be difficult to secure, particularly in high-risk countries or certain sectors (Brautigam, 2011; Dreher et al., 2022). Second, DAC lending is often accompanied by extensive monitoring and policy conditions. By contrast, Chinese officials frequently emphasize a "no strings attached" approach and avoid direct involvement in domestic policy decisions. Chinese projects are also often implemented relatively quickly, allowing governments to deliver visible infrastructure investments within short political cycles. Both anecdotal evidence (Bunte, 2019) and regional-level analysis (Isaksson and Kotsadam, 2018) suggest that these features make Chinese DF particularly attractive in more corrupt environments.

2.2 Data Description

DAC DF.—I use the OECD's Creditor Reporting System (CRS), which records more than one million DF projects undertaken by DAC members and observers from 2000–2021. The CRS tracks official development finance flows to over 150 developing countries and reports project-level information including donor and recipient identities, commitment amounts, sector classifications, and implementation details.

Chinese DF.—Data on Chinese DF come from AidData's Global Chinese Development Finance Dataset, Version 3.0 (Custer et al., 2023), which documents 20,958 projects across 165 countries from 2000–2021. Because China does not systematically report its overseas lending, the dataset is compiled from a wide range of primary and secondary sources. Projects are coded using DAC sector classifications, which allows direct comparability with the CRS data.

Project Evaluation Data.—To classify sectors according to monitoring difficulty, I use AidData's Project Performance Database (PPD), Version 2.0 (Honig et al., 2022). The PPD contains evaluations of 21,198 projects implemented by 12 bilateral and multilateral DF agencies across 183 recipient countries between 1956 and 2016. Performance ratings are standardized across evaluators and rescaled to a six-point scale, where 1 denotes highly unsatisfactory and 6 denotes highly satisfactory outcomes, based on criteria such as timeliness, efficiency, and supervision.

[2]Online Appendix is available at http://www.chansikyoon.com

Corruption.—Corruption is measured using the Corruption Perceptions Index (CPI) compiled by Transparency International. The CPI aggregates information from 13 surveys and expert assessments of public-sector corruption based on evaluations by businesspeople and country specialists. By combining multiple sources, the index helps mitigate measurement error associated with any individual survey. It also provides the broadest country and time coverage among commonly used corruption measures, covering more than 180 countries on a scale from 0 (most corrupt) to 100 (least corrupt). Among the 109 countries in my sample, the mean CPI score is 34.1 with a standard deviation of 10.9.

The empirical analysis uses the CPI as a proxy for the institutional environment affecting the use of public funds. Two commonly noted caveats in the literature are that the CPI reflects perceived corruption rather than directly observed diversion and that it may capture broader aspects of institutional quality beyond corruption alone. For the purposes of this paper, however, these distinctions are not central. The empirical section aims to document systematic correlations between institutional environments and DF allocation that motivate the mechanism developed in the model, rather than to estimate causal effects of diversion. Given its broad coverage and reduced measurement error relative to individual surveys, the CPI provides a suitable summary indicator for this purpose. The model in Section 4 interprets the index as capturing observed corruption outcomes that reflect both underlying diversion incentives and perceptions about realized misuse of public resources.

Controls.—Additional macroeconomic and political controls are drawn from several sources. Macroeconomic indicators come from the World Development Indicators, trade flows from the IMF Direction of Trade Statistics, gravity variables from CEPII (Conte et al., 2022), and geopolitical alignment from UN General Assembly voting similarity measures (Bailey et al., 2017). Further details on the CPI and control variables are provided in Online Appendix 1.2–1.3.

3 Stylized Facts

Recent research documents links between DF and corruption in recipient countries. Andersen et al. (2022) show that World Bank disbursements are associated with increased capital outflows to tax havens, while Isaksson and Kotsadam (2018) find that Chinese projects are linked to higher regional corruption in Africa. Ma-

lik et al. (2021) further show that Chinese DF is disproportionately directed toward more corrupt countries. Despite this growing evidence, systematic analysis of how corruption relates to DF allocation across donors, sectors, and projects beyond the aggregate level remains limited. Using project-level data from 2000–2021 covering nearly 110 recipient countries and more than 30 official providers[3], this section documents several stylized facts on how corruption is associated with DF allocation across these dimensions.

Because corruption is measured at the country level and varies little within countries over time, the regressions in this section rely primarily on cross-country variation. The goal is not to estimate causal effects but to document empirical regularities in the data. These correlations should therefore be interpreted as stylized facts that motivate the theoretical framework developed in Section 5, which provides a mechanism through which corruption and DF allocation interact in equilibrium.

I document four stylized facts showing that public-sector corruption is systematically associated with global DF allocation, with monitoring potentially playing a key role. First, at the aggregate level, more corrupt countries rely more heavily on Chinese DF relative to DAC DF. Second, at the project level, Chinese project size increases with corruption, whereas DAC project size does not. Third, the number of DAC-financed projects declines with corruption, while the number of Chinese-financed projects increases slightly. Fourth, the relationship between corruption and project size is disproportionately stronger in sectors that are plausibly harder to monitor. I then discuss how these patterns relate to diversion incentives and assess their robustness against alternative explanations.

Throughout this section, corruption refers to public-sector corruption in the recipient country, measured by the Corruption Perceptions Index (CPI). The CPI should be interpreted as a reduced-form proxy for diversion incentives and broader institutional frictions affecting the use of public funds. The correlations documented here should therefore not be interpreted as causal effects. Instead, they may reflect equilibrium interactions in which corruption influences DF allocation and DF inflows in turn affect measured corruption. Section 5 shows how the model helps interpret these patterns.

[3]Historically, DF providers have been called *donors* because most DAC DF was concessional. This term is too narrow given the rise of non-concessional Chinese DF. In what follows, I use DF *provider* and *donor* interchangeably to denote the country supplying DF.

3.1 Country-level Analysis

Fact 1. *In the aggregate, more corrupt countries rely more heavily on Chinese DF over DAC DF.*

As a first step, I examine which developing countries relied more heavily on DAC versus Chinese DF during 2000–2021. I estimate cross-country regressions relating the share of Chinese DF in total DF inflows to recipient-country corruption. Online Appendix 2.1 confirms the result using alternative specifications that analyze Chinese and DAC inflows separately at both the country and sector levels using panel OLS and PPML estimations, along with a range of robustness checks.

I estimate the following cross-country regression:

$$SHARE_r^{CHN} = \beta \cdot CORRUPT_r + X_r \cdot \gamma + constant + \epsilon_r,$$

where $SHARE_r^{CHN}$ denotes the share of Chinese DF in country r's total DF inflows during 2000–2021. Corruption, $CORRUPT_r$, is defined as 100 minus the average Corruption Perceptions Index over the same period so that higher values correspond to greater corruption. $\mathbf{X}_r$ is a vector of controls capturing recipient-country characteristics and bilateral political and economic factors vis-à-vis China.[4] The coefficient β captures the association between corruption and relative reliance on Chinese DF.

The regression shows a positive and statistically significant association between corruption and the share of Chinese DF. Figure 1 presents a partial regression plot of China's share against corruption. Each circle represents a recipient country and is scaled by total DF relative to GDP. The fitted line has a slope of 0.7148 ($p = 0.018$), implying that a one–standard deviation higher corruption (10.9 points) is associated with a 7.9 percentage-point higher reliance on Chinese DF during 2000–2021. Online Appendix 2.1.1 confirms the relationship using panel regressions.

[4] *Recipient characteristics:* log initial GDP per capita in 2000, average GDP per capita growth, average log population, average external debt to GDP, average public and publicly guaranteed (PPG) debt to GDP, average net FDI inflows to GDP, average inflation, and dummies for region, oil producer, English as an official language, GATT, and WTO membership. *Recipient×donor characteristics:* average political distance proxied by UNGA voting alignment, average bilateral trade, distance, and dummies for contiguity, legal origin, language, colonial relationship, religion, sibling, and FTA.

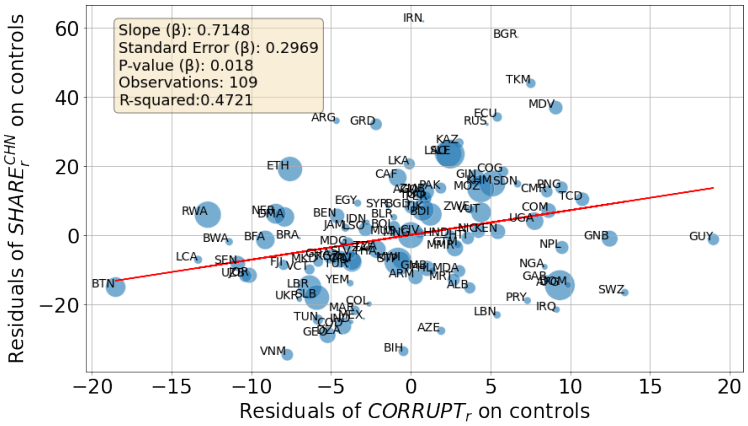


Figure 1: China's Share in Total DF Amount and Recipient Corruption

3.2 Corruption and Project Size and Count

In domestic settings, it is well established that corruption is associated with higher public spending at both the micro and macro levels (Mauro, 1995, 1996; Tanzi and Davoodi, 1998). A common interpretation in this literature is that diversion incentives lead governments to exaggerate project costs or allocate spending inefficiently. I examine whether development finance (DF) allocation exhibits patterns correlated with corruption that are consistent with this mechanism.

In the DF context, however, allocation outcomes reflect both recipient demand and donor supply conditions. Correlations between corruption and DF inflows therefore represent equilibrium outcomes shaped by these two forces, making it difficult to disentangle supply and demand—especially at the aggregate level. By examining project-level outcomes in this subsection and cross-sectoral outcomes in the next—particularly heterogeneity across DAC and Chinese financing environments with different monitoring intensity—I document patterns consistent with diversion incentives operating on the demand side, conditional on supply-side factors. I further control for a wide range of recipient and bilateral characteristics that may capture donor supply considerations, and include donor fixed effects. The resulting correlations should therefore be interpreted as conditional on these observable supply-side factors.

3.2.1 Corruption and Project Size

Fact 2. *Chinese project size is positively correlated with recipient-country corruption, whereas DAC project size shows no such relationship.*

To examine how corruption relates to project size, I estimate the following project-level regression:

$$\ln SIZE_i = FE_{d(i)s(i)t(i)} + \beta \cdot \ln CORRUPT_{r(i)} + X_{r(i)d(i)t(i)} \cdot \gamma + constant + \epsilon_i$$

where SIZE_i is the committed value of project i (in constant 2011 USD). Subscripts $r(i)$, $d(i)$, $s(i)$, and $t(i)$ denote the recipient country, donor, sector, and year, respectively. $FE_{d(i)s(i)t(i)}$ are donor–sector–year fixed effects, which help control for supply-side factors that vary across donors, sectors, and time, following Khwaja and Mian (2008). $CORRUPT_{r(i)}$ is the corruption index of the recipient country, averaged over the sample period. I take logs of the index so that the coefficient can be interpreted as an elasticity. The results are qualitatively unchanged when the index is used in levels.[5] $\mathbf{X}_{r(i)d(i)t(i)}$ includes the same recipient- and recipient–donor-specific controls as in the country-level analysis, with the addition of a loan–grant dummy since grants tend to be smaller than loans. ϵ_i is the error term. I estimate the regression separately for DAC and Chinese projects, with β capturing the correlation between corruption and project size.

Table 1 shows that Chinese project size is positively and statistically significantly correlated with recipient corruption. Columns (3)–(4) indicate that a 1% increase in the corruption index is associated with a 0.96–1.46% increase in Chinese project size. By contrast, columns (1)–(2) show no economically or statistically significant relationship between corruption and DAC project size.

3.2.2 Corruption and the Number of Projects

Fact 3. *The number of DAC projects is significantly negatively correlated with recipient-country corruption, while the number of Chinese projects is weakly positively correlated.*

[5] Variance decomposition shows that within-country variation explains only 2% of the total variance in the corruption index, which justifies using the average. Averaging also helps mitigate potential measurement error. The results are robust to using the non-averaged index (Online Appendix 2.4.3).

Table 1: Corruption and DF Project Size

	DAC projects		Chinese projects	
	(1)	(2)	(3)	(4)
ln $CORRUPT_{r(i)}$	0.211	0.098	0.960**	1.460***
	(0.167)	(0.144)	(0.395)	(0.490)
Observations	1,160,794	1,025,229	7,559	7,559
R^2	0.351	0.263	0.657	0.662
Donor×Sector×Year FE	✓	✓	✓	✓
Loan dummy & recipient controls	✓	✓	✓	✓
Recipient×Donor controls		✓		✓

Notes: Standard errors clustered at the recipient-country level are reported in parentheses.

To examine the relationship between corruption and the number of DF projects, I regress the total number of projects undertaken by each donor group in each country–year on the corruption index and controls. While I report results from country-level regressions, the main findings are robust when the analysis is conducted at the sectoral level (Online Appendix 2.1.3).

Table 2 shows that corruption is significantly negatively correlated with the number of DAC projects, while it is positively but weakly correlated with the number of Chinese projects. Columns (1)–(2) indicate that higher corruption is associated with fewer DAC projects. Using the estimated coefficient, a one–standard-deviation increase in log corruption (0.18) is associated with roughly 1.7 fewer DAC projects per year. In contrast, columns (3)–(4) suggest a small positive relationship between corruption and the number of Chinese projects, though these coefficients are not statistically significant.

Because many Chinese projects are not reported in international statistics, and more corrupt countries may be less likely to disclose projects transparently, the estimated relationship for Chinese projects likely understates the true association and should therefore be interpreted as a conservative estimate.

3.3 Corruption and DF in Hard-to-Monitor Sectors

To shed further light on the mechanisms behind the correlations documented above, I exploit cross-sectoral differences in monitoring difficulty. If diversion incentives on the demand side are relevant, corruption should be more strongly associated with DF project size and the number of projects in sectors that are harder to monitor, in the same direction as the correlations documented in the previous subsection. By

Table 2: Corruption and DF Project Count

	DAC projects		Chinese projects	
	(1)	(2)	(3)	(4)
ln $CORRUPT_r$	-9.722***	-9.345**	3.109	1.549
	(2.515)	(4.252)	(2.132)	(1.767)
Observations	88,768	53,704	2,336	2,149
R^2	0.385	0.462	0.323	0.387
Donor×Year FE	✓	✓	✓	✓
Loan dummy & recipient controls	✓	✓	✓	✓
Recipient×Donor controls		✓		✓

Notes: Standard errors clustered at the recipient-country level are reported in parentheses.

contrast, if supply-side rationing dominates—for example, if donors restrict lending in environments where monitoring is difficult and corruption is high—the association between corruption and DF allocation should be weaker or even negative in hard-to-monitor sectors. Since DF allocation reflects equilibrium outcomes shaped by both recipient demand and donor supply, this exercise does not establish causality. Rather, stronger correlations in hard-to-monitor sectors would provide suggestive evidence that diversion incentives on the demand side also play a role.

I first classify sectors into easy- and hard-to-monitor categories using a recently released project evaluation dataset that records more than 20,000 DF project assessments implemented by 12 agencies across 183 recipient countries. These evaluations cover projects financed mostly by DAC providers and do not include Chinese projects. However, the classification relies only on relative differences in monitoring difficulty across sectors. In constructing sectoral rankings, I control for evaluator characteristics, recipient-country attributes, and donor–recipient relationships, so that the resulting sectoral averages reflect monitoring difficulty conditional on these factors. I then examine whether the relationship between corruption and DF project size and counts differs across these sector groups.

The results show that corruption is associated with disproportionately larger project sizes in hard-to-monitor sectors, with the relationship statistically significant even for DAC projects. Higher corruption is also associated with a greater number of projects in hard-to-monitor sectors.

3.3.1 Classifying Sectors by Monitoring Difficulty

I rank sectors by monitoring difficulty using AidData's Project Performance Database (PPD), which evaluates more than 20,000 development finance (DF) projects imple-

mented by 12 agencies across 183 recipient countries from 1956–2016. Projects are rated on a six-point scale, where 1 denotes highly unsatisfactory and 6 denotes highly satisfactory performance. Although the evaluation criteria vary somewhat by agency, ratings typically reflect implementation efficiency and the quality of project supervision.

Average ratings differ markedly across sectors. For example, Figure 2 shows that roughly 80 percent of Emergency Response[6] projects receive ratings close to 5 or higher, whereas projects in sectors such as Industry, Mining, and Construction exhibit substantially lower average ratings. I interpret these systematic differences as reflecting variation in monitoring difficulty across sectors and use sectoral average ratings to rank sectors accordingly.

To estimate sectoral average ratings, I control for potential confounding factors—including evaluator type, recipient-country characteristics such as corruption, and donor–recipient relationships such as political ties—using recipient–donor–time fixed effects and other project characteristics so as to isolate sector-specific components of the evaluation scores. The resulting sectoral averages differ statistically significantly across sectors. The implied ranking aligns well with conventional expectations and existing evidence: sectors involving complex infrastructure and large financial transfers tend to rank as harder to monitor, whereas emergency response and short-term humanitarian sectors rank as easier to monitor. Details of the estimation strategy and sectoral rankings are reported in Online Appendix 2.3.1.

Because project performance ratings may reflect factors beyond monitoring difficulty—such as sector-specific implementation efficiency or differences in monitoring practices—I interpret the measure as capturing the overall monitoring environment of each sector rather than a pure measure of monitoring difficulty. Importantly, the analysis relies on relative differences across sectors rather than the absolute level of the ratings.

To reduce potential measurement error, I classify sectors into two groups—easy and hard to monitor—in the baseline analysis. The results are robust to using the continuous sectoral ranking instead. Although the measure may capture both monitoring difficulty and monitoring practices, either interpretation implies that diversion is more difficult to detect in certain sectors, which is the mechanism relevant for the analysis.

[6]For instance, emergency lending following natural disasters.

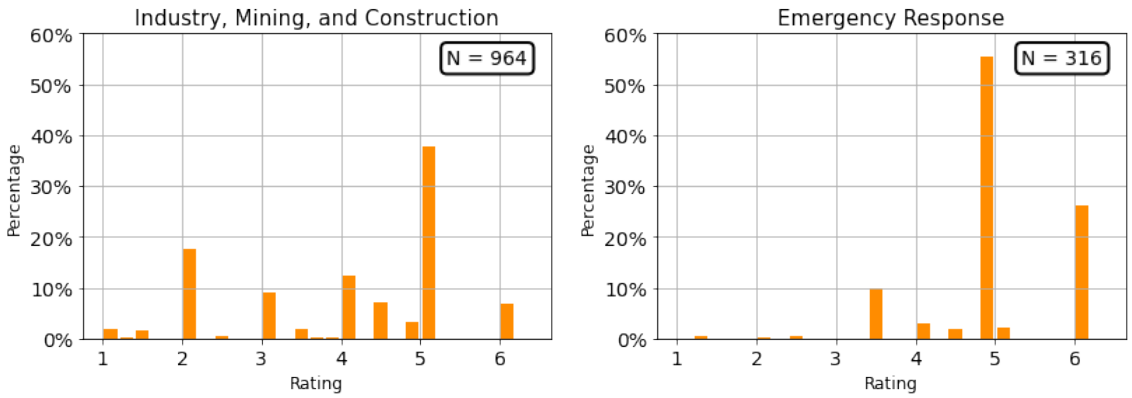


Figure 2: Average Ratings (6-point Scale) by Sectors

3.3.2 Estimating Correlations in Hard-to-Monitor Sectors

Fact 4. *In hard-to-monitor sectors, corruption is associated with disproportionately larger projects and a higher number of projects.*

Using the sectoral monitoring classification described above, I examine whether the relationship between corruption and DF allocation varies with monitoring difficulty. For ease of interpretation, I classify sectors into *low* and *high* monitoring categories based on the first quartile of the sectoral average ratings.[7]

I estimate the following regression separately for DAC and Chinese projects:

$$\begin{aligned}\ln SIZE_i =& FE_{r(i)} + FE_{d(i)s(i)t(i)} + \beta \cdot \ln CORRUPT_{r(i)} + X_{r(i)d(i)t(i)} \cdot \gamma \\ &+ \delta \cdot \ln CORRUPT_{r(i)} \times LowMonitor_{s(i)} + constant + \epsilon_i.\end{aligned}$$

$LowMonitor_{s(i)}$ is a dummy equal to 1 for projects in hard-to-monitor sectors and 0 otherwise. Its level effect is absorbed by the donor×sector×year fixed effects, $FE_{d(i)s(i)t(i)}$, so it enters only through interaction with the corruption index. The coefficient β captures the baseline association between corruption and project size, while δ captures whether this association differs in hard-to-monitor sectors. Recipient fixed effects $FE_{r(i)}$ absorb time-invariant country characteristics. For Chinese

[7] This classification also helps mitigate potential measurement error in the sectoral ratings. Five sectors—Industry, Mining, and Construction; Disaster Prevention and Preparation; Water Supply and Sanitation; Agriculture, Forestry, and Fishing; and Government and Civil Society—fall into the low-monitoring group. In robustness checks (Online Appendix 2.4.4), I confirm the results using alternative definitions of monitoring difficulty. I exclude the Emergency Response and Relief & Rehabilitation sectors, which consist mainly of donor-initiated disaster-response projects, as well as the Action Relating to Debt sector, which does not correspond to new project investments.

projects, the donor dimension of the fixed effects is redundant.

I next estimate the relationship between corruption and the number of projects using an analogous specification:

$$N_{rdst} = FE_r + FE_{dst} + \beta \cdot \ln CORRUPT_r + X_{rdt} \cdot \gamma + \delta \cdot \ln CORRUPT_r \times LowMonitor_s + constant + \epsilon_{rdst}$$

where N_{rdst} is the number of projects for recipient r from donor d in sector s and year t. The right-hand-side variables mirror those in the project-size regression, except that the control vector $\mathbf{X}_{rdt}$ does not include the loan–grant dummy.

Panel (a) of Table 3 shows that the relationship between corruption and project size is stronger in sectors that are harder to monitor. The interaction coefficient is positive across all specifications for both DAC and Chinese DF. For DAC projects, a 1% increase in corruption is associated with an additional 0.35% increase in project size in hard-to-monitor sectors relative to other sectors. For Chinese projects, the estimated interaction effect is of similar magnitude but not statistically significant. Including recipient fixed effects in columns (3) and (6) leaves the interaction coefficients qualitatively unchanged.

Panel (b) reports analogous results for the number of projects. The interaction coefficients indicate that corruption is more strongly associated with project counts in hard-to-monitor sectors, particularly for DAC projects. For example, a one-standard-deviation increase in corruption is associated with approximately 0.11 additional DAC projects in hard-to-monitor sectors relative to other sectors. For Chinese projects, the estimated interaction coefficients are positive but not statistically significant. The baseline coefficients are consistent with the regressions reported earlier without interaction terms.

3.4 Robustness Checks

The empirical patterns documented above are robust to a wide range of alternative specifications and measurement choices. First, the aggregate findings are not driven by the cross-sectional specification. Using panel regressions at both the country and sectoral levels, I confirm the positive relationship between corruption and reliance on Chinese DF. Consistent with the baseline results, DAC DF inflows are negatively correlated with corruption, whereas Chinese DF inflows are positively correlated,

Table 3: Corruption Correlation in Hard-to-monitor Sectors

Panel (a) Project sizes	DAC projects			Chinese projects		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln CORRUPT_{r(i)}$	0.087	-0.020		0.879**	1.376***	
	(0.143)	(0.131)		(0.375)	(0.459)	
$\ln CORRUPT_{r(i)} \times LowMonitor_{s(i)}$	0.347**	0.328**	0.225**	0.466	0.449	0.592
	(0.146)	(0.163)	(0.101)	(0.706)	(0.708)	(0.649)
Observations	1,133,308	1,002,107	1,133,308	7,439	7,439	7439
R^2	0.352	0.263	0.358	0.658	0.662	0.675
Donor×Sector×Year FE	✓	✓	✓	✓	✓	✓
Loan dummy & recipient controls	✓	✓	✓	✓	✓	✓
Recipient×Donor controls		✓	✓		✓	✓
Recipient FE			✓			✓
Panel (b) Project counts	DAC projects			Chinese projects		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln CORRUPT_{r}$	-0.649***	-0.599***		0.124	0.048	
	(0.142)	(0.205)		(0.105)	(0.090)	
$\ln CORRUPT_{r} \times LowMonitor_{s}$	0.477***	0.619***	0.619***	0.111	0.111	0.111
	(0.140)	(0.194)	(0.194)	(0.074)	(0.081)	(0.081)
Observations	1,495,040	1,074,080	1,074,080	46,720	42,980	42980
R^2	0.261	0.288	0.294	0.300	0.314	0.327
Donor×Sector×Year FE	✓	✓	✓	✓	✓	✓
Recipient controls	✓	✓	✓	✓	✓	✓
Recipient×Donor controls		✓	✓		✓	✓
Recipient FE			✓			✓

using both OLS and PPML estimators (Online Appendix 2.1).

Second, the project-level results are robust to alternative treatments of outliers and to alternative measures of corruption. Winsorizing or trimming project sizes leaves the main findings unchanged, and the results remain similar when the baseline CPI measure is replaced with alternative CPI series or related corruption indicators (Online Appendix 2.4.2–2.4.3). The key interaction between corruption and monitoring difficulty is also robust to alternative definitions of sectoral monitoring difficulty, including both alternative binary cutoffs and a continuous sectoral ranking (Online Appendix 2.4.4).

Third, the cross-sectoral evidence is not explained by interactions between monitoring difficulty and other observable country characteristics. A placebo exercise that interacts sectoral monitoring difficulty with a broad set of recipient and bilateral covariates leaves the corruption interaction term positive and statistically significant for DAC projects (Online Appendix 2.4.5). The results are also qualitatively similar when additional controls for public capital, capital-account openness, and democracy are included (Online Appendix 2.4.7).

Fourth, I conduct additional exercises aimed at probing interpretation rather than establishing causality. Replacing the CPI with alternative public-sector diversion measures from V-Dem yields similar patterns for Chinese projects. I also report results from an instrumental-variables exercise using settler mortality as a proxy for long-run institutional environments. These estimates reproduce the qualitative contrast between DAC and Chinese project-size correlations, but they are imprecise and should be interpreted cautiously given the smaller sample and potential weak-instrument concerns. Because the empirical analysis in this section aims to document stylized facts rather than identify causal effects, these exercises are best viewed as sensitivity checks (Online Appendix 2.4.1 and 2.4.6).

Finally, additional exercises further confirm the baseline patterns. Estimating the correlation between corruption and project size separately for each donor, instead of pooling all DAC donors, shows that Chinese projects exhibit the largest positive correlation among major donors (Online Appendix 2.2). Using corruption quartiles instead of a continuous CPI measure also yields similar results, indicating that the relationship between corruption and Chinese project size is broadly monotonic (Online Appendix 2.3.2).

Overall, these checks support the view that the empirical relationships documented in this section are not driven by a particular specification, corruption measure, monitoring classification, or a narrow set of omitted observables. Detailed results are reported in Online Appendix 2.1–2.4.

3.5 Taking Stock and Potential Explanation

Rationalizing the Facts.— Taken together, the stylized facts suggest a pattern consistent with diversion incentives interacting with differences in monitoring across financing environments. If some sources of DF are monitored more strictly than others, governments with stronger diversion incentives may prefer financing environments where diversion is harder to detect.

If Chinese DF is subject to weaker monitoring than DAC DF—as frequently discussed in policy debates and existing research—governments with stronger diversion incentives may prefer Chinese financing over more tightly monitored DAC financing. In particular, this interpretation is consistent with the fact that more corrupt countries host relatively more Chinese projects and fewer DAC projects (Fact 3), and that

Chinese project size is positively correlated with corruption while DAC project size is not (Fact 2). Taken together, these patterns are also consistent with the aggregate result that more corrupt countries rely more heavily on Chinese DF relative to DAC DF (Fact 1).

The sectoral results are also consistent with this interpretation. Even within DAC financing, some sectors are inherently harder to monitor. In these sectors, corruption is disproportionately associated with larger projects and more projects, and the relationship is statistically significant even for DAC DF (Fact 4). By contrast, for Chinese DF—where monitoring appears weaker on average—variation in cross-sectoral monitoring difficulty plays a smaller role relative to the overall relationship between corruption and project size.

Alternative Stories.— The documented correlations may also reflect supply-side considerations. For example, DAC financing may be more heavily rationed in more corrupt environments, concentrated in particular sectors, or subject to higher institutional and procedural barriers (Brautigam, 2011; Dreher et al., 2022). Such mechanisms could contribute to the aggregate association between corruption and reliance on Chinese DF (Fact 1).

However, supply-side explanations alone are less able to account for the full set of project-level and sectoral patterns. In particular, the project-size regressions are conditional on projects that have already been approved by donors, which limits the role of extensive-margin rationing in explaining those results. Moreover, if donor-side restrictions were the dominant force, stricter monitoring would plausibly lead donors to limit project size more strongly in corrupt environments, especially in sectors that are harder to monitor. The empirical patterns instead show larger projects in those sectors. Taken together, these findings are consistent with the presence of diversion incentives on the demand side interacting with monitoring constraints, although the empirical analysis itself does not attempt to fully disentangle demand and supply forces.

Another explanation emphasizes bilateral political and economic relationships between donors and recipients (Alesina and Dollar, 2000; Kuziemko and Werker, 2006). In the empirical analysis, I explicitly control for these factors using extensive bilateral covariates. The core empirical relationships between corruption and DF allocation remain robust to these controls.

Although several mechanisms may contribute to the observed correlations, ex-

plaining the full set of project-level and sectoral patterns within a unified framework naturally motivates a model that places recipient-country decision-making at center stage. The model developed below focuses on how corruption and monitoring frictions shape governments' choices over the scale, source, and sectoral allocation of DF in a two-donor environment while also taking into account donor-side financing conditions as parameters that recipients take as given.

4 A Growth Model of Corruption and DF

I develop a variant of the neoclassical growth model in which a borrowing government chooses the amount, source, and sectoral allocation of DF in the presence of public-sector corruption. The model features heterogeneous financing environments across DAC and Chinese DF and embeds these choices in a framework with private and public capital. It serves three purposes. First, it provides a disciplined framework for interpreting the stylized facts documented in Section 3. Second, it clarifies the aggregate implications of corruption and DF allocation for public-capital efficiency and development outcomes. Third, it provides a tractable framework for quantitative analysis of the welfare effects of Chinese DF in developing countries.

The core mechanism is simple. Monitoring affects how much borrowed DF can be diverted, which in turn changes the government's effective marginal cost of financing public projects. As a result, corruption distorts project size, the number of projects, provider choice, and the sectoral allocation of public investment. The section proceeds from project-level financing decisions to sector-level allocation and then to aggregate implications. I first describe the economic environment and the government's planning problem. I then characterize optimal financing and investment at the project and sector levels, derive aggregate effective public capital, and finally use the model to interpret the four stylized facts.

4.1 Model Environment

Time is discrete, indexed by $t = 0, 1, 2, \ldots$. The economy is a small open economy that produces a single good using private capital, public capital, and labor. The private sector consists of a unit measure of identical, infinitely lived households who supply labor and private capital and own firms that produce output. The public sector

consists of the government, which accumulates public capital through differentiated projects. The government finances these projects using international DF from two providers, the DAC and China.[8]

DF contracts differ across providers and sectors in interest rates, monitoring intensity, and fixed access costs. The economy takes these financing conditions as given. There is no sovereign default, and the private sector does not have access to international financial markets.

4.1.1 Private Sector

Household.—A representative household has log utility over consumption, $U(C) = \ln C$, and discounts the future at rate β. Lifetime utility is

$$\sum_{t=0}^{\infty} \beta^t U(C_t).$$

The household accumulates private capital according to : $K_{t+1} = (1 - \delta_K) \cdot K_t + I_t^K$, where δ_K is the depreciation rate and I_t^K denotes investment in period t. The household supplies labor inelastically at a constant level $L_t = L$, rents capital to firms, and receives firms' profits as the owner.

Firm.—A representative firm produces output using private capital (K), labor (L), and effective public capital (G^E) according to a Cobb–Douglas technology

$$Y = F(K, L, G^E) = A \cdot (G^E)^{\gamma} \cdot K^{\alpha} \cdot L^{1-\alpha}$$

where α and γ denote the output elasticities of private capital and effective public capital, and A is total factor productivity. The firm takes G^E as given, since public capital is provided by the government. After paying factor prices, the firm returns residual profits to the household.

In existing work (e.g., Hulten (1996)), effective public capital is often modeled as ΘG, where G denotes the book value of public capital and Θ is an exogenous efficiency

[8] In principle, the government could also use domestic resources or borrow through other external instruments such as commercial bonds. I abstract from these possibilities to focus on official DF contracts, which are the primary object of the empirical analysis. Empirically, DF is a dominant source of external financing for public investment projects in many developing countries. In the model, even if these alternative financing sources were available, DF would be strictly preferred in equilibrium because it is concessional.

parameter. In contrast, in this model the effective efficiency of public capital emerges endogenously from the government's project allocation and financing choices in the global development finance environment, as discussed in Section 5.

4.1.2 Public Sector

The government manages the public sector, accumulating and providing public capital to the private sector. With sufficient instruments to influence private decisions, it solves a planning problem in which it directly chooses household consumption, saving, and public capital accumulation.

Accumulating Public Capital.—The public sector consists of N subsectors, $\mathcal{S} = \{s_1, s_2, \ldots, s_N\}$. Within each $s \in \mathcal{S}$ lies a continuum of differentiated public projects of measure one. The government accumulates effective public capital in each project. Let $g^E_{s,j,t}$ denote the effective public capital stock in project j of sector s at time t. It evolves according to $g^E_{s,j,t+1} = (1 - \delta_G) \cdot g^E_{s,j,t} + I^E_{s,j,t}$ where δ_G is the depreciation rate of public capital and $I^E_{s,j,t}$ is investment in project j.

Providing Public Capital.—In each period, the government aggregates effective public capital from all projects and provides it to the private sector at no cost, using a two-layer structure. First, effective public capital in subsector s, $G^E_{s,t}$, is a Constant Elasticity of Substitution (CES) aggregate of project-level capital:

$$G^E_{s,t} = \Big[\int_{j \in \mathcal{J}_s} \theta_j \cdot g^E_{s,j,t}{}^{\frac{\sigma-1}{\sigma}} \, dj \Big]^{\frac{\sigma}{\sigma-1}},$$

where $\sigma > 1$ is the elasticity of substitution across projects and θ_j is project-specific productivity.

Second, the final effective public capital G^E_t, which enters the firm's production function, is a Cobb–Douglas composite of subsector aggregates:

$$G^E_t = \prod_{s \in S} (G^E_{s,t})^{\gamma_s},$$

where γ_s is the share of sector s in the public sector, with $\sum_{s \in \mathcal{S}} \gamma_s = 1$. This project- and sector-level formulation extends existing work that typically treats public capital as a single aggregate input.

Financing Public Capital.—In addition to domestic savings, the government fi-

nances public projects through international DF loans.[9]

DF loans are one-period project-level debt contracts at a fixed risk-free interest rate. Each period, the government repays outstanding debt and may issue new loans to refinance projects. There are two DF providers: the Development Assistance Committee (DAC) and China, with sector-specific gross interest rates R_s^D and R_s^C. Empirically, $1 < R_s^D < R_s^C < 1/\beta$ for all $s \in \mathcal{S}$, reflecting that DF is concessional and DAC loans are cheaper than Chinese loans.

The economy is small in the DF market and faces no aggregate supply constraint. Loans are contracted at the project level and earmarked for specific projects. Let $d_{s,j,t}^D$ and $d_{s,j,t}^C$ denote debt stocks for project j in sector s, owed to the DAC and China, respectively, at the start of period t.

The government can divert part of the funds borrowed through each DF contract for its own benefit. Let $g_{s,j,t}^X$ be the diverted amount from the outstanding DF debt for project j in period t. Note that $g_{s,j,t}^E$ is a stock variable: after production, a fraction $(1-\delta_G)$ remains. In contrast, $g_{s,j,t}^X$ does not accumulate and is fully consumed by the government within the period.[10]

DF providers cannot fully distinguish between funds allocated to effective capital and those diverted. However, they can verify that borrowed funds remain attached to the designated project. This generates a *non-fungibility constraint*:

$$g_{s,j,t}^E + g_{s,j,t}^X \geq d_{s,j,t}^D + d_{s,j,t}^C, \tag{1}$$

which requires that the book value of the project is at least as large as the outstanding DF debt.

DF providers also monitor project implementation. The DAC and China can verify that fractions $\psi_s^D \in (0,1]$ and $\psi_s^C \in (0,1]$ of their loans are allocated to effective capital. These parameters capture sector-specific monitoring intensities. The government therefore faces the monitoring constraint

$$g_{s,j,t}^E \geq \psi_s^D d_{s,j,t}^D + \psi_s^C d_{s,j,t}^C. \tag{2}$$

[9] Another major source of DF is DAC grants, which are mostly small, non-repayable projects. Because of their nature, this section focuses on loans. In Section 6, I incorporate DAC grants for quantification. Their inclusion does not alter the main theoretical results.

[10] For example, if the government borrows \$100 and allocates \$90 to effective capital while diverting \$10, then $(1-\delta_G) \times \$90$ remains as capital after production while the diverted \$10 is consumed immediately. In $t+1$, it must repay $(1+R_s^D) \times 100$ from retained capital and output.

The monitoring constraint therefore implies that the government can divert at most $1-\psi_s^D$ of a DAC loan and $1-\psi_s^C$ of a Chinese loan. Motivated by the empirical evidence discussed in Section 3, I assume $\psi_s^D \geq \psi_s^C$ for all $s \in \mathcal{S}$, reflecting that DAC projects are typically subject to stricter monitoring than Chinese projects.

Each period, issuing new DF debt for a project incurs fixed costs f_s^D and f_s^C for DAC and Chinese loans, respectively, in sector s. These fixed costs capture a range of frictions faced by recipient governments when accessing DF, including expenses related to negotiation, administration, compliance, monitoring, and reporting. More broadly, they summarize donor- and sector-specific institutional and procedural requirements that affect access to financing from the borrower's perspective, capturing broader supply-side factors beyond the interest rates and monitoring intensities explicitly modeled above. Examples include eligibility conditions, approval and procurement procedures, reporting obligations, and contractual provisions such as tied procurement, collateralization arrangements, or requirements regarding labor and inputs.

Taken together, DF contracts differ along two key margins. First, marginal financing terms differ: Chinese loans are typically more expensive but less strictly monitored than DAC loans. Second, access conditions differ through provider- and sector-specific fixed costs, which capture broader supply-side frictions affecting the availability of financing. Fixed costs are not restricted in relative magnitude across providers, allowing Chinese DF to fill financing gaps if in some sectors DAC financing is costly to access.

Government's Utility.—The government's period utility is $\tilde{U}(C, G^X; \chi) = \ln\big(C + \chi G^X\big)$, which follows the Greenwood–Hercowitz–Huffman (GHH) form (Greenwood et al., 1988). Here C denotes household consumption and $G_t^X \equiv \sum_{s\in\mathcal{S}} \int_{j\in\mathcal{J}_s} g_{s,j,t}^X dj$ denotes total diverted funds. The parameter $\chi \geq 0$ measures the value the government places on diversion. When $\chi = 0$, government utility coincides with household utility. The GHH specification implies that the marginal utility of diversion relative to consumption is constant and equal to χ.

4.2 Government's Planning Problem

At the start of period t, public projects completed in period $t-1$ become productive. The government aggregates effective public capital and provides it to the private

sector, while consuming any diverted funds. The representative firm produces output Y_t using private capital, effective public capital, and labor. The government then services outstanding DF debt, chooses new borrowing and project investments for the next period, and allocates funds between effective capital and diversion. Finally, it assigns household consumption and private investment.

The government's planning problem is defined as follows.

Definition 1 (Government's Planning Problem and Optimal Allocation) *The government solves*

$$\max_{\{C_t, K_{t+1}, \mathbf{g}^E_{t+1}, \mathbf{g}^X_{t+1}, \mathbf{d}^D_{t+1}, \mathbf{d}^C_{t+1}\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \beta^t \tilde{U}(C_t, G^X_t; \chi)$$

$$\begin{aligned}
s.t.\quad & \textit{(RC):}\ C_t + I^K_t + \sum_{s\in\mathcal{S}} \int_{j\in\mathcal{J}_s} (I^E_{s,j,t} + g^X_{s,j,t+1} + R^D_s d^D_{s,j,t} + R^C_s d^C_{s,j,t} \\
& \quad + \mathbb{I}^D_{s,j,t} f^D_s + \mathbb{I}^C_{s,j,t} f^C_s) dj \\
& \quad = Y_t + \sum_{s\in\mathcal{S}} \int_{j\in\mathcal{J}_s} (d^D_{s,j,t+1} + d^C_{s,j,t+1}) dj, \\
& \textit{(NF):}\ g^E_{s,j,t} + g^X_{s,j,t} \geq d^D_{s,j,t} + d^C_{s,j,t}, \\
& \textit{(MC):}\ g^E_{s,j,t+1} \geq \psi^D_s d^D_{s,j,t+1} + \psi^C_s d^C_{s,j,t+1}, \\
& \textit{(NX), (ND), (NC):}\ g^X_{s,j,t+1} \geq 0,\ d^D_{s,j,t+1} \geq 0,\ d^C_{s,j,t+1} \geq 0, \\
& \textit{for all } t,\ s \in \mathcal{S},\ j \in \mathcal{J}_s,\ \textit{given } k_0, \mathbf{g}^E_0, \mathbf{g}^X_0, \mathbf{d}^D_0, \mathbf{d}^C_0
\end{aligned}$$

where $\mathbf{g}^E_t = \{g^E_{s,j,t}\}_{j\in\mathcal{J}_s, s\in\mathcal{S}}$, $\mathbf{g}^X_t = \{g^X_{s,j,t}\}_{j\in\mathcal{J}_s, s\in\mathcal{S}}$, $\mathbf{d}^D_t = \{d^D_{s,j,t}\}_{j\in\mathcal{J}_s, s\in\mathcal{S}}$, $\mathbf{d}^C_t = \{d^C_{s,j,t}\}_{j\in\mathcal{J}_s, s\in\mathcal{S}}$ *denote the vectors of effective public capital, diverted funds, DAC debt, and Chinese debt, respectively, across all projects in period* t*, and* $\mathbb{I}^p_{s,j,t}$ *denotes an indicator equal to one if* $d^p_{s,j,t} > 0$*, and zero otherwise.*

The "government's optimal allocation" is a sequence $\{C_t, K_{t+1}, \mathbf{g}^E_{t+1}, \mathbf{g}^X_{t+1}, \mathbf{d}^D_{t+1}, \mathbf{d}^C_{t+1}\}_{t=0}^{\infty}$ *that solves the government's planning problem.*

Constraint (RC) is the economy-wide resource constraint. Constraints (NF) and (MC) correspond to the non-fungibility and monitoring constraints introduced earlier. Finally, (NX), (ND), and (NC) impose non-negativity on diversion and debt choices. Note that (MC) and (NX) cannot bind simultaneously.

4.3 Government's Optimal Allocation

I first characterize optimal project size and financing at the project level, and then aggregate the results to the sector and economy levels.

4.3.1 Government's Optimal Financing at the Project Level

I focus on allocations in which the non-fungibility constraint binds so that all public projects are financed with DF. A sufficient condition is $f_s^S \geq \min\{f_s^D, f_s^C\}$, where f_s^S denotes the fixed cost of self-financing a project in sector s. Together with $R_s^D < R_s^C < 1/\beta$, this implies that DF financing dominates self-financing both in marginal and fixed costs. In the quantitative analysis (Section 7), I relax this assumption for sectors not eligible for DF.

The following lemmas and proposition characterize the government's optimal project size and financing. All proofs are provided in Online Appendix 3.1-3.10.

Lemma 1 (Single-provider Financing) *In an optimal allocation, each public project is financed by a single DF provider.*

The intuition is straightforward. Because borrowing costs from each provider are constant, the government compares their effective marginal costs—determined by interest rates, monitoring intensities, and the marginal utility of diversion captured by the corruption parameter—and chooses the cheaper provider. Borrowing from both DAC and China for the same project would only incur additional fixed costs and is therefore not optimal. This property is also consistent with the empirical implementation, where each project observation in the data is associated with a single provider. While co-financing across donors may occur in practice, such arrangements appear in the data as separate donor-project observations.

Lemma 2 (All-or-nothing Diversion) *For each project, the government chooses either maximal or zero diversion, except for a knife-edge case where $\chi = R_s^p$ for some provider $p \in \{D, C\}$:*

$$g_{s,j,t+1}^E = \begin{cases} \psi_s^p d_{s,j,t+1}^p & \text{if } \chi > R_s^p \\ d_{s,j,t+1}^p & \text{if } \chi < R_s^p \end{cases}$$

Lemma 2 follows from the fact that under GHH preferences the marginal utility of diversion relative to consumption is constant and equal to χ. The government therefore compares the marginal value of diverting one unit of DF with the marginal cost of borrowing from provider p, given by the interest rate R_s^p. If $\chi > R_s^p$, diversion yields a higher marginal return than productive investment and the government diverts the maximal amount allowed by monitoring, so the monitoring constraint binds. If $\chi < R_s^p$, diversion is too costly and the government allocates all funds to effective public capital.

The resulting corner solution is a convenient implication of the GHH specification, which keeps the model tractable. Importantly, the quantitative implications of the model depend on the aggregate amount of diverted funds rather than on whether diversion occurs fully or partially within individual projects. Allowing for interior diversion choices would therefore complicate the analysis without materially affecting the aggregate mechanisms emphasized in the model. In the knife-edge case $\chi = R_s^p$, I assume the government chooses maximal diversion.

Lemma 3 (Optimal Project Size Condition) *The optimal effective public capital in j, financed by p, equates the government's marginal benefit to the interest rate:*

$$\begin{aligned} mpg^E_{s,j,t+1} + 1 - \delta^E_s &= R^p_s \qquad \text{if } \chi < R^p_s \\ \psi^p_s \cdot (mpg^E_{s,j,t+1} + 1 - \delta^E_s) + (1 - \psi^p_s) \cdot \chi &= R^p_s \qquad \text{if } \chi \geq R^p_s \end{aligned}$$

where $mpg^E_{s,j,t+1}$ is the marginal product of project j, defined as $mpg^E_{s,j,t+1} \equiv \frac{\partial Y_{t+1}}{\partial g^E_{s,j,t+1}}$.

Lemma 3 follows from combining the first-order conditions for effective public capital in project j and for its DF debt stock. When corruption is low ($\chi < R_s^p$), diversion is not attractive and the optimal project size equates the total return on effective public capital to the borrowing cost. When corruption is high ($\chi \geq R_s^p$), a fraction $1-\psi_s^p$ of each borrowed unit is diverted, generating additional utility equal to χ. The marginal benefit of borrowing therefore combines the project return (weighted by ψ_s^p) and the diversion payoff (weighted by $1-\psi_s^p$). For convenience, I define the effective marginal cost as follows.

Definition 2 (Effective Marginal Cost for the Government) *The government's effective marginal cost of financing a project in sector s from p, $\tilde{R}_s^p$, is the interest rate adjusted for capital retention after depreciation and the marginal utility of diversion:*

$$\tilde{R}_s^p \equiv \begin{cases} R_s^p - (1-\delta_s^E) & \text{if } \chi < R_s^p \\ \frac{R_s^p - (1-\psi_s^p)\cdot\chi}{\psi_s^p} - (1-\delta_s^E) & \text{if } \chi \geq R_s^p \end{cases}$$

Then, Corollary 1 simplifies Lemma 3.

Corollary 1 (Optimal Project Size Condition') *Optimal size of project j, financed by p, equates the marginal product of the project and the effective marginal cost: $mpg_{s,j,t+1}^E = \tilde{R}_s^p$.*

Note that $mpg_{s,j,t+1}^E$ is identical across projects with the same productivity within sector s. Hence, I define $mpg_{s,t+1}^E(\theta)$ as a function of project productivity θ.

Definition 3 (Effective Profit for the Government) *The government's effective profit from a project with productivity θ, financed by p, $\tilde{\pi}_{s,t+1}^p(\theta)$, is the net contribution of the project to output, after accounting for effective marginal financing costs and fixed access costs:*

$$\tilde{\pi}_{s,t+1}^p(\theta) \equiv \int_0^{\bar{g}_{s,t+1}^{Ep}(\theta)} (mpg_{s,t+1}^E(\theta) - \tilde{R}_s^p) dg_{s,j,t+1}^E - f_s^p,$$

where $\bar{g}_{s,t+1}^{Ep}(\theta)$ is the optimal project size.

Note that effective profit depends on the financing provider and increases with project productivity θ. The optimal financing of each project is characterized as follows.

Proposition 1 (Optimal Financing of a Project) *The government chooses, for each project, the DF provider that maximizes the project's effective profit.*

Proposition 1 shows that the interaction between monitoring intensity and corruption determines which provider has the lower effective marginal cost and therefore governs the equilibrium allocation of projects across providers. To illustrate this result graphically, I define productivity cutoffs à la the exporting-firms model in Melitz (2003). Zero-profit cutoffs serve as thresholds that determine whether projects operate or shut down.

Definition 4 (Zero-profit Cutoff) *For provider p, the zero-profit cutoff $\bar{\theta}_{s,t}^p$ is the productivity level at which the effective profit is zero: $\tilde{\pi}_{s,t}^p(\bar{\theta}_{s,t}^p) = 0$*

The financing indifference cutoff determines which source of funding, DAC or China, yields higher profits for the government.

Definition 5 (Financing-indifference Cutoff) *The financing-indifference cutoff* $\bar{\theta}^I_{s,t}$ *is the productivity level at which the government is indifferent between DAC and Chinese financing:* $\tilde{\pi}^C_{s,t}(\bar{\theta}^I_{s,t}) = \tilde{\pi}^D_{s,t}(\bar{\theta}^I_{s,t})$.

Figure 3a illustrates optimal project financing across productivity levels θ within a sector. First consider the case with zero diversion and equal fixed costs. Because DAC loans carry lower interest rates, the DAC profit curve (D) lies above the Chinese curve (C) for all productivity levels. Projects with productivity above the DAC zero-profit cutoff $\bar{\theta}^D$ are therefore financed by DAC DF, while less productive projects do not operate.

Next, suppose the DAC fixed cost is sufficiently higher than the Chinese. The DAC profit curve shifts downward to D' and crosses the Chinese curve at the financing-indifference cutoff $\bar{\theta}^I$. Projects with $\theta \in [\bar{\theta}^I, \infty)$ are then financed by DAC DF, while those with $\theta \in [\bar{\theta}^C, \bar{\theta}^I)$ are financed by Chinese DF. This creates a hierarchy: more productive projects are financed by DAC, while less productive projects are financed by China. This is the case in which Chinese DF fills funding gaps left by DAC DF.

Figure 3b shows cases with maximal diversion for both providers. Compared to zero-diversion cases, the profit curves become steeper as diversion lowers effective marginal costs. If DAC monitoring is sufficiently stricter than China's, the Chinese curve rotates from C to C' and the DAC curve from D to D'. All projects with $\theta \in [\bar{\theta}^C, \infty)$ are then financed by China, and DAC DF is not used. Intuitively, higher corruption χ favors providers with weaker monitoring, consistent with the stylized facts discussed in Section 5.

In general, optimal project financing depends on project-specific productivity, government corruption, and relative DF characteristics—interest rates, monitoring, and fixed costs.

4.3.2 Government's Optimal Financing at the Sectoral Level

Now, I generalize optimal financing within a sector.

Lemma 4 (Optimal Financing within a Sector) *For sector s, suppose* $\tilde{R}^p_s < \tilde{R}^q_s$.

- If $f^p_s \leq \left(\frac{\tilde{R}^q_s}{\tilde{R}^p_s}\right)^{\sigma-1} f^q_s$, *then all operating projects in sector s are financed by provider p, with only those with productivity* $\theta \geq \bar{\theta}^p_{s,t}$ *operating.*

- If $f^p_s > \left(\frac{\tilde{R}^q_s}{\tilde{R}^p_s}\right)^{\sigma-1} f^q_s$, *then only projects with* $\theta \geq \bar{\theta}^q_{s,t}$ *operate. In this case, projects with* $\theta \in [\bar{\theta}^q_{s,t}, \bar{\theta}^I_{s,t}]$ *are financed by q, while those with* $\theta \in [\bar{\theta}^I_{s,t}, \infty)$ *are financed by p.*

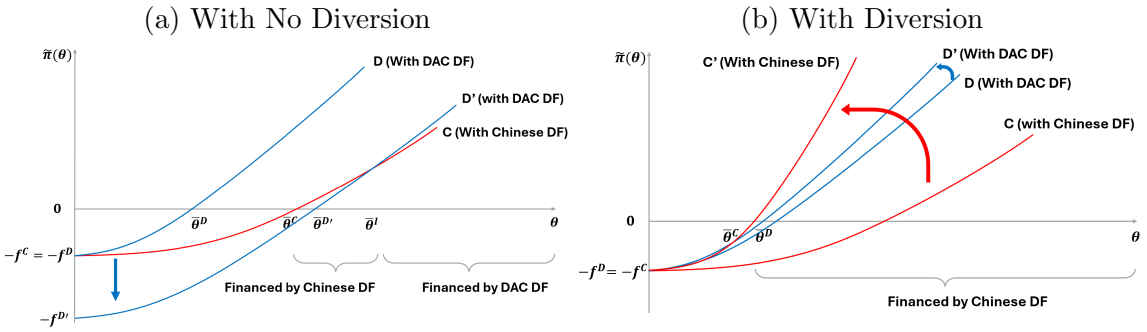


Figure 3: Optimal Financing of Each Project

Lemma 4 highlights the trade-off between marginal financing costs and fixed access costs across DF providers. Suppose provider p has a lower effective marginal cost ($\tilde{R}_s^p < \tilde{R}_s^q$). If its fixed cost is not too large relative to that of q, all operating projects are optimally financed by p. If instead p has a sufficiently higher fixed cost, a trade-off emerges: fixed costs represent a constant disadvantage, while the marginal cost advantage becomes more valuable for larger projects. As a result, less productive projects are financed by q, while more productive projects are financed by p, with the financing-indifference cutoff $\bar{\theta}_{s,t}^I$ separating the two, and this generalizes the example in Figure 3a.

The following proposition characterizes optimal financing of different sectors.

Proposition 2 (Optimal Financing of a Sector) *Let $\mathcal{S}^{pq}$ denote the set of sectors where projects with $\theta \in [\bar{\theta}^I, \infty)$ are financed by p, and projects with $\theta \in [\bar{\theta}^q, \bar{\theta}^I)$ are financed by q. Let $\mathcal{S}^p$ be the set of sectors where all projects with $\theta \geq \bar{\theta}^p$ are financed by p.*

A superscript with a tilde ($\tilde{\cdot}$) indicates that projects financed by that provider are subject to maximal diversion, while the absence of a tilde indicates zero diversion. Each sector therefore belongs to one of the following sets: $\mathcal{S}^D, \mathcal{S}^{DC}, \mathcal{S}^{\tilde{D}}, \mathcal{S}^{\tilde{D}C}, \mathcal{S}^{\tilde{D}\tilde{C}}, \mathcal{S}^{\tilde{C}}$ and $\mathcal{S}^{\tilde{C}\tilde{D}}$.

Proposition 2 shows that corruption affects DF allocation within each sector through multiple margins: it influences diversion within projects, shifts the relative marginal cost of financing across providers, and therefore changes which projects are implemented and which provider finances them.

Figure 4 illustrates Proposition 2. The horizontal axis measures the corruption parameter χ, while the vertical axis measures the relative fixed-cost disadvantage of

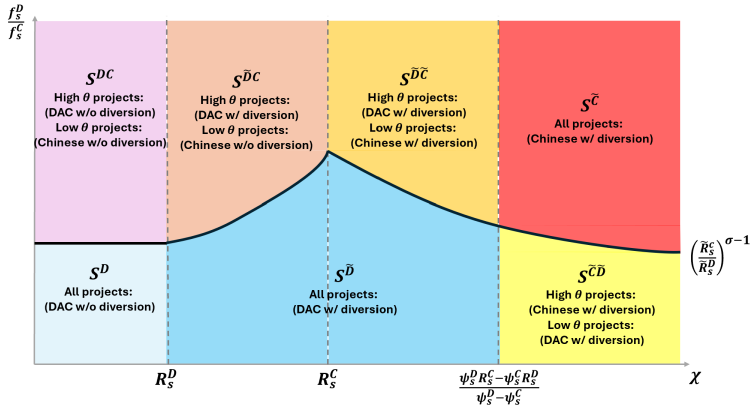


Figure 4: Optimal Financing of Different Sectors

DAC DF, f_s^D/f_s^C. The black curve represents the relative advantage of DAC DF in effective marginal cost, $(\tilde{R}_s^C/\tilde{R}_s^D)^{\sigma-1}$.

Three diversion cases emerge depending on the level of corruption. When $\chi < R_s^D$, diversion is not attractive for either provider, so both DAC and Chinese projects involve zero diversion. When $\chi \in (R_s^D, R_s^C)$, diversion occurs only for DAC projects. When $\chi \geq R_s^C$, both providers are subject to diversion. Because DAC monitoring is weakly greater than China's ($\psi_s^D \geq \psi_s^C$), the relative marginal cost advantage of DAC decreases with corruption in this case. Note that in regions $\mathcal{S}^{\tilde{D}C}$ and $\mathcal{S}^{\tilde{D}}$, corruption χ affects only DAC projects, not Chinese projects.

Within each diversion case, project allocation across providers follows the same logic as in Lemma 4: projects with higher productivity are financed by the provider with the lower effective marginal cost, while projects with lower productivity may be financed by the alternative provider if fixed costs are sufficiently different. Note that if corruption exceeds the threshold $(\psi_s^D R_s^C - \psi_s^C R_s^D)/(\psi_s^D - \psi_s^C)$, the effective marginal cost of Chinese DF falls below that of DAC DF despite DAC's lower interest rate. In this case, unless DAC's fixed-cost disadvantage is sufficiently small, all projects are financed by China ($\mathcal{S}^{\tilde{C}}$). If it is small, higher-productivity projects are financed by China and lower-productivity projects by DAC ($\mathcal{S}^{\tilde{C}\tilde{D}}$).

4.3.3 Aggregation

I derive closed-form expressions for effective public capital at both the sectoral and aggregate levels by aggregating individual projects. This aggregation is useful for two reasons. First, it links the project-level financing decisions derived above to

macroeconomic outcomes. Second, it delivers tractable expressions that summarize how corruption, monitoring, and financing conditions affect the efficiency of public capital.

I assume project-specific productivity θ in each sector s follows a Pareto distribution with lower bound $\underline{\theta}$ and shape parameter ξ; that is, $\theta \sim \text{Pareto}(\underline{\theta}, \xi)$ for each $s \in \mathcal{S}$, with cdf H_s. The Pareto distribution is standard in models with heterogeneous projects because it yields tractable aggregation and closed-form expressions. Given this distribution, effective public capital in sector s is:

$$G_{s,t}^E = \left[\int_{\underline{\theta}}^{\infty} \theta \cdot g_{s,t}^E(\theta)^{\frac{\sigma-1}{\sigma}} dH_s(\theta)\right]^{\frac{\sigma}{\sigma-1}}.$$

The following proposition expresses $G_{s,t}^E$ in the government's optimal allocation as a function of final output Y_t and model parameters:

Proposition 3 (Sectoral Effective Public Capital) *In the government's optimal allocation, effective public capital in sector s at time t is:*

$$G_{s,t}^E = \mathcal{G}_s^E \cdot Y_t^{\frac{\sigma(\xi-1)}{\xi(\sigma-1)}},$$

where $\mathcal{G}_s^E$ is a sector-specific constant depending on parameters: R_s^D, R_s^C, ψ_s^D, ψ_s^C, f_s^D, f_s^C, σ, $\underline{\theta}$, ξ, and χ.

See Online Appendix 3.7 for the full expression of $\mathcal{G}_s^E$. Proposition 3 shows that sectoral effective public capital can be expressed as a power function of aggregate output. The sector-specific constant $\mathcal{G}_s^E$ summarizes how project-level financing conditions translate into the efficiency of public capital in sector s. In particular, it depends on the distribution of project productivity $(\underline{\theta}, \xi)$, the elasticity of substitution across projects (σ), and the relative financing conditions across providers. Through the effective marginal cost terms, $\mathcal{G}_s^E$ also incorporates the effects of interest rates (R_s^D, R_s^C), monitoring intensities (ψ_s^D, ψ_s^C), and corruption (χ).

The following proposition characterizes the final effective public capital.

Proposition 4 (Final Effective Public Capital) *The final effective public capital is*

$$G_t^E = \mathcal{G}^E \cdot Y_t^{\frac{\sigma(\xi-1)}{\xi(\sigma-1)}}$$

where $\mathcal{G}^E \equiv \prod_{s\in\mathcal{S}} (\mathcal{G}_s^E)^{\gamma_s}$.

Proposition 4 shows that final effective public capital depends on the sector-specific constant $\mathcal{G}_s^E$, with the contribution weighted by its share γ_s.

5 Theoretical Exploration and Insights

5.1 Three Channels of Corruption Effects

The model highlights three channels through which corruption distorts the allocation of DF relative to a benevolent benchmark. These channels jointly explain the stylized facts in Section 3.

Definition 6 (Benevolent Allocation) *A benevolent allocation is the government's optimal allocation when it is benevolent ($\chi = 0$).*

When corruption is sufficiently high ($\chi > \min_{s,p}\{R_s^p\}$), the allocation deviates from the benevolent benchmark through three channels: *overinvestment*, *sectoral misallocation*, and *financing inefficiency*.

Overinvestment (Intensive Margin).—Lemma 3 shows that the government's optimal size of project j equates the marginal product of effective public capital, $mpg_{s,j,t}^E$, with the effective marginal cost when financed by p, $\tilde{R}_s^p$. If corruption is sufficiently high and $\chi > R_s^p$, then $\tilde{R}_s^p = \frac{R_s^p - (1-\psi_s^p)\cdot\chi}{\psi_s^p} - (1-\delta_s^E)$, which is lower than under a benevolent allocation. Since $mpg_{s,j,t}^E$ decreases with effective public capital, the lower effective marginal cost implies a larger optimal project size. The observed project size, equal to $g_{s,j,t}^E/\psi_s^p$, appears even larger in the data. This inefficiency worsens as corruption χ increases.

Higher monitoring ψ_s^p mitigates this by raising the effective marginal cost. If ψ_s^C is sufficiently low while ψ_s^D is close to one, this mechanism rationalizes the empirical finding that corruption is positively correlated with Chinese DF project size but not with DAC projects (Fact 2). It also explains why the correlation is stronger in sectors that are harder to monitor (Fact 4), corresponding to low ψ_s^p in the model.

Overinvestment (Extensive Margin).—Higher corruption lowers effective marginal costs and therefore increases the effective profit of a project with a given productivity. Graphically, the profit curve becomes steeper with higher corruption and lower monitoring intensity (Figure 5a). The zero-profit cutoff therefore falls from $\bar{\theta}^p$ to $\bar{\theta}^{p'}$, so projects that would be unprofitable under a benevolent allocation become active

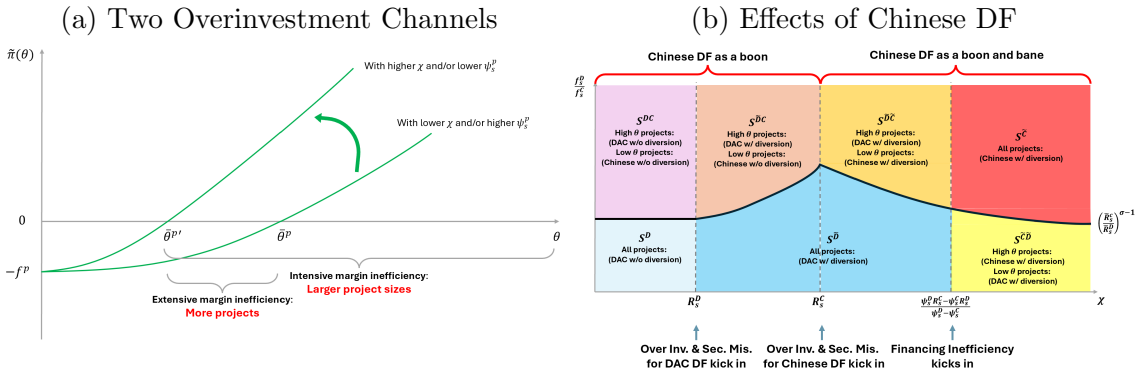


Figure 5: Channels of Inefficiency and the Effect of Chinese DF

when $\chi > R_s^p$. This channel explains the so-called *white elephant projects* (Robinson and Torvik, 2005) undertaken by corrupt governments, which generate negative social surplus. It also explains the positive correlation between corruption and the number of projects (Fact 3).

Sectoral Misallocation.—Corruption also distorts the allocation of public capital across sectors when monitoring intensity differs across sectors. For simplicity, consider two sectors s and s', both financed by provider p. Proposition 3 implies that the ratio of effective public capital between them is

$$\frac{G_{s,t}^E}{G_{s',t}^E} = \frac{\mathcal{G}_s^E}{\mathcal{G}_{s'}^E} = \underbrace{\frac{\tilde{R}_{s'}^p}{\tilde{R}_s^p}}_{\text{relative effective MC}} \times \underbrace{\left(\frac{f_{s'}^p}{f_s^p}\right)^{\frac{\xi-\sigma}{\xi(\sigma-1)}}}_{\text{relative fixed costs}} \times \underbrace{\left(\frac{\gamma_s}{\gamma_{s'}}\right)^{\frac{\sigma(\xi-1)}{\xi(\sigma-1)}}}_{\text{relative contribution to production}}.$$

In a benevolent allocation, the effective marginal cost is simply $R_s^p - (1-\delta)$. The optimal ratio of public capital across sectors then reflects their contributions to final output, adjusted for relative interest rates and fixed costs. When corruption is sufficiently high and monitoring intensities differ across sectors, distortions arise: if sector s is monitored more closely ($\psi_s^p > \psi_{s'}^p$), the government shifts resources toward s' because diversion opportunities are greater in that sector. The severity of this distortion increases with the monitoring gap. This mechanism accounts for the larger capital flows to hard-to-monitor sectors—both through bigger projects and greater project numbers—in more corrupt countries (Fact 4).

Financing Inefficiency.—Proposition 1 implies that the government chooses the financing provider that maximizes the project's effective profit. For simplicity, assume DAC and Chinese DF have identical fixed costs. The decision then depends only on

the effective marginal costs, $\tilde{R}_s^p$. In a benevolent allocation, the effective marginal cost equals the interest rate net of depreciation, so DAC DF—with its lower interest rate—is always preferred. With sufficient corruption, however, Chinese DF may become cheaper in effective marginal terms despite its higher interest rate. This occurs if and only if $\chi > \frac{\psi_s^D R_s^C - \psi_s^C R_s^D}{\psi_s^D - \psi_s^C}$. The threshold falls as the monitoring gap widens and rises as the interest-rate gap increases. This channel explains the positive correlation between corruption and reliance on Chinese DF relative to DAC (Fact 1).

Taken together, the model identifies three mechanisms through which corruption affects DF: it increases project scale and entry (*overinvestment*), reallocates investment toward weakly monitored sectors (*sectoral misallocation*), and shifts financing toward providers with weaker monitoring (*financing inefficiency*). These mechanisms jointly account for the stylized facts documented in Section 3.

5.2 Chinese DF: Boon or Bane for Citizens?

For any level of corruption, the government is (weakly) better off when Chinese DF becomes available, as it expands the set of financing options. For households, however, Chinese DF can be either a boon or a bane. It can be a boon when it fills funding gaps in sectors where cheaper DAC financing is scarce. It can also be a bane when its weaker monitoring exacerbates the inefficiencies described above.

The strength of these effects depends on both institutional features of DF providers and the borrowing country's level of corruption. The boon effect is stronger when DAC financing carries high fixed costs, which may reflect difficult negotiations, stringent policy conditions, sectoral deprioritization, or rationing in particular countries or sectors. In such cases, Chinese DF allows projects that would otherwise remain unfunded to proceed. By contrast, the bane effect is stronger when the monitoring gap between providers is large and when the government has strong diversion incentives.

The model implies that the relative importance of these forces changes with corruption (Figure 5b). When corruption is low ($\chi < R_s^C$), the government does not divert Chinese DF, so Chinese projects operate only through the boon channel by filling funding gaps. When corruption exceeds this threshold ($\chi > R_s^C$), diversion becomes attractive and the overinvestment and sectoral misallocation channels emerge. Once corruption surpasses a higher threshold, the financing-inefficiency channel also becomes active, shifting financing toward Chinese DF despite its higher interest rate.

In these regions, both boon and bane effects coexist.

Because the strength of these mechanisms varies across sectors—through differences in monitoring intensities and fixed costs—the overall welfare effect of Chinese DF depends on the sectoral allocation of projects as well as the level of corruption. Whether Chinese DF alleviates funding gaps or amplifies inefficiencies is therefore ultimately a quantitative question, which I address in Section 7.

5.3 Implications for the Efficiency of Public Capital and TFP

The model also sheds light on how corruption affects the efficiency of public capital. A large literature emphasizes that the productivity of public investment depends on institutional quality (Hulten, 1992). In this literature, effective public capital typically enters the production function through an exogenous efficiency parameter Θ, so that output takes the form: $Y = A \cdot (\Theta G)^{\gamma} K^{\alpha} L^{\lambda}$, where G denotes the book value of public capital.

In contrast, my model endogenizes the efficiency term Θ. Because effective public capital arises from the government's project-level allocation decisions, the efficiency of public capital becomes an equilibrium outcome. In particular,

$$G^E = \Theta G = \left(\prod\nolimits_s (\mathcal{G}_s^E)^{\gamma_s} \right) \cdot G.$$

The sector-specific constants $\mathcal{G}_s^E$ summarize how project-level financing conditions translate into the productivity of public capital in sector s (see Online Appendix 3.7 for their full expressions). As a result, the efficiency parameter Θ depends not only on technological parameters—such as sector shares γ_s, the elasticity of substitution σ, and the productivity distribution parameters $\underline{\theta}$ and ξ—but also on corruption χ and the characteristics of DF, including interest rates R_s^p, monitoring intensities ψ_s^p, and fixed costs f_s^p. Moreover, because sectors contribute differently to aggregate production, distortions in some sectors have larger effects on overall efficiency than others.

This framework therefore provides a microfoundation for the efficiency parameter Θ commonly used in the public capital literature. It highlights that the efficiency of public investment is shaped jointly by domestic institutions and the international financing environment, particularly in developing countries that are heavily reliant on DF. In particular, differences in DF policies across providers—such as monitoring

intensity, financing costs, and access frictions—can influence the efficiency with which public capital is accumulated and used in recipient countries.

The model also provides implications for Total Factor Productivity (TFP). When the production function is written in the conventional two-input form $Y = A \cdot K^{\alpha} L^{1-\alpha}$, TFP incorporates the contribution of effective public capital. Because corruption distorts project selection, scale, sectoral allocation, and financing choices, it affects TFP through the misallocation of public capital. The model therefore provides a framework to quantify the portion of TFP differences that arises from distortions in public investment associated with corruption and the global DF environment.

5.4 Two-Way Feedback between Corruption and DF Inflows

The model also highlights the possibility of two-way feedback between corruption and DF inflows. To clarify this mechanism, I distinguish between two notions of corruption. The first is *fundamental corruption*, captured by the parameter χ, which measures the government's valuation of diversion relative to household consumption. The second is *observed corruption*, which corresponds to the realized amount of diverted funds and is closer to the empirical corruption measures used in cross-country data, typically based on perceptions or reports of resource diversion in the public sector.

Under this distinction, the positive correlation between corruption and Chinese DF inflows observed in the data reflects two reinforcing forces. First, higher fundamental corruption (χ) increases the government's incentive to rely on Chinese DF, which is less tightly monitored and therefore more conducive to diversion. Second, greater inflows of such financing increase the total amount of funds available for diversion, thereby raising observed corruption. In this sense, corruption affects DF allocation, while DF inflows can in turn amplify measured corruption through the diversion channel. The correlations documented in the stylized facts therefore reflect an equilibrium relationship that may operate in both directions, rather than a causal effect in a single direction.

6 Calibration

I now take the model to the data and calibrate it for the 108 developing countries in the sample for which the necessary data are available. The calibrated model is then used to conduct a quantitative welfare analysis of Chinese DF in the next section.

6.1 Preliminary Steps

Incorporating DAC Grants.—I incorporate DAC grants as an additional financing source. Like DAC loans, grants are contracted at the project level but do not require repayment and typically consist of many small projects. Between 2000 and 2021, DAC grants accounted for roughly 1.3 million projects, compared with 31,459 DAC loans and 4,400 Chinese loans. The median committed amount of DAC grant projects in constant 2011 USD ($53,469) is far smaller than that of DAC loans ($18.7 million) and Chinese loans ($67 million).[11]

Given their small scale but high frequency, I model DAC grants as projects located near the lower end of the productivity distribution. This treatment allows the model to capture their empirical prevalence while ensuring that the main theoretical mechanisms—which focus on loan financing—remain unchanged. Online Appendix 5.1 provides additional details.

Incorporating Self-financing.—I also allow the government to finance projects using domestic resources. This captures sectors such as Defense, which represent a non-trivial share of public investment but are generally ineligible for international DF. In other sectors, I assume $f_s^S \geq \min\{f_s^D, f_s^C\}$, where f_s^S denotes the fixed cost of operating a self-financed project in sector s. Under this condition, self-financing is dominated by DF because it entails higher fixed and marginal costs. As a result, self-financing occurs only in the Defense sector.

Sector Classification.—The sector classification used in the quantitative analysis combines two existing systems. The OECD Development Assistance Committee sector classification (DAC-5) categorizes DF projects in the OECD Creditor Reporting System and the AidData Global Chinese DF Dataset. The IMF Classification of the

[11] For example, Australia committed $3,640 (2011 USD) in 2016 to the DAC grant project *Therapy Equipment for Disability and Rehabilitation Centre* in Vietnam. By contrast, in the same sector and country, South Korea pledged $87.3 million (2011 USD) in 2017 for the DAC loan project *Construction of Hai Phong General Hospital*.

Functions of Government (COFOG) categorizes government expenditure in the IMF Government Finance Statistics (GFS).

Because CRS and AidData record project-level commitments while COFOG reports aggregate government expenditures by function, the two datasets are not directly comparable. To align them, I construct a unified sector classification using the detailed descriptions in the IMF GFS manual (De Clerck and Wickens, 2015) and the DAC-CRS code list (OECD, 2024). This procedure yields 14 unified sector categories, reported in Online Appendix 5.2. Six DAC sectors—related to debt operations, emergency response, donor administrative costs, or unspecified categories—are excluded.

6.2 Calibration of Parameters

I calibrate the model separately for each recipient country, indexing recipient-specific parameters and variables by r. The parameters fall into four groups: common macro parameters, common DF parameters, recipient-specific parameters, and recipient–sector-specific DF parameters. Table 4 summarizes the calibration strategy.

Standard Macro Parameters.—I externally calibrate the standard macro parameters that are common across all borrower countries, with one model period corresponding to one year. The annual discount factor β is set to 0.92 following Aguiar and Gopinath (2007). The private capital share α is set to 1/3. Both the private capital depreciation rate δ_K and the public capital depreciation rate δ_G are set to 0.05. The aggregate public capital share parameter γ is set to 0.106 based on Bom and Ligthart (2014). Labor supply L and TFP A are normalized to 1.

There are no existing estimates for the elasticity of substitution across public projects within a sector, σ. Unlike firms or goods, public projects lack market prices and sales data over time, making the elasticity difficult to estimate directly. I therefore assume that substitution patterns across projects are similar to those across goods within sectors, and set $\sigma = 2.2$, the median estimate from Broda and Weinstein (2006).

Public Capital Sector Share.—Since there are no existing estimates of sectoral public capital shares γ_s, I estimate them by targeting the ratio of public expenditure in each sector to GDP. I assume that sectoral public investment shares do not differ systematically between advanced and developing economies, exploiting the fact that

Table 4: Calibration

Parameter	Values	Method	Source/Target moment
β (Discount factor)	0.92	External calib.	Aguiar and Gopinath (2007)
α (Pvt. capital share)	0.333	External calib.	Standard value
γ (Pub. capital share)	0.106	External calib.	Bom and Ligthart (2014)
δ_K (K depreciation)	0.05	External calib.	Standard value
δ_G (G_s^E depreciation)	0.05	External calib.	Standard value
σ (Elasticity of subs.)	2.2	External calib.	Broda and Weinstein (2006)
γ_s (Pub. sector share)	0.0004 - 0.3588	GMM	$\mathbb{E}$[sector share in pub. inv.]
L (Labor supply)	1	Normalization	Normalization
A (TFP)	1	Normalization	Normalization
R_s^D (DAC interest rate)	1.009 - 1.015	Data	Mean interest rates
R_s^C (China interest rate)	1.018 - 1.045	Data	Mean interest rates
ψ_s^D (DAC monitoring)	1	Normalization	Normalization
ψ_s^C (China monitoring)	0.42 - 1	FE Regression	$\mathbb{E}\left[\frac{\text{CHN proj. size}}{\text{DAC proj. size}}\right]$
χ_r (Corruption)	0 - 1.3	Upper bound	Marginal cost of DF
ξ_r (Pareto shape)	2.2 - 4.95	MLE	Upper tail of proj. size dist.
$\underline{\theta}_r$ (Pareto scale)	1	Normalization	Normalization
$f_{r,s}^G$ (DAC Grant fixed cost)	varies by $r \times s$	GMM	$\mathbb{E}$[DAC grant proj. size]
$f_{r,s}^D$ (DAC loan fixed cost)	varies by $r \times s$	GMM	$\mathbb{E}$[DAC loan proj. size]
$f_{r,s}^C$ (Chinese loan fixed cost)	varies by $r \times s$	GMM	$\mathbb{E}$[CHN loan proj. size]
$f_{r,s}^S$ (Self-financing fixed cost)	1	Normalization	Normalization

advanced economies receive little or no international DF.

For developing countries, observed expenditure shares are confounded by corruption and provider-specific monitoring, whereas in advanced economies expenditure patterns primarily reflect underlying sectoral shares γ_s. Moreover, many advanced economies are close to their steady state, making their data more suitable for estimation than those of transition economies.

The model predicts that if an advanced country self-finances its projects without diversion, the steady-state ratio of public investment in sector s to GDP is $\frac{I_s^{G*}}{Y^*} = \frac{\delta_G \gamma_s}{1/\beta - (1-\delta_G)}$. I estimate γ_s using annual data on government expenditure by sector from the IMF COFOG database. Since $\sum_{s \in \mathcal{S}} \gamma_s = 1$, the share of each sector in total public expenditure equals γ_s. I estimate these parameters using GMM with the moment conditions:[12]

[12]The IMF COFOG reports government expenditure by sector but does not separate consumption from investment. I assume that the investment share of expenditure is similar across sectors, so observed expenditure shares can serve as a proxy for sectoral investment shares. The estimation uses 38 advanced economies, as classified by the IMF. See Online Appendix 5.3 for details and the estimates.

$$\mathbb{E}\left[\gamma_s - \frac{I^G_{r,s,t}}{\sum_{s\in\mathcal{S}} I^G_{r,s,t}}\right] = 0 \quad \text{for each } s \in \mathcal{S}.$$

Interest rates.—I set the interest rate for each provider–sector pair to the average rate observed in the data, as reported in Table 5. For DAC loans, average rates are close to 1 percent in most sectors, with a maximum of 1.5 percent in General Economic, Commercial, and Labor Affairs. Chinese loan rates are substantially higher, ranging from 1.8 to 4.5 percent.

Monitoring Intensities.—For the quantitative analysis, I focus on relative monitoring intensities between DAC and Chinese DF, normalizing DAC monitoring to one in all sectors ($\psi^D_s = 1$). This normalization has two motivations. First, the empirical analysis shows that DAC project sizes exhibit little correlation with corruption in most sectors. While some correlation appears in sectors that are difficult to monitor, it is considerably smaller than for Chinese DF. Second, estimating absolute monitoring intensities is infeasible because no empirical corruption measure corresponds directly to the model's corruption parameter χ_r. Under additional identifying assumptions, however, the relative monitoring intensity between DAC and Chinese DF can be estimated for each sector.

To do so, I estimate the following fixed-effects regression:

$$\ln g^O_{r,p,s,j,t} = \text{constant} + FE_{s,p} + FE_{r,t} + \mathbf{X}_{r,p,t}\boldsymbol{\beta} + \epsilon_j,$$

where $g^O_{r,p,s,j,t}$ denotes the observed project size and $\mathbf{X}_{r,p,t}$ includes gravity variables, bilateral political distance, and $\ln(R^p_s - (1-\delta_G))$.

Identification relies on two assumptions, where *controls* denote all right-hand-side variables in the regression:

(i) $\mathbb{P}(\chi_r \geq R^C_s \mid s, p = C) = 1$

(ii) $\mathbb{E}\big[\ln \theta_j \mid p, s, \text{controls}\big] = \alpha_{rt} + \alpha_s + \mathbf{X}_{r,p,t}$.

Assumption (i) implies that countries receiving Chinese DF during the sample period are sufficiently corrupt for diversion to occur. This assumption is broadly consistent with evidence that Chinese DF tends to be concentrated in countries with relatively high corruption levels (Malik et al., 2021). If the sample were to include countries with lower corruption levels, the implied monitoring estimates would be biased upward. Accordingly, the estimates should be interpreted as an upper bound on Chinese monitoring intensity relative to DAC monitoring.

Table 5: Interest Rates and Chinese Monitoring for Each Sector

Sector name	$R_s^D - 1$ *(%)*	$R_s^C - 1$ *(%)*	ψ_s^C
Agriculture, Forestry, Fishing	0.9	2.5	0.83
Industry, Mining, Construction	1.1	3.9	0.42
Transport & Storage	1.0	3.3	1
Energy	1.3	4.0	0.84
Communications	0.9	3.1	0.65
Health	0.9	2.3	0.78
Education	0.9	2.6	0.99
General Environment Protection	1.3	3.0	1
Water Supply & Sanitation	1.1	2.7	1
Government & Civil Society	1.0	1.8	1
General Budget Support	1.1	4.5	0.73
General Economic, Commercial, Labor Affairs	1.5	3.8	1
Other Social Infrastructure & Services	1.2	2.0	1

Assumption (ii) states that differences in average project productivity between DAC and Chinese DF within a sector can be accounted for by recipient–time fixed effects, sector fixed effects, and other controls. Under these assumptions, the difference in sector–provider fixed effects satisfies $FE_{s,p=C} - FE_{s,p=D} \approx -\ln \psi_s^C$, so that $\psi_s^C \approx \exp(FE_{s,p=D} - FE_{s,p=C})$.[13]

The intuition is straightforward. Once differences in project productivity, recipient conditions, and sector-specific factors are accounted for, systematic differences in project size between Chinese and DAC financing reflect differences in monitoring intensity. Based on this premise, I estimate Chinese monitoring intensities using the sector–provider fixed effects from the regression. If $FE_{s,p=C} - FE_{s,p=D} < 0$, I set $\psi_s^C = 1$. The resulting estimates are reported in Table 5.

Productivity Distribution.—I normalize the Pareto scale parameter $\underline{\theta}_r$ to 1. This parameter shifts the overall level of output but does not affect the government's optimal DF decisions. I estimate the Pareto shape parameter ξ_r for each country r using Maximum Likelihood Estimation (MLE), exploiting properties of mixtures of Pareto distributions.

In the model, the pool of potential projects is fixed over time, and the government implements all projects with productivity above a cutoff in each period. In practice, however, projects often appear with delays—arising from lengthy negotiations with DF providers or domestic administrative procedures—which are beyond the scope of the model.

[13] See Online Appendix 5.4 for details. Grant projects are excluded from this regression because they are substantially smaller than loans and reflect productivity differences not fully captured by the controls.

As a result, projects are observed with some randomness across years, and only their initial commitments are fully recorded in the project-level data. To align the data with the model's fixed project pool, I pool all observed projects for each country across years and exploit the mixture-of-Pareto property (Hogg et al., 2013). Under this property, the pooled distribution of project sizes can be approximated by a Pareto distribution with shape parameter ξ_r/σ.

I therefore estimate ξ_r by maximizing the log-likelihood $log\mathcal{L}(\frac{\xi_r}{\sigma}, \tilde{\theta}_r) = \sum_{i=1}^{N_r} log f_r(x_i; \frac{\xi_r}{\sigma}, \tilde{\theta}_r)$ where f_r denotes the pdf of project size x_i, parameterized as a Pareto distribution with shape ξ_r/σ and scale $\bar{\theta}_r$. Details are in Online Appendix 5.5.

Corruption.—Estimating the corruption parameter χ_r directly is difficult because no empirical measure corresponds exactly to the model's concept of diversion incentives. Instead, I derive a theoretical upper bound for χ_r for each country. This bound is then used to construct a range of possible household welfare effects of Chinese DF in the counterfactual analysis.

Recall that for Chinese projects, the optimal project size in recipient country r satisfies $mpg_{r,s,j,t} = \tilde{R}^C_{r,s}$. Since the marginal product must be positive for operating projects, the effective marginal cost must also be positive. Using the definition $\tilde{R}^C_{r,s} = \frac{R^C_s - (1-\psi^C_s)\chi_r}{\psi^C_s} - (1-\delta_G)$, this requirement implies an upper bound on the corruption parameter. Solving for χ_r yields $\bar{\chi}_r = \min_s \left\{ \frac{R^C_s - \psi^C_s(1-\delta_G)}{1-\psi^C_s} \right\} - \epsilon$ where $\epsilon > 0$ is a small constant ensuring that $\tilde{R}^C_{r,s} > 0$. For each country, I compute $\bar{\chi}_r$ as the minimum across all sectors in which the country received Chinese DF. Throughout the analysis, I set $\epsilon = 0.01$.

Fixed Costs.—For each recipient country, I estimate two sets of fixed costs using GMM, targeting the average observed project size. The first set assumes a benevolent government ($\chi_r = 0$), while the second assumes maximal corruption ($\chi_r = \bar{\chi}_r$), corresponding to the upper bound derived above. Estimating fixed costs under these two scenarios allows the quantitative analysis to capture the range of possible outcomes implied by different levels of corruption.

Each set includes fixed costs for DAC grants, DAC loans, and Chinese loans—denoted $f^G_{r,s}$, $f^D_{r,s}$, and $f^C_{r,s}$ for all $s \in \mathcal{S}$—except for the Defense sector, which relies on self-financing. I normalize the self-financing cost f^S_s to 1. The following proposition characterizes the expected project size by financing source. See Online Appendix 3.9 for derivations.

Proposition 5 (Expected Project Size) *In a government's optimal allocation, the expected observed size of a project financed by $p \in \{G, D, C\}$ in sector s is*

$$\mathbb{E}[g^O_{r,p,s,j,t}|p,s] = \frac{\xi(\sigma-1)}{\Psi^p_{r,s}\tilde{R}^p_{r,s}(\xi-\sigma)}\mathcal{F}^p_{r,s}$$

where $\mathcal{F}^p_{r,s}$ is a recipient–provider–sector–specific constant that depends on $f^p_{r,s}$.

Let $m(\Xi_r)$ denote the vector of model-implied moments of average project sizes from Proposition 5, and let $\bar{m}_r$ denote the corresponding empirical moments, with $\Xi_r \equiv \{\{f^G_{r,s}, f^D_{r,s}, f^C_{r,s}\}_{s\in\mathcal{S}}\}$. I estimate Ξ_r by minimizing the quadratic objective: $(m(\Xi_r) - \bar{m}_r)' \cdot \mathcal{W} \cdot (m(\Xi_r) - \bar{m}_r)$ where $\mathcal{W}$ is a weighting matrix. Because the number of model moments equals the number of fixed-cost parameters, the system is exactly identified, and the choice of $\mathcal{W}$ does not affect the estimates.

7 Quantitative Analysis

7.1 Is Chinese DF a boon or a bane?

Using the calibrated parameters, I conduct a counterfactual analysis of steady-state household welfare with and without Chinese DF for 108 developing countries. Because the corruption parameter χ_r can only be bounded rather than precisely identified, I report a range of welfare effects for each country.

Figure 6 summarizes the results. Each vertical line represents the range of welfare effects implied by the model. The top of the line shows the percent change in steady-state household consumption from the introduction of Chinese DF under a benevolent government (relative to the no-China counterfactual). The bottom shows the change under maximal corruption ($\chi_r = \bar{\chi}_r$). In the benevolent case, corruption channels are shut down, so Chinese DF operates only through its funding-gap (boon) effect. Under maximal corruption, both boon and bane mechanisms are present.

The results display substantial heterogeneity across countries. Among the 108 economies, approximately 15% experience welfare gains across the entire range of corruption, 17% exhibit negligible welfare effects, 12% display outcomes that depend on the level of corruption, and 55% experience welfare losses when corruption approaches its upper bound.

In all countries, Chinese DF increases welfare under benevolence. In this case, Chinese DF is used only in sectors where its fixed costs are lower than those of DAC

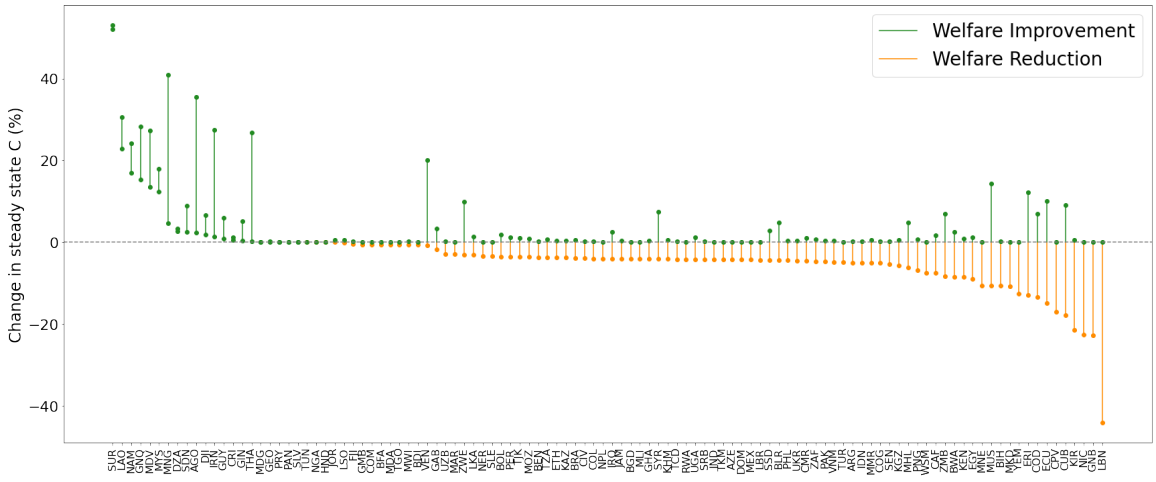


Figure 6: Welfare Effect of Chinese DF on Households

DF, thereby relaxing financing constraints. As corruption rises, however, inefficiencies associated with diversion and weaker monitoring become increasingly important, and the net welfare effect may turn negative.

The magnitude of these effects varies widely across countries. For example, in Suriname, Laos, and Namibia, Chinese DF remains welfare-improving even at the upper bound of corruption. By contrast, in countries such as Lebanon, Guinea-Bissau, and Nicaragua, welfare gains are small even under benevolence, while welfare losses can become large as corruption increases. In a few cases, including Eritrea and Cuba, the sign of the welfare effect remains indeterminate over the admissible range of corruption.

7.2 Case Studies

To understand why welfare effects differ widely across countries, I examine several case studies. Two factors primarily drive this heterogeneity. The first is the level of maximal corruption. Countries such as Guinea-Bissau, Kiribati, Lebanon, and Nicaragua—located at the right end of Figure 6—experience some of the largest welfare losses largely because their estimated corruption upper bound (1.381) is substantially higher than the sample median (1.093).

The second, and more informative, factor is the sectoral allocation of Chinese DF. To illustrate this mechanism, I compare three countries with similar values of the corruption upper bound $\bar{\chi}_r$ but very different welfare outcomes: Suriname ($\bar{\chi}_r = 1.171$),

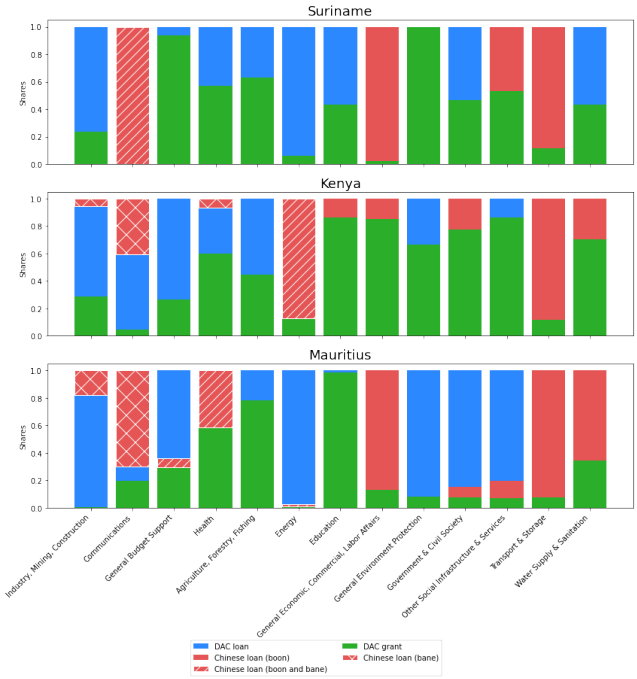


Figure 7: DF Composition by Sectors in Suriname, Kenya, and Mauritius

Kenya ($\bar{\chi}_r = 1.093$), and Mauritius ($\bar{\chi}_r = 1.093$). Figure 7 shows the composition of DF across sectors in these countries, measured by the total committed amount between 2000 and 2021. Sectors are ordered along the horizontal axis by Chinese monitoring intensity (ψ_s^C), while bars are stacked by financing source in ascending order of average project size.

For example, in Kenya's *Industry, Mining, and Construction* sector, DAC grant projects have the smallest average size and account for roughly 30% of total DF. DAC loans are larger and represent about 65%, while Chinese loans—although the largest on average—account for only about 5%.

Red bars without patterns denote Chinese loans that generate only the boon effect; those with an "x" pattern denote loans that generate only the bane effect; and those with a diagonal "/" pattern represent loans subject to both effects. All sectors to the right of *Education* have monitoring intensity $\psi_s^C = 1$. In these sectors, Chinese DF can generate only the boon effect by filling financing gaps left by DAC DF.

Case 1 (Boon): Suriname.— Figure 6 shows that Chinese DF raises steady-state household consumption in Suriname (1st from the left of the figure) by about 50%, regardless of government corruption. The magnitude partly reflects that the coun-

terfactual removes Chinese DF entirely in a small economy where Chinese financing represents a sizable share of public investment (Chinese debt stock to GDP ratio as of 2017 estimated by Horn et al. (2021) is over 10%) and fills sectors in which DAC financing is largely absent; because the comparison is made in steady state, the resulting differences in public capital accumulation translate into large long-run consumption gaps. The top panel of Figure 7 indicates that Suriname directed Chinese DF mainly to sectors with full monitoring intensity ($\psi_s^C = 1$). In the General Economic, Commercial, Labor Affairs, Social Infrastructure, and Transport & Storage sectors, Chinese DF closed funding gaps without efficiency losses.

The only sector in which corruption affects outcomes is Communications. Under a benevolent government, Chinese DF benefits this sector—where DAC financing is limited—without generating inefficiencies. In the data, Suriname receives only small DAC grant projects in Communications and no DAC loans. In the model, the absence of DAC loans implies that the fixed cost of DAC loan financing in this sector-country pair is extremely high relative to Chinese DF. As a result, Chinese DF finances projects that would otherwise remain unfunded. Under maximal corruption, both positive and negative effects arise, but because DAC loans are unavailable and DAC grants are minimal, the model predicts that the boon effect dominates even at high corruption. This mechanism explains the large steady-state consumption gains.

Case 2 (Bane): Kenya.— In Kenya (sixteenth from the right in Figure 6), Chinese DF closes financing gaps in some sectors, particularly Transport & Storage, without generating inefficiencies. However, when corruption is high ($\chi_r > R_s^C$), Chinese DF generates primarily bane effects in Industry, Mining, Construction, Communications, and Health.

In these sectors, DAC loans are present and smaller on average, implying lower fixed costs ($f_s^D < f_s^C$). Consequently, the model predicts that those large China-financed projects could instead have been financed by DAC loans at lower interest rates and without diversion. Because these sectors also exhibit low monitoring intensity, diversion incentives are particularly strong. The resulting inefficiencies outweigh the funding-gap benefits, leading to net welfare losses.

Case 3 (Ambiguous): Mauritius.— Mauritius (thirteenth from the right) combines features of Suriname and Kenya, and the welfare impact of Chinese DF depends strongly on the level of corruption. Chinese DF closes financing gaps without inefficiency in the General Economic, Commercial, and Labor Affairs; Transport &

Storage; and Water Supply & Sanitation sectors. In contrast, outcomes differ in Industry, Mining, Construction, and Communications. With a benevolent government, Chinese DF complements limited DAC financing. With corruption, however, Chinese DF generates primarily bane effects in these sectors.

7.3 Policy Implications

I focus on how DF providers can affect citizen welfare in recipient countries, abstracting from other economic or geopolitical objectives they may pursue.

DAC.— The model suggests two channels through which DAC lending practices may influence welfare when Chinese DF is present. One channel is monitoring. If DAC and Chinese monitoring standards were closer, the monitoring gap between providers would shrink, reducing the scope for diversion-driven distortions. A second channel is the cost of accessing DAC financing. Lower effective access costs—such as simplified procedures or faster disbursements—would reduce the fixed costs of DAC lending (f_s^D) and allow DAC financing to compete more effectively in sectors where Chinese DF currently fills financing gaps. The model also suggests that these effects may be particularly relevant in sectors and countries where Chinese DF is most susceptible to diversion.

China.— The model also highlights the role of monitoring intensity in shaping the efficiency of Chinese DF. Stronger monitoring would reduce diversion incentives and mitigate inefficiencies associated with corruption. Alternatively, even without major changes in monitoring practices, welfare outcomes may improve if Chinese DF is directed toward sectors where DAC financing is scarce or costly. In such sectors, Chinese DF primarily generates funding-gap (boon) effects rather than diversion-driven inefficiencies.

Sectoral Specialization.— More broadly, the model implies that welfare outcomes depend not only on differences in lending practices but also on how DF providers specialize across sectors. Chinese DF can improve outcomes by concentrating on sectors where DAC financing is limited due to high fixed costs or institutional constraints. Conversely, DAC providers may have comparative advantages in sectors where stronger monitoring is important for limiting diversion. A sectoral division of roles across providers can therefore reduce inefficiencies arising from corruption while still expanding the overall availability of DF.

Core Message.— Overall, the model implies that both DAC and Chinese DF can support public investment in developing countries, but inefficiencies arise when differences in lending practices are exploited by corrupt governments. These distortions reflect the interaction between monitoring intensity, financing costs, and sectoral allocation. Policies that narrow the monitoring gap between providers or that promote efficient sectoral specialization across providers can therefore improve the efficiency of public capital in recipient countries.

8 Conclusion

Amid China's rise as a major provider of development finance (DF), debate has centered on whether Chinese DF benefits citizens by filling funding gaps left by traditional donors in the Development Assistance Committee (DAC) or harms them through weaker monitoring and greater opportunities for misuse. This paper provides a systematic framework to evaluate these competing views by combining new stylized facts from project-level data with a theoretical model and quantitative analysis.

The data show that recipient-country corruption is associated with greater reliance on Chinese DF, reflected in more and larger projects, particularly in sectors that are harder to monitor. I interpret these patterns through a growth model in which governments choose how much DF to divert under provider-specific monitoring intensities. The model highlights three channels through which corruption reduces efficiency: overinvestment in projects, sectoral misallocation toward weakly monitored sectors, and financing inefficiency arising from reliance on costlier sources of finance with weaker oversight. These mechanisms imply that Chinese DF has a dual nature. It can complement DAC finance by filling funding gaps in underfunded sectors, but it can also amplify inefficiencies when monitoring is weak and governments are prone to corruption.

A quantitative assessment across 108 developing countries reveals substantial heterogeneity in welfare outcomes. While about 15% of countries experience welfare gains from the availability of Chinese DF, roughly 55% may face sizable welfare losses when corruption is high. These outcomes depend not only on the overall level of corruption but also on how Chinese DF is allocated across sectors.

More broadly, the analysis shows that the efficiency of public capital in develop-

ing countries depends not only on domestic institutions but also on the global DF environment. Differences in monitoring intensity, financing costs, and access conditions across providers shape how public investment is allocated and how efficiently it contributes to growth. Understanding these interactions is therefore essential for assessing the welfare consequences of DF in a world with increasingly diverse providers.

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