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

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Abstract

I present the first comprehensive analysis of how developing countries choose the amount, sources, and sectoral allocation of development finance (DF) as China has emerged alongside traditional providers. Using project-level data from nearly 110 countries (2000–2021), I show corruption is linked to greater reliance on Chinese DF. A growth model with government diversion and provider-specific monitoring explains these patterns. Calibrated to 108 countries, the model finds 15% of countries gain while 55% may face welfare losses due to Chinese DF. Coordination between China and traditional providers could improve citizen welfare.

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1 Introduction

In recent years, Chinese development loans to developing countries have attracted growing attention, particularly due to their association with corruption scandals. Evidence on the effect of these loans is mixed: some indicate that these loans help developing countries by addressing financing gaps (Dreher et al., 2021), while others suggest that weaker monitoring may increase the risk of misuse (Isaksson and Kotsadam, 2018). This paper systemically addresses this debate—prominent in both academic research and policy discussions—by documenting new stylized facts on the relationship between corruption and international development finance (DF) flows, and by developing a growth model that both explains these patterns and provides a quantitative assessment of whether Chinese DF ultimately improves or harms citizen welfare. More broadly, I offer the first comprehensive analysis of how developing countries determine the amount, sources, and sectoral allocation of DF.

Both conceptual and practical gaps have limited research on these questions. Conceptually, DF has long been driven by the Development Assistance Committee (DAC), a group of advanced economies that provided highly concessional, grant-based finance. As a result, DF was often seen primarily as donor-driven aid. In practice, however, recipient governments actively seek diverse forms of finance, including loans. China's emergence as a major nontraditional provider—offering loans at higher interest rates and often suspected of weaker monitoring standards—underscores the importance of recipient demand. Practically, systematic analysis has only recently become possible thanks to new project-level data covering both DAC and Chinese DF.

The paper makes four main contributions. First, project-level data analysis shows that, compared to DAC, China has financed larger and more projects in more corrupt countries, especially in harder-to-monitor sectors. Second, I develop a growth model with borrowing government's diversion choices under differing monitoring intensities of DAC and Chinese DF to explain these patterns. Third, the model yields insights on how corruption reduces DF efficiency, how Chinese DF can either support or harm citizen welfare, how DF shapes public capital efficiency, and how corruption and DF inflows reinforce each other. Finally, calibrating the model for 108 developing countries, I quantify in which countries Chinese DF benefits or harms citizen welfare.

While I primarily focus on the demand side of DF, it is important to acknowledge the supply side. Motivations for China's or other countries' lending may include expanding political or economic influence, exporting labor or materials, and other economic or geopolitical objectives. These factors are not modeled explicitly but are considered throughout. In the empirics, they are controlled for, and I also find patterns that cannot be fully explained by supply-side factors alone. In the modeling and quantification, these factors are partially incorporated into the framework as DF parameters that the borrowing government takes as given.

Stylized Facts.—In the empirical analysis, I show that recipient-country corruption is associated with greater reliance on Chinese DF relative to DAC DF, particularly in hard-to-monitor sectors. Using project-level data on more than 1,030,000 DF projects across nearly 110 developing countries and 30 official providers from 2000 to 2021, I document four new stylized facts.

First, at the country level, higher public-sector corruption, measured by the Corruption Perceptions Index, is linked to greater reliance on China: a one-standard-deviation increase in corruption corresponds to a 7.9 percentage point rise in China's share of DF inflows. Second, at the project level, Chinese project size is positively correlated with corruption, while DAC project size shows no significant correlation. Third, the number of DAC projects declines with corruption, whereas the number of Chinese projects rises. Fourth, across sectors, I find that project size in hard-to-monitor sectors grows disproportionately with corruption, with the total effect remaining significant even for DAC projects.

Model.—To interpret the stylized facts and conduct welfare analysis, I develop a variant of the neoclassical growth model that incorporates government corruption, public investment, and the endogenous use of DAC and Chinese DF. The economy has a private and a public sector. The private sector is standard: a representative household supplies labor and private capital to firms, and a representative firm produces a final good using labor, private capital, and public capital.

The main departures from literature arise in the public sector where the government accumulates public capital. First, public capital is not monolithic, but a composite of differentiated projects across subsectors, directly linking to the project-level data. Second, the government is corrupt and can divert part of public investment for its own benefit, generating an endogenous wedge between the book value and effective value of public capital. This extends prior work that treats inefficiency as an exogenous loss. Third, the government endogenously chooses how much to finance with DAC and Chinese DF, rather than receiving exogenous lump-sum transfers from providers.

The key tension lies in choosing between DAC and Chinese DF. DAC DF offers lower interest rates but stronger monitoring, while Chinese DF is more expensive but allows greater diversion. This trade-off varies across sectors because interest rates and monitoring intensities are provider–sector specific. In addition, securing DF entails fixed costs that differ by provider and sector. As a result, Chinese DF can improve household welfare despite higher interest rates, provided its fixed costs are sufficiently lower than DAC's in some sectors.

I solve the government's planning problem, in which it chooses private and public investment to maximize utility, defined over household consumption and diversion. Corruption is captured by a parameter measuring the government's relative valuation of diversion versus consumption. I characterize the government's decisions—how much DF to use, from which source, and in which sectors.

Theoretical Insights.—The model highlights four key insights. First, corruption distorts DF choices through three channels: (1) the government overinvests in each project and undertakes too many projects for diversion; (2) resources shift toward sectors with weaker monitoring; and (3) Chinese DF, despite higher interest rates, is chosen over DAC DF because of lax monitoring. These mechanisms explain the stylized facts: the positive correlation between corruption and both project counts and sizes, the disproportionate effects in hard-to-monitor sectors, and the stronger reliance on Chinese DF at the aggregate level.

Second, Chinese DF has a dual impact on recipient countries. It expands financing options, especially where DAC DF is prohibitively costly to secure, but in corrupt countries it can amplify inefficiencies through the three corruption channels. The overall welfare effect depends not only on corruption levels but also on which sectors Chinese DF finances.

Third, the efficiency of public capital—often treated as an exogenous parameter in prior work—emerges here as an endogenous outcome of the interaction between corruption and DF characteristics. I derive an expression analogous to the conventional efficiency parameter, but one that depends on both the corruption parameter and DF features. This implies that DF providers can directly shape the efficiency of public capital in recipient countries.

Fourth, the model suggests a two-way feedback between corruption and DF. Corruption affects DF inflows, while DF inflows influence measured corruption. I distinguish between (1) fundamental corruption, captured by a parameter reflecting the government's preference for diversion over household consumption, and (2) actual diversion, which aligns with survey-based indices of corruption risk. Thus, the observed correlation between corruption and Chinese DF reflects both forces: higher fundamental corruption attracts more Chinese DF, which in turn increases diversion and raises measured corruption.

Quantification.—I calibrate the model for 108 developing economies to assess whether Chinese DF ultimately enhances or undermines household welfare. For each country, I estimate a range of welfare effects, with the actual outcome depending on corruption levels, which can only be bounded with available data. Relative to a counterfactual steady state without Chinese DF, about 15% of countries experience clear welfare gains, 29% show negligible or ambiguous effects, and 55% face potentially large welfare losses.

Case studies reveal that heterogeneity in outcomes reflects not only the level of corruption but also the sectors receiving Chinese DF. When allocated to sectors with monitoring standards close to those of DAC DF, or where DAC DF is difficult to secure, Chinese DF can generate positive welfare effects by filling funding gaps. By contrast, when concentrated in sectors with much weaker monitoring, Chinese DF tends to produce substantial welfare losses. The key policy implication is that coordination between the DAC countries and China on lending practices could enhance citizen welfare in recipient countries.

Related Literature.—This paper contributes to the literature on global capital allocation, particularly two rapidly growing subfields. The first is the study of official capital flows. While the literature has traditionally focused on private capital, recent work highlights the comparable importance of official flows (Horn et al., 2020; Avdjiev et al., 2022). The second examines China's expanding role in global capital markets (Coppola et al., 2021; Horn et al., 2021; Clayton et al., 2023). A major catalyst has been the introduction of novel datasets on Chinese DF (Dreher et al., 2021), which have spurred research into the allocation and effects of Chinese DF (Isaksson and Kotsadam, 2018; Knutsen and Kotsadam, 2020).

This paper advances both areas. First, I establish new stylized facts on DF, a central form of official capital flows, and provide a theoretical framework to explain them. Second, I introduce the first macro-development model to integrate Chinese DF, analyzing its interaction with corruption, DAC DF, and public investment, and quantifying its welfare implications.

Second, this study contributes to the literature on the effects of public-sector corruption on economic growth. Early empirical work links institutional quality to growth through various channels (Mauro, 1995; Tanzi and Davoodi, 1998; Keefer and Knack, 2007; Acemoglu et al., 2001). On the theoretical side, De la Croix and Delavallade (2009); Svensson (2000); Robinson and Torvik (2005) provide microfoundations for the relationship between rent-seeking and public investment, while within macroeconomic growth frameworks, Aguiar and Amador (2011); Chakraborty and Dabla-Norris (2011) study how political frictions shape growth outcomes.

This paper adds to this field in two ways. First, using project-level data, I find suggestive evidence that corruption and diversion motives systematically shape DF decisions, which directly affect public investment. Second, I develop a theoretical framework that identifies multiple channels through which corruption and DF interact to influence growth, and I quantify their welfare implications.

Third, this study contributes to the literature on public expenditure and growth. Early empirical work shows that public capital significantly contributes to output growth (Aschauer, 1989), a result reinforced by later studies (Calderón et al., 2015; Bom and Ligthart, 2014). On the theoretical side, Barro (1990); Glomm and Ravikumar (1994); Futagami et al. (1993) extend the Cobb–Douglas framework to include public capital, focusing on taxation and expenditure policy, while more recent studies continue this line of inquiry (Agénor, 2010; Berg et al., 2012, 2019). At the same time, Hulten (1992, 1996) highlight that the effective value of public capital may fall short of its nominal value due to inefficiencies and weak institutions, prompting subsequent efforts to measure such losses (Dabla-Norris et al., 2012; Gupta et al., 2014).

This paper advances the literature in three ways. First, unlike prior models that assume tax financing, I examine an environment where governments rely on DF, a setting increasingly relevant for developing countries. Second, I treat public capital as a portfolio of differentiated projects across sectors, rather than a single aggregate input. Third, instead of assuming an exogenous efficiency loss, I endogenize it by linking corruption to DF choices, thereby deriving aggregate efficiency as an outcome.

Lastly, this study contributes to the literature on DF allocation and impact. Early work on foreign aid analyzes donor choices in recipient selection (Alesina and Dollar, 2000; Kuziemko and Werker, 2006) and the effects of aid on growth, often with mixed findings (Boone, 1996; Burnside and Dollar, 2004; Hansen and Tarp, 2001; Rajan and Subramanian, 2008). More recent studies use instruments to isolate exogenous variation in DF flows (Galiani et al., 2017; Temple and Van de Sijpe, 2017) at the aggregate level. Theoretical models usually treat aid as an exogenous lump-sum transfer (Adam and Bevan, 2006; Chatterjee and Turnovsky, 2007), with few exceptions such as Franco-Rodriguez et al. (1998), who endogenizes aid in partial equilibrium.

This paper makes two contributions. Empirically, it uses project-level data to document how diversion motives may shape DF allocation. Theoretically, it introduces a growth model in which DF use is endogenous—rather than an exogenous transfer—and interacts with corruption across multiple sectors.

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 Backgrounds & Data Description

2.1 Institutional Backgrounds

Development Finance.—Development finance (DF) refers to cross-border resource flows aimed at fostering development in recipient countries, distinct from commercial loans or bonds. It has two key features: (1) DF is contracted at the project level, with funds earmarked for specific initiatives; and (2) it primarily involves official flows between governments or multilateral agencies, with only a minor role for private institutions.[1]

Development Assistance Committee.—Established in 1960s, the Development Assistance Committee (DAC) brings together 32 developed countries that follow shared standards for providing development assistance to foster growth and improve living standards in developing nations. The DAC has historically set global norms for DF and supplied the majority of such flows, typically on concessional terms with very low interest rates and large grant components. Members include the United States, Japan, Germany, and the United Kingdom, along with other advanced economies

[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.

from Europe, North America, and the Asia-Pacific. The Committee also works with eight multilateral organizations as DAC observers, including the World Bank and the International Monetary Fund (IMF), and with eight DAC participants, such as Saudi Arabia and Qatar, that are not members but coordinate closely with DAC activities.

Chinese Development Finance.—Over the past two decades, China has become a major provider of DF, nominally pursuing the same goal of fostering growth in developing countries but through a model distinct from the DAC. Most Chinese loans are near market rates and largely non-concessional. State-owned lenders often rely on both collateral arrangements, and contracts typically exclude borrowers from multilateral restructuring processes such as those of the Paris Club. They also reserve broad rights to cancel loans or demand immediate repayment under political or economic contingencies (Gelpern et al., 2021). Many agreements further contain confidentiality clauses that obscure contract details, in sharp contrast to the DAC's emphasis on transparency. Horn et al. (2021) estimate that about half of China's official overseas lending to developing countries goes unreported to the IMF or World Bank.

Despite these unfavorable terms, Chinese DF remains attractive for several reasons. First, concessional DAC loans are often harder to secure, especially in certain sectors and in high-risk countries (Brautigam, 2011; Dreher et al., 2022). Second, DAC finance typically comes with stringent policy conditions, close monitoring, and demands for transparency or institutional reforms, which can be burdensome for recipient governments. By contrast, Chinese officials promote their DF as "no strings attached," avoiding interference in domestic policy. Chinese projects also tend to be implemented quickly, allowing borrowing-country politicians to showcase visible short-term results. Both anecdotal (Bunte, 2019) and regional-level evidence (Isaksson and Kotsadam, 2018) suggest that these features make Chinese DF especially appealing in corrupt environments.

Global DF Landscape.—The landscape of DF has changed dramatically over the past two decades. Most strikingly, the total volume of Chinese DF is now comparable to that of all DAC members combined (Figure 1a). Because many Chinese projects remain undisclosed due to confidentiality clauses, China's true footprint is likely even larger. The number of countries drawing on Chinese DF has also reached levels similar to those relying on DAC DF (Figure 2). Sectoral patterns differ across providers, with China especially prominent in transport and storage, communications, energy, industry, mining, construction, and multisector projects (Figure 1b).

(a) Total DF Supply by Donor Groups (b) Total DF Supply by Sectors

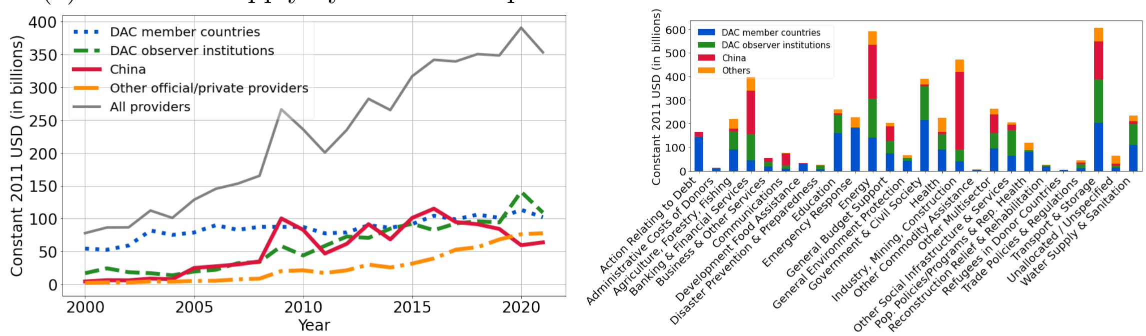

Figure 1: Total DF Supply by Donor Groups and Sectors (2000-2021)

(a) Recipients of DAC DF (b) Recipients of Chinese DF

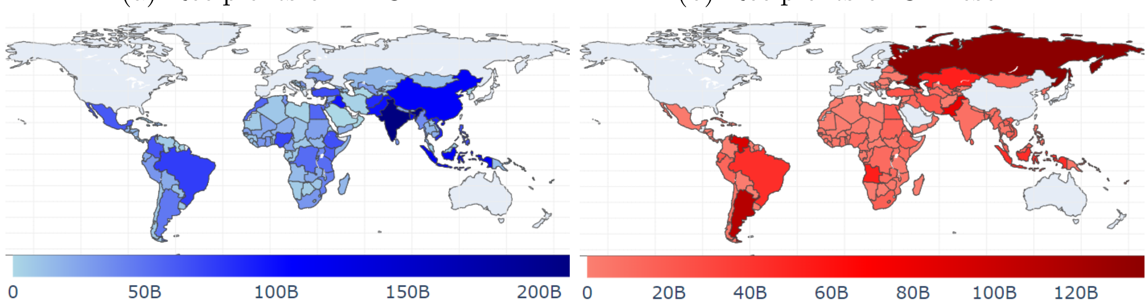

Figure 2: Recipients and the Amounts of DAC and Chinese DF (2000-2021)

The scale of Chinese DF and its broad reach highlight the need for a more nuanced framework to study the global DF system, beyond traditional concessional paradigms. Sectoral heterogeneity further shows that aggregate-level analyses miss key dynamics in how governments interact with two distinct types of DF providers.[2] A micro-level approach is therefore essential to capture the complex allocation mechanisms and their implications for development outcomes.

2.2 Data Description

DAC DF Projects.—I use the OECD's Creditor Reporting System (CRS), which records more than a million DF projects undertaken by DAC members and observers from 2000-2021. It tracks aid and resource flows to over 150 developing countries,

[2]Historically, DAC countries have been called *donors* because most 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.

with each entry including donor and recipient information, commitment amounts, sector classification, and other implementation specifics. Coverage has been nearly complete since 2003.

Chinese DF Projects.—Chinese DF is drawn from AidData's Global Chinese Development Finance Dataset, Version 3.0, covering 20,958 projects across 165 countries from 2000–2021. Compiled from diverse primary and secondary sources due to China's non-reporting and confidentiality clauses, it provides the most comprehensive record of Chinese DF. Projects are coded to DAC standards, allowing direct comparability with DAC data.

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

Corruption.—I use the Corruption Perceptions Index (CPI) compiled by Transparency International. The CPI aggregates 13 sources on public sector corruption, reflecting assessments by businesspeople and country experts. It covers over 180 countries and ranges from 0 (most corrupt) to 100 (least corrupt). Among the 109 countries in my sample, the mean is 34.1 with a standard deviation of 10.9.

Controls.—I include macro indicators from the World Development Indicators, trade flows from IMF Direction of Trade, gravity variables from CEPII (Conte et al., 2022), and countries' UN General Assembly voting alignment (Bailey et al., 2017). In robustness checks, I further add the Chinn–Ito capital openness index (Chinn and Ito, 2008) and the Polity IV democracy index. For further details on the CPI and controls, see Appendix 1.2 -1.3.

3 Stylized Facts on Corruption and Global DF Allocation

Recent research highlights associations between DF and recipient-country corruption. Andersen et al. (2022) document higher capital outflows to tax havens from developing countries following World Bank disbursements. Bunte (2019) suggest that some governments with high corruption levels turn to Chinese DF because its weaker oversight allows greater scope for diversion. Isaksson and Kotsadam (2018) report increases in regional corruption linked to Chinese projects in Africa, while Malik et al. (2021) show that Chinese DF is disproportionately directed toward more corrupt countries. Although both anecdotal and aggregate-level evidence point to a relationship, systematic evidence on how public sector corruption correlates with DF allocation at the sectoral and project levels—across comprehensive samples of recipients and providers—remains limited. Using project-level data from 2000–2021 covering nearly 110 recipient countries and more than 30 official providers, I examine how corruption is associated with DF inflows.

I document four stylized facts showing that public sector corruption is systematically associated with global DF allocation, with monitoring potentially playing a crucial role. In the aggregate, more corrupt countries rely more heavily on Chinese DF than on DAC DF. At the project level, corruption is positively correlated with Chinese project size but not with DAC project size, and the number of DAC projects declines with corruption while the number of Chinese projects rises slightly. Finally, the correlation between corruption and project size is disproportionately stronger in hard-to-monitor sectors. I then relate these patterns to diversion motives 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, which reflects overall institutional quality. For ease of exposition, I sometimes describe the correlation between corruption and outcomes as the *corruption effect*, though the results are "correlations", not causation. The patterns may also reflect two-way feedback, where corruption shapes DF inflows and DF inflows influence corruption. In Section 5, I show how the model sheds light on both directions.

3.1 Corruption and Aggregate Reliance on DAC vs. Chinese DF

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 have relied more heavily on DAC versus Chinese DF over the past two decades (2000–2021). I find that, in the aggregate, more corrupt countries rely more on China than on DAC (Fact 1). I show this using a cross-country regression with the share of Chinese DF in total DF inflows, while in Appendix 2.1 I confirm the result by analyzing the values of DAC and Chinese DF separately at both the country and sectoral levels, using panel OLS and PPML estimations, along with a range of robustness checks.

I examine the relationship between China's share of total DF inflows and recipient-country corruption using the following cross-country regression:

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

where $SHARE_r^{CHN}$ is the share (%) of Chinese DF received by country r from 2000–2021 relative to the value of its total DF inflows from all official providers. 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 for recipient-country characteristics and bilateral political and socioeconomic factors vis-à-vis China.[3] The coefficient β captures the correlation between corruption and relative reliance on Chinese DF.

The regression shows a significant positive association between corruption and the share of Chinese DF at the country level. Figure 3 presents a partial regression plot of China's share against corruption, where each circle represents a recipient country, scaled by total DF-to-GDP. The fitted line has a slope of 0.7148 ($p = 0.018$), implying that, after controlling for other variables, a one–standard deviation increase in corruption (10.9 points) is associated with a 7.9 percentage point higher reliance on Chinese DF over the past two decades. In Appendix 2.1.1, I confirm the result using panel regressions.

[3] *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$\times$donor characteristics:* average Ideal Point Distance, average bilateral trade, distance, and dummies for contiguity, legal origin, language, colonial relationship, religion, sibling, and FTA.

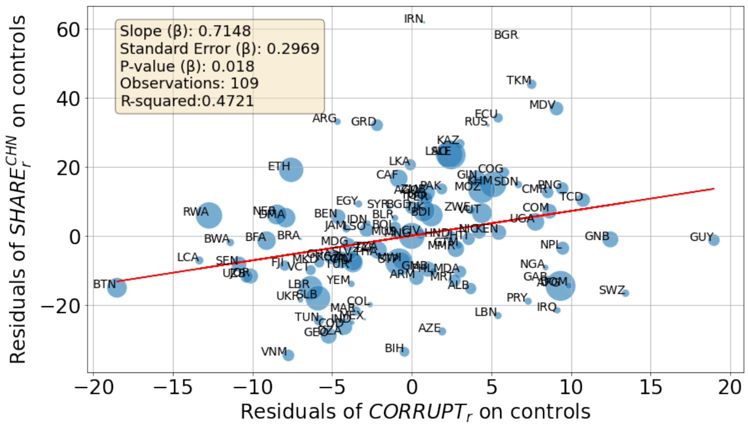

Figure 3: China's Share in Total DF Amount and Recipient Corruption

3.2 Corruption and Project Size and Count

It is well established that higher public-sector corruption tends to increase public spending at both the micro and macro levels (Mauro, 1995, 1996; Tanzi and Davoodi, 1998), often through cost exaggeration and inefficient allocation driven by diversion motives. By the same logic, corrupt governments may inflate the costs of DF projects, resulting in more and/or larger projects.

Leveraging the granularity of project-level DF data, I test this hypothesis and also examine whether the aggregate correlation between corruption and DF inflows reflects project size, project count, or both. The results show that Chinese project sizes are positively correlated with corruption, while DAC project sizes exhibit no systematic relationship. By contrast, the number of DAC projects declines with corruption, whereas the number of Chinese projects increases.

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.*

I first test how corruption relates to project size by estimating 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

Table 1: Corruption Effect on 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		✓		✓

$r(i)$, $d(i)$, $s(i)$, 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 partially control for supply-side factors, à la Khwaja and Mian (2008). $CORRUPT_{r(i)}$ is the corruption index of the recipient country, averaged over the sample period.[4] $\mathbf{X}_{r(i)d(i)t(i)}$ 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 association between corruption and project size in each case.

Table 1 shows that Chinese project size is statistically significantly positively 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 that corruption has no economically or statistically significant effect on 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 marginally positively correlated.*

To examine the relationship between corruption and the number of DF projects,

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

Table 2: Corruption Effect on 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		✓		✓

I regress the total count of projects by each donor groups in each year on corruption index and controls. While I report results from country-level regressions, main findings are robust at the sectoral level (Appendix 2.1.3).

Table 2 shows that corruption is significantly negatively correlated with the number of DAC projects, while it is marginally positively correlated with the number of Chinese projects. Columns (1)–(2) indicate that a 1% increase in the corruption index is associated with about 9.4 fewer DAC projects yearly. In contrast, columns (3)–(4) suggest that a 1% increase in corruption is linked to roughly 1.5–3.1 additional Chinese projects, though these coefficients are not statistically significant. Since many Chinese projects are not reported in international statistics, and more corrupt countries are less likely to disclose projects transparently, the Chinese estimates are likely biased downward.

3.3 Corruption and DF in Hard-to-Monitor Sectors

To investigate the mechanism behind the corruption effect on project size, I exploit cross-sectoral differences in monitoring difficulty. If diversion motives matter, corruption should be more strongly correlated with projects in sectors that are harder to monitor. I classify sectors into easy- and hard-to-monitor categories using DF project evaluation data, and then estimate the corruption effect on project size and count within each group. The results show that corruption has a disproportionately larger effect on project size in hard-to-monitor sectors, with the net effect statistically significant even for DAC projects. Higher corruption is also associated with even more projects in hard-to-monitor sectors.

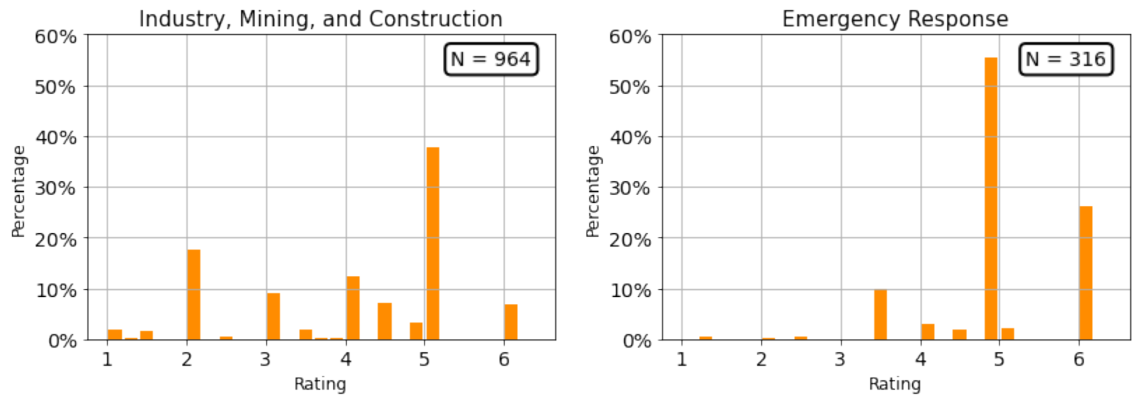

Figure 4: Average Ratings (6-point Scale) by Sectors

3.3.1 Classifying Sectors by Monitoring Difficulty

I rank sectors by monitoring difficulty using AidData's Project Performance Database (PPD), which evaluates over 20,000 DF projects implemented by 12 agencies across 183 recipient countries from 1956–2016. Projects are rated on a six-point scale, with 1 indicating highly unsatisfactory and 6 highly satisfactory performance. While the criteria vary somewhat by agency, ratings typically reflect efficiency of implementation and quality of supervision. Average ratings differ markedly across sectors. For example, Figure 4 shows that 80 percent of Emergency Response[5] projects are rated near 5 or above, whereas the average in Industry, Mining, and Construction is much lower. I interpret such differences as indicative of relative monitoring difficulty and use average ratings to rank sectors accordingly. To estimate sectoral average ratings, I control for potential confounders—including evaluator type, recipient country characteristics such as corruption, and donor–recipient relationships such as political ties—to isolate sector-specific effects. Such average ratings differ statistically significantly across sectors. The full strategy and results are reported in Appendix 2.3.

3.3.2 Estimating Corruption Effects in Hard-to-Monitor Sectors

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

Using sectoral average ratings, I test whether the relationship between corruption and project size or project count varies with monitoring difficulty. To aid interpre-

[5] For instance, emergency lending after natural disasters.

tation, I classify sectors into *low* and *high* monitoring categories based on the first quartile of the extracted sectoral average ratings.[6]

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

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

$LowMonitor_{s(i)}$ 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 *level effect* of corruption, while δ captures the *interaction effect* of corruption with monitoring difficulty. For Chinese projects, the donor dimension of the fixed effects is redundant.

I next estimate the level and interaction effects of corruption on the number of projects using the following specification:

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

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 effect of corruption on project size is disproportionately larger in sectors that are harder to monitor. The estimated level effect of corruption is consistent with the earlier regression without the interaction term, while the interaction coefficient is positive for both DAC and Chinese DF across all specifications. This supports the hypothesis that in hard-to-monitor sectors, higher corruption amplifies project size through diversion motives. A 1% increase in corruption is associated with an additional 0.35% increase in DAC project size and a

[6] This also helps mitigate potentially remaining measurement errors 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 (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 disaster-response projects initiated by donors, as well as the Action Relating to Debt sector, which is not relevant to new projects.

Table 3: Corruption Effect 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			✓			✓

0.45% increase in Chinese project size, though not statistically significant for Chinese projects. For DAC projects, the interaction effect exceeds the level effect in both magnitude and significance. By contrast, for Chinese projects the level effect is much stronger than the interaction effect. Including recipient fixed effects in columns (3) and (6) leaves the interaction effects qualitatively unchanged.

Panel (b) indicates that corruption is also associated with a greater number of projects in hard-to-monitor sectors, particularly for DAC projects. A 1% increase in corruption corresponds to 0.62 more DAC projects in these sectors relative to others. For Chinese projects, the estimated interaction effects on project counts are positive but not statistically significant. The estimated level effects are consistent with the regressions without the interaction term.

3.4 Taking Stock and Potential Explanation

Rationalizing the Facts through Diversion Motive.—The stylized facts suggest that public sector corruption and diversion motives play a central role in shaping global DF flows, and that Chinese DF is monitored less strictly than DAC DF. If Chinese DF is indeed subject to weaker monitoring, governments with diversion motives will prefer it over more tightly monitored DAC DF. This explains why more corrupt countries host more Chinese projects and fewer DAC projects (Fact 3). Projects from stricter DAC donors are thus more likely to be allocated to cleaner countries with weaker diversion motives. In addition, lenient monitoring allows corrupt governments to inflate project sizes, producing a strong positive correlation between Chinese project size and corruption, while stricter DAC oversight and the sorting of cleaner countries yield no such relationship (Fact 2). Together, these mechanisms imply that, at the aggregate level, more corrupt countries rely more heavily on Chinese DF relative to DAC DF (Fact 1).

Although DAC projects are generally subject to stricter monitoring, some sectors are inherently harder to oversee and thus create opportunities for diversion. In these sectors, corruption is disproportionately correlated with project size, and the effect is significant even for DAC projects, contributing to a higher project count and larger projects (Fact 4). A similar pattern may appear in Chinese projects, but because Chinese DF is already less strictly monitored, variation across sectors matters less for the overall pattern. This explains why, for DAC projects, the interaction between corruption and monitoring difficulty dominates the level effect, while for Chinese projects the level effect remains stronger than the interaction effect.

Alternative Stories.—One narrative attributes reliance on Chinese DF to supply-side constraints: DAC DF may be rationed for certain countries, overlook specific sectors, or be harder to secure (Brautigam, 2011; Dreher et al., 2022). Since the stylized facts reflect equilibrium outcomes of both demand and supply, they do not dismiss this account. However, supply factors alone cannot explain all the facts. They may explain the aggregate correlation between corruption and reliance on China (Fact 1)—if DAC DF is rationed in corrupt countries—but they cannot account for the project- and sector-level patterns (Facts 2–4).

Another explanation emphasizes bilateral political and economic ties between donors and recipients (Alesina and Dollar, 2000; Kuziemko and Werker, 2006). While this perspective may also help explain Fact 1, it cannot account for Facts 2–4. Moreover, I explicitly control for these factors by including extensive bilateral covariates, and the core results on corruption and DF flows remain robust.

Comprehensive Modeling Approach.—While the empirical findings highlight the role of diversion motives, they do not rule out alternative narratives such as supply-side constraints or bilateral ties. These explanations are not mutually exclusive, and it is likely that multiple forces shape DF allocation simultaneously. In the model, I incorporate these elements by allowing governments to choose between DAC and Chinese DF under diversion motives, taking into account donor-specific characteristics such as interest rates, monitoring intensity, and fixed costs of securing projects. Supply-side factors and bilateral ties are embedded in these DF parameters. Although the model does not endogenize how these parameters are determined, I estimate them from the data in the quantitative analysis and assess the welfare implications of Chinese DF for recipient countries.

3.5 Robustness Checks

I conduct a series of robustness checks, detailed in Appendix 2.4, and find that the qualitative results remain unchanged. These include: instrumenting corruption with settler mortality; alternative outlier treatments; different transformations of the corruption measure; alternative classification of sectors; placebo tests using interactions between corruption and other recipient characteristics; replacing the corruption index with a more direct measure of diversion risk; and controlling for capital openness, public capital stock, and democracy.

4 A Growth Model of Corruption and Development Finance

I develop a variant of the neoclassical growth model that incorporates public sector corruption and the strategic use of DF from both the DAC and China across sectors. The model is designed to: (i) generate theoretical insights consistent with the stylized facts in Section 3; (ii) derive aggregate macroeconomic implications, including the effects of corruption on the efficiency of public capital and DF use; and (iii) provide a framework for quantitative analysis to assess the welfare effects of Chinese DF in developing countries.

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. It has two sectors. 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 by borrowing at risk-free interest rates from international DF providers, both the DAC and China. There is no default, and the private sector does not have access to international financial markets.

4.1.1 Private Sector

Household.—The representative household has log utility over a single good, $U(C) = \ln C$, and discounts the future by β. Lifetime utility is:

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

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

Firm.—The firm produces output Y with a Cobb–Douglas technology using private capital (K), labor (L), and effective public capital (G^E):

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

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

In existing work (e.g., Hulten (1996)), effective public capital is often modeled as ΘG, with G the book value of capital and Θ an exogenous efficiency parameter. In my model, the counterpart to Θ is endogenously determined by the government's optimization in the global DF 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, which typically treats public capital as a single monolithic input.

Financing Public Capital.—In addition to domestic savings, the government finances public projects through international development finance (DF) loans.[7]

[7] 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 the quantitative analysis (Section 6), I incorporate DAC grants to improve the model's fit, showing that their inclusion does not alter the main theoretical results.

DF loans are one-period 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.[8]

DF providers cannot distinguish between funds allocated to $g_{s,j,t}^E$ and those diverted to $g_{s,j,t}^X$. However, they can verify that borrowed funds are earmarked for the designated project and not used for other projects, household consumption, or private investment. Thus, the government faces 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 project j not fall below its total outstanding DF debt.

The DAC and China can verify that fractions $\psi_s^D \in (0,1]$ and $\psi_s^C \in (0,1]$ of their DF contracts, respectively, are allocated to $g_{s,j,t}^E$. These parameters capture sector-specific monitoring intensities. Thus, the government faces a *monitoring constraint* for project j:

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

Equivalently, it may divert at most $1-\psi_s^D$ of a DAC loan and $1-\psi_s^C$ of a Chinese loan. I assume $\psi_s^D \geq \psi_s^C$ for all $s \in \mathcal{S}$.

[8]For example, suppose the government borrows \$100 from the DAC and can allocate \$90 to effective public capital and divert \$10. After production, it retains $(1-\delta_G) \times 90$ in effective capital but fully consumes the diverted \$10. In $t+1$, it must repay $(1+R_s^D) \times 100$ from retained capital and output.

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 capture expenses related to negotiation, administration, monitoring, reporting, and other unmodeled costs. They reflect each provider's internal policy toward the borrower in a given sector, shaped by bilateral political, diplomatic, social, or economic relations.

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

4.2 Government's Planning Problem

At the start of period t, public projects are completed according to investment and DF decisions made in $t-1$. The government aggregates effective public capital from all projects and provides it to the private sector, while consuming any diverted funds. The representative firm then produces output Y_t using private capital, effective public capital, and labor. The government services all outstanding DAC and Chinese debt, including interest and fixed costs, using output and the depreciated stocks of private and public capital. It then issues new DF debt to finance projects for the next period, allocating funds between effective capital and diversion. Finally, it sets household consumption and private investment, with the household consuming as assigned. Period t then ends. The government's planning problem and optimal allocation are then defined as follows.

Definition 1 (Government's Planning Problem and Optimal Allocation) *The "government's planning problem" is defined as:*

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

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

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.*

(RC) is the economy-wide resource constraint: the left-hand side includes household consumption, private investment, public investment and diversion, and DF payments, while the right-hand side includes output and new DF issuance. (NF) and (MC) are the non-fungibility (Eq. (1)) and monitoring (Eq. (2)) constraints. (NX), (ND), and (NC) impose non-negativity on diverted funds, DAC debt, and Chinese debt, respectively. Note that (MC) and (NX) cannot bind simultaneously.

4.3 Characterization of the Government's Optimal Allocation

I first characterize the optimal size and financing of public capital at the project level, then at the sector level, and finally in the aggregate.

4.3.1 Government's Optimal Financing at the Project Level

I focus on allocations in which the non-fungibility constraints always bind—that is, all public projects are fully financed by DF. A sufficient condition is $f^S_s \geq \min\{f^D_s, f^C_s\}$

where f_s^S is the fixed cost of self-financing a project in sector s. Together with $R_s^D < R_s^C < 1/\beta$, this implies that self-financing is more costly than DF financing, both in fixed and marginal terms. In the quantitative analysis (Section 7), I relax this condition 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 Appendix 3.

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

The intuition behind Lemma 1 is that the government faces constant marginal borrowing costs from each DF provider. These costs equal the interest rate, adjusted for the marginal benefit of diversion, which depends on monitoring intensity and the relative marginal utility of diversion to consumption. Under GHH preferences, this relative marginal utility is constant at χ. Since interest rates and monitoring intensities are also constant, the government compares these costs and chooses the cheaper provider. Borrowing from multiple providers for the same project is not optimal, as it would also incur additional fixed costs. This property is also useful when taking the model to the data, since each project is associated with a single provider in the data.

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 $p \in \{D, C\}$:*

$$g^E_{s,j,t+1} = \begin{cases} \psi_s^p d^p_{s,j,t+1} & \text{if } \chi > R_s^p \\ d^p_{s,j,t+1} & \text{if } \chi < R_s^p \end{cases}$$

Lemma 2 follows from the fact that under GHH preferences the relative marginal utility of diversion to consumption is constant at χ. The government compares this constant χ with the constant interest rate. If χ exceeds the interest rate, it is optimal to maximally divert DF, and the monitoring constraint binds. If χ is lower, diversion is too costly and the government chooses minimal diversion. 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 project j, financed by provider 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 public capital in 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 ($\chi < R^p_s$), the optimal project size equates the project's total return to the interest rate. When corruption is high ($\chi \geq R^p_s$), the marginal benefit has two components: a ψ^p_s share from the project's return and a $1 - \psi^p_s$ share from the marginal utility of diversion, χ. 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 provider* p*,* $\tilde{R}^p_s$*, is the interest rate adjusted for capital retention after depreciation and the marginal utility of diversion:*

$$
\tilde{R}^p_s \equiv \begin{cases} R^p_s - (1-\delta^E_s) & \text{if } \chi < R^p_s\\ \frac{R^p_s - (1-\psi^p_s)\cdot\chi}{\psi^p_s} - (1-\delta^E_s) & \text{if } \chi \geq R^p_s \end{cases}
$$

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:* $mpg^E_{s,j,t+1} = \tilde{R}^p_s$.

Note that $mpg^E_{s,j,t+1}$ is identical across projects with the same productivity within sector s. Hence, I define $mpg^E_{s,t+1}(\theta)$ 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 provider* p*,* $\tilde{\pi}^p_{s,t+1}(\theta)$*, is the increase in final output due to the project net of the effective marginal cost and the fixed cost:*

$$
\tilde{\pi}^p_{s,t+1}(\theta) \equiv \int_0^{\bar{g}^{Ep}_{s,t+1}(\theta)} (mpg^E_{s,t+1}(\theta) - \tilde{R}^p_s) dg^E_{s,j,t+1} - f^p_s,
$$

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

Note that effective profit depends on the financing provider and increases with project productivity θ. The following proposition characterizes the optimal financing of each project.

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 government selects the DF provider that maximizes a project's contribution to final output, taking into account interest rates, fixed costs, and any additional utility from diversion. To illustrate this result graphically, I define productivity cutoffs in the spirit of the exporting-firms model in Melitz (2003). Zero-profit cutoffs serve as thresholds that determine whether projects operate or shut down, distinguishing those that generate enough revenue to cover costs from those that do not.

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

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 5a illustrates optimal project financing across productivity levels θ within a sector. First, suppose the government chooses zero diversion with both DAC and Chinese DF and that fixed costs are the same. Since the DAC interest rate is lower, its effective profit curve (D) lies above the Chinese curve (C) for all $\theta > 0$. In this case, all projects with productivity above the DAC zero-profit cutoff ($\bar{\theta}^D$) are financed by DAC DF, while those below the cutoff 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

(a) With No Diversion

(b) With Diversion

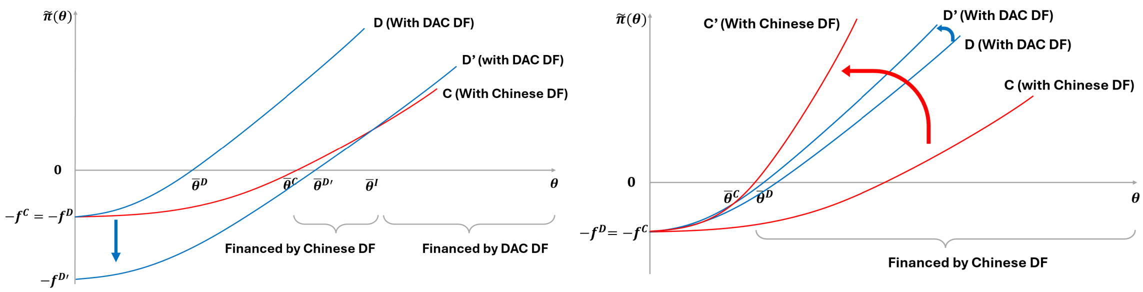

Figure 5: Optimal Financing of Each Project

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 5b 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 productivity, government corruption, and relative DF characteristics—interest rates, monitoring intensities, 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 $f^p_s \leq \left(\frac{\tilde{R}^q_s}{\tilde{R}^p_s}\right)^{\sigma_s - 1} f^q_s$, 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 $f^p_s > \left(\frac{\tilde{R}^q_s}{\tilde{R}^p_s}\right)^{\sigma_s - 1} f^q_s$, 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.

Lemma 4 highlights the trade-off between the relative effective marginal costs and fixed costs of the two DF providers. Recall that the corruption χ and monitoring intensity enter the effective marginal cost and suppose p has a lower cost ($\tilde{R}_s^p < \tilde{R}_s^q$). If its fixed cost is not too high relative to q's, all projects are optimally financed by p. If instead p has a lower marginal cost but a sufficiently higher fixed cost, a trade-off emerges: the fixed cost is a constant disadvantage, while the marginal cost advantage grows with project productivity. As a result, projects with productivity above the financing-indifference cutoff $\theta_{s,t}^I$ are financed by p, and those below are financed by q, which generalizes the example in Figure 5a.

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 (˜) indicates that projects financed by the provider are subject to maximal diversion, the absence of a tilde indicates zero diversion. each sector belongs to one of the seven 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 $\mathcal{S}^{\tilde{C}\tilde{D}}$.

Figure 6 illustrates Proposition 2 graphically. The vertical axis measures the relative fixed-cost disadvantage of DAC DF, f_s^D/f_s^C, and the horizontal axis the government's corruption parameter χ. The black line represents the relative advantage of DAC DF in effective marginal cost, $(\tilde{R}_s^C/\tilde{R}_s^D)^{\sigma-1}$.

When $\chi < R_s^D$, the government is not corrupt enough to divert funds, so it chooses zero diversion for both DAC and Chinese DF. In this region, effective marginal costs equal interest rates plus depreciation, making DAC's relative advantage independent of χ. If DAC's fixed-cost disadvantage does not exceed this advantage, all projects are financed by DAC without diversion ($\mathcal{S}^D$). If it does, projects with productivity above the financing-indifference cutoff are financed by DAC, and those below by China—again without diversion ($\mathcal{S}^{DC}$).

If $\chi \in (R_s^D, R_s^C)$, the government diverts only from DAC DF, so the relative advantage of DAC DF increases in χ. If $\chi \geq R_s^C$, the government chooses maximal diversion for both providers. Since monitoring intensity is no higher for Chinese DF ($\psi_s^D \geq \psi_s^C$), DAC's relative advantage in effective marginal cost is then weakly decreasing in χ. In these regions, project financing by productivity follows the same logic as before. In $\mathcal{S}^{\tilde{D}}$, $\mathcal{S}^{\tilde{D}C}$, and $\mathcal{S}^{\tilde{D}\tilde{C}}$, where $\chi \in [R_s^C, (\psi_s^D R_s^C - \psi_s^C R_s^D)/(\psi_s^D - \psi_s^C))$,

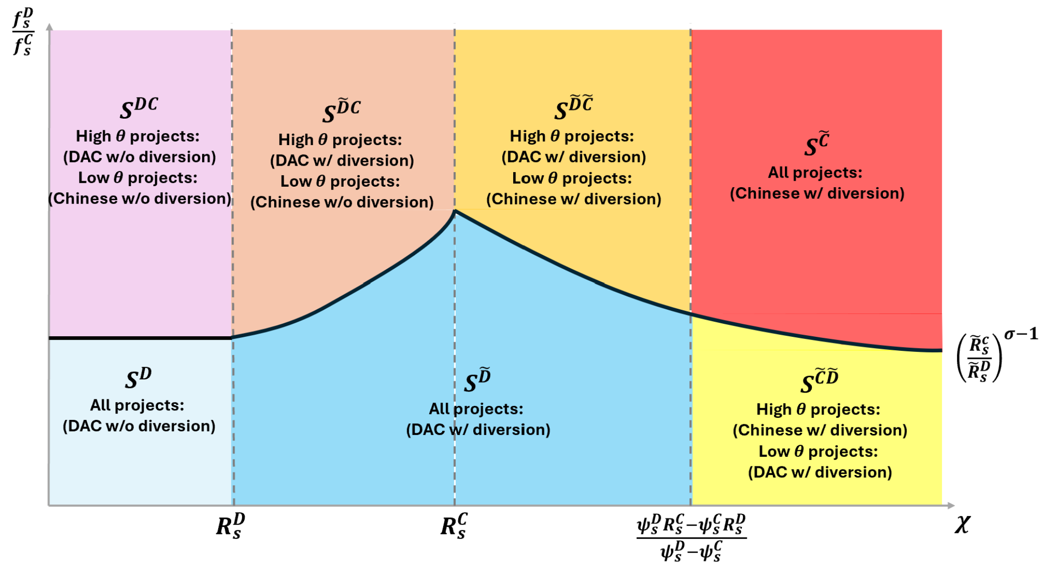

Figure 6: Optimal Financing of Different Sectors

higher-productivity projects are financed by DAC. In $\mathcal{S}^{\tilde{D}C}$, corruption χ affects only DAC projects, not Chinese projects.

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 the sector level, $G_{s,t}^E$, and in the aggregate, G_t^E, by aggregating individual projects. 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. Given this distribution, effective public capital in sector s is:

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

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:*

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

where $\mathcal{G}^E_s$ is a sector-specific constant depending on parameters: R^D_s, R^C_s, ψ^D_s, ψ^C_s, f^D_s, f^C_s, σ, $\underline{\theta}$, ξ, and χ.

See Appendix 3.7 for the full expression of $\mathcal{G}^E_s$. Proposition 3 shows that sectoral effective public capital depends on the distribution of project productivity ($\underline{\theta}$, ξ) and the elasticity of substitution across projects (σ). It is further shaped by the relative effective marginal and fixed costs (f^D_s, f^C_s), where the effective marginal costs reflect interest rates (R^D_s, R^C_s), monitoring intensities (ψ^D_s, ψ^C_s), and the corruption parameter (χ).

The following proposition characterizes the final effective public capital.

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

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

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

Proposition 4 shows that final effective public capital depends on parameters governing the productivity distribution, the aggregation technology, and the interaction between corruption and DF characteristics. The contribution of each sector is weighted by its share γ_s.

5 Theoretical Exploration and Insights

In this section, I present four insights. First, the model accounts for the empirical findings through three channels by which corruption distorts the efficient use of DF. Second, I explore the dual impact of Chinese DF on household welfare. Third, I analyze how corruption in the global DF environment affects the efficiency of public capital. Fourth, I show the possibility of two-way feedback between corruption and DF use.

5.1 Three Channels of Corruption Effects

The model shows that corruption distorts the efficient use of DF through three channels, which map directly to the stylized facts on global DF allocation established in Section 3. I begin with a benchmark allocation:

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, $mpg^E_{s,j,t}$, 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 $mpg^E_{s,j,t}$ decreases with effective public capital $g^E_{s,j,t}$, this leads to overinvestment in project j. The observed project size, $g^E_{s,j,t}/\psi_s^p$, appears even larger in the data, further highlighting the overinvestment. 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 channel explains 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 (Fact4), corresponding to low ψ_s^p in the model.

Overinvestment (Extensive Margin).—Compared to a benevolent allocation, higher corruption lowers the effective marginal cost and thereby raises the effective profit of a project with a given productivity. Graphically, the profit curve becomes steeper with higher corruption and lower monitoring intensity (Figure 7a). The zero-profit cutoff falls from $\bar{\theta}^p$ to $\bar{\theta}^{p\prime}$, so projects that would be unprofitable under a benevolent allocation operate 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.—For simplicity, consider two sectors s and s', both financed by provider p. Proposition 3 implies that the ratio of effective public capital

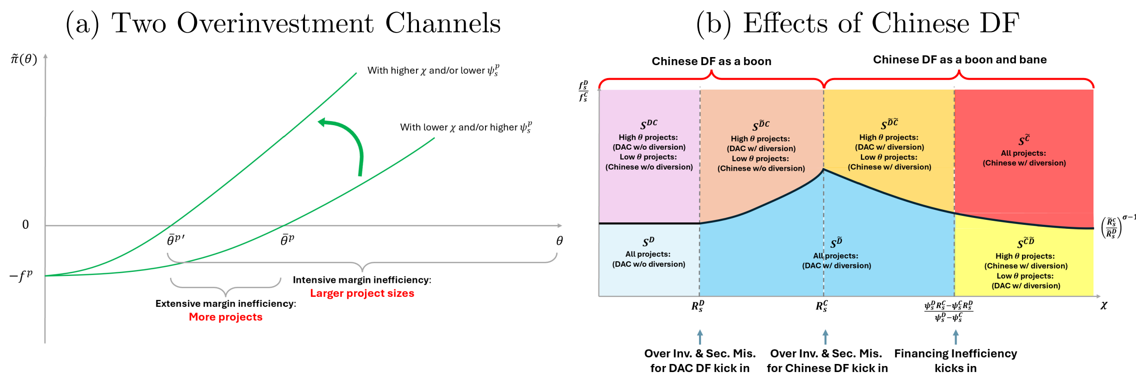

Figure 7: Channels of Inefficiency and the Effect of Chinese DF

between them is

$$\frac{G^E_{s,t}}{G^E_{s',t}} = \frac{\mathcal{G}^E_s}{\mathcal{G}^E_{s'}} = \underbrace{\frac{\tilde{R}^p_{s'}}{\tilde{R}^p_s}}_{\text{relative effective MC}} \times \underbrace{\left(\frac{f^p_{s'}}{f^p_s}\right)^{\frac{\xi-\sigma}{\xi(\sigma-1)}}}_{\text{relative fixed costs}} \times \underbrace{\left(\frac{\gamma_s}{\gamma_{s'}}\right)^{\frac{\sigma(\xi-1)}{\xi(\sigma-1)}}}_{\text{relative contribution to production}} .$$

In a benevolent allocation, the effective marginal cost is simply $R^p_s - (1-\delta)$. The optimal ratio of public capital across sectors then reflects their contributions to final output, adjusted for relative interest rates and fixed costs. With sufficiently high corruption and unequal monitoring intensities, distortions arise: if sector s is monitored more closely ($\psi^p_s > \psi^p_{s'}$), the government shifts resources toward s', generating sectoral misallocation. 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 3 shows that the optimal financing choice for project j is the provider that maximizes the government's effective profit, $\tilde{\pi}^p_{s,j,t+1}$. For simplicity, assume DAC and Chinese DF have identical fixed costs. The decision then depends only on the effective marginal costs, $\tilde{R}^p_s$. In a benevolent allocation, $\tilde{R}^p_s$ equals the interest rate plus depreciation, so DAC DF—with its lower interest rate—is always chosen. With sufficient corruption, however, it is possible that $\tilde{R}^C_s < \tilde{R}^D_s$, making Chinese DF optimal despite its higher interest rate. This occurs if and only if $\chi > \frac{\psi^D_s R^C_s - \psi^C_s R^D_s}{\psi^D_s - \psi^C_s}$. 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).

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, depending on the degree of government corruption.

Chinese DF as a Boon.—Chinese DF can help fill funding gaps left by DAC DF, especially when DAC financing carries very high fixed costs. Such costs may reflect difficult negotiations, stringent policy conditions, sectoral deprioritization, or rationing in certain countries and sectors, which limit DAC DF to only the most productive projects. By contrast, if Chinese DF entails lower fixed costs, through factors such as quicker implementation, lenient policy conditions, and easy negotiations, its availability supports broader public investment, raising final output and improving household consumption.

Chinese DF as a Bane.—When corruption is high, the adverse effects of Chinese DF dominate through the three channels discussed above. The government may switch to Chinese DF despite its higher interest rates, expand projects excessively, and misallocate resources across sectors when monitoring intensities differ. Together with the extra budgetary burden due to the higher interest rates of Chinese DF, these distortions may ultimately reduce household consumption.

In summary, whether Chinese DF is a boon or a bane depends on the borrowing country's level of corruption (χ), and also on how difficult it is to secure DAC and Chinese DF, reflected on the relative fixed costs (f_s^D/f_s^C). The three inefficiency channels emerge gradually as corruption rises, as illustrated in Figure 7b. If $\chi < R_s^C$, the government does not divert Chinese DF, and it only has a boon effect by filling funding gaps. When $\chi > R_s^C$, the overinvestment and sectoral misallocation channels are triggered. Once χ surpasses a higher threshold, the financing-inefficiency channel also takes effect, amplifying the bane. In these regions, both boon and bane effects coexist. Whether Chinese DF alleviates funding gaps or exacerbates inefficiencies varies across sectors, and its net effect on households at the aggregate level is 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 shapes the efficiency of public capital. Prior research shows that the efficiency of public investment depends on institutional quality (Hulten, 1992). Subsequent studies quantify cross-country differences in public capital efficiency (Dabla-Norris et al., 2012; Gupta et al., 2014), typically assuming that public capital G enters the production function with a constant efficiency term Θ: $Y = A \cdot (\Theta G)^{\gamma} K^{\alpha} L^{\lambda}$. In most of this literature, Θ is taken as exogenous.

My model complements existing approaches by endogenizing Θ, which emerges from the government's optimal choices:

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

See Appendix 3.7 for the full expressions of the sector-specific constants $\mathcal{G}_s^E$. My model's counterpart to Θ is shaped not only by the production technology (sector shares γ_s, elasticity of substitution σ, and productivity distribution parameters $\bar{\theta}$ and ξ) but also by corruption χ and DF parameters (interest rates R_s^p, monitoring intensities ψ_s^p, and fixed costs f_s^p). Moreover, sectors contribute heterogeneously to aggregate efficiency. This framework refines our understanding of public capital efficiency and highlights the role of corruption and DF. It also implies that DF providers can influence recipient-country efficiency through their DF policies.

My model also speaks to how misallocation affects Total Factor Productivity (TFP) (Restuccia and Rogerson, 2008). Taken to the traditional two-input framework, $Y = A \cdot K^{\alpha} L^{1-\alpha}$, my model allows for a decomposition of TFP, A. In particular, the model helps isolate the share of TFP changes that stem from public capital misallocation and from efficiency losses due to corruption and the global DF environment.

5.4 Two-Way Feedback between Corruption and DF Inflows

The model highlights the possibility of two-way feedback: corruption shapes DF inflows, and DF inflows in turn influence corruption. 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*, proxied by the actual amount of diverted funds, consistent with empirical corruption indices based on surveys of resource diversion or expropriation in the public sector.

In this framework, the correlation between corruption and Chinese DF inflows observed in the data reflects two reinforcing forces. Higher fundamental corruption (χ) increases reliance on Chinese DF, which is less tightly monitored and more susceptible to diversion. Greater DF inflows then amplify actual diversion, raising observed corruption.

6 Calibration

In this section, I apply the model to data for each developing country and calibrate it for the welfare analysis in Section 7. As preliminary steps, I incorporate two additional financing sources—DAC grants and self-financing—and classify sectors into 14 categories. I then calibrate the model parameters.

6.1 Preliminary Steps

Incorporating DAC Grants.—I incorporate DAC grants as an additional financing source. Like DAC loans, they are contracted at the project level but do not require repayment and typically consist of many small projects. From 2000 to 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).[9]

Given their small scale but high frequency, I model DAC grants as projects located near the lower end of the productivity distribution. This ensures that including them does not alter the main theoretical findings, which focus on loans. Appendix 5.1 provides further details on this extension and its implications.

Incorporating Self-financing.—I also allow for self-financing, where the government funds projects without external support. This captures the Defense sector, which constitutes a non-trivial share of public investment in most countries but is ineligible

[9] 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 loan project Construction of Hai Phong General Hospital.

for DF. In other sectors, I assume $f_s^S \geq \min\{f_s^D, f_s^C\}$, where f_s^S is the fixed cost of operating a self-financed project in sector s. Thus, self-financing is dominated by DF in these sectors due to higher fixed and marginal costs. Consequently, self-financing applies only to Defense sector.

Sector Classification.—The classification of the public sector draws on two sources: the OECD Development Assistance Committee sector classification (DAC-5) and the IMF Classification of Functions of Government (IMF COFOG). DAC-5 codes are used in the OECD's Creditor Reporting System (CRS) and in AidData's Global Chinese Development Finance Dataset to categorize international DF flows. IMF COFOG is used in the IMF's Government Finance Statistics (GFS) to classify government expenditure by function.

While CRS and AidData provide bilateral commitment data for each development project between donors and borrowers, they do not capture aggregate expenditure by recipient governments across sectors. To align these DF datasets with IMF GFS expenditure data, I use the detailed descriptions in the IMF GFS manual (De Clerck and Wickens, 2015) and the DAC-CRS code list (OECD, 2024) to construct a unified sector classification.[10]

This yields 14 unified categories, reported in Appendix 5.2. These categories span all sectors from both classifications, except for six DAC-5 sectors that are excluded because they relate to debt activities, emergency response, donor administrative costs, or unspecified categories.

6.2 Calibration of Parameters

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

Standard Macro Parameters.—I externally calibrate the standard macro parameters that are common across all borrower countries, with one period corresponding to a 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

[10] Most sectors map straightforwardly across the two systems, but some require merging, as they correspond to an intersection or union of multiple sectors in the other classification. In such cases, I merge them into a single category to cover all relevant sectors.

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	$\mathbb{E}[\frac{\text{CHN proj. size}}{\text{DAC proj. size}}]$
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

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 each sector, σ. Unlike firms or goods, public projects lack market prices and sales data over time, making elasticity difficult to estimate. I therefore assume that substitution patterns are similar to those across goods within sectors, and set $\sigma = 2.2$, the median estimate from Broda and Weinstein (2006).[11]

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 γ_s in developing countries does not differ systematically from that in advanced economies, exploiting the fact that advanced economies are not eligible for international DF.

For developing countries, observed expenditure shares are confounded by corruption and provider-specific monitoring, whereas in advanced economies expenditure patterns are primarily driven by γ_s. Moreover, many advanced economies are close to their steady state, which makes their data more suitable for estimation than that 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

$$\frac{I_s^{G*}}{Y^*} = \frac{\delta_G \gamma \gamma_s}{1/\beta - (1-\delta_G)}.$$

I estimate γ_s using annual data on government expenditure by sector from the IMF COFOG. Since $\sum_{s \in \mathcal{S}} \gamma_s = 1$, the share of each sector in total public expenditure equals γ_s. I estimate them using GMM with moment conditions:[12]

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

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

[11] It is well established that complementarities prevail across sectors, while substitutabilities ($\sigma > 1$) dominate across firms within sectors (Baqaee and Farhi, 2019). I assume the same for public projects.

[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 data for 38 advanced economies, as classified by the IMF. See Appendix 5.3 for details and the estimates.

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 percent in Government & Civil Society to 4.5 percent in General Budget Support.

Monitoring Intensities.—For the quantification, I focus on relative monitoring intensities between DAC and Chinese DF, normalizing DAC intensities to one in all sectors ($\psi_s^D = 1$). This approach has two motivations. First, in the empirical analysis, DAC project sizes show little correlation with corruption in most sectors. While some correlation appears in hard-to-monitor sectors, it is far smaller than for Chinese DF. Second, estimating absolute monitoring intensities is infeasible, as no cardinal corruption measure corresponds directly to the model's corruption parameter χ_r. Under some identifying assumptions, however, I can estimate the relative monitoring intensity between DAC and Chinese DF for each sector.

Consider the following fixed-effects regression model, where $g^O_{r,p,s,j,t}$ is the observed project size and $\mathbf{X}_{r,p,t}$ includes gravity variables, bilateral political distance, and $\ln(R_s^p - (1 - \delta_G))$:

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

I make the following assumptions, where *controls* denote all right-hand-side variables of the model:

- Assumption 1: $\mathbb{P}(\chi_r \geq R_s^C | s, p = C) = 1$
- Assumption 2: $\mathbb{E}\big[\ln \theta_j | p, s, controls\big] = \alpha_{rt} + \alpha_s + \mathbf{X}_{r,p,t}$

Assumption 1 implies that all countries using Chinese DF during the sample period are sufficiently corrupt to divert funds. Since most Chinese DF is directed toward countries with above-average corruption indices (Malik et al., 2021), this assumption is plausible. If anything, it biases estimates toward overestimating the monitoring intensity of Chinese DF. If the sample includes countries with insufficient corruption, actual monitoring intensity would be lower. Hence, the estimates should be interpreted as an upper bound on Chinese DF monitoring intensities relative to the DAC.

The second assumption states that differences in average productivity between DAC and Chinese DF within a sector can be controlled for by including recipient–time fixed effects, sector fixed effects, and other controls. Under Assumptions 1 and 2, the difference in sector–provider fixed effects in the regression model satisfies $FE_{s,p=C} - FE_{s,p=D} \approx -\ln \psi_s^C$ [13] so that

$$\psi_s^C \approx \exp^{FE_{s,p=D} - FE_{s,p=C}} .$$

The intuition is straightforward: once differences in project productivity, recipient conditions, and sector-specific factors are accounted for, the relative size of Chinese versus DAC projects reflects differences in monitoring intensity. Based on this premise, I estimate Chinese DF monitoring intensities by running fixed-effects regressions and using the estimated sector–provider fixed effects. If $FE_{s,p=C} - FE_{s,p=D}$ is negative, I set $\psi_s^C = 1$. Estimates of ψ_s^C are reported in Table 5.

The results suggest that Chinese projects in Industry, Mining, and Construction are the most vulnerable to corruption and diversion, followed by Communications, General Budget Support, and Health. By contrast, monitoring in Transport & Storage, Education, General Environment Protection, Water Supply & Sanitation, Government & Civil Society, General Economic, Commercial, and Labor Affairs, and Other Social Infrastructure & Services does not significantly differ from that of DAC DF. In these sectors, the three corruption channels are absent, and Chinese DF benefits households by filling funding gaps left by DAC DF.

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 the 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 protracted negotiations with DF providers or domestic administrative processes—that are beyond the scope of this paper.

Because of these lags, 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 and use the mixture-of-Pareto property (Hogg et al., 2013). The pooled

[13] See Appendix 5.4 for details. Note that this includes only loan projects; grant projects are excluded since they are systematically smaller and reflect productivity differences not fully captured by the controls.

Table 5: Interest Rates and Chinese Monitoring for Each Sector

Sector name	$R^D_s - 1$ *(%)*	$R^C_s - 1$ *(%)*	ψ^C_s
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

distribution of project sizes has a pdf resembling a Pareto 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 parameter ξ_r/σ and scale parameter $\bar{\theta}_r$. Details are in Appendix 5.5.

Corruption.—Estimating the corruption parameter χ_r for each country is challenging because no direct empirical counterpart exists. Instead, I identify a theoretical upper bound for χ_r in each country. I then use this bound to construct a range of household welfare effects of Chinese DF in the counterfactual analysis.

Recall that for Chinese projects, the optimal project size in recipient country r satisfies $mpg_{r,s,j,t} = \tilde{R}^C_{r,s}$. Because the marginal product must be positive, the effective marginal cost, $\tilde{R}^C_{r,s} = \frac{R^C_s - (1-\psi^C_s)\chi_r}{\psi^C_s} - (1 - \delta_G)$, must also be positive for operating projects. This condition implies an upper bound on corruption:

$$\bar{\chi}_r = \min_s \left\{ \frac{R^C_s - \psi^C_s(1 - \delta_G)}{1 - \psi^C_s} \right\} - \epsilon.$$

where $\epsilon > 0$ is a small number ensuring $\tilde{R}^C_{r,s} > 0$. For each country, I compute $\bar{\chi}_r$ as the minimum across all sectors in which it received Chinese DF. I set $\epsilon = 0.01$.

Fixed Costs.—For each recipient country, I estimate two sets of fixed costs using GMM, targeting the average project size. The first assumes a benevolent government ($\chi_r = 0$), and the second assumes maximal corruption ($\chi_r = \bar{\chi}_r$). 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 next proposition characterizes the average project size by sources. See Appendix 3.9 for details.

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. Since the fixed costs are exactly identified, the choice of $\mathcal{W}$ is inconsequential.

7 Quantitative Analysis

7.1 Is Chinese DF a boon or a bane?

Using the estimated parameters, I conduct a counterfactual analysis of household welfare in the steady state with and without Chinese DF for 108 developing countries. Because I can only identify an upper bound for the corruption parameter χ_r, rather than its exact value, I report a range of welfare effects for each country. Figure 8 summarizes the results. Each vertical line shows this range: the top indicates the percent change in steady-state household consumption from the advent of Chinese DF under a benevolent government (relative to the no-China counterfactual), while the bottom indicates the change under maximal corruption ($\chi_r = \bar{\chi}_r$). In the former

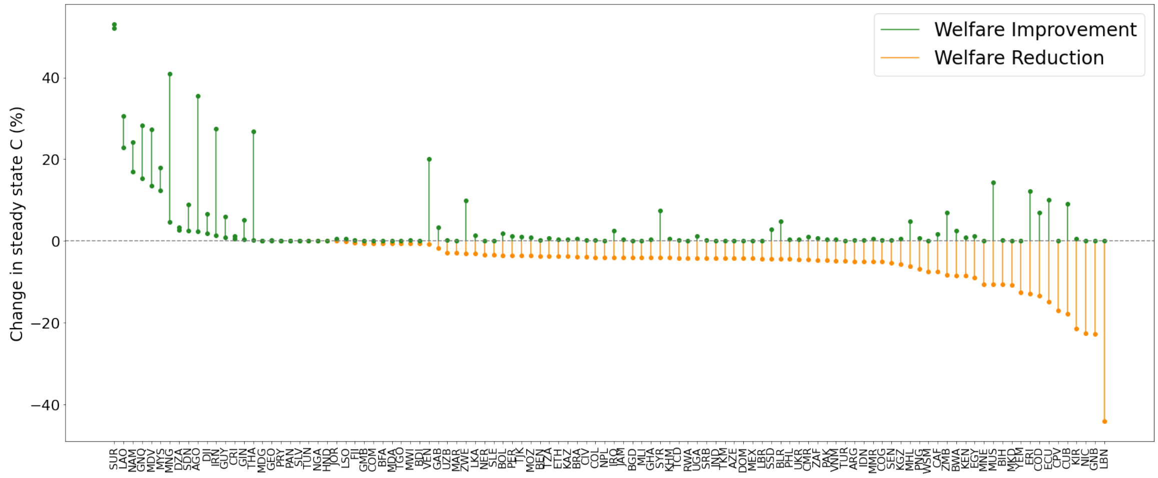

Figure 8: Welfare Effect of Chinese DF on Households

case, the corruption channels are shut down, so Chinese DF delivers its full boon effect; in the latter, both boon and bane effects operate.

The results reveal substantial heterogeneity. Among the 108 economies, about 15% experience clear welfare gains, 17% negligible effects, 12% ambiguous outcomes depending on corruption, and 55% potentially large welfare losses from Chinese DF. In all countries, Chinese DF is beneficial under benevolence, since it is used only in sectors where its fixed costs are lower than those of DAC DF. Yet as corruption rises, the effect becomes ambiguous. In countries such as Suriname, Laos, and Namibia, Chinese DF remains welfare-improving even at the upper bound of corruption. By contrast, in Lebanon, Guinea-Bissau, and Nicaragua, welfare gains are minimal even under benevolence, while losses can be large under corruption. In some cases—such as Eritrea and Cuba—the effect is indeterminate.

7.2 Case Studies

To examine why welfare effects differ so widely across countries, I conduct case studies. Two sources drive this heterogeneity. The first is the level of maximal corruption. Countries such as Guinea-Bissau, Kiribati, Lebanon, and Nicaragua, at the right corner of Figure 8, may face some of the largest welfare reductions simply because their maximal corruption estimates (1.381) are far higher than the median (1.093). The second, and more interesting, source is which sectors are financed by China. To highlight this channel, I compare three economies with similar values of the corruption upper bound $\bar{\chi}_r$ but very different welfare outcomes. Figure 9 shows the impact of Chinese DF on each sector in Suriname ($\bar{\chi}_r = 1.171$), Kenya ($\bar{\chi}_r = 1.093$), and Mauritius ($\bar{\chi}_r = 1.093$). The figure reports DF composition across sectors, measured by the total amount committed between 2000 and 2021. Sectors are ordered along the horizontal axis by the monitoring intensity of China (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 about 30% of total DF. DAC loans are larger, accounting for roughly 65%, while Chinese loans are the largest on average but represent only about 5%.

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

Case 1 (Boon): Suriname.—Figure 8 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 top panel of Figure 9 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 where corruption matters is Communications. With a benevolent government, Chinese DF benefits this sector, which receives little DAC DF, without inefficiencies. Under maximal corruption, both positive and negative effects arise. Yet, because DAC loans are absent and DAC grants minimal, the model predicts the boon effect dominates, even at high corruption. This accounts for the large consumption gains in the steady state.

Case 2 (Bane): Kenya.—In Kenya (16th from the right in Figure 8), Chinese DF helps close funding gaps in some sectors, particularly Transport & Storage, without inefficiency. However, when corruption is high ($\chi_r > R_s^C$), Chinese DF generates only bane effects in Industry, Mining, Construction, Communications, and Health. In these sectors, DAC loans are present, smaller on average, and hence associated with lower fixed costs ($f_s^D < f_s^C$). This implies that Chinese loan projects could instead have been financed by DAC loans at lower rates and without diversion.

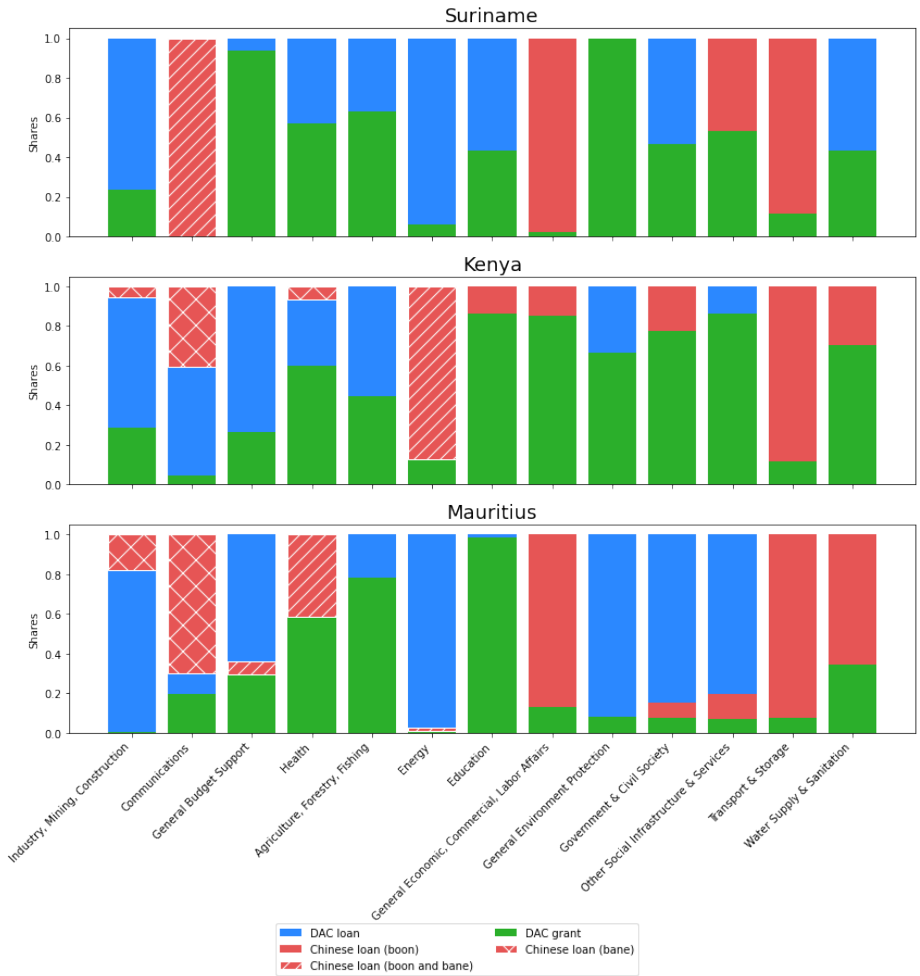

Figure 9: DF Composition by Sectors in Suriname, Kenya, and Mauritius

These sectors also have very low monitoring intensity, which amplifies the negative effects. In the Energy sector, Chinese DF has mixed effects: boon effects because DAC loans are absent and fixed costs are high, but also potential inefficiencies. Overall, the strong bane effects in low-monitoring sectors outweigh the limited boon effects, leaving households worse off in steady state (Figure 8).

Case 3 (Ambiguous): Mauritius.—Mauritius (13th from the right) combines features of Suriname and Kenya, with welfare outcomes highly dependent on the actual level of corruption. Chinese DF closes funding gaps without inefficiency in General Economic, Commercial, Labor Affairs, Transport & Storage, and Water Supply & Sanitation. Yet, in Industry, Mining, Construction, and Communications, outcomes diverge: with a benevolent government, Chinese DF complements insufficient DAC loans; with corruption, Chinese DF yields only bane effects. The effects in General Budget Support and Health are also mixed.

7.3 Policy Implications

The quantitative analysis yields several policy implications, focusing on how DF providers can maximize citizen welfare in recipient countries. I abstract from other economic or geopolitical objectives they may pursue.

DAC.—As China's role in DF expands, DAC DF is no longer the sole option for developing countries. Chinese funds can help close financing gaps, but in highly corrupt environments they may be chosen over cheaper, better-monitored DAC loans, leading to inefficiency. To mitigate this, the DAC could pursue two strategies. One is to coordinate with China to strengthen monitoring standards, which would narrow the monitoring gap and reduce both financing inefficiencies and overinvestment. If coordination proves infeasible, the DAC could instead lower the effective cost of its DF—either by relaxing monitoring requirements (ψ_s^D), which reduces the monitoring gap ($\psi_s^D - \psi_s^C$) but risks greater overinvestment, or by cutting fixed costs (f_s^D) through simplified procedures and faster disbursements. Targeting sectors and countries where Chinese DF is most likely to be diverted would further enhance the effectiveness of these measures.

China.—China could strengthen monitoring to reduce both overinvestment and financing inefficiencies. Even without major changes to its lending practices, it can improve outcomes by targeting sectors and countries where DAC finance is scarce, as in Suriname's Communications sector.

Core Message.—Both DAC and Chinese DF can substantially support developing countries, but inefficiencies arise when differences in lending practices are exploited by corrupt governments. The central policy implication is the need for coordination between the two providers, not only at the country level but also at the sectoral level. Whether through the DAC making loans more accessible or China strengthening monitoring and targeting specific sectors, cooperation is essential. As the theoretical results suggest, greater coordination in the global DF community could markedly improve the efficiency of public capital in recipient countries—helping them grow in the sun of DF without the shadow of corruption.

8 Conclusion

This paper shows that corruption is closely linked to greater reliance on Chinese DF relative to DAC DF, with more and larger projects in more corrupt countries and in sectors that are harder to monitor. A neoclassical growth model explains these patterns, identifying three channels through which corruption lowers efficiency: overinvestment, misallocation of resources toward weakly monitored sectors, and preference for costlier DF sources with looser oversight.

The model highlights the dual nature of Chinese DF. On the one hand, it can fill funding gaps left by DAC DF, especially in sectors where DAC support is scarce. On the other, it can exacerbate inefficiencies when oversight is weak and governments are corrupt. A quantitative analysis across 108 developing countries confirms that welfare effects vary widely, from large gains to net losses, depending not only on the level of corruption but also on which sectors are financed by China.

These findings suggest several directions for further study. Incorporating sovereign debt and default dynamics could clarify how DAC and Chinese DF interact under fiscal stress. Examining how providers set interest rates, monitoring, and fixed costs would shed light on the supply side of DF competition. Future work should also consider the broader geopolitical context. Finally, as longer data series become available, assessing the long-run effects of Chinese DF will be essential to understanding its lasting role in the global DF landscape.

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