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

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Abstract

Since the 1960s, the Development Assistance Committee (DAC) has facilitated development finance (DF) from developed to developing countries, with China becoming a major DF provider in the past two decades. This paper offers the first comprehensive analysis of how developing countries strategically determine the amount, sources, and sectoral allocation of DF. Using project-level DF data and corruption indices from over 130 countries from 2000 to 2021, I find a positive correlation between corruption and reliance on Chinese DF compared to DAC, with more corrupt countries receiving larger Chinese projects—a trend not seen with DAC funds. Particularly in sectors that are hard to monitor, this effect is disproportionately larger, even affecting DAC projects. I also introduce a multi-sector neoclassical growth model that examines how corruption influences government investment decisions when both the DAC and Chinese DF are available with distinctive characteristics. The model shows that corruption leads to inefficiency by promoting overinvestment, favoring less monitored sectors and favoring more expensive but less monitored DF sources. It also shows that Chinese DF can both fill funding gaps left by the DAC and exacerbate inefficiencies due to lax monitoring. Additionally, the model derives the efficiency of public capital as an endogenous interaction between corruption and DF environments, typically treated as exogenous in the literature. Finally, a quantitative analysis estimates the impact of Chinese DF on household welfare across 108 countries.

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1 Introduction

Capital is the cornerstone of economic growth, particularly in the early developmental stages. Since the early 1960s, developed countries have channeled substantial capital into developing countries through government-to-government official development finance (DF) to boost public expenditure and growth. Although extensive research has explored the socioeconomic impacts of this capital infusion, often with mixed results, several critical aspects remain underexplored: How much DF do developing countries decide to use? How is this capital allocated across sectors? Moreover, the emergence of non-traditional DF providers like China in the past decade poses an additional pressing question: From which providers do countries choose to secure DF? Understanding these dynamics helps clarify global capital allocation patterns, illuminate the varied results concerning DF effectiveness, and provide policy insights for international coordination.

This paper presents the first comprehensive analysis of how developing countries strategically determine the amount, sources, and sectoral allocation of international development finance (DF), offering four main contributions. First, by analyzing project-level data, I establish that corruption in the public sector of recipient countries influences DF flows, with these relationships varying across sectors and sources. Second, motivated by these findings, I construct a general equilibrium growth model where a potentially corrupt government makes public investment decisions across different sectors. This model incorporates DF from both traditional providers (Development Assistance Committee countries, DAC) and China, each with distinct attributes. Third, using this model, I demonstrate how corruption can undermine the efficient use of DF and public capital, both at the project and aggregate levels. Lastly, calibrating the model for each developing country, I conduct quantitative analyses to explore the long-term welfare impacts of corruption, assess China's role as a DF provider, and examine the benefits of coordination among DF providers.

In the empirical analyses, I use project-level datasets that encompass DF projects from more than 150 developing countries, financed by 38 official providers between 2000 and 2021. Country-level regressions reveal distinct patterns in DF flows: Public sector corruption in recipient countries measured by the widely used Corruption Perception Index is negatively correlated with the total amount and count of DAC DF projects, and positively correlated with those of Chinese DF projects toward the recipient countries.

Further analysis at the project level elucidates the country-level trends, showing a positive correlation between corruption and both the size and count of Chinese DF projects, contrasted with a negative correlation for the count of DAC projects. Notably, the size of DAC projects shows no significant correlation with corruption. Regressions for each provider reveal that project size is most significantly and positively correlated with recipient corruption in Chinese projects, with the size of projects in the most corrupt quartile being 0.46% larger on average than in the least corrupt countries. These findings are consistent with the diversion narrative, wherein corrupt governments may overinvest to divert funds, especially given that DAC projects are typically more strictly monitored, a condition that aligns with anecdotal evidence found in the literature. The positive correlation with Chinese DF count and the negative correlation with DAC count suggest that countries with greater corruption favor Chinese DF, as it allows for greater diversion. The positive correlation with the size of Chinese projects reflects both a selection of countries with more diversion motives and the inflation of project sizes due to less stringent monitoring, while the insignificant correlation with DAC project size likely indicates the opposite.

To further validate the potential for monitoring and diversion motives, I exploit sectoral heterogeneity in monitoring. I construct a novel measure of sectoral monitoring intensity by regressing project-level implementation ratings on sector dummies and controls and then collecting the estimated coefficients for sector dummies. This measure supports the widely held, yet previously untested, belief that projects involving financial transfers, long-term engagements, and multi-sector operations are particularly harder to monitor. By incorporating this measure into my regression analyses, I find that project size correlates even more strongly with corruption in sectors with lower monitoring intensity. Interestingly, even the size of DAC projects exhibits significant correlations with corruption in less monitored sectors, an effect not observed without accounting for heterogeneous sectoral monitoring intensity.

In sectoral level analysis, I find that recipient corruption is positively correlated with China's share in total DF amount in each sector. However, this effect is not significantly stronger in sectors with less monitoring intensity. Although the corruption index many not exclusively capture diversion motives and there may be alternative narratives, I show that the corruption and diversion story can best explain all the empirical findings jointly compared to alternative explanations.

In the model section, I develop a novel variant of the neoclassical growth model that integrates public sector corruption, project-level public investment, and the endogenous use of DF from both the DAC and China. It is designed to achieve three primary objectives: 1) to explain the empirical findings at the project level; 2) to derive aggregate-level implications in a tractable manner; and 3) to establish a growth model framework that is rich enough for quantitative analyses using both micro- and macro-level data.

The model features two sectors: the standard private sector, characterized by representative households, the accumulation of private capital, and the production of a final good, and a public sector managed by a potentially corrupt government. Within the public sector, the government invest in a continuum of differentiated public projects across various subsectors, each with heterogeneous productivity levels. Public investment forms public capital and it enters the production function of the final good as an additional input along with private capital and labor. The government has the opportunity to divert a portion of public investment for personal gain, embedding a corruption dynamic into the investment process. To finance these projects, the government can secure DF from either DAC or China. DAC DF offers lower interest rates and higher monitoring intensities than Chinese DF, presenting a crucial tradeoff for a government: while DAC DF is less costly, it offers fewer opportunities for diversion compared to Chinese DF. Additionally, financing each project with either type of DF incurs distinct fixed costs, and these DF characteristics vary across sectors.

I solve the government's planning problem where it optimally chooses both private and public investments to maximize its utility, which depends on the representative household's consumption and the total diverted public capital. Corruption is modeled through a parameter that quantifies the government's relative valuation of diverted capital versus household consumption. I characterize the government's optimal financing decisions regarding the amount and source of DF at both the project and sectoral levels. The model identifies three channels via which corruption distorts the efficient DF choices in equilibrium:

1. *Overinvestment*: Corruption reduces the effective marginal cost of public investments for corrupt governments, as they derive additional utility from diversion. This results in overinvestment both at intensive margin, by promoting excessive investment in each project, and extensive margin, by initiating projects with lower productivity that may yield negative profits.

2. *Sectoral Misallocation*: Allocation is skewed toward sectors with less stringent monitoring.

3. *Financing Inefficiency*: Despite lower interest rates from DAC DF, a corrupt government may prefer Chinese DF due to its lower monitoring intensity, which facilitates easier diversion.

The model not only clarifies the empirical findings but also reveals the dual impact of Chinese DF on recipient countries at the aggregate level. On one hand, Chinese DF can be potentially benefiting borrowing countries by providing alternative financing options. This is especially relevant when the fixed costs of using DAC DF are too high for certain sectors. On the other hand, with high corruption, the presence of Chinese DF may increase inefficiencies through the previously described channels. This negative effect becomes more significant as the recipient country's level of corruption rises and the gap in monitoring between the two DF sources grows, highlighting the potential need for better coordination between DF providers.

Moreover, the model has significant implications for the longstanding discourse on the efficiency of public capital. It suggests that efficiency, often treated as a fixed external parameter in existing literature, may actually arise from the complex endogenous interplay between public sector corruption and the DF characteristics. I theoretically derive an expression that mirrors the traditional efficiency parameter form seen in literature but is functionally dependent on the corruption parameter and DF characteristics. This insight indicates that for developing countries, which commonly rely on DF, there might be a significant opportunity for international coordination to enhance the efficiency of public capital.

In the quantitative analyses, I calibrate the model to individual recipient countries. I estimate the model parameters using both micro and macro data. Subsequently, I explore the long-term effects of corruption and monitoring by DF providers on economic growth and household welfare. I conduct counterfactual analyses to assess the potential benefits or detriments of the advent of Chinese DF for specific countries. Additionally, I examine the implications of policy coordination between the DAC and China and explore how international DF flows might differ under various scenarios.

Related literature. First, I contribute to the literature on the allocation and impact of DF. Initial works focus on foreign aid, examining donor choices in country selection for aid disbursement (Alesina and

Dollar, 2000; Kuziemko and Werker, 2006). On the recipient side, the literature explores the effects of foreign aid on GDP growth, often yielding mixed results (Boone, 1996; Burnside and Dollar, 2004; Hansen and Tarp, 2001; Rajan and Subramanian, 2008). Recent studies seek instruments to identify exogenous changes in DF flows (Galiani et al., 2017; Temple and Van de Sijpe, 2017), yet these empirical efforts are typically at the aggregate level. Theoretically, most research treats DF as an exogenous lump-sum transfer among other endogenous fiscal variables (Adam and Bevan, 2006; Chatterjee and Turnovsky, 2007), with an exception being Franco-Rodriguez et al. (1998), who models foreign aid as an endogenous fiscal variable in partial equilibrium.

Empirically, my work pioneers the use of project-level data to investigate the demand-side drivers of DF allocation, revealing that the diversion motives of recipient governments might significantly influence the global DF allocation. Theoretically, this study is the first to propose a general equilibrium growth model that integrates the endogenous use of DF, examining its interactions with corruption.

Second, I contribute to the literature exploring the effect of public expenditure on economic growth. Early empirical research (Aschauer, 1989), shows that public capital significantly contributes to output growth, a finding echoed by subsequent studies (Bom and Ligthart, 2014; Calderón et al., 2015). Early theoretical works (Barro, 1990; Futagami et al., 1993; Glomm and Ravikumar, 1994) expand the Cobb-Douglas production function to include public capital as an input, focusing on optimal government taxation and expenditure. Recent works continue this exploration (Agénor, 2010; Berg et al., 2019, 2012). Meanwhile, Hulten (1992, 1996) suggest that the effective value of public capital may differ from its nominal value due to management inefficiencies and poor institution. Subsequent works (Dabla-Norris et al., 2012; Gupta et al., 2014; Herrera and Ouedraogo, 2018) try to quantify such inefficiencies.

My contributions to this literature are primarily theoretical. First, my model diverge from prior models that assume tax financing for public investments by studying an environment where the government uses DF, which is closer to reality. Second, rather than treating public capital as a monolithic input, I model it as comprising numerous differentiated projects in multiple sectors. Third, while previous models assume an exogenous fraction of public investment is lost due to inefficiencies, I offer a framework that links corruption and endogenous DF choices, thereby determining the aggregate efficiency loss.

Third, this study intertwines with the literature on the effect of public sector corruption on economic growth. Early empirical works (Keefer and Knack, 2007; Mauro, 1996, 1995, 1998; Tanzi and Davoodi, 1998) show that corruption adversely affects economic growth by distorting efficient public investment. On the theoretical front, Acharya et al. (2020); De la Croix and Delavallade (2009); Robinson and Torvik (2005); Svensson (2000) provide microfoundations for the interplay between rent-seeking and public investment. Within macroeconomic growth frameworks, Aguiar and Amador (2011); Chakraborty and Dabla-Norris (2011) investigate how political frictions can influence economic outcomes.

My contributions to this field are twofold. First, using microdata and constructing a novel measure of sectoral monitoring intensity, I provide suggestive evidence that public sector corruption and diversion motives significantly influence public investment decisions at the project-level. Second, I theoretically delineate multiple mechanisms through which corruption and DF interact to influence economic growth.

Lastly, this research intersects with the literature on global capital allocation, particularly within two nascent and fast-growing subfields. The first concerns the burgeoning interest in official capital flows. Horn et al. (2020) and Avdjiev et al. (2022) highlight that while the literature traditionally focuses on cross-border flows of private capital, it often overlooks official capital flows despite their comparable magnitude. The second explores the growing influence of China in the global capital landscape and its role in shaping international capital flows (Clayton et al., 2023; Coppola et al., 2021; Florez-Orrego et al., 2023; Horn et al., 2021). Especially, Dreher et al. (2021) introduces a novel dataset on Chinese overseas DF activities, which spearheads a significant body of research studying the impacts of Chinese DF projects on various socioeconomic outcomes (Isaksson and Kotsadam, 2018; Knutsen and Kotsadam, 2020; Mueller, 2022).

This paper contributes significantly to these areas. First, it explores the determinants behind a key category of official capital flows—development finance—both empirically and theoretically. Second, it is the first to formally model the role of Chinese DF, examining its interplay with corruption and DAC DF.

Outline. The remainder of the paper is organized as follows: Section 2 provides key background information on DF and describes the data. In Section 3, I conduct empirical analyses to examine the effect of corruption on DF usage, using project-level data. Section 4 presents a growth model motivated by the empirical findings. Section 5 derives theoretical insights from the model. Section 6 brings the model to the data and conducts counterfactual analyses. Finally, Section 7 concludes the paper.

2 Institutional Backgrounds & Data Description

2.1 Institutional Backgrounds

Development finance. International development finance (DF) encompasses cross-border resource flows designed to foster development in recipient countries, distinct from commercial loans or bonds. DF is characterized by several unique aspects: 1) DF is contracted at the project level, with funds earmarked for specific development projects; 2) It primarily involves official capital flows between governments or multinational agencies, with a minor role for private institutions; and 3) DF terms are typically concessional, featuring interest rates significantly lower and maturities longer than market rates, often including substantial grant components.

The Organization for Economic Co-operation and Development (OECD) categorizes DF into two main types: Official Development Assistance (ODA) and Other Official Flows (OOF). ODA encompasses transactions such as grants and loans that have a grant element exceeding specific thresholds, thus qualifying as concessional. In contrast, OOF consists of non-concessional flows that do not meet these criteria. Historically, the terms "foreign aid" or "ODA" were predominantly used, as most DF qualified as ODA. However, with the emergence of new providers like China, who often offer non-concessional DF, there is an increasing need to refine DF definitions and clarify the distinctions between ODA and OOF.

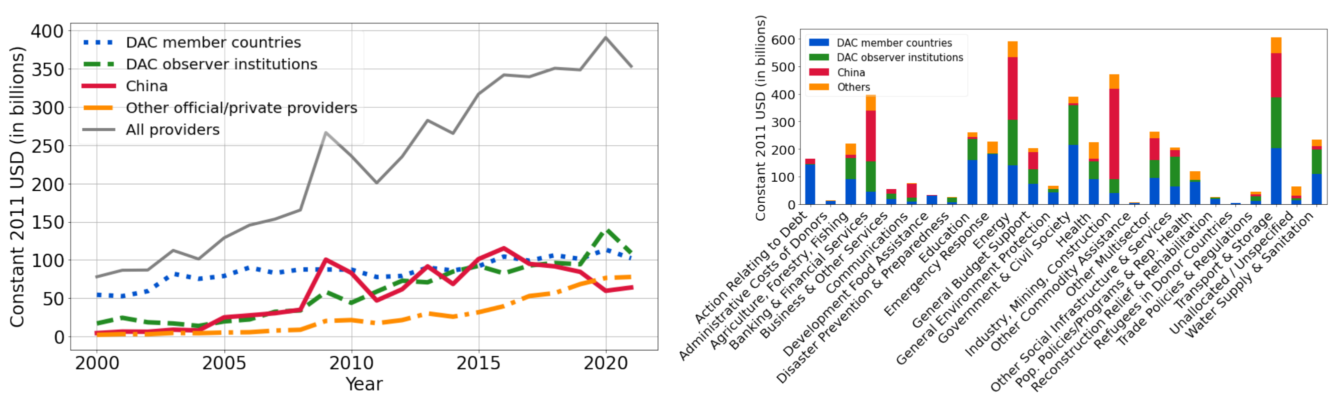
Development Assistance Committee. The Development Assistance Committee (DAC), established in 1960, consists of 32 countries committed to adhering to shared standards in providing development assistance to developing nations, aimed at fostering development and improving living standards. Historically, the DAC has not only set the global norm for DF activities but also provided the majority of DF, with most of them falling under concessional ODA. This has significantly shaped practices and standards across countries and organizations involved in DF. "Member countries" include advanced economies such as the United States, Japan, Germany, and the United Kingdom, among others from Europe, North America, and the Asia-Pacific. The Committee also works closely with seven multinational organizations as "DAC observers," which include the World Bank and the International Monetary Fund (IMF). Additionally, there are seven "DAC participants," such as Saudi Arabia and Qatar, that are not official members but actively coordinate with the DAC.

Chinese development finance. In the last two decades, China has emerged as a significant provider of DF, adhering to the traditional objective of promoting economic growth and development in developing countries. However, China's DF model exhibits unique features that distinguish it from the DAC approach. Firstly, most Chinese DF projects are classified under OOF, often with interest rates near market levels and distinctive non-concessional terms. For instance, Chinese state-owned lenders utilize both formal and informal collateral arrangements to maximize repayment prospects. These contracts often stipulate exclusion from any multilateral restructuring processes, such as those managed by the Paris Club—which largely overlaps with the DAC—and retain rights to cancel loans and demand immediate repayment under various circumstances, including unrelated political and economic situations (Gelpern et al., 2021). Moreover, many agreements include confidentiality clauses that obscure the details and even the existence of contracts from international statistics, marking a stark contrast to the DAC's commitment to data transparency. Horn et al. (2021) estimate that approximately 50% of China's official overseas lending to developing countries is not reported to the IMF or World Bank.

Despite such unfavorable terms, Chinese DF remains appealing to developing countries for several reasons. First, a significant factor is the limited availability of concessional DF from the DAC, particularly in specific sectors and high-risk countries. Second, DF from the DAC often comes with stringent policy conditions, intense monitoring, and demands for transparency and institutional reforms, which can be burdensome and unappealing to governments facing corruption issues. In contrast, Chinese officials promote their DF as having "no strings attached," thus avoiding interference in the domestic policies of borrowing countries. Additionally, Chinese projects are implemented relatively rapidly, enabling politicians in borrowing countries to demonstrate highly visible, short-term successes. Motivated by an extensive literature on political capture in public investments (Alesina and Passalacqua, 2016; Andersen et al., 2022), a growing number of recent studies provide both anecdotal (Bunte, 2019) and aggregate-level evidence (Knutsen and Kotsadam, 2020) that support the narrative of public sector corruption associated with Chinese DF.

Global DF landscape. The global landscape of Development Finance (DF) has undergone significant transformations over the past two decades. Most notably, the total volume of Chinese DF has surpassed that of all DAC member countries combined, as depicted in Figure 1a. Given the substantial number of Chinese DF projects that remain undisclosed due to confidentiality clauses, China's actual impact on the global DF landscape is likely even more pronounced. Additionally, the number of countries utilizing Chinese DF has reached levels comparable to those relying on DAC DF, as illustrated in Figure 2. The sectoral distribution of DF also shows considerable variation across donor groups, with China's contributions especially significant in sectors such as Transport and Storage, Communications, Energy, Industry, Mining, Construction, and Other Multisector areas, as highlighted in Figure 1b.

The sheer magnitude of Chinese DF and the wide range of its recipient countries underscore the need for a broader and more nuanced framework to examine the global DF landscape, moving beyond traditional concessional DF paradigms. The sectoral heterogeneity indicates that an aggregate-level analysis of DF flows is inadequate to fully capture the complex dynamics between borrowing governments and two heterogeneous DF providers.[1] A detailed, micro-level investigation is essential to thoroughly understand the intricate interactions and the impacts of these financial flows on development outcomes.

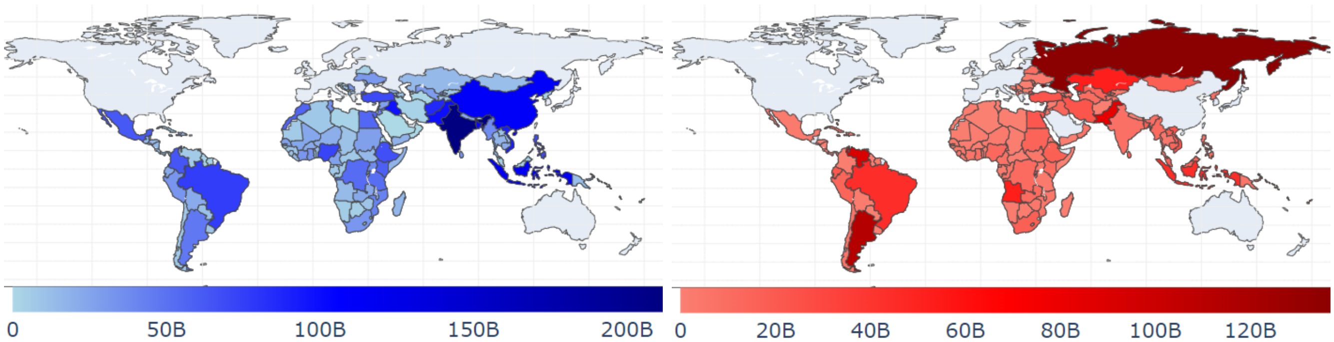


(a) Total DF supply by Donor Groups

(b) DF Distribution by Sectors

Figure 1: Total DF Supply by Donor Groups and Sectors (2000-2021)
Source: Credit Reporting System & AidData Global Chinese Development Finance Dataset Version 3.0.

[1] Historically, DAC countries have been referred to as "donors" since most DF was concessional. However, the term "donor" is too narrow to encompass different types of DF providers, especially considering the non-concessional nature of Chinese DF. Hereinafter, I use "DF provider" and "donor" interchangeably to indicate the country that is the source of DF.



(a) Recipients of DAC DF

(b) Recipients of Chinese DF

Figure 2: Geographic Distribution of DF Usage
Note: The colors represent the total amount of DF from the DAC and China in constant 2011 USD from 2000 to 2021.
Source: Credit Reporting System & AidData Global Chinese Development Finance Dataset Version 3.0.

2.2 Data Description

2.2.1 Project-level Development Finance Data

DAC projects. For DAC DF projects, I use the Creditor Reporting System (CRS) project-level dataset available in the OECD database. This comprehensive dataset covers the volume, origin, and types of aid and resource flows to over 150 developing countries. It includes detailed information for each project, such as recipient and donor information, project title, description, commitment amount, and sector classification, among others. The data are sourced from official statistical reports submitted to the OECD by DAC members. The comprehensiveness of CRS commitment information by DAC members has steadily increased from 70 percent in 1995 to over 90 percent in 2000, reaching nearly 100 percent for flows since 2003.

Chinese projects. For Chinese development finance projects, I use the Global Chinese Development Finance Dataset Version 3.0 from AidData. This uniquely detailed dataset includes 20,958 development projects funded by Chinese government institutions and state-owned entities across 165 recipient countries from 2000 to 2021. Given that China does not report its overseas development finance activity to international organizations like DAC countries do, and due to the prevalence of confidentiality clauses in Chinese projects, this dataset is compiled through meticulous collection and synthesis of a vast array of unstructured project-level information from governments, international organizations, companies, journalists, and research institutions. It provides the most comprehensive view of Chinese overseas development finance activity available and is widely recognized in academic literature, notably since its introduction by Custer et al. (2023). An additional feature of this dataset is that each project is classified and codified according to DAC standards, enabling direct comparability with DAC projects.

Project evaluation data. For constructing sectoral monitoring intensity measure, I use AidData's Project Performance Database Version 2.0, introduced by Honig et al. (2022). It contains evaluations of 21,198 development projects across 183 recipient countries from 1956 to 2016. It includes holistic performance ratings from 12 bilateral and multilateral development finance agencies. The project ratings in the PPD are standardized across different types of evaluators and rescaled to a 6-point scale, where 1 represents highly unsatisfactory performance and 6 denotes highly satisfactory performance. These ratings assess overall project performance on criteria such as timeliness, efficiency, effectiveness, and supervision.

2.2.2 Recipient Country Corruption Measure and Other Control Variables

For measuring corruption of each country, I use the Corruption Perception Index (CPI) provided by Transparency International. The CPI aggregates measures of public sector corruption from 13 different sources, reflecting the views of business people and country experts. It covers over 180 countries and is scaled from 0 to 100, where 0 signifies the highest level of perceived corruption and 100 the lowest. For further details on the CPI, see Appendix A.2. For other control variables, see Appendix A.3 .

3 Stylized Facts on the Impact of Corruption on Global DF Allocation

Recent findings indicate that public sector corruption and elite capture significantly impact the global allocation of development finance (DF). Andersen et al. (2022) reports a notable increase in capital flows to tax havens from developing countries following World Bank disbursements. Some corrupt governments show a preference for Chinese DF due to its lenient oversight, increasing the risk of fund misuse (Bunte, 2019). Isaksson and Kotsadam (2018) document heightened regional corruption associated with Chinese DF projects in Africa, and Malik et al. (2021) find that a significant portion of Chinese DF is directed towards countries with higher-than-average corruption levels. Motivated by these findings, I investigate the influence of recipient country corruption on DF usage, analyzing project-level data from 2000 to 2021 across 165 countries. I examine the impacts of corruption at the country, project, and sectoral levels and document six stylized facts. Subsequently, I propose an explanation that encompasses all the facts and discuss its validity relative to alternative explanations. Lastly, I outline the robustness tests conducted.

3.1 Country Level Analysis

FACT 1: *Public sector corruption in recipient countries is negatively correlated with the total amount and count of DAC DF projects, and positively correlated with those of Chinese DF projects at the aggregate level.*

Amount of DF inflows. I first investigate the influence of corruption on bilateral DF inflows at the aggregate level. For each recipient country r receiving DF from donor d in year t, I use OLS to estimate

$$\ln\left(1 + DF_{rdt}\right) = FE_{dt} + \beta \cdot \ln CORRUPT_r + \mathbf{X}_{rdt} \cdot \gamma + constant + \epsilon_{rdt},$$

where DF_{rdt} represents the total amount committed in constant 2011 USD by donor d for recipient r in year t. The corruption measure, $CORRUPT_r$, is calculated by subtracting the average Corruption Perception Index (CPI) from 100, where 0 indicates minimal and 100 indicates maximal corruption.[2] The vector $\mathbf{X}_{rdt}$ includes control variables at the recipient level—such as geographic region dummies, language, economic indicators (e.g., real GDP per capita, inflation, external debt stock to GDP ratio, population)—and at the bilateral level—such as political, economic, and historical ties. FE_{dt} represents donor-year fixed effects, and ϵ_{rdt} is the error term.

The coefficient β captures the elasticity of DF inflows with respect to changes in corruption, measured by the Corruption Perception Index, and I henceforth refer to it as the "corruption effect." I conduct separate regressions to estimate the corruption effect on DF inflows from the DAC and from China. For Chinese DF analysis, the donor subscript d is omitted.

As an alternative model, I estimate the corruption effect using the Poisson Pseudo Maximum Likelihood (PPML) method following Silva and Tenreyro (2006). PPML is extensively employed in trade literature to estimate trade elasticities, particularly with bilateral trade data that often includes many zero values. Similarly, bilateral DF data also presents zero values, making PPML an appropriate choice for analysis. I estimate the following model:

$$\mathbb{E}\left[DF_{rdt}\middle|\mathbf{X}\right] = exp\Big(FE_{dt} + \beta \cdot \ln CORRUPT_r + \mathbf{X}_{rdt} \cdot \gamma + constant\Big)$$

where $\mathbf{X}$ represents the vector of all predictor variables on the right-hand side.

Columns (1) through (4) of Table 1 summarize the results. Panel (a) reports the results for Development Assistance Committee (DAC) DF flows, and Panel (b) covers Chinese DF flows. Columns (1) and (3) include DF flows from all DAC member countries and observer institutions. In columns (2) and (4), DAC observer institutions are excluded due to the absence of recipient-donor control variables. Both under OLS and PPML, excluding these institutions does not significantly affect the estimates. A 1% increase in the corruption measure is associated with approximately a 0.84-1.3% decrease in DF inflows from a DAC donor. Conversely, Chinese DF inflows are positively correlated with recipient country corruption, with the corruption effect estimated at 3.2 using PPML and 4.2 using OLS when all control variables are included.

Count of DF projects. I replace the log of DF amount in the dependent variable with the total count of DF projects by each donor in each year. This substitution is particularly relevant in studies on Chinese DF which often use the total count alongside the total amount due to the confidentiality clauses in many Chinese projects that obscure amount information (Dreher et al., 2021). In columns (5) and (6) of Table 1, OLS estimates indicate that a 1% increase in corruption leads to approximately 8-9 fewer projects from a DAC donor, and 1.6-3.7 more Chinese projects each year.

[2] Variance decomposition indicates that the within-country variation accounts for only 2% of the variance in the CPI, which justifies the use of the average CPI.

Table 1: Aggregate Effect of Corruption on Total DF Inflows

	(1)	(2)	(3)	(4)	(5)	(6)
	Total amount				Total count	
(a) DAC DF						
ln $CORRUPT_r$	-1.275*	-1.299	-0.835*	-0.889	-9.053***	-7.946*
	(0.658)	(0.812)	(0.462)	(0.561)	(2.542)	(4.422)
Observations	89,604	54,362	75,620	48,436	89,604	54,362
R^2	0.572	0.633	0.623	0.683	0.385	0.460
(b) Chinese DF						
ln $CORRUPT_r$	5.518	4.161	2.562**	3.195***	3.723*	1.549
	(3.949)	(3.947)	(1.199)	(1.059)	(2.179)	(1.767)
Observations	2,156	1,964	2,156	1,964	2,358	2,149
R^2	0.280	0.338	0.431	0.530	0.306	0.387
Model	OLS	OLS	PPML	PPML	OLS	OLS
Donor×Year FE	✓	✓	✓	✓	✓	✓
Recipient controls	✓	✓	✓	✓	✓	✓
Recipient×Donor controls		✓		✓		✓

Panel (a) depicts the results for bilateral DF flows from DAC donors. Panel (b) shows those from China. In all specifications, standard errors are clustered at the recipient level. The dependent variable is the log of 1+ total DF amount for columns (1) and (2), total DF amount for columns (3) and (4), and total count of DF projects for columns (5) and (6). DAC institutions are excluded in the sample for columns (2), (4), and (6) due to the lack of recipient by donor controls. For PPML estimations, the pseudo R^2 is reported.

FACT 2: *China's share of the total DF amount is positively correlated with recipient corruption.*

Panel regression. To study corruption effect on recipients' reliance on Chinese DF relative to DAC DF, I use OLS to estimate:

$$SHARE_{rt}^{CHN} = FE_t + \beta \cdot CORRUPT_r + \mathbf{X}_{rt} \cdot \gamma + constant + \epsilon_{rt}.$$

Here, $SHARE_{rt}^{CHN}$ represents China's percentage share of the total DF amount used by recipient country r in year t. FE_t denotes time fixed effects. $\mathbf{X}_{rt}$ includes recipient-level controls, including r's bilateral relationships with China. β captures the effect of a one-unit increase in corruption, as measured by the Corruption Perception Index, on a country's reliance on Chinese DF compared to DAC DF.

Estimates in columns (1) and (2) of Table 2 indicate that a ten-point increase in the corruption index is associated with an increase in the share of Chinese DF by approximately 5.7%p. In columns (3) and (4), the sample is restricted to observations where China's share ranges from 0 to 100 percent, ensuring that both DAC and Chinese DF are used. This yields qualitatively similar results, with the coefficient even stronger at 0.64. These findings suggest that the results are not driven by outliers where a recipient country relies exclusively on either Chinese or DAC DF.

Table 2: Aggregate Corruption Effect on China's Share of Total DF Inflows

	Full sample		If $SHARE_{rt}^{CHN} \in (0, 100)$	
	(1)	(2)	(3)	(4)
$CORRUPT_r$	0.575***	0.562***	0.675***	0.644***
	(0.157)	(0.154)	(0.188)	(0.179)
Observations	1,960	1,960	1,542	1,542
R^2	0.184	0.234	0.196	0.237
Year FE & Recipient controls	✓	✓	✓	✓
Recipient×Donor controls		✓		✓

Note: The dependent variables are China's percent share in total DF inflow for each recipient-year pair. Standard errors are clustered at the recipient level. Columns (1) and (2) include all observations. In columns (3) and (4), samples are restricted to observations where China's share ranges from 0 to 100 percent, ensuring that both DAC and Chinese DF are represented.

Cross section regression. To further explore the long-term corruption effect on recipients' reliance on Chinese DF, I conduct the following cross-section regression:

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

where $SHARE_r^{CHN}$ represents the total amount of Chinese DF used by recipient r from 2000 to 2021, divided by the total DF amount from all donors over the same period. $\mathbf{X}_r$ includes recipient-level controls, such as the initial log GDP per capita in 2000 and the averages of the same controls used in the panel regression from 2000 to 2021. Figure 3 presents a partial regression plot of China's share versus corruption, with statistics from the regression. Each circle represents a recipient country, with the size of the circles reflecting the relative size of total DF usage to GDP ratio. The linear fitted line shows a statistically significant positive slope of 0.7148, with a p-value of 0.018. This indicates that, controlling for other factors, countries with a corruption index 10 points higher relied on Chinese DF 7.2 %p more.

3.2 Project Level Analysis

To investigate why recipient country's corruption is correlated positively with Chinese DF and negatively with DAC DF inflows at the aggregate level, I conduct project-level analyses.

FACT 3: *DF project size is positively correlated with recipient country's corruption, with the largest magnitude observed in Chinese DF projects, whereas the correlation is not significant for DAC projects.*

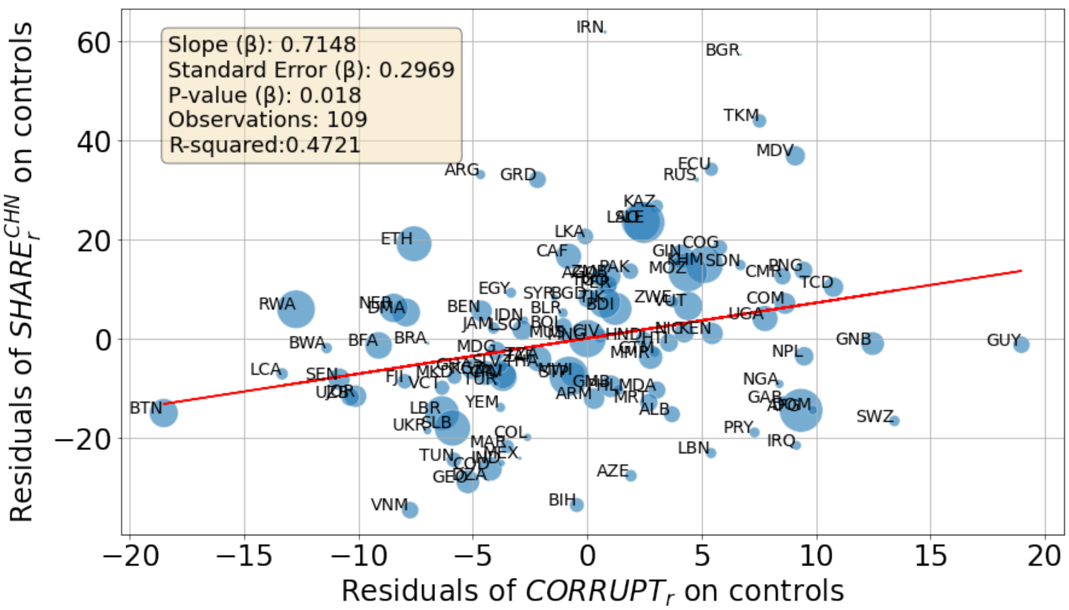


Figure 3: China's Share in Total DF Amount and Recipient Corruption

Note: This figure displays a partial regression plot of China's percent share in total DF amount versus recipient countries' corruption. The slope of the red line represents the OLS estimate of β from the following cross-section regression: $SHARE_r^{CHN} = \beta \cdot CORRUPT_r + \mathbf{X}_r \cdot \gamma + constant + \epsilon_r$. Standard errors are clustered at the recipient level.

Corruption effect on project sizes. It is widely recognized (Mauro, 1996, 1998; Tanzi and Davoodi, 1998) that elevated levels of corruption within the public sector lead to increased public expenditures. This increase is often attributed to cost exaggeration and inefficient resource allocation, driven by diversion motives. Similarly, more corrupt governments might have an incentive to inflate the cost of DF projects, leading to larger project sizes. I test this hypothesis by running a project-level regression:

$$\ln SIZE_i = FE_{d(i)s(i)t(i)} + \beta \cdot \ln CORRUPT_{r(i)} + \mathbf{X}_{r(i)d(i)t(i)} \cdot \gamma + constant + \epsilon_i \tag{1}$$

Here, $SIZE_i$ represents the committed amount for DF project i in constant 2011 USD. Subscripts $r(i)$, $d(i)$, $s(i)$, and $t(i)$ respectively indicate the recipient country, donor, sector, and year associated with project i. $FE_{d(i)s(i)t(i)}$ denotes donor-sector-year fixed effects. $CORRUPT_{r(i)}$ represents the corruption index of project i's recipient country r, averaged over the sample period. $\mathbf{X}_{r(i)d(i)t(i)}$ includes the same control variables used in the country-level analysis, plus a dummy for whether the project is financed by a loan or a grant. ϵ_i represents the error term. I run the regression separately for DAC and Chinese projects.

In Table 3, two results stand out. First, the estimated corruption effect is positive for all donor groups, indicating that higher corruption levels are generally associated with larger project sizes. Second, while the coefficients for DAC projects are neither statistically significant nor large in magnitude (0.102), those for Chinese projects are both statistically significant and substantial. A 1% increase in the corruption index is associated with a 1.5% increase in the size of Chinese projects.

These results suggest that the diversion motive is present to some extent in projects from all donor groups, but it is most pronounced in Chinese projects and moderate for DAC projects. This finding aligns with anecdotal evidence that while DAC donors tend to enforce more rigorous cost-benefit analysis and monitoring, China is comparatively more lenient (Wissenbach and Wang, 2017).

Table 3: Corruption Effect on DF Project Sizes

	DAC projects		Chinese projects	
	(1)	(2)	(3)	(4)
ln $CORRUPT_{r(i)}$	0.219	0.102	0.960**	1.460***
	(0.165)	(0.142)	(0.395)	(0.490)
Observations	1,183,235	1,045,455	7,559	7,559
R^2	0.354	0.265	0.657	0.662
Fixed Effects	Donor×Sector×Year	Donor×Sector×Year	Sector×Year	Sector×Year
Loan dummy & recipient controls	✓	✓	✓	✓
Recipient×Donor controls		✓		✓

Note: The dependent variables are the log of project size in constant 2011 USD. Projects from DAC institutions are excluded in column (2) due to the lack of recipient by donor controls. Standard errors are clustered at the recipient level.

Corruption effect for each donor. To further explore the differential impact of recipient countries' corruption on various donors, I conduct a regression similar to Equation (1), analyzing each donor separately. For country donors, all control variables are included, while recipient-donor controls are omitted for institutional donors. In these donor-by-donor regressions, the donor subscript $d(i)$ becomes redundant. Figure 4 summarizes the results. The Y-axis represents the estimated corruption effect, and the X-axis displays the number of recipient countries that borrowed from each donor from 2000 to 2021. Each circle represents a donor, with the size of the circles indicating the total amount provided by each donor during the same period.

The figure first reveals that China is one of the most significant DF providers in terms of both the total amount and the number of recipient countries. Notably, the estimated corruption effect for Chinese projects is substantially stronger than for all other donors. While some DAC donors also show positive coefficients, these are markedly closer to zero, indicating that Chinese DF projects are particularly affected by the public sector corruption in recipient countries.

FACT 4: *DF project size shows a stronger positive correlation with recipient country's corruption in sectors with less intense monitoring. In these sectors, the correlation is statistically significant even for DAC projects. (For Chinese projects, the magnitude of corruption effect through the interaction with less monitoring is not as large as its main effect.)*

To further investigate the diversion motive behind the corruption effect on project sizes, I exploit the varying levels of monitoring intensity across different sectors. I begin by constructing a new measure of sectoral

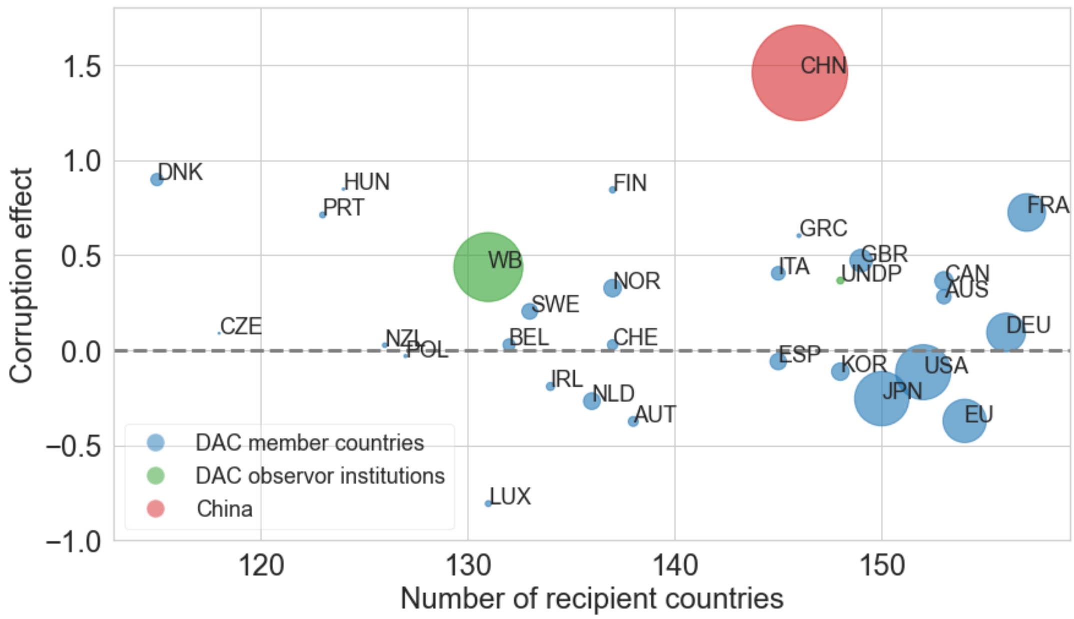


Figure 4: Corruption Effect on the Relative Importance of Each Donor

Note: Each circle represents a donor, and the relative sizes reflect the total amount of DF supplied by each donor from 2000 to 2021. This figure only includes donors that have engaged with more than 100 recipient countries for two reasons: first, the coefficients for other donors are poorly estimated due to limited observations; second, other donors are considered to play a relatively less important role as they are utilized by a smaller set of countries. Figure B.1 depicts all donors used in the analyses. Corruption effect is the OLS estimate of β from $\ln SIZE_i = FE_{d(i)s(i)t(i)} + \beta \cdot \ln CORRUPT_{r(i)} + \mathbf{X}_{r(i)d(i)t(i)} \cdot \gamma + constant + \epsilon_i$.

monitoring intensity. I then demonstrate that the corruption effect on project size is more pronounced in sectors with lower monitoring intensity.

Construction of sectoral monitoring intensity measure. Using individual project evaluation data from the AidData Project Performance Data (PPD), I develop a measure of sectoral monitoring intensity through the following regression:

$$RATINGS_i = FE_{r(i)d(i)t(i)} + \sum_j \gamma_j \cdot D^j_{s(i)} + \mathbf{X}_{r(i)d(i)s(i)t(i)} \cdot \beta + constant + \epsilon_i.$$

Here, $RATINGS_i$ represents a six-point scale rating of DF project i, based on criteria related to efficient implementation and supervision, where a score of 6 indicates the most satisfactory implementation. $FE_{r(i)d(i)t(i)}$ denotes recipient-donor-year fixed effects, which absorb both time-varying and invariant characteristics of recipient countries and donors, including, but not limited to, institutional quality, geography, economic or political relationships, and year-specific effects. $\mathbf{X}_{r(i)d(i)s(i)t(i)}$ includes control variables such as the log of the recipient country's total project amount in each sector, reflecting recipient-sector-specific effects related to sector size. Additionally, dummy variables for evaluator type are included to control for potential biases by evaluating agencies, and the log of project size is also incorporated. $D^j_{s(i)}$ is a dummy variable that indicates whether project i belongs to sector j. Then, γ_j captures the average ratings of projects within each sector, controlling for other effects specific to the recipient, donor, year, evaluator, and project and sector size. I interpret the estimated γ_j values as reflecting the intrinsic difficulty in monitoring each sector, which subsequently influences the efficiency and susceptibility to poor management or misuse of DF projects, and refer to it as "sectoral monitoring intensity."

Table B.1 presents the estimation results for the control variables as well as the F- and χ^2 test results. The tests evaluate the null hypothesis that all coefficients of the sector dummies are jointly zero. The results allow me to reject this null hypothesis under bootstrapping and clustering standard errors at various levels, indicating that sector-specific effects on project ratings are significant.

Figure 5 depicts the OLS estimates of sectoral monitoring intensity along with the distribution of bootstrapped estimates, illustrating the heterogeneity in monitoring intensity across sectors. Three key observations emerge from the analysis. First, there is significant heterogeneity in monitoring intensity across different sectors. Second, sectors that involve unexpected events, in-kind transfers, or short-term projects, such as Emergency Response, Reconstructive Relief & Rehabilitation, Development Food Assistance, and Other Commodity Assistance, rank highly in terms of monitoring intensity. In contrast, sectors involving long-term and large-scale projects, financial transfers, or complex multi-sectoral features, such as Industry, Mining, Construction, Water Supply and Sanitation, Agriculture, Forestry, and Fishing, are ranked at the bottom. This aligns with the conventional wisdom that it is more challenging to divert resources in unexpected, short-term, in-kind projects, whereas it is relatively easier in planned, long-term, large-scale projects involving complex structures and financial transfers, reducing the likelihood of detection. Third, in addition to sectors involving unexpected and unplanned humanitarian projects, the Health and Education sectors also rank highly. This corroborates previous literature indicating that corrupt governments tend to reduce public expenditure on health and education, as these sectors do not offer as many lucrative opportunities for government officials compared to other sectors (Mauro, 1998).

Regression exercises with interaction terms. Using the monitoring intensity measure, I test whether the effect of corruption on project size varies across sectors depending on monitoring intensity. For easier interpretation, I employ a binary version of the monitoring intensity index, classifying sectors into low and high monitoring categories, with the 1st quartile serving as the threshold. To ensure relevance to premeditated misappropriation, I exclude three sectors: Action Relating to Debt, Emergency Response, and Reconstruction Relief & Rehabilitation. Subsequently, I run the following regression, which is identical to the earlier project level regression except for the inclusion of an interaction term:

$$\ln SIZE_i = FE_{d(i)s(i)t(i)} + \beta \cdot CORRUPT_{r(i)} + \delta \cdot CORRUPT_{r(i)} \times LowMonitor_{s(i)} + \mathbf{X}_{r(i)d(i)t(i)} \cdot \gamma + constant + \epsilon_i.$$

$LowMonitor_{s(i)}$ is a dummy variable that takes the value of 1 if project i belongs to one of the low monitoring sectors and 0 otherwise. Its main effect is absorbed by the donor-sector-time fixed effects, and it enters the

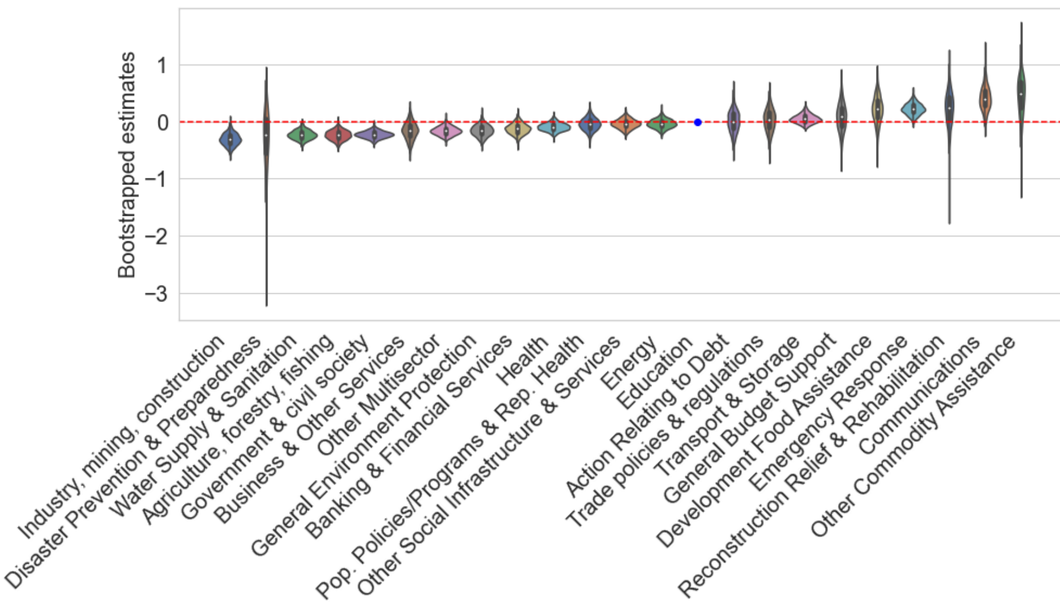


Figure 5: Bootstrapped Estimates of Sectoral Monitoring Intensity

Note: This figure shows the OLS estimate of the sector dummy coefficient from regressing DF project implementation ratings on sector dummies and other controls, along with the distribution of bootstrapped estimates for each sector dummy. The bootstrap simulation is conducted 1,000 times.

model as an interaction term with the corruption index. The coefficient δ captures the "interaction effect" of corruption and low monitoring sectors. Hereinafter, I refer to β as the "main effect" of corruption when I need to distinguish it from the interaction effect.

Table 4 reports the results. The estimated main effect of corruption is similar to the regression without an interaction term. Meanwhile, the coefficient of the interaction term is positive for all donor groups across all specifications, supporting the hypothesis that in sectors with low monitoring intensity, higher corruption leads to an even more inflated project size due to diversion motives. A 1% increase in corruption is associated with an additional 0.35% increase in project size for DAC projects and a 0.45% increase for Chinese projects. Notably, the interaction effect dominates the main effect of corruption for DAC projects, both in terms of magnitude and statistical significance. Conversely, the main effect of corruption on Chinese project sizes is much stronger than its effect through the interaction with low monitoring.

Corruption effect by corruption quartiles. To quantify how the size of DF projects from different donor groups in various sectors differs by recipient countries across different corruption quartiles, and to test whether the corruption effect is pronounced linearly across these quartiles, I employ OLS to run the

Table 4: Corruption Effect on Project Size Through Interaction with Sectoral Monitoring Intensity

	DAC projects		Chinese projects	
	(1)	(2)	(3)	(4)
$\ln CORRUPT_{r(i)}$	0.088	-0.023	0.879**	1.376***
	(0.140)	(0.129)	(0.375)	(0.459)
$\ln CORRUPT_{r(i)} \times LowMonitor_{s(i)}$	0.368**	0.353**	0.466	0.449
	(0.147)	(0.164)	(0.706)	(0.708)
Observations	1,155,291	1,021,935	7,439	7,439
R^2	0.355	0.264	0.658	0.662
Fixed Effects	Donor×Sector×Year	Donor×Sector×Year	Sector×Year	Sector×Year
Loan dummy & recipient controls	✓	✓	✓	✓
Recipient×Donor controls		✓		✓

Note: The dependent variables are the log of project size in constant 2011 USD. Projects from DAC institutions are excluded in column (2) due to the lack of recipient by donor controls. Standard errors are clustered at the recipient level.

following regression:

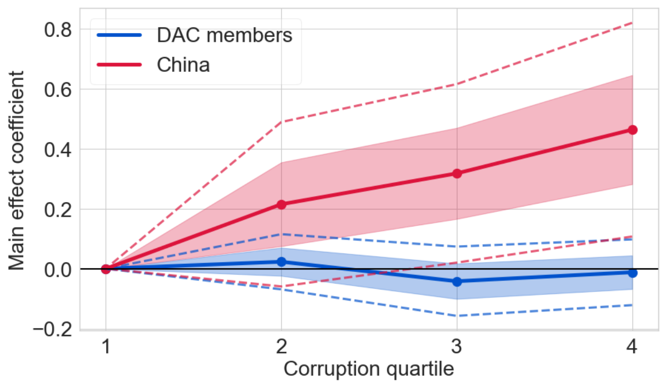
$$\begin{aligned}\ln SIZE_i =& FE_{d(i)s(i)t(i)} + \sum_{q=2}^{4} \beta_q \cdot CORRUPTQ^q_{r(i)} \\ &+ \sum_{q=2}^{4} \delta_q \cdot CORRUPTQ^q_{r(i)} \times LowMonitor_{s(i)} + \mathbf{X}_{r(i)d(i)t(i)} \cdot \gamma + constant + \epsilon_i,\end{aligned}$$

where $CORRUPTQ^q_{r(i)}$ is a dummy variable that takes the value of 1 if recipient r belongs to the qth quartile with respect to the corruption measure among countries included in the previous project size regression. The other predictors are the same as before. Then, β_q measures the percentage by which projects in countries in the qth quartile of corruption are larger compared to those in the least corrupt countries. δ_q captures the additional effect of corruption in sectors with low monitoring intensities.

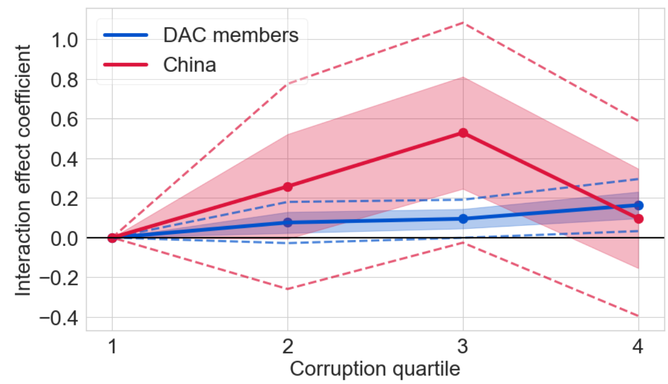
Figure 6 displays the point estimates along with 68% and 90% confidence intervals for the main effects (β_q) and interaction effects (δ_q). Panel (a) reveals that in countries in the most corrupt quartile, project size is, on average, greater by 0.46%, and 0.32% for countries in the third quartile—both statistically significant. Although the effect for the second quartile is not statistically significant, the estimates suggest that the main effect of corruption on Chinese projects is pronounced linearly across all quartiles. Conversely, the main corruption effect for DAC projects is not significantly different from zero across all quartiles, aligning with the qualitative findings from the previous regressions.

Panel (b) shows that in sectors with low monitoring intensity, DAC projects also feature significantly larger project sizes compared to those in the first quartile, with estimates displaying linearity across quartiles. However, the interaction effect for Chinese projects is only statistically significant in the third quartile, and the effects do not demonstrate linearity. These results corroborate the notion that Chinese

DF projects are generally monitored more leniently than those by DAC donors, making them potentially more susceptible to corruption and misappropriation, regardless of the sector. Consequently, the differential effect of corruption across sectors is not as significant as the overall effect of corruption on Chinese projects. In contrast, projects funded by DAC donors generally undergo more intense monitoring and are less susceptible to misappropriation by corrupt governments. However, even DAC projects experience some degree of misappropriation in sectors that are intrinsically difficult to monitor.



(a) Main effect



(b) Interaction effect

Figure 6: Corruption Effect by Corruption Quartiles and Sectoral Monitoring Intensities

Note: Each dot represents the OLS estimate of dummy variables for corruption quartiles and their interaction with binary sectoral monitoring intensity for each donor group. Dashed lines indicate the 90% confidence intervals, and shaded areas represent the 68% confidence intervals. Standard errors are clustered at the recipient level. Table B.2 reports the estimates and regression statistics.

3.3 Sectoral Level Analysis

FACT 5: (a) *At the sectoral level, both the total amount and count of DAC projects are negatively correlated with corruption, while the correlations are positive for Chinese projects.* **(b)** *The negative correlation for DAC projects is mitigated in sectors with less intense monitoring. This interaction effect is not very significant for Chinese projects.*

Sectoral corruption effect on DF inflows. I examine how a recipient country's corruption affects its DF inflows at the sectoral level. To do this, I run the following regression:

$$DF_{rdst} = FE_{dst} + \beta \cdot \ln CORRUPT_r + \delta \cdot \ln CORRUPT_r \times LowMonitor_s + \mathbf{X}_{rdt} \cdot \gamma + constant + \epsilon_{rdst}.$$

Here, DF_{rdst} represents either the total count or log total commitment amount (in constant 2011 USD) of DF projects for recipient country r by donor d in sector s for year t. The other predictors are consistent with those used in the project-level regressions. I employ OLS and PPML for estimation.

Columns (1) and (2) of Table 5 indicate that higher corruption is associated with a smaller total commitment amount and total count of DAC projects at the sectoral level. Given that the corruption effect on project size was estimated to be moderate in the previous analysis, its negative effect on the sector total amount appears to be driven primarily by its impact on the number of projects, as shown in column (5). Conversely, the positive estimates of the interaction effect for the total count, combined with that on project size, contribute to a positive effect on the sector total amount in sectors with low monitoring.

Meanwhile, columns (3), (4), and (6) show that both the total count and amount of Chinese DF projects are positively correlated with corruption through both the main effect and the interaction effect. Given that the main and the interaction effects on Chinese DF counts are not significantly different in column (6), the dominance of the main effect on total amounts in column (4) appears to be driven by the predominance of the main effect on project size.

Table 5: Sectoral Corruption Effect on DF Inflows

	Total amount				Total count	
	DAC DF		Chinese DF		DAC DF	Chinese DF
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln CORRUPT_r$	-1.259***	-1.221***	0.740	2.768**	-0.565**	0.089
	(0.351)	(0.417)	(0.683)	(1.154)	(0.255)	(0.106)
$\ln CORRUPT_r \times LowMonitor_s$	0.781***	1.180	1.373**	2.143	0.620***	0.101
	(0.241)	(0.990)	(0.541)	(1.893)	(0.211)	(0.099)
Observations	932,092	732,884	34,547	30,674	932,092	36,637
R^2	0.463	0.574	0.157	0.497	0.294	0.311
Model	OLS	PPML	OLS	PPML	OLS	OLS
Donor×Sector×Year FE	✓	✓	✓	✓	✓	✓
Recipient, Recipient×Donor controls	✓	✓	✓	✓	✓	✓

Note: The dependent variables are the log of 1 + total DF commitment amount for each recipient-donor-sector-year pair in constant 2011 USD for columns (1) and (3), total DF amount for columns (2) and (4), and total count for columns (5) and (6). Standard errors are clustered at the recipient level.

FACT 6: (a) *At the sectoral level, China's share of the total DF amount is positively correlated with recipient corruption.* **(b)** *The magnitude of this correlation does not significantly increase in sectors with less intense monitoring.*

Lastly, I quantify the sectoral corruption effect on China's share by estimating a panel regression:

$$SHARE^{CHN}_{rst} = FE_{st} + \beta \cdot CORRUPT_r + \delta \cdot \ln CORRUPT_r \times LowMonitor_{s(i)} + \mathbf{X}_{rt} \cdot \gamma + constant + \epsilon_{rst}.$$

Here, $SHARE^{CHN}_r$ indicates China's percentage share of the total DF used by recipient r in sector s in year t. β and δ capture the sectoral main effect and interaction effect of corruption, respectively. Table 6 summarizes the results. In panels (a) and (b), all observations are included, while in panels (c) and (d), the sample is restricted to observations with nonzero use of both Chinese and DAC DF. The estimates imply that a ten-point increase in the corruption measure is associated with an increase in China's amount share by approximately 1.1%p with the full sample and 4.2%p with the restricted sample, aligning with the effects at the aggregate level. However, the corruption effect through interaction with low monitoring intensity is not significant. With full samples, the estimates are not statistically significantly different from zero. Although the estimates are statistically significant with restricted samples with a negative sign, the magnitude is not economically as significant as the main effect.

Table 6: Sectoral Corruption Effect on China's Share of Total DF Inflows

	Full sample		If $SHARE^{CHN}_{rt} \in (0, 100)$	
	(1)	(2)	(3)	(4)
$CORRUPT_r$	0.132***	0.109***	0.436***	0.416***
	(0.048)	(0.041)	(0.137)	(0.144)
$CORRUPT_r \times LowMonitor_s$	-0.005	-0.005	-0.093***	-0.093***
	(0.005)	(0.005)	(0.025)	(0.024)
Observations	34,548	34,548	4,160	4,160
R^2	0.022	0.027	0.095	0.100
Sector×Year FE & Recipient controls	✓	✓	✓	✓
Recipient×Donor controls		✓		✓

Note: Dependent variables are China's percent share in total DF inflow for each recipient-sector-year pair. Standard errors are clustered at the recipient level. Columns (1) and (2) include all observations. In columns (3) and (4), samples are restricted to observations where China's share ranges from 0 to 100 percent, ensuring inclusion of both DAC and Chinese DF.

3.4 Taking Stock and Potential Explanation

The findings support the hypothesis that public sector corruption and the diversion motive of recipient governments are significant drivers of global development finance (DF) flows. This can be explained by the varying monitoring intensity among DF providers and sectors. There is anecdotal evidence suggesting that Chinese DF is monitored more leniently compared to DAC DF. If a government with a misappropriation motive must choose between two donors, it would prefer the one with less stringent monitoring. Consequently, more corrupt countries are likely to have a greater number of projects from the lenient donor and fewer projects from the stricter donor (FACT 1 and 5a). This suggests that projects from strict DAC donors are more likely to be allocated to cleaner countries with weaker misappropriation motives. The selection of countries with stronger diversion motives and the inflation of project sizes due to less stringent monitoring lead to a significantly positive correlation between Chinese project sizes and corruption, while the opposite effects result in an insignificant correlation between DAC project sizes and corruption (FACT 3). Meanwhile, although DAC projects are generally strictly monitored, certain sectors that are intrinsically difficult to monitor might still offer lucrative opportunities for diversion. In these sectors, corruption could be positively correlated with DAC project size. This additional corruption effect may also be present in Chinese projects. However, since Chinese projects are generally monitored more leniently, the variation in sectoral monitoring intensity might not significantly influence overall Chinese projects. This is reflected in the data as a significant correlation of the interaction effect between corruption and monitoring intensity on project size and count for DAC, dominating the main effect, while the main effect is much more pronounced than the interaction effect for Chinese projects (FACT 4 and 5b).

At the aggregate level, the strict monitoring of DAC projects and lenient monitoring of Chinese DF, along with the resultant sorting of more corrupt countries towards Chinese DF and associated project size inflation, lead to a negative correlation of recipient corruption with total DAC DF amount and a positive correlation with Chinese DF amount (FACT 1). This pattern also suggests that more corrupt countries rely more heavily on Chinese DF compared to DAC DF (FACT 2). This effect on relative reliance on Chinese DF is likely to manifest at the sectoral level as well (FACT 6a). However, the corruption effect through interaction with low monitoring intensity is not likely to be observed for the China's share at the sectoral level (FACT 6b). This is because the ratio of the two DF sources is determined by the *gap* in monitoring intensity between them, not just the general level of monitoring in a sector. A sector with generally less monitoring does not necessarily correspond to a sector that features a wider gap in monitoring between China and DAC.

An alternative narrative could be a supply-side story where the DAC rations recipients based on corruption and the resulting default risk. However, it is unlikely that this explanation primarily drives the empirical results. First, in all analyses, I include the recipient country's external debt stock to GDP and public and publicly guaranteed debt stock to GDP, which might better capture debt stress and default risk. Second, since many DAC DF projects are concessional and include grant components, it is less likely that DAC DF flows are primarily driven by default risk and expectations of returns. Third, while this narrative might explain the negative correlation of corruption with aggregate DAC flows and the positive correlation with China's share, it cannot account for the project-level and sectoral findings. Another potential explanation could involve the importance of bilateral political or economic ties between donors and recipients. I control for these factors as well by including a range of bilateral control variables. These factors also do not sufficiently explain the project- and sectoral-level findings.

Although the empirical findings strongly support the corruption and diversion narrative as a significant driver of global development finance (DF) allocation, they do not rule out another prevalent narrative in the literature: that Chinese DF can mitigate the limited availability of DAC DF, particularly in certain sectors. In the subsequent model section, inspired by the empirical findings, I incorporate both the diversion motive and the heterogeneous monitoring by DF providers and sectors. Simultaneously, I also consider the possibility that Chinese DF can alleviate the limited availability of DAC DF.

3.5 Robustness Checks

2SLS with an instrument variable. There is a possibility that the Corruption Perception Index (CPI) used in the main analysis might be correlated with some omitted variables or might suffer from reverse causality. To check the robustness of the main findings, I employ an instrumental variable approach. Following Acemoglu et al. (2001), I use settler mortality in recipient countries during the colonial era as an instrument for corruption. This exercise qualitatively confirms the baseline results that recipient corruption is positively correlated with Chinese project size, an effect not pronounced for DAC projects. For detailed methodology and estimation results, see Table B.3.

Outlier treatments. In the baseline analysis of project size, I include all observations of projects with a positive commitment amount. To test the robustness of the main results and explore whether they are influenced by outliers, I vary the treatment of outliers. Table B.4 reports the estimated corruption effect when outliers are winsorized at 1%, at 2%, and trimmed at 1% and 2%. The results are not qualitatively different.

Alternative corruption measure. In the main analysis of project size, I use the average Corruption Perception Index (CPI) of recipient countries over the sample period. To confirm the robustness, I use the raw normalized CPI over 2000-2021, the old CPI averaged over 2000-2011, and the new CPI averaged over 2012-2021. Table B.5 shows that the estimates are qualitatively similar to the baseline results.

Alternative monitoring intensity measure. In the main text, I use a binary version of sectoral monitoring intensity for straightforward interpretation. Table B.6 confirms that the baseline findings are qualitatively robust to alternative monitoring intensity measures, including a continuous one.

Placebo test. The significant estimates of the interaction between corruption and sectoral monitoring intensity for DAC projects might be capturing the interaction effects of sectoral monitoring intensity with other recipient characteristics correlated with corruption. To address this possibility, I conduct a placebo test that includes various interactions between other control variables and sectoral monitoring intensity. Table B.7 shows that in all specifications, the interaction effect of corruption is significantly positive. Table B.8 reports the coefficients of all placebo interaction terms.

Direct measure of misappropriation risk. I replace the Corruption Perception Index (CPI) with indices that more directly measure the public sector diversion risk in recipient countries. While the CPI is a holistic measure of public sector corruption, it may capture aspects not directly relevant to diversion. To ensure that the main results are driven by diversion motives, I use the Public Corruption Index and the

Executive Corruption Index from V-Democracy. These indices specifically measure the prevalence of misappropriation and bribery in the public sector and among executives, respectively. I repeat the interaction regression with these alternative measures and confirm the baseline results. Table B.9 reports these results.

Additional controls. I test the robustness of the baseline results at the project, sectoral, and country levels by including additional control variables. These variables were not used in the main analyses due to their limited availability across a significant number of countries or years. I include the log of the total public capital stock to control for potential differential effects by the relative size of the public sector, the capital openness index from Chinn and Ito (2008) to account for the effect of recipient countries' capital control policies on DF flows, and the Polity IV score to control for the impact of the degree of democracy on DF flows. Table B.10 reports the results, indicating that the main findings are qualitatively unaffected.

4 A Growth Model of Public Corruption and Development Finance

I develop a novel variant of the Neoclassical growth model that incorporates public sector corruption and the strategic use of DF from both the DAC and China across various sectors. This model is designed to: 1) provide theoretical insights consistent with the stylized facts outlined in Section 3, particularly regarding the correlation between corruption and the size of development finance projects from different sources and sectors; 2) derive macroeconomic implications at the aggregate level, focusing on the impact of corruption on public capital efficiency and on the efficient use of DF; and 3) create a rich framework for quantitative analysis to evaluate the impact of Chinese DF on household welfare across developing countries.

4.1 Model Environment

Time is discrete, indexed by t, and spans from 0 to infinity. The economy is a small open economy that produces a single good using private capital, public capital, and labor as inputs. It comprises two main sectors: 1) the standard private sector where a measure-one population of infinitely-lived identical households own and provide private capital and labor, and also own firms that produce output; and 2) the public sector where the government invests in public capital through differentiated public projects. The government has access to the international development finance (DF) market, securing funding for each public project at risk-free interest rates from the DAC and China. There is no default. The private sector does not have access to international financial market.

4.1.1 Private Sector

Household. The representative household derives utility from consuming a single good, represented by the utility function $U(C)$, and discounts future utility with $\beta \in (0,1)$. The lifetime utility is given by:

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

where $U' > 0$ and $U'' < 0$. 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 t. The household supplies labor inelastically at a constant rate $L_t = L$ and rents capital to the firm each period, which it also owns, and receives all the firm's profits.

Firm. The firm uses the following Cobb-Douglas technology to produce output Y using private capital (K), labor (L), and effective public capital (G^E):

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

where α and γ are the output elasticities of private capital and effective public capital, respectively, and A is total factor productivity. The firm takes the amount of effective public capital G^E, provided for free by the government, as given. After paying for the use of labor and private capital, the residual output is returned to the household as profit. In existing works, the effective public capital is usually assumed to be in the form of ΘG where G is the book value of public capital and Θ is an exogenous efficiency parameter. In my model, the counterpart to Θ is endogenously determined through a government's optimization given global DF environment, which I discuss in Section 5.

4.1.2 Public Sector

The public sector is managed by the government which potentially plays two roles. First, the government implements fiscal policy to influence household consumption and private capital accumulation. Second, it accumulates and provides public capital to the private sector. Since this paper primarily focuses on the government's role as a provider of public capital, I abstract from the fiscal role and study the government's planning problem in which it directly chooses household consumption and saving.

Accumulation of effective public capital. There are N subsectors that make up the public sector. Let $\mathcal{S} = \{s_1, s_2, \ldots, s_N\}$ denote the set of subsectors. Within each $s \in \mathcal{S}$, there is a continuum of differentiated public projects with measure one. The government accumulates effective public capital in each project. Let $g_{s,j,t}^E$ denote effective public capital stock in project j in sector s in period t. It follows the law of motion: $g_{s,j,t+1}^E = (1-\delta_G) \cdot g_{s,j,t}^E + I_{s,j,t}^E$ where δ_G is depreciation rate of public capital and $I_{s,j,t}^E$ is investment in j.

Provision of effective public capital. In each period, the government aggregates the public capital in all public projects and provides it to the private sector without any fee. The aggregation features two layers. First, the effective final public capital G_t^E, which enters the firm's production function, is a Cobb-Douglas composite of the effective public capital in each subsector $G_{s,t}^E$:

$$G_t^E = \prod_{s \in S} (G_{s,t}^E)^{\gamma_s},$$

where γ_s denotes the sector s share within the public sector ($\sum_{s \in \mathcal{S}} \gamma_s = 1$). Second, $G_{s,t}^E$ is a Constant Elasticity of Substitution (CES) aggregation of effective public capital in all projects within s. Let $\mathcal{J}_s$ denote the set of differentiated public projects within sector s. Then,

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

where $\sigma > 1$ is the elasticity of substitution between various projects within a sector, and θ_j denotes project-specific productivity. My modeling approach of public capital at the project- and sectoral level complements the existing works that usually treat public capital as a monolithic input.

Financing of public capital. The government can fund its public projects through international development finance (DF) loans.[3] DF loans are one-period debt contract with a fixed risk-free interest rate. The government should repay all the outstanding DF debt in each period and can issue new debt to refinance its projects for next period. 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. Based on observation in data, $1 < R_s^D < R_s^C < \frac{1}{\beta}$ for all $s \in \mathcal{S}$, reflecting the concessional nature of DF and that DAC DF is more concessional than Chinese DF. The economy is small in the DF market so it is not subject to any aggregate DF supply constraint. DF loans are contracted at project level and earmarked for each specific project. Let $d_{s,j,t}^D$ and $d_{s,j,t}^C$ denote the debt stock for financing project j in sector s, owed to the DAC and China, respectively, measured at the beginning of period t.

The government can divert some portion of the funds borrowed through each DF contract for its own good. Let $g_{s,j,t}^X$ denote the amount of diverted funds from all the outstanding DF debt stocks for project j in period t. For each j, DF providers cannot fully distinguish between the portion that goes into the effective public capital $g_{s,j,t}^E$ and the diverted portion $g_{s,j,t}^X$. However, they can fully verify whether the borrowed funds are earmarked for a designated project and are not used for other projects, household

[3] In practice, another major source of DF is DAC grants, which consist of many small projects that do not need to be repaid. Due to their non-repayable nature, this section focuses on DF loans. In the quantitative analysis in Section 6, I incorporate DAC grants to improve the quantitative fit, ensuring that the main theoretical results are not qualitatively affected by the inclusion of DAC grants.

consumption or private investment. Hence, the government faces the "non-fungibility constraint" for j:

$$g^E_{s,j,t} + g^X_{s,j,t} \geq d^D_{s,j,t} + d^C_{s,j,t}.$$

It implies that the book value for j should not be less than the total outstanding DF debt for the project.

The DAC and China can verify that $\psi^D_s \in (0,1]$ and $\psi^C_s \in (0,1]$ fractions, respectively, of their DF contract go into $g^E_{s,j,t}$. ψ^D_s and ψ^C_s are the sector-specific monitoring intensities of each provider. Hence, the government faces an additional "monitoring constraint" for j:

$$g^E_{s,j,t} \geq \psi^D_s d^D_{s,j,t} + \psi^C_s d^C_{s,j,t}.$$

In other words, it can divert only up to $1-\psi^D_s$ and $1-\psi^C_s$ fractions of a DAC and a Chinese DF contract, respectively. Based on the empirical analysis, I assume $\psi^D_s \geq \psi^C_s$ for all $s \in \mathcal{S}$.

In addition, issuing new DF debt each period incurs fixed costs f^D_s and f^C_s for DAC and Chinese DF, respectively, in sector s. They capture costs related to negotiation, legal compliance, administration, monitoring, reporting, transfer of natural resources to the provider, payment to the provider's inputs and other expenses that are not explicitly modeled in the paper. Such fixed costs reflect each provider's internal policy against the borrowing country in each sector, potentially based on the bilateral political, diplomatic, social or economic relationship.

Government's utility. The government has its own period utility function $\tilde{U}(C, G^X; \chi)$, with $\tilde{U}'_C > 0$, $\tilde{U}''_C < 0$, and $\tilde{U}'_{G^X} > 0$, where C is the representative household's consumption, and G^X is the total amount of diverted funds, defined as $G^X_t \equiv \sum_{s\in\mathcal{S}} \int_{j\in\mathcal{J}_s} g^X_{s,j,t} dj$. The corruption parameter $\chi \geq 0$ captures the extent to which the government values diverted public capital. A higher χ indicates a greater value placed on diversion, reflecting higher corruption. The function satisfies:

1. $\tilde{U}(C, G^X; \chi = 0) = U(C)$: If $\chi = 0$, the government's period utility is the same as the household's.
2. $\dfrac{\partial^2 \tilde{U}}{\partial \chi \partial G^X} > 0$: The marginal utility of diversion is increasing in χ.

4.2 Government's Planning Problem and Optimal Allocation

Timing. The timing in the government's planning problem is as follows. At the beginning of each period t, public projects materialize according to the government's public investment and DF decisions in the previous period. The government aggregates effective public capital in all projects and provides it to the private sector. At the same time, it consumes the diverted portions from each project, if any. Then, the firm produces output Y_t using existing private capital, effective public capital and labor. The government pays down all the outstanding debt to the DAC and China including the interests and fixed costs, out of the output and the remaining private capital and effective public capital after depreciation. It then issues new DF debts to finance its public projects in the next period. In doing so, it assigns some portion to the effective public capital and the rest to diversion. It also makes consumption and private investment decision and the household consumes as much as the government assigns. Period t ends.

Planning problem. Let $\mathbf{g}_t^E = \{g_{s,j,t}^E\}_{j\in\mathcal{J}_s, s\in\mathcal{S}}$, $\mathbf{g}_t^X = \{g_{s,j,t}^X\}_{j\in\mathcal{J}_s, s\in\mathcal{S}}$,$\mathbf{d}_t^D = \{d_{s,j,t}^D\}_{j\in\mathcal{J}_s, s\in\mathcal{S}}$, and $\mathbf{d}_t^C = \{d_{s,j,t}^C\}_{j\in\mathcal{J}_s, s\in\mathcal{S}}$ denote the vectors of effective public capital, diverted funds, the DAC debt stock, and Chinese debt stock in period t for all public projects. And let $\mathbb{I}_{s,j,t}^p$ be an indicator that takes the value of one if $d_{s,j,t}^p > 0$ for provider $p \in \{D, C\}$ and zero otherwise. The government's planning problem and optimal allocation are defined as follows.

Definition 1. (Government's Planning Problem and Optimal Allocation). Given the model environment, the "government's planning problem" is defined as:

$$\max_{\{C_t, K_{t+1}, \mathbf{g}_{t+1}^E, \mathbf{g}_{t+1}^X, \mathbf{d}_{t+1}^D, \mathbf{d}_{t+1}^C\}_{t=0}^{\infty}} \quad \sum_{t=0}^{\infty} \beta^t \cdot \tilde{U}(C_t, G_t^X; \chi)$$

$$\begin{aligned}
\text{subject to} \quad & \text{(RC): } C_t + I_t^K + \sum_{s\in\mathcal{S}} \int_{j\in\mathcal{J}_s} (I_{s,j,t}^E + G_{s,j,t+1}^X + R_s^D d_{s,j,t}^D + R_s^C d_{s,j,t}^C + \mathbb{I}_{s,j,t}^D f_s^D + \mathbb{I}_{s,j,t}^C f_s^C) dj \\
& = Y_t + \sum_{s\in\mathcal{S}} \int_{j\in\mathcal{J}_s} (d_{s,j,t+1}^D + d_{s,j,t+1}^C) dj, \\
& \text{(NF): } g_{s,j,t}^E + g_{s,j,t}^X \geq d_{s,j,t}^D + d_{s,j,t}^C, \\
& \text{(MC): } g_{s,j,t+1}^E \geq \psi_s^D d_{s,j,t+1}^D + \psi_s^C d_{s,j,t+1}^C, \\
& \text{(NX), (ND), (NC): } g_{s,j,t+1}^X \geq 0,\ d_{s,j,t+1}^D \geq 0,\ d_{s,j,t+1}^C \geq 0, \\
& \text{for all } t, s \in \mathcal{S}, j \in \mathcal{J}_s, \ \text{given } k_0, \mathbf{g}_0^E, \mathbf{g}_0^X, \mathbf{d}_0^D, \mathbf{d}_0^C,
\end{aligned}$$

The "government's optimal allocation" is a sequence $\{C_t, K_{t+1}, \mathbf{g}_{t+1}^E, \mathbf{g}_{t+1}^X, \mathbf{d}_{t+1}^D, \mathbf{d}_{t+1}^C\}_{t=0}^{\infty}$ that solves the government's planning problem.

(RC) is the economy-wide resource constraint where the left-hand side consists of household consumption, private investment, public investment and diversion, and DF payments, while the right-hand side consists of output and new DF issuance. (NF) and (MC) are the non-fungibility and monitoring constraints. (NX), (ND), and (NC) are non-negativity constraints for diverted funds, the DAC debt stock, and Chinese debt stock, respectively. Note that (MC) and (NX) cannot bind at the same time.

4.3 Characterization of the Government's Optimal Allocation

To characterize the optimal allocation, I assume the following forms of utility functions. The household has log utility, $U(C) = \ln C$. The government's period utility takes a Greenwood-Hercowitz-Huffman

(GHH, Greenwood et al. (1988)) form, $\tilde{U}(C, G^X; \chi) = \ln\big(C + \chi \cdot G^X\big)$. The GHH form allows for a tractable closed-form solution, as the marginal utility of diversion relative to that of consumption is constant and equal to the corruption parameter χ. I first characterize the optimal size and financing of public capital at the project level, then at the sectoral level, and finally the aggregation of public projects.

4.3.1 Government's Optimal Financing at the Project Level

I focus on allocations in which the non-fungibility constraints always bind. In other words, all public projects are financed fully by DF. Sufficient condition for such allocations is $f_s^S \geq \min\{f_s^D, f_s^C\}$ where f_s^S denotes fixed cost for operating a project in sector s with self-financing. Intuitively, together with $R_s^D < R_s^C < 1/\beta$, it implies that self-financing is costlier than DF-financing both in terms of fixed cost and marginal cost. In the quantitative analysis (Section 6), I relax the condition in the sectors that are not eligible for DF.

The following lemmas and proposition then determine the government's optimal size and financing of each project.

Lemma 1. In an optimal allocation, each public project is financed by a single DF provider.

Proof. See Appendix C.1. □

The intuition behind Lemma 1 stems from the fact that the government faces constant marginal costs when borrowing from each DF provider. These costs consist of the interest rate, adjusted for the marginal benefit from diversion, which depends on monitoring intensity and the marginal utility of diversion relative to household consumption. Under GHH preference, the relative marginal utility is constant as χ. Since both interest rates and monitoring intensities are also constant, the government compares these constant costs and chooses a cheaper option. As a result, it is not optimal to borrow from more than one provider for the same project, as doing so would also incur additional fixed cost.

Lemma 2. For each project, the government chooses either maximal or zero diversion except for a knife-edge case where $\chi = R_s^p$ for a provider $p \in \{D, C\}$:

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

Proof. See Appendix C.2. □

Lemma 2 is also based on the fact that the relative marginal utility of diversion to household consumption is constant as χ under GHH preference. The government compares χ with the interest rate which is also constant. If χ exceeds the interest rate, it is optimal to maximally divert the DF, causing the monitoring constraint to bind; if χ is lower, diversion is too costly for the government, and minimal diversion is optimal. In a knife-edge case, I assume that the government chooses maximal diversion.

Lemma 3. Optimal size of effective public capital in each project, financed by p, equates the marginal benefit to the government to the interest rate:

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

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

Proof. See Appendix C.3, also for Corollary 1. □

Lemma 3 is derived by combining the first order conditions for the effective public capital in project j and for the DF debt stock in the project. It shows that when the government is not highly corrupt ($\chi < R^p_s$), the optimal project size is determined by equating the total return on project j to the interest rate. If the government is sufficiently corrupt ($\chi \geq R^p_s$), the marginal benefit consists of two components: ψ^p_s fraction from total return on the project, and $1 - \psi^p_s$ fraction from the marginal utility of diversion, χ. It is convenient to define the effective marginal cost for the government 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 defined as the interest rate adjusted for capital retention after depreciation and the marginal utility of diversion:

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

Then, Corollary 1 simplifies Lemma 3.

Corollary 1. 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 the same for all projects with the same productivity within the same sector. Hence, I define $mpg^E_{s,t+1}(\theta)$ as a function of project productivity. Next, I define the effective profit as follows.

Definition 3. (Effective Profit for the Government). The government's effective profit from a project with productivity θ, when financed by p, $\tilde{\pi}^p_{s,t+1}(\theta)$, is the total 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 the effective profit depends on by which provider the project is financed and is increasing in project productivity θ. The following proposition pins down the optimal financing for each project.

Proposition 1. (Optimal Financing at the Project Level). In an optimal allocation, for each project, the government chooses a DF provider that maximizes the effective profit from the project.

Proof. See Appendix C.4. □

Proposition 1 shows that the government selects the DF provider that maximizes the project's contribution to final output, considering interest rates, fixed costs, and any additional utility from diverting the DF. To graphically illustrate the proposition, I define some productivity cutoffs similarly to the exporting firms model in Melitz (2003).

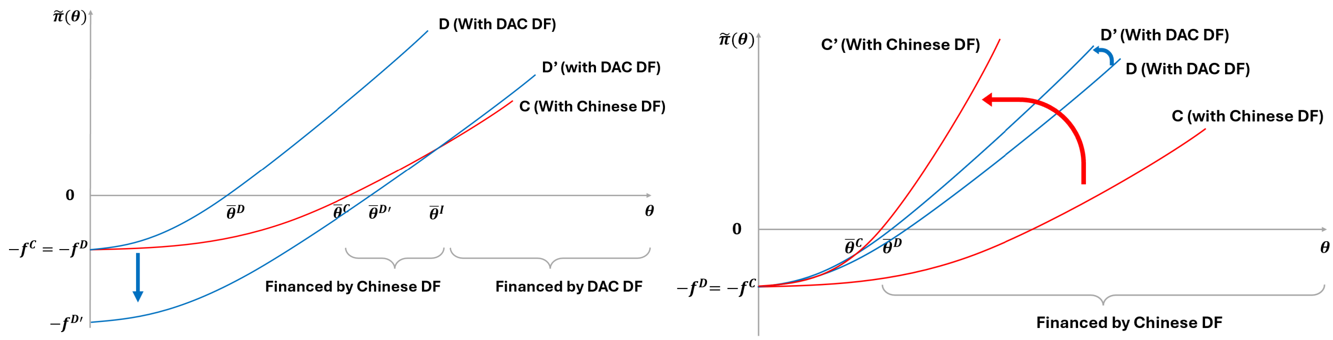
Definition 4. (Zero Profit Cutoffs). For a DF provider p, the zero-profit cutoff, $\bar{\theta}^{p}_{s,t}$, is the productivity at which the government's effective profit is zero: $\tilde{\pi}^{p}_{s,t}(\bar{\theta}^{p}_{s,t}) = 0$

Definition 5. (Financing Indifference Cutoff). The financing indifference cutoff, $\bar{\theta}^{I}_{s,t}$, is the productivity at which the government is indifferent between the 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 7 illustrates optimal financing of projects with different productivity θ within a sector in some examples. First, suppose that the government chooses zero diversion both with the DAC and Chinese DF and that the fixed costs are the same for the two providers. Then, since the interest rate for the DAC DF is lower than the Chinese, the effective profit curve for the DAC DF (D) will be above that for Chinese DF (C) for all $\theta > 0$ as in Figure 7a. In this case, all projects with productivity greater than the DAC zero-profit cutoff ($\bar{\theta}^{D}$) are financed by the DAC DF. Projects with productivity below the cutoff are not operated.

Now, suppose that fixed cost for the DAC DF is sufficiently greater than that for the Chinese DF. Then, the DAC effective profit curve shifts downward to D' and it crosses the China effective profit curve at the financing indifference cutoff $\bar{\theta}^{I}$. In this case, projects with $\theta \in [\bar{\theta}^{I}, \infty)$ are financed by the DAC DF and projects with $\theta \in [\bar{\theta}^{C}, \bar{\theta}^{I})$ are financed by Chinese DF.

Figure 7b depicts the cases when the government chooses maximal diversion for both DF. Compared to zero-diversion cases, the effective profit curves become steeper as the extra marginal utility from diversion lowers the effective marginal costs. If monitoring intensity for the DAC is sufficiently higher than that for Chinese DF, such decrease in the effective marginal cost is even greater for the Chinese DF and the effective profit curves rotate from C to C' and from D to D'. In this case, all projects with $\theta \in [\bar{\theta}^{C}, \infty)$ are financed by Chinese DF and the DAC DF is not used. In general, optimal financing of each project is determined by its productivity, the government's corruption, and the relative DF characteristics including the interest rates, monitoring intensities, and fixed costs.



(a) Zero diversion and different fixed costs

(b) Maximal diversion and the same fixed costs

Figure 7: Optimal financing of each project

4.3.2 Government's Optimal Financing at the Sectoral Level

Now, I characterize optimal financing at the sectoral level. The following lemma shows how each sector is financed depending on the effective marginal costs $\tilde{R}^p_s$ and the fixed costs f^p_s.

Lemma 4. For sector s, without loss of generality, suppose $\tilde{R}^p_s < \tilde{R}^{p'}_s$. If $f^p_s \leq (\tilde{R}^{p'}_s/\tilde{R}^p_s)^{\sigma_s-1} \cdot f^{p'}_s$, all operating projects in sector s are financed by p, with only those with productivity $\theta \geq \bar{\theta}^p_{s,t}$ operating. If $f^p_s > (\tilde{R}^{p'}_s/\tilde{R}^p_s)^{\sigma_s-1} \cdot f^{p'}_s$, only projects with $\theta_s \geq \bar{\theta}^{p'}_{s,t}$ operate. In this case, projects with $\theta_s \in [\bar{\theta}^{p'}_{s,t}, \bar{\theta}^I_{s,t}]$ are financed by p', while those with $\theta \in [\bar{\theta}^I_{s,t}, \infty)$ are financed by p

Proof. See Appendix C.5. □

Lemma 4 highlights the trade-off between the relative effective marginal costs and fixed costs of the two DF sources. If p features a lower effective marginal cost ($\tilde{R}^p_s < \tilde{R}^{p'}_s$) and its fixed cost is also not too high relative to p''s, it is optimal to finance all projects using p. However, if p has a lower marginal effective cost but a sufficiently higher fixed cost than p', a trade-off arises. The higher fixed cost of p is a constant disadvantage, but the advantage of p's lower marginal effective cost increases with project productivity. Consequently, projects with productivity above a certain threshold (the financing indifference cutoff, $\theta^I_{s,t}$) are financed by p, while those below this threshold are financed by p'.

In turn, the following proposition characterizes optimal financing at the sectoral level.

Proposition 2. (Optimal Financing at the Sectoral Level). Let $\mathcal{S}^{pp'}$ denote the set of sectors where projects with $\theta \geq \bar{\theta}^I$ are financed by p, and projects with $\theta < \bar{\theta}^I$ are financed by p'. And let $\mathcal{S}^p$ denote the set of sectors where all projects with $\theta \geq \bar{\theta}^p$ are financed by p. A superscript with a tilde ($\tilde{}$) indicates that projects financed by the provider are subject to maximal diversion, while one without a tilde indicates zero diversion. Each sector is in one of the seven: $\mathcal{S}^D, \mathcal{S}^{DC}, \mathcal{S}^{\tilde{D}}, \mathcal{S}^{\tilde{D}C}, \mathcal{S}^{\tilde{D}\tilde{C}}, \mathcal{S}^{\tilde{C}}$ and $\mathcal{S}^{\tilde{C}\tilde{D}}$.

Proof. See Appendix C.6 for the full proposition and its proof. □

Figure 8 illustrates the proposition graphically. The vertical axis is the disadvantage of the DAC DF in terms of fixed costs relative to Chinese DF, f_s^D/f_s^C, and the horizontal axis is the government's corruption parameter. The black line is the advantage of the DAC DF in terms of effective marginal cost relative to Chinese DF, $(\tilde{R}_s^C/\tilde{R}_s^D)^{\sigma-1}$. First, if $\chi < R_s^D$, since the government is not corrupt enough, it chooses zero diversion for both the DAC and Chinese DF. In this region, since the effective marginal costs are equal to the interest rates plus depreciation rate, the relative advantage of the DAC DF is invariant to χ. If the relative disadvantage of the DAC DF does not exceed its advantage, all projects are financed by the DAC DF without diversion and the sector belongs to $\mathcal{S}^D$. If it does, projects with productivity greater than the financing indifference cutoff are financed by the DAC DF and those below the cutoff are financed by Chinese DF, all without diversion ($\mathcal{S}^{DC}$).

If $\chi \in (R_s^D, R_s^C)$, the government chooses diversion only for the DAC DF. Hence, the relative advantage of the DAC DF is increasing in χ. If $\chi \geq R_s^C$, the government chooses maximal diversion for both DF. Since the monitoring intensity is not greater for Chinese DF ($\psi_s^D \geq \psi_s^C$), the relative advantage of the DAC DF in terms of effective marginal cost is weakly decreasing in χ. In these regions, financing of projects by productivity depends on the relative advantage and disadvantage of the DAC DF similarly to the previous case. In all $\mathcal{S}^{\tilde{D}}$, $\mathcal{S}^{\tilde{D}C}$ and $\mathcal{S}^{\tilde{D}\tilde{C}}$ where $\chi \in [R_s^C, \frac{\psi_s^D R_s^C - \psi_s^C R_s^D}{\psi_s^D - \psi_s^C})$, projects with higher productivity are financed by the DAC.

If the corruption exceeds the threshold $\frac{\psi_s^D R_s^C - \psi_s^C R_s^D}{\psi_s^D - \psi_s^C}$, the effective marginal cost for the Chinese DF becomes lower than that for the DAC DF despite the lower DAC DF interest rate. In this case, unless the disadvantage of the DAC DF in terms of fixed cost is sufficiently low, all projects are financed by Chinese DF ($\mathcal{S}^{\tilde{C}}$). If it is sufficiently low, projects with higher productivity are financed by China and those with lower productivity are financed by the DAC ($\mathcal{S}^{\tilde{C}\tilde{D}}$).

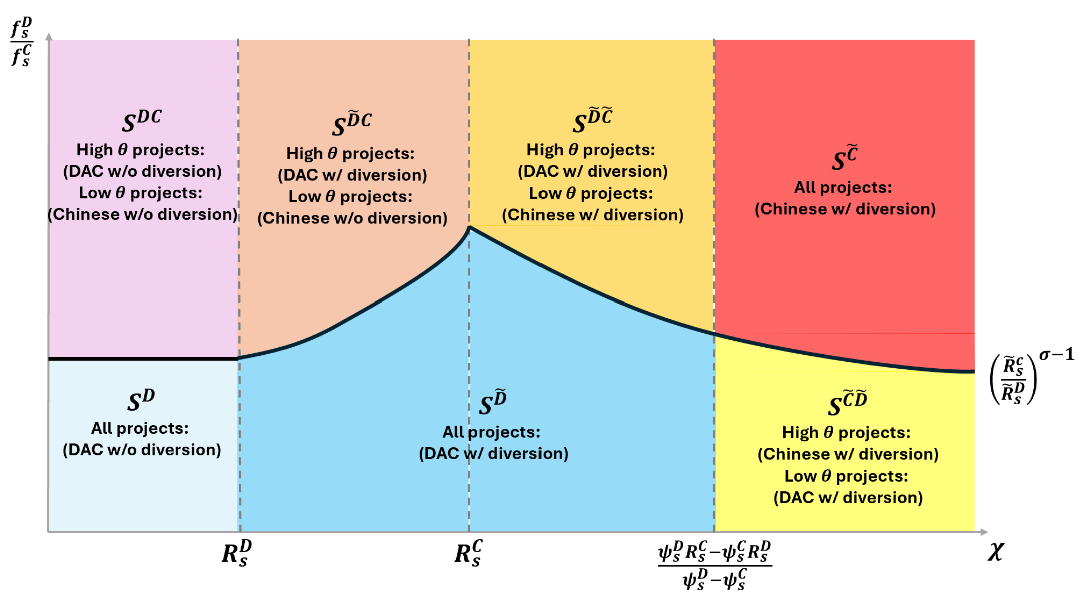


Figure 8: Optimal financing of each sector

4.3.3 Aggregation

I derive closed-form expressions for effective public capital in each sector, $G^E_{s,t}$, and the final effective public capital, G^E_t, by aggregating public capital in each individual projects. For that, I assume project-specific productivity θ in each sector s follows a Pareto distribution with a lower bound $\underline{\theta}$ and shape parameter ξ (i.e., $\theta \sim \text{Pareto}(\underline{\theta}, \xi)$ for each $s \in \mathcal{S}$). The probability density function $h_s(\theta) = \frac{\xi \underline{\theta}^{\xi}}{\theta^{\xi+1}}$ and cumulative distribution function $H_s(\theta) = 1 - \left(\frac{\underline{\theta}}{\theta}\right)^{\xi}$ describe the distribution of project-specific productivity in each sector. The effective public capital in each sector, $G^E_{s,t}$, can be expressed as:

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

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

Proposition 3. (Sectoral Effective Public Capital). In a government's optimal allocation, the effective public capital in sector s for period t is given by:

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

where $\mathcal{G}^E_s$ is a sector-specific constant consisting of parameters: $R^D_s, R^C_s, \psi^D_s, \psi^C_s, f^D_s, f^C_s, \sigma, \underline{\theta}, \xi$, and χ.

Proof. See Appendix C.7 for the full proposition and its proof. □

Proposition 3 shows that effective public capital in each sector is determined by the underlying distribution of project productivity ($\underline{\theta}$ and ξ) and elasticity of substitution between projects (σ). Additionally, it is shaped by the relative effective marginal costs and fixed costs (f^D_s and f^C_s) of the DF sources, with the effective marginal costs incorporating the interest rates (R^D_s and R^C_s), monitoring intensities (ψ^D_s and ψ^C_s), and corruption parameter (χ).

In turn, the following proposition pins down the final effective public capital.

Proposition 4. (Final Effective Public Capital). The final effective public capital, G^E_t, is given by:

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

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

Proposition 4 shows that the final effective public capital is shaped by parameters that govern the underlying productivity distribution, aggregation technology, and the interaction between corruption and DF characteristics in each sector. However, the influence of each sector is determined by the sector share γ_s.

5 Theoretical Exploration and Insights

In this section, I present three theoretical insights: First, I explain the empirical findings through three distinct 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 the implications of corruption within the global DF environment on the efficiency of public capital.

5.1 Three Channels of Corruption Effect

Through the lens of the model, I show that corruption distorts the efficient use of DF via three distinct channels and relate them to the stylized facts on global DF allocation established in Section 3. I first define a benchmark allocation as follows.

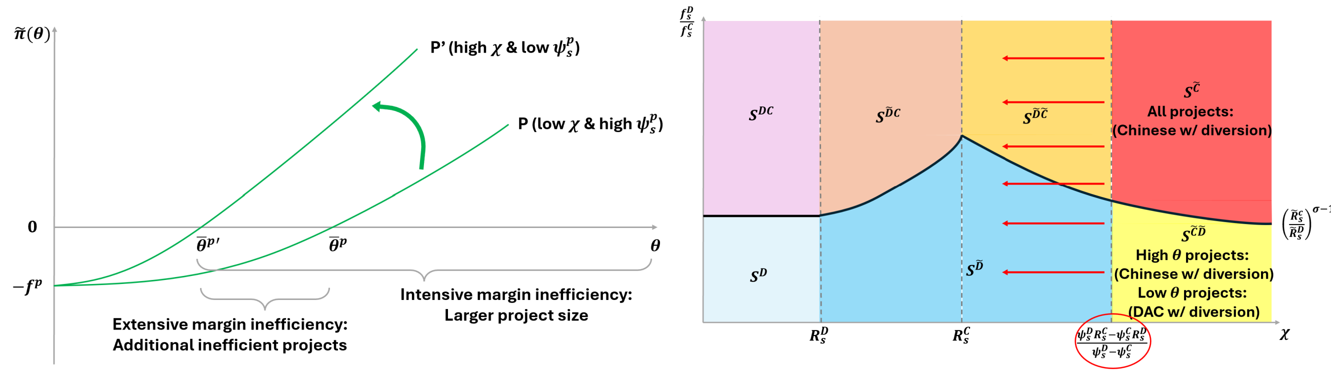
Definition 6. (Benevolent Allocation). A benevolent allocation is a government's optimal allocation when it is benevolent ($\chi = 0$).

Sufficiently high corruption ($\chi > \min_{s,p}\{R_s^p\}$) leads to deviation from the benevolent allocation through three channels: overinvestment, sectoral misallocation, and financing inefficiency.

5.1.1 Overinvestment Channel

Intensive margin. Lemma 3 shows that the government's optimal size of project j equates the marginal product of effective public capital, $mpg_{s,j,t}^E$, and the effective marginal cost when it is financed by p, $\tilde{R}_s^p$. If the government is corrupt enough ($\chi > R_s^p$), $\tilde{R}_s^p = \frac{R_s^p - (1-\psi_s^p)\cdot\chi}{\psi_s^p} - (1 - \delta_s^E)$, which is lower than in a benevolent allocation. Since $mpg_{s,j,t}^E$ is decreasing in the effective public capital $g_{s,j,t}^E$, this leads to overinvestment in project j. The actual project size, $\frac{g_{s,j,t}^E}{\psi_s^p}$, would appear even larger in the data, further highlighting the overinvestment. This inefficiency worsens with increased corruption, χ, as it further reduces the effective marginal cost. However, higher monitoring intensity, ψ_s^p, can mitigate this by raising the effective marginal cost. If ψ_s^C is sufficiently low while ψ_s^D is close to 1, this channel can explain the empirical finding that corruption is positively correlated with Chinese DF project sizes, but not with the DAC project sizes. Moreover, it explains why such correlation is stronger in sectors that are harder to monitor, which corresponds to the sectors with low ψ_s^p in my model.

Extensive margin. Compared to a benevolent allocation, higher corruption reduces the effective marginal cost and in turn increases the effective profit from a project for a given productivity. Graphically, the effective profit curve will become steeper with higher corruption and lower monitoring intensity as in Figure 9a. The zero-profit cutoff decreases from $\bar{\theta}^p$ to $\bar{\theta}^{p'}$. As a result, projects that are not profitable in a benevolent allocation are operated. This channel explains cases where some governments invest in large public projects that appear unprofitable and illogical.



(a) Overinvestment Channel

(b) Financing Inefficiency Channel

Figure 9: Channels of Corruption Effect

5.1.2 Sectoral Misallocation Channel

For simplicity, consider two sectors, s and s', both financed by p. Proposition 3 implies that the ratio of effective public capital between the two sectors is:

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

In a benevolent allocation, the effective marginal cost is simply $R^p_s - (1-\delta)$. Hence, the optimal ratio would be determined by each sector's contribution to final output, accounting for relative interest rates and fixed costs. However, distortion arises if the government is sufficiently corrupt and the monitoring intensity differs between sectors. If sector s has more intense monitoring ($\psi^p_s > \psi^p_{s'}$), more resources are allocated to sector s', leading to sectoral misallocation. This channel worsens as the gap in monitoring intensities increases.

5.1.3 Financing Inefficiency Channel

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, suppose both DAC and Chinese DF feature identical fixed costs. Then, the decision depends solely on the effective marginal costs, $\tilde{R}^p_s$. In a benevolent allocation, $\tilde{R}^p_s$ is the interest rate plus depreciation rate and hence, DAC DF with lower interest rate is always chosen. If the government is sufficiently corrupt, however, it is possible that $\tilde{R}^C_s < \tilde{R}^D_s$ and Chinese DF is chosen despite its higher interest rate. This is if and only if $\chi > \frac{\psi^D_s R^C_s - \psi^C_s R^D_s}{\psi^D_s - \psi^C_s}$. Note that the threshold is decreasing in the monitoring intensity gap and is increasing in the interest rate gap. Graphically, such changes lead to an expansion of parameter spaces where a sector relies on Chinese DF for high productivity projects as in Figure 9b. This channel explains the stylized fact that corruption is positively (negatively) correlated with the number and the total amount of Chinese (DAC) projects.

5.2 Implication of the Rise of Chinese DF

For any corruption level, the government is weakly better off due to the availability of Chinese DF as it offers more choice sets. However, Chinese DF can be either a boon or a bane for the household depending on the government's corruption.

Chinese DF as a boon. Chinese DF can fill funding gaps left by the DAC DF. If the DAC DF features harsh negotiation process, demands abrupt policy reforms, de-emphasizes a sector, or even rations a country in certain sectors, the fixed costs of DAC DF can be prohibitively high, limiting DAC DF to only a few highly productive projects. In such cases, the availability of Chinese DF can be beneficial, enabling more public investment, boosting final output, and improving household consumption.

Chinese DF as a bane. If the government is highly corrupt, the bane effect of Chinese DF becomes dominant through the three channels. The government might switch to Chinese DF with higher interest rates, overinvest in projects, and misallocate resources across sectors if monitoring intensity varies. These factors can negatively impact household consumption.

In summary, whether Chinese DF is a boon or a bane depends on the borrowing country's level of corruption. Note that the three inefficiency channels of corruption kick in gradually depending on the level of corruption as in Figure 10. If $\chi < R_s^C$, the government does not divert any Chinse DF and Chinese DF only has a boon effect by filling the funding gap. If $\chi > R_s^C$, the overinvestment and the sectoral misallocation channel kick in. If χ surpasses a certain threshold, the financing inefficiency channel kicks in, worsening the bane effect. In those areas, both the boon and the bane effects are present. Note that whether Chinese DF is a boon or a bane can vary across sectors and the net effect on the household's consumption at the aggregate level is a quantitative question, which I explore in Section 6.

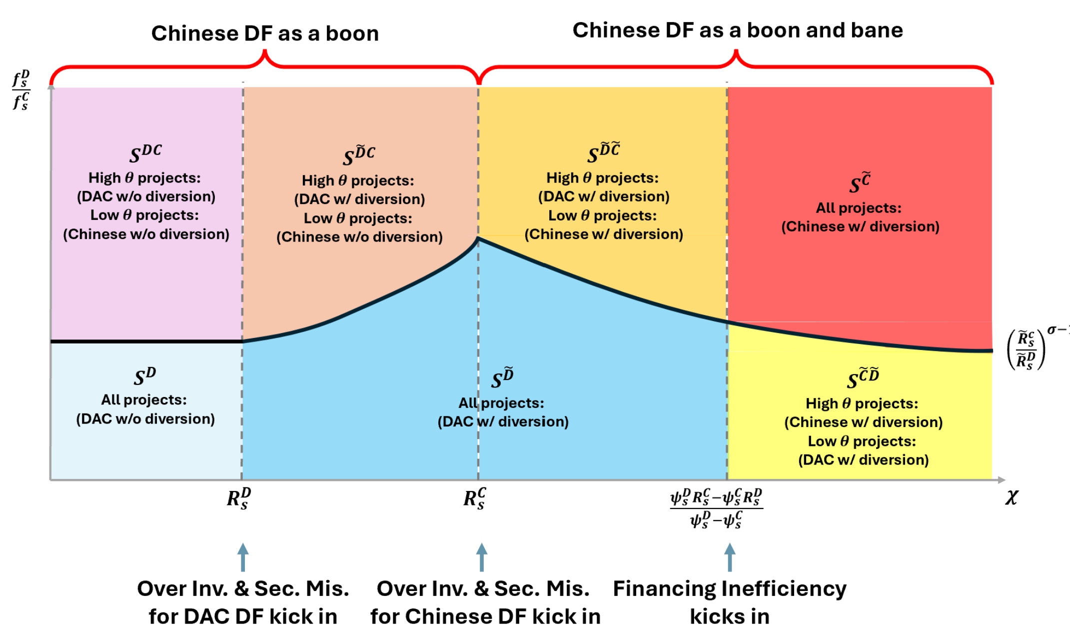


Figure 10: Boon and Bane effects of Chinese DF

5.3 Implication on the Efficiency of Public capital

The theoretical framework presented in this paper offers important insights into the efficiency of public capital. Previous research establishes that the efficiency of public capital utilization varies with a country's institutional quality, a concept introduced by Hulten (1992). Subsequent studies (Dabla-Norris et al., 2012; Gupta et al., 2014) quantify public capital efficiency across countries, often assuming that public capital G enters production function with a constant efficiency term, Θ, multiplied to it: $Y = A \cdot (\Theta G)^{\gamma} K^{\alpha} L^{1-\alpha-\gamma}$. In most existing works, Θ is treated as an exogenous constant.

My model complements existing approaches by making Θ an endogenous variable that emerges from the government's optimal choices, influenced by corruption and DF characteristics:

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

My model counterpart to Θ is a function not only of the underlying aggregation technology (sector share γ_s, elasticity of substitution σ, and productivity distribution parameters $\bar{\theta}$ and ξ) but also of the corruption χ and DF characteristics (interest rates R_s^p, monitoring intensities ψ_s^p, and fixed costs f_s^p). Also note that each sector's contribution to the aggregate-level efficiency is heterogeneous. This approach refines our understanding of public capital efficiency and provides a richer perspective on its determinants within different institutional contexts. It also implies that the DF providers can affect the recipient country's efficiency of public capital through their DF policies.

6 Quantitative Analysis

I apply the model to data from each developing country and calibrate it accordingly. Subsequently, I perform a counterfactual analysis to determine which countries' households benefit or suffer due to the introduction of Chinese development finance.

6.1 Preliminary Steps

6.1.1 Incorporating DAC Grants and Self-Financing

DAC grants. I incorporate DAC grants as an additional source of financing. Similar to DAC loans, these grants are contracted at the project level but do not require repayment and typically consist of 'many small' projects. From 2000 to 2021, DAC grant projects totaled roughly 1.3 million counts, compared to 31,459 for DAC loans and 4,400 for Chinese loans. The median committed amount for DAC grant projects in constant 2011 dollars ($53,469) is substantially smaller than that of DAC loans ($18.7 million) and Chinese loans ($67 million).[4]

[4] An example of a DAC grant project is 'Therapy Equipment for Disability and Rehabilitation Centre' project in Vietnam, to which Australia committed $3,640 in constant 2011 dollars in 2016. The amount contrasts with a loan project in the same

Due to their smaller scale but higher frequency, I model DAC grants as projects near the lower end of the productivity distribution. This ensures that including them does not qualitatively change the primary findings from the model section, which focuses on loans. Typically, DAC grants are obtained through negotiations between the recipient country and DAC agencies. For simplicity, I assume that the DAC evaluates each project's marginal product and equates it to a shadow cost—the hypothetical cost to the borrower under a loan agreement. Grants are monitored with the same intensity, ψ_s^D, as DAC loans. Consequently, the optimal size of a grant-financed project j, as determined by the DAC, $\bar{g}_{s,j,t}^{EG}$, is calculated using the same equation as for DAC loans: $mpg_{sjt}^E = \tilde{R}_s^D$.
However, the DAC imposes a maximum project size, approving grants only if $\bar{g}_{s,j,t}^{EG} \leq T_s$ for a positive T_s. This approach aligns with the policies of many DAC grant agencies, which set funding caps for individual applications. Additionally, grant financing incurs a fixed cost, denoted by f_s^G for sector s. I can then denote the government's effective profit from a grant-financed project by $\tilde{\pi}_{s,t}^G$, similarly to loan projects. The zero-profit cutoff, $\bar{\theta}_{s,t}^G$, is also defined in the same way, as the productivity at which $\tilde{\pi}_{s,t}^G(\bar{\theta}_{s,t}^G) = 0$. Furthermore, I define an additional productivity threshold, $\bar{\theta}_{s,t}^T$, where the optimal project size equals the grant cap, such that $\bar{g}_{s,t}^{EG}(\bar{\theta}_{s,t}^T) = T_s$.

Considering that grant project sizes are on average significantly smaller than loan projects, I further assume that in sectors with finite T_s, the DAC sets the grant size cap T_s to ensure $\bar{\theta}_{s,t}^T = \min\{\bar{\theta}_{s,t}^D, \bar{\theta}_{s,t}^C\}$. This can be achieved by setting $T_s = \min\{f_s^D \cdot (\tilde{R}_s^D)^{\sigma-1}, f_s^C \cdot (\tilde{R}_s^C)^{\sigma-1}\}$.

This assumption implies that the DAC does not allow borrowing countries to receive grants for projects that are productive enough to generate positive effective profits for the government, even if financed by loans. Suppose that $T_s > \min\{f_s^D \cdot (\tilde{R}_s^D)^{\sigma-1}, f_s^C \cdot (\tilde{R}_s^C)^{\sigma-1}\}$, so that $\bar{\theta}_{s,t}^T > \min\{\bar{\theta}_{s,t}^D, \bar{\theta}_{s,t}^C\}$. In this case, the borrowing country would choose DAC grants for some projects, even though it could make positive profits with DAC or Chinese loans. Considering the cost of providing grants without any expected returns, it is unrealistic that the DAC would allow this to happen.

This assumption also excludes the case where $T_s < \min\{f_s^D \cdot (\tilde{R}_s^D)^{\sigma-1}, f_s^C \cdot (\tilde{R}_s^C)^{\sigma-1}\}$. Therefore, there are no projects in the middle of the productivity distribution that are neither eligible for grants nor profitable with loans, which makes the quantification more tractable. It is also likely that the DAC sets the grant and loan conditions in such a way that it does not leave out projects that are fairly productive in the middle of the distribution while financing only less productive projects at the bottom. As a result, the optimal sectoral financing results in Proposition 2 carry over, except that in each category, projects with productivity $\theta \in [\bar{\theta}_{s,t}^G, \min\{\bar{\theta}_{s,t}^D, \bar{\theta}_{s,t}^C\})$ are now financed by DAC grants in addition to the loan-financed projects. The aggregation result in Proposition 3 can also be extended. See Appendix C.10 for details.

Finally, the framework allows for scenarios where a sector is entirely funded by DAC grants, with or

sector in Vietnam such as 'Construction of Hai Phong General Hospital,' for which South Korea pledged $87.3 million in constant 2011 USD in 2017.

without diversion, when $T_s \to \infty$. These categories are denoted by $S^{\tilde{G}}$ and S^G.

Self-financing. I also allow for self-financing, where the government does not rely on external sources to finance a project. This is to incorporate the military sector, which constitutes a non-trivial portion of the public sector in most countries but is not eligible for DF. In other sectors, I assume $f_s^S \geq \min\{f_s^D, f_s^C\}$, where f_s^S denotes the fixed cost for operating a project in sector s with self-financing. Hence, self-financing is dominated by DF due to the higher fixed costs and marginal costs in those sectors. As a result, self-financing is only considered for projects in the military sector.

6.1.2 Sector Classification

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

The CRS and AidData record information on the bilateral commitments for each development project between borrower and donor countries but do not provide any information on the actual expenditure of borrower countries in each sector at an aggregate level. To leverage IMF GFS's expenditure data alongside DF datasets, I consult the detailed descriptions in the IMF GFS manual (De Clerck and Wickens, 2015) and the DAC-CRS code list (OECD, 2024), and construct a unified sector classification.

Although many sectors can be straightforwardly matched across the two classifications, a few sectors correspond to an intersection or a union of multiple sectors in the other classification. In such cases, I merge the sectors into a single category to encompass all the relevant sectors in both classifications. As a result, I classify the sectors into 14 categories, as shown in Table E.1. These 14 categories encompass all sectors in both classifications, except for six sectors in the OECD DAC-5, which I excluded because they are either debt-related activities, emergency responses, administrative costs to donors, or unspecified.

6.2 Calibration

I calibrate the model for each recipient country. Hereinafter, parameters and variables with an r subscript denote recipient country r. I group the parameters into four categories: common macro parameters, common DF characteristics, recipient country characteristics, and recipient-sector-specific DF parameters. Table 7 summarizes the calibration strategy.

Table 7: Calibration

Parameter	Description	Value	Method	Source/Target moment
Common Macro				
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.	
γ_s	Pub. sector share	0.0004 - 0.3588	GMM	$\mathbb{E}$[expenditure share]
DF character.				
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	
ψ_s^C	China monitoring	0.42 - 1	FE Regression	avg. project size relative to DAC
Recipient character.				
χ_r	Corruption	0 - 1.3	Upper bound	marginal cost of DF
ξ_r	Pareto shape	2.2 - 4.95	MLE	project size distribution
$\underline{\theta}_r$	Pareto scale	1	Normalization	
Recipient-sector-DF				
$f_{r,s}^G$	Grant fixed cost		GMM	$\mathbb{E}$[project size]
$f_{r,s}^D$	DAC loan fixed cost		GMM	$\mathbb{E}$[project size]
$f_{r,s}^C$	Chinese loan fixed cost		GMM	$\mathbb{E}$[project size]

6.2.1 Common Macro Parameters

Standard parameters. I externally calibrate the standard macro parameters that are common across all borrower countries. The annual discount rate, β, for emerging economies is set to 0.92 (Aguiar and Gopinath, 2007). I set the private capital share, α, to 1/3. The private capital depreciation rate, δ_K, and the public capital depreciation rate, δ_G, are both set to 0.05. The aggregate public capital share parameter, γ, is set to 0.106, following Bom and Ligthart (2014).

There are no existing estimates on the elasticity of substitution across public projects within each sector, σ. Unlike data on firms or goods, public projects lack comparable market prices or sales data observed over time, making it difficult to estimate elasticity. Therefore, I assume that the elasticity is similar to that for goods within sectors. I set σ to 2.2, which is the median estimate for the elasticity of substitution across goods from (Broda and Weinstein, 2006).[5]

Public capital sector share. Since there are no existing estimates of sectoral public capital shares, γ_s,

[5]It is well known that while complementarities prevail *across* sectors, substitutabilities ($\sigma > 1$) dominate across firms *within* sectors (Baqaee and Farhi, 2019).

I estimate them by targeting the ratio of public expenditure on each sector to GDP. I assume that the γ_s values for developing countries are not significantly different from those of advanced economies, and I exploit the fact that advanced economies are not eligible for international DF.

While the observed public expenditure share for developing countries is confounded by the complex interaction between the borrower's corruption and the monitoring intensity of different DF providers, the expenditure share for advanced economies is primarily driven by γ_s. Furthermore, advanced economies are relatively free from severe public sector corruption and diversion. Lastly, many advanced economies are considered to be in steady state, which enables a relatively straightforward estimation compared to using data from emerging economies that are on a transition path.

The model predicts that if an advanced country self-finances a development project j in sector s without diversion, the ratio of public investment in sector s to GDP in steady state is characterized as:

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

See Appendix E.3 for the derivation. I use the data on each country's public expenditure on each sector each year from IMF COFOG. Since $\sum_{s\in\mathcal{S}} \gamma_s = 1$, it follows that the share of each sector in total public expenditure is γ_s. I estimate γ_s using Sequential Least Squares Programming (SLSQP), which minimizes the squared distance between γ_s and the mean of the corresponding sector share, with the constraint that $\sum_{s\in\mathcal{S}} \gamma_s = 1$. This approach is equivalent to the Generalized Method of Moments (GMM) with the following moment conditions:[6]

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

The estimates are summarized in Table 8.

6.2.2 DF Provider Characteristics

Interest rates. I set the interest rates for each provider-sector pair to the mean interest rates observed in the data, as summarized in Table 9. For DAC loans, the mean interest rates are close to 1 percent in most sectors, with the maximum being 1.5 percent in the General Economic, Commercial, and Labor Affairs sector. The interest rates for Chinese loans are significantly higher, ranging from 1.8 percent (Government & Civil Society) to 4.5 percent (General Budget Support).

Monitoring Intensities. For the quantitative analysis, I focus on the relative monitoring intensities

[6] The IMF COFOG provides information on government expenditure in each sector but does not distinguish between government consumption and government investment. Assuming that the fractions of total expenditure going to government investment are not too different across sectors, the sector share in the government's total expenditure can serve as a reasonable proxy for the sector share in government investment. For estimation, I include 38 advanced economies based on the IMF's classification.

Table 8: Sectoral public capital share

Sector name	**Sector share** γ_s
Agriculture, Forestry, Fishing	0.0119
Industry, Mining, Construction	0.0029
Transport & Storage	0.0573
Energy	0.0053
Communications	0.0004
Health	0.1429
Education	0.1297
General Environment Protection	0.0169
Water Supply & Sanitation	0.0196
Government & Civil Society	0.0449
General Budget Support	0.1434
General Economic, Commercial, Labor Affairs	0.0253
Other Social Infrastructure & Services	0.3613
Defense	0.0382
Sum	**1**

between DAC and Chinese DF, normalizing the monitoring intensities for DAC DF in all sectors to 1 ($\psi_s^D = 1$). There are two reasons for this approach. First, in the empirical analysis, DAC project sizes are not significantly correlated with corruption in most sectors. While I find a correlation in sectors that are difficult to monitor, it is much smaller than the correlation observed for Chinese DF. Secondly, it is extremely challenging to estimate the exact values of monitoring intensities for both DAC and Chinese DF across all sectors since there is no cardinal corruption measure that corresponds empirically to the model's corruption parameter, χ_r. However, under certain identifying assumptions, I can estimate the relative monitoring intensity between DAC and Chinese DF for each sector.

To estimate monitoring intensities for Chinese DF, I begin with the model equation that determines the optimal size of effective public capital for project j, $g^E_{r,p,s,j,t}$. The actual size of project j observed in the data, $g^O_{r,p,s,j,t}$, is equal to $g^E_{r,p,s,j,t}/\Psi^p_{r,s}$, where $\Psi^p_{r,s}$ is ψ^p_s if country r diverts DF from provider p in sector s, and 1 otherwise. Hence,

$$g^O_{r,p,s,j,t} = \frac{1}{\Psi^p_s}\big(\frac{\gamma\gamma_s\theta_j}{\tilde{R}^p_{r,s}}\big)^\sigma Y^\sigma_{r,t}(G^E_{r,s,t})^{1-\sigma}.$$

Taking the log and approximating $\ln \tilde{R}^p_{r,s} = \ln\Big(\frac{R^p_s-(1-\psi^p_s)\chi_r}{\psi^p_s} - (1-\delta_G)\Big)$ to the first order around $\chi_r = R^p_s$ and $\psi^p_s = 1$, I obtain:

$$\ln g^O_{r,p,s,j,t} \approx -\ln \Psi^p_s + \sigma \ln \theta_j + \sigma \ln \gamma\gamma_s + \sigma \ln Y_{r,t} + (1-\sigma)\ln G^E_{r,s,t} - \sigma \ln(R^p_s - (1-\delta_G)).$$

Note that the equality holds for $p = D$ since $\psi_s^D = 1$. Since $Y_{r,t}$, $G^E_{r,s,t}$, and $\gamma\gamma_s$ are invariant to p, the difference in the log project size between DAC and Chinese DF arises from three components: monitoring intensity, interest rate, and potential selection bias in productivity θ_j. My model predicts that the productivity cutoffs determining the average size of DAC and Chinese DF projects are driven by the borrowing country's corruption, recipient-provider bilateral and sector-specific fixed costs, and interest rates. Based on this, I control for variables that might affect these factors to account for the systemic difference in the productivity of DAC and Chinese projects. Then, with some additional identifying assumptions, the difference in average project size—controlling for all these factors—can be attributed to the difference in monitoring intensity.

Consider the following fixed effect regression model. $\mathbf{X}_{r,p,t}$ includes the 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* indicate all the right-hand side variables of the fixed effect 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 states that all countries using Chinese DF during the sample period are corrupt enough to divert the funds. Considering that the majority of Chinese DF is directed toward countries with higher-than-average corruption indices (Malik et al., 2021), this assumption is reasonable. If anything, the bias would lean toward overestimating the monitoring intensity of Chinese DF. Therefore, if there are recipient countries with insufficient corruption in the sample, the actual monitoring intensity should be lower. As a result, the estimate under this assumption should be considered an upper bound of Chinese DF monitoring intensities relative to the DAC.

The second assumption states that I can control for the difference in average productivity between DAC and Chinese DF in a sector by including recipient-time fixed effects, sector fixed effects, and control variables. Under the two assumptions, I can show that the difference in sector-provider fixed effects for each sector in the fixed effect regression model is $FE_{s,p=C} - FE_{s,p=D} \approx -\ln \psi_s^C$ and hence

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

See Appendix E.4 for the derivation. The economic intuition behind the estimation strategy is that, by controlling for other factors that might affect the productivity of projects and other recipient- and sector-specific factors influencing project size, the relative size of Chinese projects compared to DAC projects should primarily reflect differences in monitoring intensity.

Based on this premise, I conduct fixed effect regressions and use the estimated sector-provider fixed effects for each sector to estimate Chinese DF monitoring intensities. In case $FE_{s,p=C} - FE_{s,p=D}$ is estimated to be negative, I set ψ_s^C to 1. It is important to note that this analysis includes only loan projects and excludes grant projects, as grant projects are systematically smaller than loan projects and reflect productivity differences not fully controlled for by the control variables. The estimates of ψ_s^C are reported in Table 9.

The estimates suggest that Chinese projects in the Industry, Mining, and Construction sector are potentially the most vulnerable to corruption and diversion by recipient countries, followed by the Communications, General Budget Support, and Health sectors, compared to DAC-funded projects. Conversely, monitoring intensity in sectors such as Transport & Storage, Education, General Environment Protection, Water Supply & Sanitation, Government & Civil Society, General Economic, Commercial, Labor Affairs, and Other Social Infrastructure & Services does not significantly differ from that of the DAC. In these sectors, the three corruption channels are absent, and Chinese development finance serves solely to benefit recipient country households by bridging the funding gaps left by DAC DF.

Table 9: Interest rate and monitoring intensity by DF provider-sector

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

6.2.3 Recipient Country Characteristics

Productivity distribution. I normalize the Pareto scale parameter, $\underline{\theta}_r$, to 1, as this normalization is innocuous for the quantitative results. I estimate the Pareto shape parameter, ξ_r, for each country (r) using the Maximum Likelihood Estimation (MLE) method, exploiting the properties of the mixture of Pareto distributions. In my model, the pool of potential projects is fixed over time, and the government operates all projects with productivity above a certain cutoff in each period. However, in practice, there may be lags between the government's planning and the actual implementation of each project. These delays could be due to various factors, such as lengthy negotiations with DF providers or domestic administrative or legislative lags, which are beyond the scope of this paper.

As a result, in the data, each project appears with some randomness in different years. Moreover, only the information on the initial commitment is fully observable in the project-level data, and each project does not reappear in later years. In other words, projects are sporadically observed in different years regardless of their productivity. To calibrate the distribution of a fixed project pool to the data, I pool all the projects in a way that leverages the unique properties of the mixture of Pareto distributions. It turns out that I can estimate the shape parameter, ξ_r, by simply pooling all the observations. See Appendix E.5 for details. Based on that, I maximize the following log-likelihood function for each recipient country r:

$$log\mathcal{L}(\frac{\xi_r}{\sigma}, \tilde{\theta}_r) = \sum_{i=1}^{N_r} log f_r(x_i; \frac{\xi_r}{\sigma}, \tilde{\theta}_r).$$

where f_r is a pdf of project size x_i which has the same functional form as Pareto distribution with shape parameter ξ_r/σ and some scale parameter $\bar{\theta}_r$.

I focus on fitting the right tail rather than using all observations, following the literature that utilizes the Pareto distribution.[7] For each recipient, I fit the top 1 percent of samples and estimate the shape parameter as in Head et al. (2014). My model requires $\xi_r > \sigma$ and that the estimated value for ξ_r/σ be greater than 1. Among 112 countries with enough sample sizes (> 30), all except for 17 have estimates of ξ_r/σ greater than 1. For those with estimates lower than 1 and those with less than 30 projects at the top 1%, I set the value to 1.014, which is the lowest estimate among those greater than 1. Figure E.2 shows the histogram of estimated ξ_r/σ. Figure E.1 shows the QQ plot and fitted density of the projects with summary statistics for three selected countries with the most sample sizes.

Corruption. While estimating the corruption parameter χ_r for each developing country is extremely challenging due to the lack of an empirical counterpart, I can determine the upper bound of the parameter for each country. Hence, I use the range of corruption parameter and provide a range of household's welfare changes due to Chinese DF for each developing country in counterfactual analysis.

Recall that for Chinese projects, the optimal condition of project size in recipient country r is given by: $mpg_{r,s,j,t} = \tilde{R}^C_{r,s}$. Since the marginal product of a project must always be positive, this implies that 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. This provides the upper bound of χ_r as $\frac{R^C_s - \psi^C_s(1-\delta_G)}{1-\psi^C_s}$. For each country, I collect these upper bounds from all the sectors in which the country used Chinese DF projects and take the minimum of those bounds. Hence, the upper bound of

[7] See Appendix E.5 for discussion on fitting the right tail.

corruption for country r, $\bar{\chi}_r$, is:

$$\bar{\chi}_r = \min_s \{ \frac{R_s^C - \psi_s^C(1-\delta_G)}{1-\psi_s^C} \} - \epsilon.$$

Note that I subtract a small value $\epsilon > 0$ to ensure that $\tilde{R}_{r,s}^C$ is strictly positive. I set $\epsilon = 0.01$.

6.2.4 Recipient-Sector-Provider Characteristics

Fixed costs. For each recipient country, I estimate two sets of fixed costs using the Generalized Method of Moments (GMM). One assumes that the government is benevolent, so $\chi_r = 0$, and the other assumes the government is maximally corrupt, so $\chi_r = \bar{\chi}_r$. Each set of fixed costs consists of DAC grant, DAC loan, and Chinese loan fixed costs: $f_{r,s}^G$, $f_{r,s}^D$, and $f_{r,s}^C$ for all $s \in \mathcal{S}$, except for the military sector, which relies on self-financing. I normalize the fixed cost for self-financing, f_s^S, to 1. The following proposition determines the average project size by sources of financing in each sector.

Proposition 5. (Expected Size of Projects by Sources) The expected observed size of a project financed by $p \in \{G, D, C\}$ in sector s is given by:

$$\mathbb{E}[g_{r,p,s,j,t}^O | p, s] = \frac{\xi(\sigma-1)}{\Psi_{r,s}^p \tilde{R}_{r,s}^p (\xi - \sigma)} \mathcal{F}_{r,s}^p.$$

$\mathcal{F}_{r,s}^p$ is recipient-provider-sector specific constant.

Proof. See Appendix C.9 for the full proposition and its proof. □

Let the vector of model moments of average project sizes implied by Proposition 5 be denoted by $g(\Theta_r)$, and let $\bar{g}_r$ represent the empirical moments, where $\Theta_r \equiv \{\{f_{r,s}^G, f_{r,s}^D, f_{r,s}^C\}_{s\in\mathcal{S}}\}$. I estimate Θ_r by minimizing the following objective function:

$$(g(\Theta_r) - \bar{g}_r)' \cdot \mathcal{W} \cdot (g(\Theta_r) - \bar{g}_r)$$

where $\mathcal{W}$ is a weighting matrix.

6.3 Steady State and Counterfactual Analyses

6.3.1 Is Chinese DF a boon or a bane?

Using the estimated parameters, I conduct a counterfactual analysis to compare household welfare in the steady state with and without Chinese DF for 108 developing countries. Since I can only establish bounds for the corruption parameter χ_r for each country, rather than determining its exact value, I provide a range of welfare implications for each country. The results are summarized in Figure 11. The figure shows the range of changes in steady state household consumption due to the advent of Chinese DF. The top of each line corresponds to the percent change in steady state household consumption with the advent of Chinese DF, assuming the country's government is benevolent, compared to the no-China counterfactual. The bottom represents the percent change when assuming the government's corruption parameter is at its upper bound ($\chi_r = \bar{\chi}_r$), compared to the no-China counterfactual. In the former scenario, the corruption effect of Chinese DF via the three channels is shut down, maximizing the boon effect. In the latter, both the boon and bane effects are present.

The results show significant heterogeneity in the effect of Chinese DF on household welfare. First, note that in all countries, Chinese DF is welfare-improving if the government is benevolent. However, as a country's corruption increases, the welfare effect of Chinese DF becomes ambiguous. In countries such as Suriname, Laos, and Namibia, Chinese DF is robustly welfare-improving even with maximal corruption. On the contrary, in countries such as Lebanon, Guinea-Bissau, and Nicaragua, the welfare improvement due to Chinese DF is estimated to be very small, even in the benevolent government case, while the potential welfare reduction is estimated to be substantial as corruption increases. Lastly, the effect is ambiguous in countries like Mauritius, Eritrea, and Cuba.

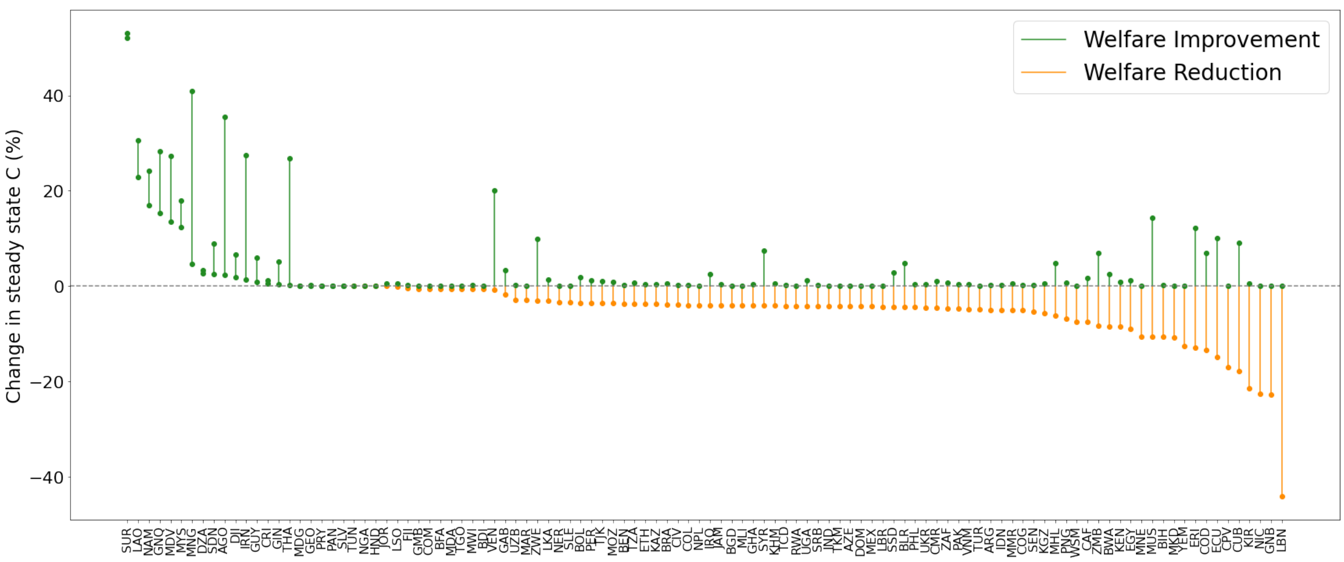


Figure 11: Welfare effect of Chinese DF on households

To investigate why the welfare effect is so heterogeneous, I conduct case studies with countries that have similar values for the corruption upper bound, $\bar{\chi}_r$. Figure 12 shows the effect of Chinese DF in each sector in Suriname, Kenya, and Mauritius through the lens of the model, assuming maximal corruption ($\chi_r = \bar{\chi}_r$) in those countries. It depicts the composition of DF in each sector in terms of the total amount used between 2000 and 2021 in those countries. The horizontal axis represents sectors in ascending order of the monitoring intensity of Chinese DF (ψ_s^C). The bars are stacked from bottom to top in ascending order of average project size.

For example, in the Industry, Mining, and Construction sector in Kenya, the average size of DAC grant projects is the smallest, compared to DAC loan projects and Chinese loan projects, and the total amount accounts for about 30%. DAC loan projects have the second-largest average size, accounting for 65% of the total. Chinese loan projects have the largest average size, making up about 5%. Red bars without patterns correspond to Chinese loans with only the boon effect. Red bars with no pattern correspond to Chinese loans with only the boon effect. Red bars with an "x" pattern represent Chinese loans with only the bane effect, and red bars with a diagonal "/" pattern represent projects with both boon and bane effects. Note that all sectors to the right of Education have a monitoring intensity of $\psi_s^C = 1$. In these sectors, all Chinese DF has only the boon effect, as it fills the funding gap left by DAC DF.

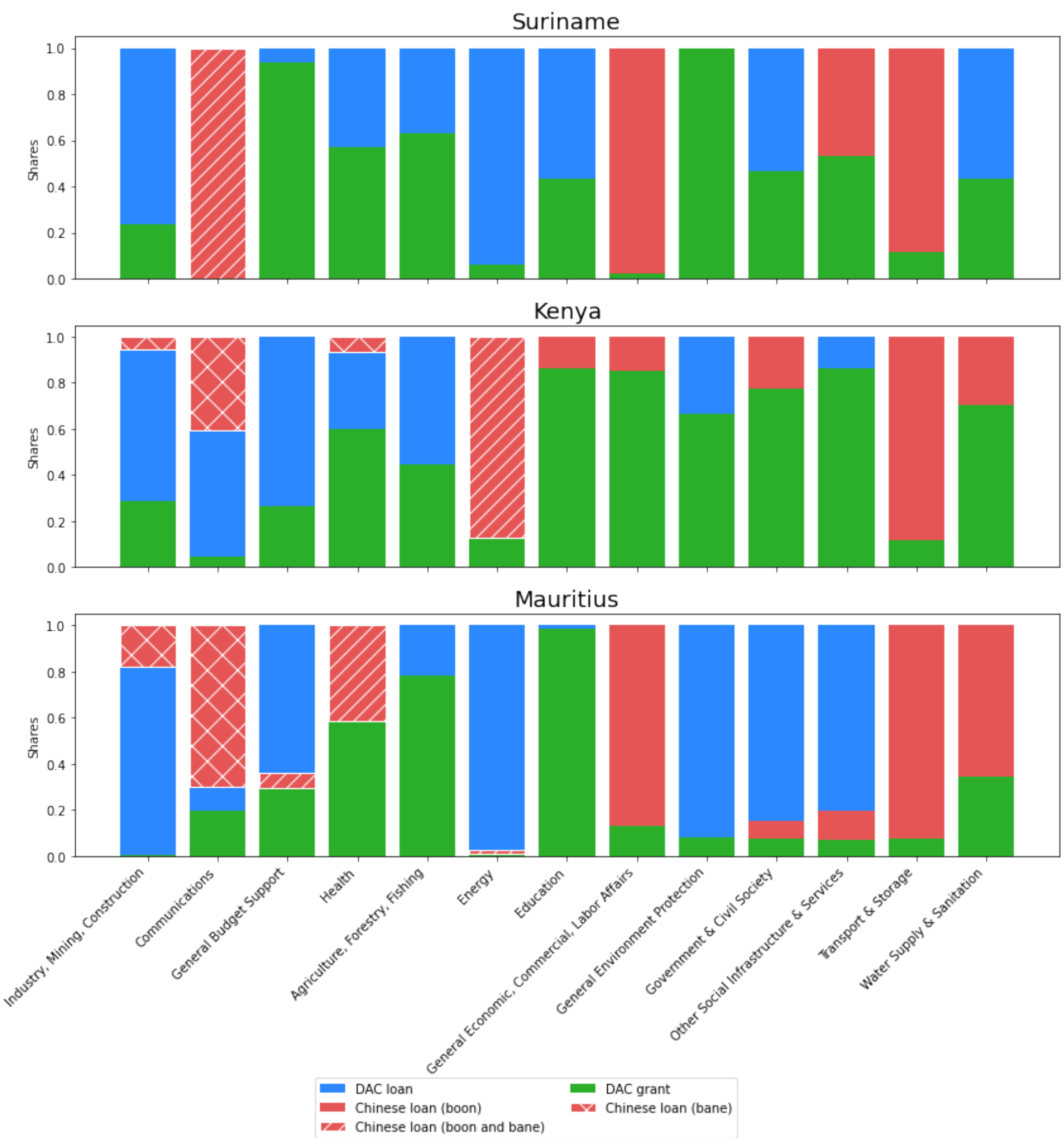


Figure 12: DF composition by sectors in Suriname, Kenya, and Mauritius

Case 1 (boon): Suriname. Figure 11 shows that households in Suriname are estimated to experience about a 50% increase in steady-state consumption due to Chinese DF, regardless of the government's corruption. The top panel in Figure 12 shows that Suriname primarily used Chinese DF in sectors with full monitoring intensity ($\psi_s^C = 1$). Chinese DF significantly fills the funding gap in the General Economic, Commercial, Labor Affairs, Social Infrastructure, and Transport & Storage sectors without causing any efficiency distortions.

The only sector where the effect of Chinese DF depends on corruption is the Communications sector. If the government is benevolent, the model estimates that Chinese DF will benefit the Communications sector, which suffers from a severe lack of DAC DF, without introducing inefficiencies. If the government is maximally corrupt, there will be both positive and negative impacts. However, since no DAC loans are observed and DAC grants are minimal, the model predicts that the boon effect will far outweigh the bane effect in the Communications sector, even with maximal corruption. This explains the substantial increase in consumption in the steady state, regardless of corruption.

Case 2 (bane): Kenya. In Kenya, Chinese DF fills funding gaps without any inefficiency in some sectors, especially in the Transport & Storage sector. However, the model estimates that if the government is sufficiently corrupt ($\chi_r > R_s^C$), Chinese DF has only a bane effect in the Industry, Mining, Construction, Communications, and Health sectors. Since DAC loans are available in these sectors and have a smaller average size than Chinese loans, the model estimates that the DAC loan fixed costs f_s^D are significantly lower than the Chinese loan fixed costs f_s^C. This suggests that all the Chinese loan projects could have been financed by DAC loans at lower interest rates and without any diversion.

Note that these three sectors have very low monitoring intensities, which amplifies the bane effects. In the Energy sector, Chinese DF has both boon and bane effects, as DAC loans do not appear in the data, and the model estimates that DAC loan fixed costs are sufficiently high. In Kenya, the bane effects in the three sectors with low monitoring intensity are estimated to outweigh the boon effects in other sectors, leading to a mostly negative welfare impact on households in the steady state, as shown in Figure 11.

Case 3 (ambiguous): Mauritius. Mauritius is an ambiguous case where the sign of the welfare effect significantly depends on the level of corruption. Its situation resembles a mix of Suriname and Kenya. Chinese DF substantially fills funding gaps without inefficiency, particularly in the General Economic, Commercial, Labor Affairs, Transport & Storage, and Water Supply & Sanitation sectors. However, it may suffer from bane effects in the Industry, Mining, Construction, and Communications sectors. In these sectors, if the government is benevolent, the model estimates that DAC loans are insufficient, but if the government is sufficiently corrupt, Chinese DF has only a bane effect.

The effect is ambiguous in the General Budget Support and Health sectors. Overall, whether the boon or bane effect dominates depends on the level of corruption, making the welfare implication inconclusive.

Guinea-Bissau, Kiribati, Lebanon, and Nicaragua. Figure 11 shows that welfare reduction can be significant in countries with maximal corruption. The magnitude of this reduction is much larger than in other countries. This is simply because the upper bounds of corruption, $\bar{\chi}_r$, are much higher in these countries compared to others.

7 Conclusion

Since the 1960s, developed countries, led by the Development Assistance Committee (DAC), have played a pivotal role in channeling capital to developing countries to promote growth, with China emerging as a significant provider of development finance (DF) in the past two decades. This paper offers the first comprehensive analysis of how developing countries strategically determine the amount, sources, and sectoral allocation of DF. Using project-level DF data and public sector corruption indices from over 150 countries between 2000 and 2021, I find that corruption is positively correlated with reliance on Chinese DF relative to DAC DF, with larger Chinese project sizes observed in more corrupt countries—a trend not seen with DAC DF.

I find a even stronger positive correlation between corruption and project size in harder-to-monitor sectors, even for DAC projects. I then develop a neoclassical growth model in which a potentially corrupt government makes public investment decisions, incorporating both DAC and Chinese DF with heterogeneous interest rates and monitoring intensities across sectors that affect the government's ability to divert funds. The model reveals three ways in which corruption reduces efficiency: through overinvestment, favoring less-monitored sectors, and opting for costlier DF sources with weaker monitoring.

The model also highlights the dual impact of Chinese DF, which can either fill funding gaps left by DAC DF or exacerbate inefficiency due to less stringent monitoring. Additionally, it endogenizes the efficiency of public capital as an interaction between corruption and DF environments, a factor previously considered exogenous in the literature. Finally, a quantitative analysis evaluates how Chinese DF impacts household welfare across 108 developing countries.

This paper opens rich avenues for future research on the topic of global DF landscape. One area not addressed here is the potential for debt default. It would be interesting to explore the interaction between DAC and Chinese DF within the framework of a sovereign debt and default model. Second, this paper focuses on the optimal choices of developing countries, given supply-side factors such as interest rates, monitoring intensities, and fixed costs. A future line of inquiry could investigate how the DAC and China strategically set these parameters. Lastly, empirically examining the long-term effects of DAC and Chinese DF on recipient countries' growth, while accounting for corruption, could provide valuable insights. Given that Chinese DF has only been available for the past two decades, with a significant surge in supply occurring just a decade ago, studying its long-term impact with more data would be particularly worthwhile.

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Appendix

A Data Cleaning

A.1 Consolidated Development Finance Dataset

A.1.1 Development Assistance Committee (DAC) and non-Chinese development finance data

For DAC and non-Chinese development finance data, I rely on two sources: AidData Core Research Release (version 3.1) and Creditor Reporting System (CRS). The former was introduced in Tierney et al. (2011) and updated in AidData (2017). It includes commitment information for over 1.5 million development finance project funded by 96 donors between 1947 and 2013. It is primarily based on the CRS project-level development finance dataset but also on some other sources. I only use the observations that are from the CRS because those from the other sources include projects for advanced economies that are not eligible for official development assistance (ODA) by OECD DAC, which are not of interest of this paper. It drops 100,773 observations, which is 6.45 percent of the total number of observations. I extend the dataset to until 2017 by manually appending CRS datasets for 2014 through 2017 which are available on OECD website. After appending the CRS datasets, I have 2,220,635 observations. For the analyses in the paper, I clean the data according to the following steps.

1. I keep official projects while dropping private or vague projects. A project is classified into those categories according to the following criteria.

   (a) A project is official if *flow_name* is either 'ODA Grant-Like', 'ODA Grants' 'ODA Grant-Like', 'ODA Grants', 'ODA Loans', 'OOF LOANS(NON-EXPORT CREDIT)', or 'Other Official Flows (non Export Credit)' (2,184,790 changes). A project is private if *flow_name* is either "Private Development Finance" or "Private Grants"" (29,683 changes).

   (b) If *flow_name* is missing, a project is regarded as official if the *donor* is an official multinational organization (722 changes), and regarded as private if *donor* is a private institute (1,834 changes).

   (c) The rest of projects are classified as vague (3,606 changes).

   (d) It results in 2,185,512 official projects (98.42 percent), 31,517 private projects (1.42 percent), and 3,606 vague projects (0.16 percent).

2. To avoid double counting, an observation is dropped if *initial_report* code is either 2 ('revision', 6 observations), 3 ('previously reported activity (increase/decrease of earlier commitment, disbursement on earlier commitment)', 417,494 observations), or 5 ('provisional data', 2 observations). The remaining observations fall into either 1 ('new activity reported', 1,363,322 observations) or 8 ('commitment is estimated as equal to disbursement', 401,714 observations). To be conservative, I drop 2,974 observations with missing *initial_report*.

A.1.2 Chinese development finance data

I rely on the AidData's Global Chinese Development Finance Dataset (version 2.0) introduced in Dreher et al. (2022). It captures information on 13,427 official development projects funded by Chinese government institutions or state-owned entities between 2000 and 2017. I drop observations if *RecommendedForAggregates* is 'No'. It is based on the pre-selected criteria by AidData. Specifically, it excludes all canceled projects, suspended projects, and projects that never reached the official commitment stage. Additionally, it avoids double counting by excluding delayed funding allocation of previously signed financial agreements and debt forgiveness activities of previous projects. As a result, 2,578 observations are dropped.

A.1.3 Consolidated development finance dataset

I combine the two datasets from above to construct a consolidated dataset that encompasses both Chinese and non-Chinese development finance projects. I drop observations if recipient is an organization or a group of countries, not a country. The resulting dataset contains information on 1,474,201 development finance projects for 187 recipient countries funded by 84 official donors. Time series coverage is 1973-2017 for projects funded by non-China donors and 2000-2017 for projects funded by China. Among these, 4,268 China-funded projects are missing information on commitment amount. A full list of the recipient countries and donors is as follows. Asterisk (*) indicates the countries that were removed from the OECD DAC ODA-eligible list at some point before 2017.

- Recipient countries
  - Afghanistan, Albania, Algeria, Angola, Anguilla*, Antigua and Barbuda, Argentina, Armenia, Aruba*, Azerbaijan, Bahamas*, Bahrain*, Bangladesh, Barbados*, Belarus, Belize, Benin, Bermuda*, Bhutan, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Brunei Darussalam*, Bulgaria, Burkina Faso, Burundi, Cabo Verde, Cambodia, Cameroon, Cayman Islands*, Central African Republic, Chad, Chile, China, Colombia, Comoros, Congo, Cook Islands, Costa Rica, Cote d'Ivoire, Croatia*, Cuba, Curacao, Cyprus*, Democratic People's Republic of Korea, Democratic Republic of the Congo, Djibouti, Dominica, Dominican Republic, Ecuador, Egypt, El Salvador, Equatorial Guinea, Eritrea, Eswatini, Ethiopia, Falkland Islands*, Fiji, French Polynesia*, Gabon, Gambia, Georgia, Ghana, Gibraltar*, Grenada, Guam, Guatemala, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, Hong Kong*, China, India, Indonesia, Iran, Iraq, Israel*, Jamaica, Jordan, Kazakhstan, Kenya, Kiribati, Korea*, Kosovo, Kuwait*, Kyrgyzstan, Laos, Lebanon, Lesotho, Liberia, Libya*, Macao*, Madagascar, Malawi, Malaysia, Maldives, Mali, Malta*, Marshall Islands, Martinique*, Mauritania, Mauritius, Mayotte, Mexico, Micronesia, Moldova, Mongolia, Montenegro, Montserrat, Morocco, Mozambique, Myanmar, Namibia, Nauru, Nepal, Netherlands Antilles*, New Caledonia*, Nicaragua, Niger, Nigeria, Niue, North Macedonia, Northern Marianas*, Oman*, Pakistan, Palau, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Qatar*, Romania, Russia, Rwanda, Saint Helena, Saint Lucia, Saint Vincent and the Grenadines, Samoa, Sao Tome and Principe, Saudi Arabia*, Senegal, Serbia, Seychelles, Sierra Leone, Singapore*, Sint Maarten (Dutch part), Slovenia*, Solomon Islands, Somalia, South Africa, South Sudan, Sri Lanka, St. Kitts & Nevis*, Sudan, Suriname, Syria, Taiwan*, Tajikistan, Tanzania, Thailand, Timor-Leste, Togo, Tokelau, Tonga, Trinidad and Tobago*, Tunisia, Turkey, Turkmenistan, Turks and Caicos Islands*, Tuvalu, Uganda, Ukraine, United Arab Emirates*, Uruguay, Uzbekistan, Vanuatu, Venezuela, Viet Nam, Virgin Islands (UK)*, Wallis and Futuna, West Bank and Gaza Strip, Yemen, Zambia, Zimbabwe
- Donors

– **Countries**

  * **DAC members (1,224,554 observations)**: Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Japan, Korea, Lithuania, Luxembourg, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, United Kingdom, United States
  * **DAC participants (1,810 observations)**: Kuwait, Romania, Saudi Arabia, United Arab Emirates
  * **non-DAC (10,989 observations)**: Azerbaijan, China (10,741 observations), Croatia, Latvia, Timor-Leste

– **Organizations**

  * **DAC members (28,686 observations)**: EU Institutions, European Bank for Reconstruction & Development (EBRD), European Communities (EC)
  * **DAC observers (195,473 observations)**: African Development Bank (AFDB), African Development Fund (AFDF), Asian Development Bank (ASDB), Asian Infrastructure Investment Bank, IDB Invest, Inter-American Development Bank (IADB), International Fund for Agricultural Development (IFAD), International Monetary Fund (IMF), Joint United Nations Programme on HIV/AIDS (UNAIDS), Organization for Security and Co-operation in Europe (OSCE), United Nations Children's Fund (UNICEF), United Nations Development Programme (UNDP), United Nations Economic Commission for Europe (UNECE), United Nations High Commissioner for Refugees (UNHCR), United Nations Peacebuilding Fund (UNPBF), United Nations Population Fund (UNFPA), United Nations Relief and Works Agency for Palestine Refugees in the Near East (UNRWA), World Bank - International Bank for Reconstruction and Development (IBRD), World Bank - International Development Association (IDA), World Health Organization (WHO)
  * **non-DAC (12,689 observations)**: Adaptation Fund, Arab Bank for Economic Development in Africa (BADEA), Arab Fund for Economic & Social Development (AFESD), Caribbean Development Bank, Center of Excellence in Finance, Central Emergency Response Fund, Climate Investment Funds, Council of Europe Development Bank, Development Bank of Latin America, Global Alliance for Vaccines & Immunization (GAVI), Global Environment Facility (GEF), Global Fund, Global Fund to Fight Aids Tuberculosis and Malaria (GFATM), Global Green Growth Institute (GGGI), Green Climate Fund, International Finance Corporation, International Labour Organisation, Islamic Development Bank (ISDB), New Development Bank, Nordic Development Fund (NDF), OPEC Fund for International Development (OFID)

A.2 Corruption Perception Index

The full list of data sources used to construct the Corruption Perception Index is as follows.

1. African Development Bank Country Policy and Institutional Assessment
2. Bertelsmann Stiftung Sustainable Governance Indicator
3. Bertelsmann Stiftung Transformation Index
4. Economist Intelligence Unit Country Risk Service
5. Freedom House Nations in Transit
6. Global Insight Country Risk Ratings
7. IMD World Competitiveness Center World Competitiveness Yearbook Executive Opinion Survey
8. Political and Economic Risk Consultancy Asian Intelligence

9. The PRS Group International Country Risk Guide
10. World Bank Country Policy and Institutional Assessment
11. World Economic Forum Executive Opinion Survey
12. World Justice Project Rule of Law Index Expert Survey
13. Varieties of Democracy (V-Dem)

I use the average corruption for two main reasons:

1. Methodological Change: In 2012, there was an adjustment in the CPI construction methodology, primarily involving a change in scale. This adjustment occurs within my sample period (2000-2021). To ensure comparability across the years, I normalize the pre-2012 values to match the post-2012 scaling. The average of this normalized series is used to minimize any potential bias introduced by the scale change.

2. Missing Values: Variance decomposition analysis indicates that the within-country variation in CPI is much smaller (2%) than the cross-country variation (98%) and some countries have missing annual values, using the average CPI maximizes the dataset's robustness, both temporally and cross-sectionally.

In robustness tests, I experiment with different versions of the corruption measure — the raw normalized series, average old series, and average new series — and confirm that the main results remain qualitatively unchanged. FE_{dt} represents donor-year fixed effects, $\mathbf{X}_{rdt}$ is a vector of control variables, and ϵ_{rdt} is the error term. I conduct the regression separately for each donor group: DAC members and observers, and China. Standard errors are clustered at the recipient country level.

A.3 Other Control Variables

I incorporate additional control variables from diverse sources to enrich the analysis. Macroeconomic indicators for recipient countries are sourced from the World Development Indicators (WDI). Bilateral trade data is obtained from the IMF Direction of Trade (DOT). To adjust DAC project values from current to constant dollar terms, I utilize inflator data from OECD DAC. Gravity variables, which include geographic and economic characteristics influencing trade, are drawn from the CEPII gravity database, as updated by Conte et al. (2022). Additionally, I employ Ideal Point Distance, a measure of countries' bilateral voting alignment during United Nations General Assembly sessions, constructed by Bailey et al. (2017).

B Additional Tables and Graphs

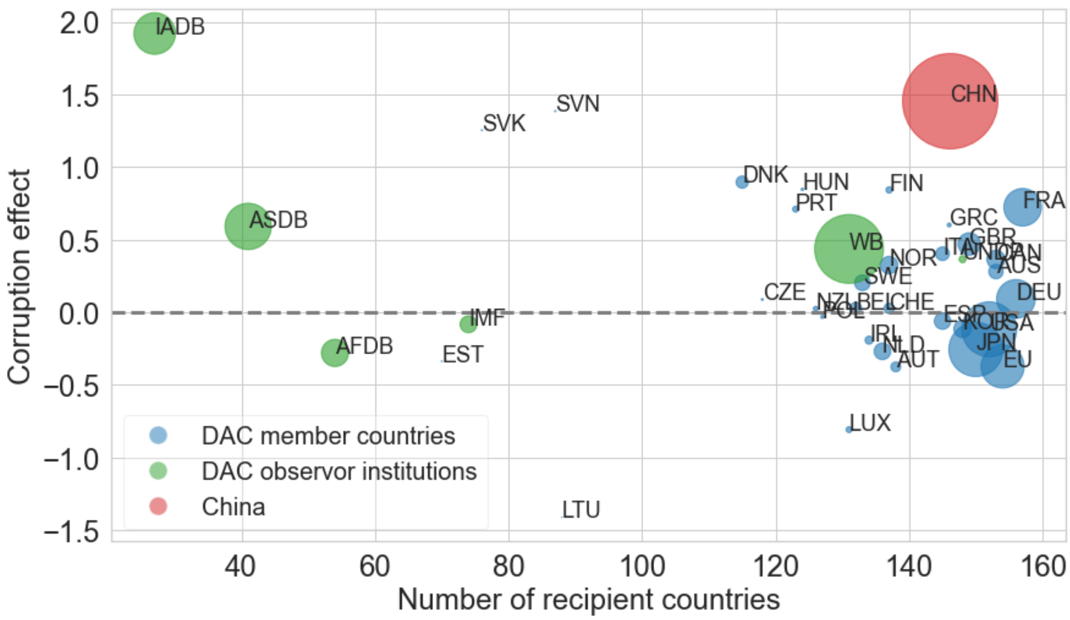


Figure B.1

Note: The colors reflect the total amount of DF from the DAC and China in constant 2011 USD over 2000-2021.
Source: Credit Reporting System & AidData Global Chinese Development Finance Dataset Version 3.0.

This approach exploits institutional differences among countries colonized by Europeans and is based on three premises. First, different types of colonization strategies were employed. In some colonies, Europeans set up extractive institutions that provided little protection for private property and few checks against government misappropriation. The primary purpose of these institutions was to transfer resources from the colonies to the colonizers. In other colonies, Europeans migrated and settled, replicating European institutions with strong private property protection and checks against government misappropriation. The second premise is that these colonization strategies were largely influenced by the feasibility of settlement, which was mainly determined by the disease environment. The third premise is that colonial institutions persist even after independence, with extractive institutions continuing to serve as misappropriation tools for the local government instead of the colonizers.

Based on these premises, Acemoglu et al. (2001) use data on the mortality rates of soldiers, bishops, and sailors stationed in the colonies between the seventeenth and nineteenth centuries as an instrument for current institutional quality. In a similar vein, I use the mortality rate as an instrument for the current Corruption Perception Index.

Table B.1

	(1)	(2)	(3)	(4)	(5)
Log project size	0.037***	0.037**	0.037	0.037***	0.037***
	(0.012)	(0.014)	(0.024)	(0.014)	(0.015)
Log sector total projects amount	0.036**	0.036**	0.036**	0.036**	0.036**
	(0.016)	(0.017)	(0.012)	(0.016)	(0.018)
Evaluator = inde. eval. office	-0.208***	-0.208**	-0.208***	-0.208***	-0.208**
	(0.076)	(0.091)	(0.004)	(0.080)	(0.095)
Evaluator = internal	0.049	0.049	0.049	0.049	0.049
	(0.257)	(0.363)	(0.115)	(0.320)	(0.388)
Observations	8786	8786	8786	8786	8786
R^2	0.426	0.426	0.426	0.426	0.426
F (χ^2) statistic for sector dummies	4.81	5.88	1140.79	4.17	122.48
P-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
SE clustering	None	Recipient	Donor	Recipient×Sector	Bootstrapped
Recipient×Donor×Year FE	✓	✓	✓	✓	✓
Sector dummies	✓	✓	✓	✓	✓

Null hypothesis of F test is that all coefficients of the sector dummies are jointly zero.

The second-stage regression is the same as equation 3.2. In the first stage, I run the following regression:[8]

$$\ln CPI_{r(i)} = FE_{d(i)s(i)t(i)} + \beta \cdot \ln Mortality_{r(i)} + \mathbf{X}_{r(i)d(i)t(i)} \cdot \gamma + constant + \nu_i.$$

The first-stage regression includes all the fixed effects and control variables used in the second stage. The results are summarized in Table **??**. The first-stage results in panel (c) show that higher settler mortality predicts lower CPI, equivalently higher corruption, which is consistent with the theory. The Cragg-Donald Wald F-statistic indicates that the instrument is strong if the error terms are independent. However, the Kleibergen-Paap rk Wald F-statistic and rk LM p-value suggest some possibility of a weak instrument if the error terms are not independent. Consequently, the second-stage coefficients for log CPI are not very precisely estimated. Nonetheless, the point estimates are consistent with the main exercises: the estimate for DAC members is close to zero, while the estimate for China is negative and of much greater magnitude. It is important to note that many observations are dropped compared to the baseline analysis, as settler mortality data is only available for countries that had been colonized by Europeans.

[8]The dependent variable and mortality rate vectors are a stack of repeated recipient-specific values over different combinations of donor, sector, and time.

Table B.2

	(1)	(2)	(3)	(4)
(a) DAC projects				
$CORRUPT_{r(i)}$ Q4	0.076	0.046	0.021	-0.012
	(0.058)	(0.053)	(0.056)	(0.056)
$CORRUPT_{r(i)}$ Q3	0.012	-0.011	-0.015	-0.042
	(0.050)	(0.055)	(0.053)	(0.059)
$CORRUPT_{r(i)}$ Q2	0.054	0.048	0.040	0.023
	(0.042)	(0.044)	(0.045)	(0.047)
$CORRUPT_{r(i)}$ Q4 $\times$ $LowMonitor_{s(i)}$			0.155***	0.164**
			(0.058)	(0.067)
$CORRUPT_{r(i)}$ Q3 $\times$ $LowMonitor_{s(i)}$			0.082*	0.095*
			(0.042)	(0.049)
$CORRUPT_{r(i)}$ Q2 $\times$ $LowMonitor_{s(i)}$			0.044	0.076
			(0.045)	(0.053)
Observations	1,183,235	1,045,455	1,155,291	1,021,935
R^2	0.354	0.265	0.355	0.264
(b) Chinese projects				
$CORRUPT_{r(i)}$ Q4	0.300*	0.489**	0.272	0.464**
	(0.169)	(0.188)	(0.170)	(0.182)
$CORRUPT_{r(i)}$ Q3	0.467***	0.458***	0.340*	0.318**
	(0.174)	(0.158)	(0.182)	(0.152)
$CORRUPT_{r(i)}$ Q2	0.244	0.302*	0.160	0.215
	(0.151)	(0.156)	(0.144)	(0.140)
$CORRUPT_{r(i)}$ Q4 $\times$ $LowMonitor_{s(i)}$			0.107	0.097
			(0.249)	(0.251)
$CORRUPT_{r(i)}$ Q3 $\times$ $LowMonitor_{s(i)}$			0.468	0.529*
			(0.289)	(0.283)
$CORRUPT_{r(i)}$ Q2 $\times$ $LowMonitor_{s(i)}$			0.250	0.258
			(0.259)	(0.264)
Observations	7,559	7,559	7,439	7,439
R^2	0.658	0.662	0.658	0.663
Donor×Sector×Year FE	✓	✓	✓	✓
Loan dummy, Population, GDP PC	✓	✓	✓	✓
Other recipient controls	✓	✓	✓	✓
Recipient×Donor controls		✓		✓
SE clustering	Recipient	Recipient	Recipient	Recipient

Note: The colors reflect the total amount of DF from the DAC and China in constant 2011 USD over 2000-2021.

Table B.3

	DAC members		China	
	(1) OLS	(2) IV	(3) OLS	(4) IV
(a) OLS				
$CORRUPT_{r(i)}$	0.006		0.022*	
	(0.004)		(0.012)	
(b) IV Second-stage				
$CORRUPT_{r(i)}$		-0.011		0.036
		(0.012)		(0.026)
(c) IV First-stage				
$Mortality_{r(i)}$		1.846**		2.104***
		(0.709)		(0.770)
Observations	747,357	747,357	5,005	5,005
R^2 (first-stage R^2 for IV)	0.269	0.421	0.688	0.576
Cragg-Donald Wald F stat.		4.9e+04		464.141
Kleibergen-Paap rk Wald F stat.		6.790		7.467
Kleibergen-Paap rk LM (P-value)		0.0388		0.0339
Donor×Sector×Year FE	✓	✓	✓	✓
Loan dummy, Population, GDP PC	✓	✓	✓	✓
Other recipient controls	✓	✓	✓	✓
Recipient×Donor controls	✓	✓	✓	✓
SE clustering	Recipient	Recipient	Recipient	Recipient

Note: The colors reflect the total amount of DF from the DAC and China in constant 2011 USD over 2000-2021.

Table B.4

	Baseline	Winsor (1%)	Winsor (2%)	Trim (1%)	Trim (2%)
	(1)	(2)	(3)	(4)	(5)
(a) DAC member countries					
$CORRUPT_{r(i)}$	-0.023	-0.014	-0.012	-0.015	-0.018
	(0.129)	(0.128)	(0.125)	(0.118)	(0.111)
$CORRUPT_{r(i)} \times LowMonitor_{s(i)}$	0.353**	0.345**	0.343**	0.329**	0.317**
	(0.164)	(0.157)	(0.152)	(0.140)	(0.121)
Observations	1,021,935	1,021,935	1,021,935	1,001,389	980,976
R^2	0.264	0.259	0.256	0.235	0.220
(b) projects by China					
$CORRUPT_{r(i)}$	1.376***	1.345***	1.332***	1.325***	1.182***
	(0.459)	(0.451)	(0.445)	(0.425)	(0.403)
$CORRUPT_{r(i)} \times LowMonitor_{s(i)}$	0.449	0.447	0.403	0.269	-0.097
	(0.708)	(0.692)	(0.669)	(0.598)	(0.515)
Observations	7,439	7,439	7,439	7,291	7,151
R^2	0.662	0.666	0.669	0.662	0.660
Donor×Sector×Year FE	✓	✓	✓	✓	✓
Loan dummy, Population, GDP PC	✓	✓	✓	✓	✓
Other recipient controls	✓	✓	✓	✓	✓
Recipient×Donor controls	✓	✓	✓	✓	✓
SE clustering	Recipient	Recipient	Recipient	Recipient	Recipient

Note: The colors reflect the total amount of DF from the DAC and China in constant 2011 USD over 2000-2021.

Table B.5

	Baseline	Normalized CPI	Avg. old CPI (0-10)	Old CPI (0-10)
	(1)	(2)	(3)	(4)
(a) DAC projects				
$CORRUPT_{r(i)}$	-0.023	-0.091	-0.891	-2.636
	(0.129)	(0.123)	(2.567)	(2.401)
$CORRUPT_{r(i)} \times LowMonitor_{s(i)}$	0.353**	0.308*	6.305**	6.988**
	(0.164)	(0.170)	(2.814)	(2.703)
Observations	1,021,935	987,837	1,021,935	412,323
R^2	0.264	0.262	0.264	0.254
(b) Chinese projects				
$CORRUPT_{r(i)}$	1.376***	1.257***	27.034***	21.696***
	(0.459)	(0.448)	(6.763)	(7.544)
$CORRUPT_{r(i)} \times LowMonitor_{s(i)}$	0.449	0.445	12.418	-4.602
	(0.708)	(0.893)	(14.647)	(11.583)
Observations	7,439	7,030	7,439	2,175
R^2	0.662	0.666	0.663	0.635
Donor×Sector×Year FE	✓	✓	✓	✓
Loan dummy, Population, GDP PC	✓	✓	✓	✓
Other recipient controls	✓	✓	✓	✓
Recipient×Donor controls	✓	✓	✓	✓
SE clustering	Recipient	Recipient	Recipient	Recipient

Note: The colors reflect the total amount of DF from the DAC and China in constant 2011 USD over 2000-2021.

Table B.6

	Binary (=1 if $\leq$ Q1)	Binary (=1 if $\leq$ Q2)	Continuous (-1 $\times$ Monitor)
	(1)	(2)	(3)
(a) DAC projects			
$CORRUPT_{r(i)}$	-0.023	-0.190	-0.067
	(0.129)	(0.135)	(0.122)
$CORRUPT_{r(i)} \times LowMonitor_{s(i)}$	0.353**	0.008***	0.025***
	(0.164)	(0.002)	(0.009)
Observations	1,021,935	1,021,935	1,021,935
R^2	0.264	0.264	0.264
(b) Chinese projects			
$CORRUPT_{r(i)}$	1.376***	1.196**	1.383***
	(0.459)	(0.477)	(0.466)
$CORRUPT_{r(i)} \times LowMonitor_{s(i)}$	0.449	0.009	0.026
	(0.708)	(0.008)	(0.021)
Observations	7,439	7,439	7,439
R^2	0.662	0.662	0.662
Donor×Sector×Year FE	✓	✓	✓
Loan dummy, Population, GDP PC	✓	✓	✓
Other recipient controls	✓	✓	✓
Recipient×Donor controls	✓	✓	✓
SE clustering	Recipient	Recipient	Recipient

Note: The colors reflect the total amount of DF from the DAC and China in constant 2011 USD over 2000-2021.

Table B.7

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$CORRUPT_{r(i)}$	-0.023	-0.020	0.008	-0.012	-0.017	-0.003	0.023
	(0.129)	(0.129)	(0.137)	(0.132)	(0.136)	(0.135)	(0.138)
$CORRUPT_{r(i)} \times LowMonitor_{s(i)}$	0.353**	0.347**	0.259*	0.325**	0.330**	0.290**	0.218**
	(0.164)	(0.156)	(0.132)	(0.140)	(0.128)	(0.121)	(0.109)
Observations	1,021,935	1,021,935	1,021,935	1,021,935	1,021,935	1,021,935	1,021,935
R^2	0.264	0.264	0.265	0.265	0.265	0.265	0.265
Recipient region × $LowMonitor_{s(i)}$		✓				✓	✓
Population / GDP PC × $LowMonitor_{s(i)}$			✓		✓		✓
Recipient character. × $LowMonitor_{s(i)}$			✓				✓
Recipient×Donor character. × $LowMonitor_{s(i)}$				✓			✓
All continuous controls × $LowMonitor_{s(i)}$					✓		✓
All dummy controls × $LowMonitor_{s(i)}$						✓	✓
Donor×Sector×Year FE	✓	✓	✓	✓	✓	✓	✓
Loan dummy, Population, GDP PC	✓	✓	✓	✓	✓	✓	✓
Other recipient controls	✓	✓	✓	✓	✓	✓	✓
Recipient×Donor controls	✓	✓	✓	✓	✓	✓	✓
SE clustering	Recipient	Recipient	Recipient	Recipient	Recipient	Recipient	Recipient

Note: The colors reflect the total amount of DF from the DAC and China in constant 2011 USD over 2000-2021.

Table B.8

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$CORRUPT_{r(i)}$	-0.023	-0.020	0.008	-0.012	-0.017	-0.003	0.023
	(0.129)	(0.129)	(0.137)	(0.132)	(0.136)	(0.135)	(0.138)
$CORRUPT_{r(i)} \times LowMonitor_{s(i)}$	0.353**	0.347**	0.259*	0.325**	0.330**	0.290**	0.218**
	(0.164)	(0.156)	(0.132)	(0.140)	(0.128)	(0.121)	(0.109)
America $\times$ $LowMonitor_{s(i)}$		0.029				0.074	0.119*
		(0.051)				(0.065)	(0.065)
Asia $\times$ $LowMonitor_{s(i)}$		0.076				0.053	0.125***
		(0.048)				(0.048)	(0.044)
Middle East $\times$ $LowMonitor_{s(i)}$		0.119				0.042	0.083
		(0.072)				(0.096)	(0.095)
Oceania $\times$ $LowMonitor_{s(i)}$		0.085				0.088	-0.024
		(0.069)				(0.064)	(0.075)
Europe $\times$ $LowMonitor_{s(i)}$		-0.001				-0.078	-0.076
		(0.108)				(0.110)	(0.102)
GDP PC growth $\times$ $LowMonitor_{s(i)}$			-0.396		-0.158		-0.594
			(0.355)		(0.333)		(0.371)
Inflatioin $\times$ $LowMonitor_{s(i)}$			-0.000		-0.000		0.000
			(0.000)		(0.000)		(0.000)
Public debt/GDP $\times$ $LowMonitor_{s(i)}$			-0.000		-0.000		-0.000
			(0.001)		(0.001)		(0.001)
FDI inflows/GDP $\times$ $LowMonitor_{s(i)}$			-0.000		0.000		-0.000
			(0.002)		(0.002)		(0.002)
Oil producer $\times$ $LowMonitor_{s(i)}$			0.000			-0.102***	-0.002
			(0.038)			(0.035)	(0.034)
English $\times$ $LowMonitor_{s(i)}$			-0.033			0.030	0.035
			(0.047)			(0.046)	(0.044)
GATT $\times$ $LowMonitor_{s(i)}$			-0.062			-0.055	-0.016
			(0.042)			(0.055)	(0.049)
WTO $\times$ $LowMonitor_{s(i)}$			-0.058			-0.066	-0.099*
			(0.056)			(0.061)	(0.054)
Log population $\times$ $LowMonitor_{s(i)}$			-0.037***		-0.043***		-0.050***
			(0.013)		(0.010)		(0.011)
Log GDP PC $\times$ $LowMonitor_{s(i)}$			-0.042		-0.027		-0.054**
			(0.026)		(0.023)		(0.024)
Contiguous $\times$ $LowMonitor_{s(i)}$				-0.091		-0.120	0.011
				(0.135)		(0.108)	(0.153)
Common leg. origin (pre) $\times$ $LowMonitor_{s(i)}$				-0.023		-0.016	-0.017
				(0.083)		(0.074)	(0.054)
Common leg. origin (post) $\times$ $LowMonitor_{s(i)}$				-0.047		-0.040	-0.047
				(0.067)		(0.064)	(0.040)
Common language $\times$ $LowMonitor_{s(i)}$				-0.141**		-0.135**	-0.137**
				(0.059)		(0.062)	(0.057)
Common colonizer $\times$ $LowMonitor_{s(i)}$				0.195		0.284	0.371
				(0.270)		(0.274)	(0.260)
Distance $\times$ $LowMonitor_{s(i)}$				-0.000	0.000		0.000
				(0.000)	(0.000)		(0.000)
Common religion $\times$ $LowMonitor_{s(i)}$				-0.067		-0.104	-0.125
				(0.082)		(0.082)	(0.080)
Sibling ever $\times$ $LowMonitor_{s(i)}$				-0.037		-0.067	-0.037
				(0.075)		(0.080)	(0.079)
Colony ever $\times$ $LowMonitor_{s(i)}$				0.184***		0.160**	0.151**
				(0.070)		(0.065)	(0.063)
Ideal Point Distance $\times$ $LowMonitor_{s(i)}$				-0.012	0.003		-0.037
				(0.034)	(0.033)		(0.030)
Bilateral trade $\times$ $LowMonitor_{s(i)}$				-0.004	-0.006		-0.005
				(0.004)	(0.004)		(0.004)
FTA $\times$ $LowMonitor_{s(i)}$				-0.074			-0.024
				(0.048)			(0.042)
Observations	1,021,935	1,021,935	1,021,935	1,021,935	1,021,935	1,021,935	1,021,935
R^2	0.264	0.264	0.265	0.265	0.265	0.265	0.265

Note: The colors reflect the total amount of DF from the DAC and China in constant 2011 USD over 2000-2021.

Table B.9

	Baseline (CPI)	Public misapp.	Executive misapp.
	(1)	(2)	(3)
(a) DAC projects			
$CORRUPT_{r(i)}$	-0.023		
	(0.129)		
$CORRUPT_{r(i)} \times LowMonitor_{s(i)}$	0.353**		
	(0.164)		
Public misappropriation index		-0.010	
		(0.035)	
Public misapp. $\times$ $LowMonitor_{s(i)}$		0.015	
		(0.040)	
Executive misappropriation index			-0.019
			(0.031)
Executive misapp. $\times$ $LowMonitor_{s(i)}$			0.011
			(0.033)
Observations	1,021,935	1,020,106	1,020,106
R^2	0.264	0.264	0.264
(b) Chinese projects			
$CORRUPT_{r(i)}$	1.376***		
	(0.459)		
$CORRUPT_{r(i)} \times LowMonitor_{s(i)}$	0.449		
	(0.708)		
Public misappropriation index		0.335***	
		(0.105)	
Public misapp. $\times$ $LowMonitor_{s(i)}$		-0.100	
		(0.236)	
Executive misappropriation index			0.225**
			(0.092)
Executive misapp. $\times$ $LowMonitor_{s(i)}$			-0.260
			(0.178)
Observations	7,439	7,333	7,333
R^2	0.662	0.665	0.665
Donor×Sector×Year FE	✓	✓	✓
Loan dummy, Population, GDP PC	✓	✓	✓
Other recipient controls	✓	✓	✓
Recipient×Donor controls	✓	✓	✓
SE clustering	Recipient	Recipient	Recipient

Note: Both measures are continuous between zero and one, with higher values indicating higher corruption, unlike the CPI.

Table B.10

	(1)	(2)	(3)	(4)
	Log project size	$SHARE^{CHN}_{rst}$	Total amount	$SHARE^{CHN}_{rt}$
(a) DAC DF				
$CORRUPT_r$	-0.104		-1.760***	
	(0.125)		(0.417)	
$CORRUPT_r \times LowMonitor_s$	0.333**			
	(0.158)			
Observations	754334		34387	
R^2	0.261		0.706	
(b) Chinese DF				
$CORRUPT_r$	1.610***	0.545***	3.268***	0.645***
	(0.606)	(0.146)	(1.195)	(0.201)
$CORRUPT_r \times LowMonitor_s$	0.663	-0.093***		
	(0.790)	(0.027)		
Observations	4,811	2,954	1,395	1,082
R^2	0.623	0.101	0.595	0.319
Level	Project	Sector	Country	Country
Model	OLS	OLS	PPML	OLS
Fixed Effects	Donor×Sector×Year	Sector×Year	Donor×Year	Year
Recipient controls	✓	✓	✓	✓
Recipient×Donor controls	✓	✓	✓	✓
Capital openness (Chinn-Ito)	✓	✓	✓	✓
Democracy (Polity IV)	✓	✓	✓	✓
Log public capital	✓	✓	✓	✓
SE clustering	Recipient	Recipient	Recipient	Recipient

Note: The colors reflect the total amount of DF from the DAC and China in constant 2011 USD over 2000-2021.

C Omitted Proofs

C.1 Proof of Lemma 1

Let's set a Lagrangian for the government's planning problem.

$$
\begin{aligned}
\mathcal{L} = & \sum_{t=0}^{\infty} \beta^t \tilde{U}(C_t, G_t^X) \\
& + \sum_{t=0}^{\infty} \beta^t \lambda_t \Big(Y_t + (1-\delta_K)K_t + \sum_{s \in S} \int_{j \in J_s} (1-\delta_s^E) g_{s,j,t}^E dj + T_t - C_t - K_{t+1} - \sum_{s \in S} \int_{j \in J_s} (R_s^D d_{s,j,t}^D + R_s^C d_{s,j,t}^C + \mathbb{I}_{s,j,t}^D f_s^D + \mathbb{I}_{s,j,t}^C f_s^C) dj \Big) \\
& + \sum_{t=0}^{\infty} \sum_{s \in S} \int_{j \in J_s} \beta^{t+1} \mu_{s,j,t+1}^E \Big(g_{s,j,t+1}^E - \psi_s^D d_{s,j,t+1}^D - \psi_s^C d_{s,j,t+1}^C \Big) dj + \sum_{t=0}^{\infty} \sum_{s \in S} \int_{j \in J_s} \beta^{t+1} \mu_{s,j,t+1}^X \Big(d_{s,j,t+1}^D + d_{s,j,t+1}^C - g_{s,j,t+1}^E \Big) dj \\
& + \sum_{t=0}^{\infty} \sum_{s \in S} \int_{j \in J_s} \beta^{t+1} \mu_{s,j,t+1}^D d_{s,j,t+1}^D dj + \sum_{t=0}^{\infty} \sum_{s \in S} \int_{j \in J_s} \beta^{t+1} \mu_{s,j,t+1}^C d_{s,j,t+1}^C dj
\end{aligned}
$$

Then, the first order condition for C_{t+1} is

$$[C_{t+1}]: \quad \tilde{U}'_C(C_{t+1}, G_{t+1}^X) = \lambda_{t+1}.$$

The first order conditions for $d_{s,j,t+1}^D$ and $d_{s,j,t+1}^C$ are

$$
\begin{aligned}
[d_{s,j,t+1}^D]: &\quad \tilde{U}'_{G^X}(C_{t+1}, G_{t+1}^X) - \lambda_{t+1} R_s^D - \mu_{s,j,t+1}^E \psi_s^D + \mu_{s,j,t+1}^X + \mu_{s,j,t+1}^D = 0 \\
[d_{s,j,t+1}^C]: &\quad \tilde{U}'_{G^X}(C_{t+1}, G_{t+1}^X) - \lambda_{t+1} R_s^C - \mu_{s,j,t+1}^E \psi_s^C + \mu_{s,j,t+1}^X + \mu_{s,j,t+1}^C = 0.
\end{aligned}
$$

GHH preference implies that $\tilde{U}'_{G^X}/\tilde{U}'_C = \chi$. Substituting for λ_{t+1} and using the GHH assumption, $[d_{s,j,t+1}^D]$ and $[d_{s,j,t+1}^C]$ can be rearranged as

$$
\begin{aligned}
[d_{s,j,t+1}^D]: &\quad \chi - R_s^D - \psi_s^D \frac{\mu_{s,j,t+1}^E}{\lambda_{t+1}} + \frac{\mu_{s,j,t+1}^X}{\lambda_{t+1}} + \frac{\mu_{s,j,t+1}^D}{\lambda_{t+1}} = 0 \\
[d_{s,j,t+1}^C]: &\quad \chi - R_s^C - \psi_s^C \frac{\mu_{s,j,t+1}^E}{\lambda_{t+1}} + \frac{\mu_{s,j,t+1}^X}{\lambda_{t+1}} + \frac{\mu_{s,j,t+1}^C}{\lambda_{t+1}} = 0.
\end{aligned}
$$

I prove by contradiction that it is not optimal to use both DF sources for project j. Suppose that both DF are used so that $d_{s,j,t+1}^D > 0$ and $d_{s,j,t+1}^C > 0$. By complementary slackness, $\mu_{s,j,t+1}^D = \mu_{s,j,t+1}^C = 0$. Note that either the monitoring constraint or the non-negativity constraint for misappropriation should be slack by construction. In other words, $\mu_{s,j,t+1}^E = 0$ or $\mu_{s,j,t+1}^C = 0$. I show that in either case, it is contradictory that both DF are used. First, suppose $\mu_{s,j,t+1}^E = 0$. Then, $[d_{s,j,t+1}^D]$ implies that $\frac{\mu_{s,j,t+1}^X}{\lambda_{t+1}} = R_s^D - \chi$ while $[d_{s,j,t+1}^D]$ implies that $\frac{\mu_{s,j,t+1}^X}{\lambda_{t+1}} = R_s^C - \chi$. Since $R_s^C \neq R_s^D$, it is contradictory. Now suppose that $\mu_{s,j,t+1}^C = 0$. Similarly, $[d_{s,j,t+1}^D]$ and $[d_{s,j,t+1}^C]$ can be satisfied at the same time only in a knife-edge case where $(\chi - R_s^D)/\psi_s^D = (\chi - R_s^C)/\psi_s^C$. Hence, the government finances each project j with only one DF source. $\square$

C.2 Proof of Lemma 2

Consider the Lagrangian for the government's planning problem as in the proof of Lemma 1. By Lemma 1, project j is financed by only one DF source. Suppose it is financed by $p \in \{D, C\}$. With the GHH preference assumption, the first order condition for $d^p_{s,j,t+1}$ can be modified as

$$[d^D_{s,j,t+1}]: \quad \chi - R^p_s - \psi^p_s \frac{\mu^E_{s,j,t+1}}{\lambda_{t+1}} + \frac{\mu^X_{s,j,t+1}}{\lambda_{t+1}} + \frac{\mu^p_{s,j,t+1}}{\lambda_{t+1}} = 0.$$

Since $d^p_{s,j,t+1} > 0$, complementary slackness implies that $\mu^p_{s,j,t+1} = 0$. Meanwhile, it is impossible by construction that the monitoring constraint and the non-negativity constraint for misappropriation bind at the same time. Hence, either $\mu^E_{s,j,t+1} = 0$ or $\mu^X_{s,j,t+1} = 0$ should hold. Suppose that $\mu^E_{s,j,t+1} = 0$. Then, $\frac{\mu^X_{s,j,t+1}}{\lambda_{t+1}} = R^p_s - \chi$. Since $\frac{\mu^X_{s,j,t+1}}{\lambda_{t+1}} \geq 0$, this is possible only if $R^p_s \geq \chi$. Moreover, if $R^p_s > \chi$, $\mu^X_{s,j,t+1} > 0$ and the non-negativity constraint for misappropriation should bind resulting in $g^E_{s,j,t+1} = d^p_{s,j,t+1}$. Now, suppose that $\mu^X_{s,j,t+1} = 0$. Then, $\frac{\mu^E_{s,j,t+1}}{\lambda_{t+1}} = (\chi - R^p_s)/\psi^p_s$. Since $\frac{\mu^E_{s,j,t+1}}{\lambda_{t+1}} \geq 0$, this is possible only if $R^p_s \leq \chi$. Moreover, if $R^p_s < \chi$, $\mu^E_{s,j,t+1} > 0$ and the monitoring constraint should bind resulting in $g^E_{s,j,t+1} = \psi^p_s d^p_{s,j,t+1}$. Since $R^p_s < \chi$ and $R^p_s > \chi$ are mutually exclusive and collectively exhaustive except for the knife-case where $R^p_s = \chi$, it concludes the proof. □

C.3 Proof of Lemma 3 and Corollary 1

Consider the Lagrangian $\mathcal{L}$ for the government's planning problem. Lemma 1 implies that each project j is financed by one DF source. Suppose it is financed by $p \in \{D, C\}$. The FOCs for the effective public capital in project j, $g^E_{s,j,t+1}$, and the p debt stock for j, $d^p_{s,j,t+1}$, can be rearranged as

$$[g^E_{s,j,t+1}]: \quad -\chi + mpg^E_{s,j,t+1} + 1 - \delta^E_s + \frac{\mu^E_{s,j,t+1}}{\lambda_{t+1}} - \frac{\mu^X_{s,j,t+1}}{\lambda_{t+1}} = 0$$
$$[d^D_{s,j,t+1}]: \quad \chi - R^p_s - \psi^p_s \frac{\mu^E_{s,j,t+1}}{\lambda_{t+1}} + \frac{\mu^X_{s,j,t+1}}{\lambda_{t+1}} = 0$$

where $mpg^E_{s,j,t+1} \equiv \frac{\partial Y_{t+1}}{\partial g^E_{s,j,t+1}}$. If $\chi < R^p_s$, by Lemma 2, the government chooses zero misappropriation hence $\mu^E_{s,j,t+1} = 0$ and $\mu^X_{s,j,t+1}/\lambda_{t+1} = R^p_s - \chi$. Plugging these into $[g^E_{s,j,t+1}]$,

$$mpg^E_{s,j,t+1} + 1 - \delta^E_s = R^p_s.$$

Now suppose $\chi > R^p_s$. Lemma 2 implies that the government chooses maximal misappropriation hence $\mu^X_{s,j,t+1} = 0$ and $\mu^E_{s,j,t+1}/\lambda_{t+1} = (\chi - R^p_s)/\psi^p_s$. Plugging theses into $[g^E_{s,j,t+1}]$ yields

$$\psi^p_s(mpg^E_{s,j,t+1} + 1 - \delta^E_s) + (1 - \psi^p_s)\chi = R^p_s.$$

It concludes the proof of Lemma 3. Corollary 1 can be proven simply by rearranging the last two equations so that only $mpg^E_{s,j,t+1}$ remains on the left hand side. $\square$

C.4 Proof of Proposition 1

Lemma 1 and 2 imply that for each project, the government chooses among 4 financing options (2 by 2); DAC versus China and maximal versus zero misappropriation. Lemma 3 pins down the optimal size of a project when financed with each of the 4 options as $\bar{g}^{Ep}_{s,j,t}$ such that $mpg^E_{s,j,t} = \tilde{R}^p_s$. If a project is financed without misappropriation, the contribution of the project to the utility of the government is

$$\tilde{U}'_C \cdot \left(\int_0^{\bar{g}^{Ep}_{s,j,t}} (mpg^E_{s,j,t} + (1-\delta^E_s) - R^p_s) dg - f^p_s \right).$$

With maximal misappropriation, it is

$$\begin{aligned}
&\tilde{U}'_C \cdot \left(\int_0^{\bar{g}^{Ep}_{s,j,t}} (mpg^E_{s,j,t} + (1-\delta^E_s) - \frac{R^p_s}{\psi^p_s}) dg - f^p_s \right) + \tilde{U}'_{G^X} \cdot \left(\frac{1-\psi^p_s}{\psi^p_s} \bar{g}^{Ep}_{s,j,t} \right) \\
&= \tilde{U}'_C \cdot \left[\int_0^{\bar{g}^{Ep}_{s,j,t}} (mpg^E_{s,j,t} + (1-\delta^E_s) - \frac{R^p_s}{\psi^p_s}) dg - f^p_s + \frac{\tilde{U}'_{G^X}}{\tilde{U}'_C} \frac{1-\psi^p_s}{\psi^p_s} \bar{g}^{Ep}_{s,j,t} \right] \\
&= \tilde{U}'_C \cdot \left[\int_0^{\bar{g}^{Ep}_{s,j,t}} (mpg^E_{s,j,t} + (1-\delta^E_s) - \frac{R^p_s}{\psi^p_s} + \frac{1-\psi^p_s}{\psi^p_s}\chi) dg - f^p_s \right] \\
&= \tilde{U}'_C \cdot \left[\int_0^{\bar{g}^{Ep}_{s,j,t}} (mpg^E_{s,j,t} + (1-\delta^E_s) - \frac{R^p_s - (1-\psi^p_s)\chi}{\psi^p_s}) dg - f^p_s \right]
\end{aligned}$$

Using the definition of $\tilde{R}^p_s$ and $\tilde{\pi}^p_{s,j,t}$, either without misappropriation or with maximal misappropriation, the contribution of the project to the government's utility can be written as $\tilde{U}'_C \cdot \tilde{\pi}^p_{s,j,t}$. Note that the choice of financing options affects the Lagrangian for the planning problem only through this term. Since $\tilde{U}'_C$ is a common factor, it is optimal for the government to choose the financing option that maximizes the effective profit $\tilde{\pi}^p_{s,j,t}$. $\square$

C.5 Proof of Lemma 4

In an optimal allocation, the cutoffs can be expressed in terms of output Y_t and the effective public capital stock in sector s for period t, $G^E_{s,t}$, as follows:

$$\bar{\theta}^p_{s,t} = \frac{\left((\sigma_s - 1) f^p_s\right)^{\frac{1}{\sigma_s}}}{\gamma \gamma_s Y_t} (G^E_{s,t} \tilde{R}^p_s)^{\frac{\sigma_s - 1}{\sigma_s}},$$

$$\bar{\theta}^I_{s,t} = \frac{\left((\sigma_s - 1)(f^p_s - f^{p'}_s)\right)^{\frac{1}{\sigma_s}}}{\gamma \gamma_s Y_t} (G^E_{s,t} \tilde{R}^p_s \tilde{R}^{p'}_s)^{\frac{\sigma_s - 1}{\sigma_s}} \left[\frac{1}{(\tilde{R}^{p'}_s)^{\sigma_s - 1} - (\tilde{R}^p_s)^{\sigma_s - 1}} \right]^{\frac{1}{\sigma_s}}.$$

Corollary 1 implies that

$$\begin{aligned}
& mpg^{E}_{s,j,t+1} = \tilde{R}^{p}_{s} \\
\iff & \theta_{s,j}\gamma\gamma_s \frac{Y_{t+1}}{G^{E}_{t+1}} \frac{G^{E}_{t+1}}{G^{E}_{s,t+1}} \left(\frac{G^{E}_{s,t+1}}{g^{E}_{s,j,t+1}}\right)^{\frac{1}{\sigma_s}} = \tilde{R}^{p}_{s} \\
\iff & g^{E*}_{s,j,t+1} = \left(\frac{\theta_{s,j}\gamma\gamma_s}{\tilde{R}^{p}_{s}} Y_t\right)^{\sigma_s} (G^{E}_{s,t+1})^{1-\sigma_s}
\end{aligned}$$

And the effective profit is

$$\begin{aligned}
\tilde{\pi}^{p}_{s} &= \int_{0}^{g^{E*}_{s,j,t+1}} (mpg^{E}_{s,j,t+1} - \tilde{R}^{p}_{s}) dg^{E}_{s,j,t+1} - f^{p}_{s} \\
&= \int_{0}^{g^{E*}_{s,j,t+1}} \left(\theta_{s,j}\gamma\gamma_s \frac{Y_{t+1}}{G^{E}_{s,t+1}} \left(\frac{G^{E}_{s,t+1}}{g^{E}_{s,j,t+1}}\right)^{\frac{1}{\sigma_s}} - \tilde{R}^{p}_{s}\right) dg^{E}_{s,j,t+1} - f^{p}_{s} \\
&= \theta_{s,j}\gamma\gamma_s Y_{t+1} (G^{E}_{s,t+1})^{\frac{1-\sigma_s}{\sigma_s}} \int_{0}^{g^{E*}_{s,j,t+1}} (g^{E}_{s,j,t+1})^{-\frac{1}{\sigma_s}} dg^{E}_{s,j,t+1} - \tilde{R}^{p}_{s} g^{E*}_{s,j,t+1} - f^{p}_{s} \\
&= \theta_{s,j}\gamma\gamma_s Y_{t+1} (G^{E}_{s,t+1})^{\frac{1-\sigma_s}{\sigma_s}} \frac{\sigma_s}{\sigma_s - 1} (g^{E*}_{s,j,t+1})^{\frac{\sigma_s - 1}{\sigma_s}} - \tilde{R}^{p}_{s} g^{E*}_{s,j,t+1} - f^{p}_{s} \\
&= \frac{\sigma_s}{\sigma_s - 1} \left(\theta_{s,j}\gamma\gamma_s Y_{t+1}\right)^{\sigma_s} (\tilde{R}^{p}_{s} G^{E}_{s,t+1})^{1-\sigma_s} - \left(\theta_{s,j}\gamma\gamma_s Y_{t+1}\right)^{\sigma_s} (\tilde{R}^{p}_{s} G^{E}_{s,t+1})^{1-\sigma_s} - f^{p}_{s} \\
&= \frac{1}{\sigma_s - 1} \left(\theta_{s,j}\gamma\gamma_s Y_{t+1}\right)^{\sigma_s} (\tilde{R}^{p}_{s} G^{E}_{s,t+1})^{1-\sigma_s} - f^{p}_{s}
\end{aligned}$$

Zero-profit cutoff can be obtained by equating $\tilde{\pi}^{p}_{s}$ to zero.

$$\begin{aligned}
& \tilde{\pi}^{p}_{s}(\bar{\theta}^{p}_{s,t+1}) = 0 \\
\iff & \bar{\theta}^{p}_{s,t+1} = \frac{\left((\sigma_s - 1) f^{p}_{s}\right)^{\frac{1}{\sigma_s}}}{\gamma\gamma_s Y_t} (G^{E}_{s,t} \tilde{R}^{p}_{s})^{\frac{\sigma_s - 1}{\sigma_s}}
\end{aligned}$$

Now, I compare $\tilde{\pi}^{p}_{s}(\theta)$ and $\tilde{\pi}^{p'}_{s}(\theta)$. Let's define the difference function $diff(\theta) \equiv \tilde{\pi}^{p}_{s}(\theta) - \tilde{\pi}^{p'}_{s}(\theta)$.

$$\begin{aligned}
diff(\theta) &= \frac{1}{\sigma_s - 1} \left(\theta\gamma\gamma_s Y_{t+1}\right)^{\sigma_s} (G^{E}_{s,t+1})^{1-\sigma_s} ((\tilde{R}^{p}_{s})^{1-\sigma_s} - (\tilde{R}^{p'}_{s})^{1-\sigma_s}) - (f^{p}_{s} - f^{p'}_{s}). \\
&= \frac{1}{\sigma_s - 1} \left(\theta\gamma\gamma_s Y_{t+1}\right)^{\sigma_s} (G^{E}_{s,t+1})^{1-\sigma_s} (\tilde{R}^{p}_{s} \tilde{R}^{p'}_{s})^{1-\sigma_s} \left((\tilde{R}^{p'}_{s})^{\sigma_s - 1} - (\tilde{R}^{p}_{s})^{\sigma_s - 1}\right) - (f^{p}_{s} - f^{p'}_{s})
\end{aligned}$$

Suppose that $\tilde{R}^{p'}_{s} > \tilde{R}^{p}_{s}$. Then, $diff(\theta)$ is strictly increasing in θ.Let's first find the productivity $\bar{\theta}^{I}_{s,t+1}$ that makes the difference zero so the government is indifferent between p and p'.

$$\begin{aligned}
& diff(\bar{\theta}^{I}_{s,t}) = 0 \\
\iff & \bar{\theta}^{I}_{s,t} = \frac{\left((\sigma_s - 1)(f^{p}_{s} - f^{p'}_{s})\right)^{\frac{1}{\sigma_s}}}{\gamma\gamma_s Y_t} (G^{E}_{s,t} \tilde{R}^{p}_{s} \tilde{R}^{p'}_{s})^{\frac{\sigma_s - 1}{\sigma_s}} \left[\frac{1}{(\tilde{R}^{p'}_{s})^{\sigma_s - 1} - (\tilde{R}^{p}_{s})^{\sigma_s - 1}}\right]^{\frac{1}{\sigma_s}}
\end{aligned}$$

The cutoff is well-defined only if $f_s^p > f_s^{p'}$. Otherwise, the difference is always positive hence it is optimal to choose p over p' for all θ. If $f_s^p > f_s^{p'}$, for all $\theta > \bar{\theta}^I_{s,t+1}$, $\tilde{\pi}_s^p(\theta) > \tilde{\pi}_s^{p'}(\theta)$ while for all $\theta \leq \bar{\theta}^I_{s,t+1}$, $\tilde{\pi}_s^p(\theta) \leq \tilde{\pi}_s^{p'}(\theta)$. In sector s, for there to be any active project that is financed by p', the cutoffs should be such that $\bar{\theta}_s^{p'} < \bar{\theta}_s^I$.

$$\begin{aligned}
&\bar{\theta}_s^{p'} < \bar{\theta}_s^I \\
\iff &\frac{\left((\sigma_s-1)f_s^{p'}\right)^{\frac{1}{\sigma_s}}}{\gamma\gamma_s Y_t}(G^E_{s,t}\tilde{R}_s^{p'})^{\frac{\sigma_s-1}{\sigma_s}} < \frac{\left((\sigma_s-1)(f_s^p-f_s^{p'})\right)^{\frac{1}{\sigma_s}}}{\gamma\gamma_s Y_t}(G^E_{s,t}\tilde{R}_s^p\tilde{R}_s^{p'})^{\frac{\sigma_s-1}{\sigma_s}}\left[\frac{1}{(\tilde{R}_s^{p'})^{\sigma_s-1}-(\tilde{R}_s^p)^{\sigma_s-1}}\right]^{\frac{1}{\sigma_s}} \\
\iff &f_s^{p'} < (f_s^p-f_s^{p'})(\tilde{R}_s^p)^{\sigma_s-1}\frac{1}{(\tilde{R}_s^{p'})^{\sigma_s-1}-(\tilde{R}_s^p)^{\sigma_s-1}} \\
\iff &f_s^{p'}((\tilde{R}_s^{p'})^{\sigma_s-1}-(\tilde{R}_s^p)^{\sigma_s-1}) < (f_s^p-f_s^{p'})(\tilde{R}_s^p)^{\sigma_s-1} \\
\iff &f_s^{p'}(\tilde{R}_s^{p'})^{\sigma_s-1} < f_s^p(\tilde{R}_s^p)^{\sigma_s-1} \\
\iff &\left(\frac{\tilde{R}_s^{p'}}{\tilde{R}_s^p}\right)^{\sigma_s-1} f_s^{p'} < f_s^p.
\end{aligned}$$

Hence, if $f_s^p \leq \left(\frac{\tilde{R}_s^{p'}}{\tilde{R}_s^p}\right)^{\sigma_s-1} f_s^{p'}$, all projects that make a positive effective profit when financed by p' can make a higher profit when financed by p. Therefore, all operating projects in sector s is financed by p. If $f_s^p > \left(\frac{\tilde{R}_s^{p'}}{\tilde{R}_s^p}\right)^{\sigma_s-1} f_s^{p'}$, projects with $\theta \geq \bar{\theta}^I_{s,t+1}$ are financed by p and projects with $\theta \in [\bar{\theta}^{p'}_{s,t+1}, \bar{\theta}^I_{s,t+1})$ are financed by p'. $\square$

C.6 Proof of Proposition 2

(Optimal Financing at the Sectoral Level). Let $S^{pp'}$ denote the set of sectors where projects with $\theta \geq \bar{\theta}^I$ are financed by p, and projects with $\theta < \bar{\theta}^I$ are financed by p'. And let S^p denote the set of sectors where all projects with $\theta \geq \bar{\theta}^p$ are financed by p. A superscript with a tilde $(\tilde{\ })$ indicates maximal diversion, while a superscript without a tilde indicates zero diversion. Each sector falls into one of the following seven categories based on corruption levels and fixed costs:

	$\chi < R_s^D$	$R_s^D < \chi < R_s^C$	$R_s^C < \chi < \frac{\psi_s^D R_s^C - \psi_s^C R_s^D}{\psi_s^D - \psi_s^C}$	$\frac{\psi_s^D R_s^C - \psi_s^C R_s^D}{\psi_s^D - \psi_s^C} < \chi$
$f_s^D \leq (\frac{\tilde{R}_s^C}{\tilde{R}_s^D})^{\sigma_s-1} f_s^C$	$s \in S^D$	$s \in S^{\tilde{D}}$	$s \in S^{\tilde{D}}$	$s \in S^{\tilde{C}\tilde{D}}$
$f_s^D > (\frac{\tilde{R}_s^C}{\tilde{R}_s^D})^{\sigma_s-1} f_s^C$	$s \in S^{DC}$	$s \in S^{\tilde{D}C}$	$s \in S^{\tilde{D}\tilde{C}}$	$s \in S^{\tilde{C}}$

First, suppose $\chi < R_s^D < R_s^C$. Lemma 2 implies that it is optimal to choose zero misappropriation for both DAC and China. Then, $\tilde{R}_s^D = R_s^D - (1-\delta_s^E) < R_s^C - (1-\delta_s^E) = \tilde{R}_s^C$. Lemma 4 implies that if $f_s^D \leq (\frac{\tilde{R}_s^C}{\tilde{R}_s^D})^{\sigma_s-1} f_s^C$, all projects in sector s are financed by DAC and hence $s \in S^D$ while if $f_s^D > (\frac{\tilde{R}_s^C}{\tilde{R}_s^D})^{\sigma_s-1} f_s^C$, projects with $\theta \geq \bar{\theta}^I_{s,t+1}$ are financed by DAC and projects with $\theta \in [\bar{\theta}^C_{s,t+1}, \bar{\theta}^I_{s,t+1})$ are financed by China and hence $s \in S^{DC}$.

Second, suppose $R_s^D < \chi < R_s^C$. Lemma 2 implies that the government chooses maximal misappropriation for DAC and zero misappropriation for China. Then, $\tilde{R}_s^D = \frac{R_s^D - (1-\psi_s^D)\chi}{\psi_s^D} - (1-\delta_s^E) < R_s^C - (1-\delta_s^E) = \tilde{R}_s^C$. Lemma 4 implies that if f_s^D is not greater than the threshold, all projects are financed by DAC so $s \in S^{\tilde{D}}$ while if f_s^D is greater than the threshold, projects with $\theta \geq \bar{\theta}_{s,t+1}^I$ are financed by DAC and projects with $\theta \in [\bar{\theta}_{s,t+1}^C, \bar{\theta}_{s,t+1}^I)$ are financed by China and hence $s \in S^{\tilde{D}C}$.

Third, suppose $R_s^D < R_s^C < \chi < \frac{\psi_s^D R_s^C - \psi_s^C R_s^D}{\psi_s^D - \psi_s^C}$. By Lemma 2, the government chooses maximal misappropriation for both DAC and China. Since $\chi < \frac{\psi_s^D R_s^C - \psi_s^C R_s^D}{\psi_s^D - \psi_s^C}$, $\tilde{R}_s^D = \frac{R_s^D - (1-\psi_s^D)\chi}{\psi_s^D} - (1-\delta_s^E) < \frac{R_s^C - (1-\psi_s^C)\chi}{\psi_s^C} - (1-\delta_s^E) = \tilde{R}_s^C$. The rest follows a similar logic to the one used for the above two cases.

Lastly, suppose $\frac{\psi_s^D R_s^C - \psi_s^C R_s^D}{\psi_s^D - \psi_s^C} < \chi$. By Lemma2, the government chooses maximal misappropriation for both DAC and China. However, $\tilde{R}_s^D > \tilde{R}_s^C$. Hence, Lemma 4 implies that if $f_s^C \leq (\frac{\tilde{R}_s^D}{\tilde{R}_s^C})^{\sigma_s - 1} f_s^D$, all projects are financed by China so $s \in S^{\tilde{C}}$. If $f_s^C > (\frac{\tilde{R}_s^D}{\tilde{R}_s^C})^{\sigma_s - 1} f_s^D$, projects with $\theta \geq \bar{\theta}_{s,t+1}^I$ are financed by China and projects with $\theta \in [\bar{\theta}_{s,t+1}^D, \bar{\theta}_{s,t+1}^I)$ are financed by DAC so $s \in S^{\tilde{C}\tilde{D}}$. □

C.7 Proof of Proposition 3

(Aggregation of the Sectoral Effective Public Capital). The effective public capital in sector s for period t is given by:

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

where

$$\mathcal{G}_s^{E} = \begin{cases} \mathcal{G}_s^{E,D} \cdot \mathcal{G}_s & \text{if } s \in (S^{D} \cup S^{\tilde{D}}) \\ \mathcal{G}_s^{E,C} \cdot \mathcal{G}_s & \text{if } s \in S^{\tilde{C}} \\ \mathcal{G}_s^{E,DC} \cdot \mathcal{G}_s & \text{if } s \in (S^{DC} \cup S^{\tilde{D}C} \cup S^{\tilde{D}\tilde{C}}) \\ \mathcal{G}_s^{E,CD} \cdot \mathcal{G}_s & \text{if } s \in S^{\tilde{C}\tilde{D}}. \end{cases}$$

Here, $\mathcal{G}_s$ is a factor not related to the financing choices, defined as:

$$\mathcal{G}_s \equiv \left(\sigma_s - 1\right)^{\frac{\sigma_s-\xi_s}{\xi_s(\sigma_s-1)}} \left(\gamma\gamma_s\right)^{\frac{\sigma_s(\xi_s-1)}{\xi_s(\sigma_s-1)}} \left(\frac{\xi_s {\theta_{min}^{s}}^{\xi_s}}{\xi_s - \sigma_s}\right)^{\frac{\sigma_s}{\xi_s(\sigma_s-1)}}$$

and the other financing-specific factors are:

$$\mathcal{G}_s^{E,D} \equiv (\tilde{R}_s^{D})^{-1}(f_s^{D})^{\frac{\sigma_s-\xi_s}{\xi_s(\sigma_s-1)}}, \quad \mathcal{G}_s^{E,DC} \equiv \left[f_s^{C}\big(\frac{(\tilde{R}_s^{C})^{1-\sigma_s}}{f_s^{C}}\big)^{\frac{\xi_s}{\sigma_s}} + (f_s^{D} - f_s^{C})\big(\frac{(\tilde{R}_s^{D})^{1-\sigma_s} - (\tilde{R}_s^{C})^{1-\sigma_s}}{f_s^{D} - f_s^{C}}\big)^{\frac{\xi_s}{\sigma_s}}\right]^{\frac{\sigma_s}{\xi_s(\sigma_s-1)}}$$

$$\mathcal{G}_s^{E,C} \equiv (\tilde{R}_s^{C})^{-1}(f_s^{C})^{\frac{\sigma_s-\xi_s}{\xi_s(\sigma_s-1)}}, \quad \mathcal{G}_s^{E,CD} \equiv \left[f_s^{D}\big(\frac{(\tilde{R}_s^{D})^{1-\sigma_s}}{f_s^{D}}\big)^{\frac{\xi_s}{\sigma_s}} + (f_s^{C} - f_s^{D})\big(\frac{(\tilde{R}_s^{C})^{1-\sigma_s} - (\tilde{R}_s^{D})^{1-\sigma_s}}{f_s^{C} - f_s^{D}}\big)^{\frac{\xi_s}{\sigma_s}}\right]^{\frac{\sigma_s}{\xi_s(\sigma_s-1)}}.$$

Suppose that sector s is financed by a single provider, say p. Corollary 1 implies that the optimal project size for each j in sector s is $g_{s,j,t+1}^{E*} = (\theta_{s,j}\gamma\gamma_s Y_{t+1}/\tilde{R}_s^{p})^{\sigma_s}(G_{s,t+1}^{E})^{1-\sigma_s}$. Plugging this into the definition of

$G^E_{s,t+1}$, I get

$$\begin{aligned}
G^E_{s,t+1} &= \left[\int_{j\in J_s} \theta_{s,j} {g^E_{s,j,t+1}}^{\frac{\sigma_s-1}{\sigma_s}} dj\right]^{\frac{\sigma_s}{\sigma_s-1}} \\
&= \left[\int_{\theta_s} \theta_s {g^E_{s,j,t+1}}^{\frac{\sigma_s-1}{\sigma_s}} dH_s(\theta_s)\right]^{\frac{\sigma_s}{\sigma_s-1}} \\
&= \left[\int_{\theta_s} \theta_s \left((\frac{\theta_s\gamma\gamma_s Y_{t+1}}{\tilde{R}^p_s})^{\sigma_s} (G^E_{s,t+1})^{1-\sigma_s}\right)^{\frac{\sigma_s-1}{\sigma_s}} dH_s(\theta_s)\right]^{\frac{\sigma_s}{\sigma_s-1}} \\
&= (\frac{\gamma\gamma_s Y_{t+1}}{\tilde{R}^p_s})^{\sigma_s} (G^E_{s,t+1})^{1-\sigma_s} (\xi_s {\theta^s_{min}}^{\xi_s})^{\frac{\sigma_s}{\sigma_s-1}} \left[\int_{\bar{\theta}^p_{s,t+1}}^{\infty} \theta_s^{\sigma_s-\xi_s-1} d\theta_s\right]^{\frac{\sigma_s}{\sigma_s-1}} \\
&= (\frac{\gamma\gamma_s Y_{t+1}}{\tilde{R}^p_s})^{\sigma_s} (G^E_{s,t+1})^{1-\sigma_s} (\xi_s {\theta^s_{min}}^{\xi_s})^{\frac{\sigma_s}{\sigma_s-1}} \left[\frac{1}{\sigma_s-\xi_s} \theta_s^{\sigma_s-\xi_s}\Big|_{\bar{\theta}^p_{s,t+1}}^{\infty}\right]^{\frac{\sigma_s}{\sigma_s-1}} \\
&= (\frac{\gamma\gamma_s Y_{t+1}}{\tilde{R}^p_s})^{\sigma_s} (G^E_{s,t+1})^{1-\sigma_s} (\frac{\xi_s {\theta^s_{min}}^{\xi_s}}{\xi_s-\sigma_s})^{\frac{\sigma_s}{\sigma_s-1}} \left[\left(\frac{((\sigma_s-1)f^p_s)^{\frac{\sigma_s-\xi_s}{\sigma_s}}}{(\gamma\gamma_s Y_{t+1})^{\sigma_s-\xi_s}} (G^E_{s,t+1}\tilde{R}^p_s)^{\frac{(\sigma_s-1)(\sigma_s-\xi_s)}{\sigma_s}}\right)\right]^{\frac{\sigma_s}{\sigma_s-1}} \\
&= (\gamma\gamma_s Y_{t+1})^{\frac{\sigma_s(\xi_s-1)}{\sigma_s-1}} (\tilde{R}^p_s)^{-\xi_s} (G^E_{s,t+1})^{1-\xi_s} ((\sigma_s-1)f^p_s)^{\frac{\sigma_s-\xi_s}{\sigma_s-1}} (\frac{\xi_s {\theta^s_{min}}^{\xi_s}}{\xi_s-\sigma_s})^{\frac{\sigma_s}{\sigma_s-1}}
\end{aligned}$$

Rearranging,

$$G^E_{s,t+1} = \frac{((\sigma_s-1)f^p_s)^{\frac{\sigma_s-\xi_s}{\xi_s(\sigma_s-1)}}}{\tilde{R}^p_s} (\frac{\xi_s {\theta^s_{min}}^{\xi_s}}{\xi_s-\sigma_s})^{\frac{\sigma_s}{\xi_s(\sigma_s-1)}} (\gamma\gamma_s Y_{t+1})^{\frac{\sigma_s(\xi_s-1)}{\xi_s(\sigma_s-1)}}$$

Now, suppose that sector s is financed by both p and p' and $\tilde{R}^p_s < \tilde{R}^{p'}_s$. Lemma 5 implies that projects with $\theta \geq \bar{\theta}^I_{s,t+1}$ are financed by p and projects with $\theta \in [\bar{\theta}^{p'}_{s,t+1}, \bar{\theta}^I_{s,t+1})$ are financed by p'. Then,

$$
\begin{aligned}
G^E_{s,t+1} &= \left[\int_{j\in J_s} \theta_{s,j} {g^E_{s,j,t+1}}^{\frac{\sigma_s-1}{\sigma_s}} dj\right]^{\frac{\sigma_s}{\sigma_s-1}} \\
&= \left[\int_{\theta_s} \theta_s {g^E_{s,j,t+1}}^{\frac{\sigma_s-1}{\sigma_s}} dH_s(\theta_s)\right]^{\frac{\sigma_s}{\sigma_s-1}} \\
&= \left[\int_{\bar{\theta}^{p'}_{s,t+1}}^{\bar{\theta}^I_{s,t+1}} \theta_s {g^E_{s,j,t+1}}^{\frac{\sigma_s-1}{\sigma_s}} dH_s(\theta_s) + \int_{\bar{\theta}^I_{s,t+1}}^{\infty} \theta_s {g^E_{s,j,t+1}}^{\frac{\sigma_s-1}{\sigma_s}} dH_s(\theta_s)\right]^{\frac{\sigma_s}{\sigma_s-1}} \\
&= (\gamma\gamma_s Y_{t+1})^{\sigma_s}(G^E_{s,t+1})^{1-\sigma_s}(\xi_s {\theta^s_{min}}^{\xi_s})^{\frac{\sigma_s}{\sigma_s-1}}\left[(\tilde{R}^{p'}_s)^{1-\sigma_s}\int_{\bar{\theta}^{p'}_{s,t+1}}^{\bar{\theta}^I_{s,t+1}} \theta_s^{\sigma_s-\xi_s-1} d\theta_s + (\tilde{R}^{p}_s)^{1-\sigma_s}\int_{\bar{\theta}^I_{s,t+1}}^{\infty} \theta_s^{\sigma_s-\xi_s-1} d\theta_s\right]^{\frac{\sigma_s}{\sigma_s-1}} \\
&= (\gamma\gamma_s Y_{t+1})^{\sigma_s}(G^E_{s,t+1})^{1-\sigma_s}(\xi_s {\theta^s_{min}}^{\xi_s})^{\frac{\sigma_s}{\sigma_s-1}}\left[\frac{(\tilde{R}^{p'}_s)^{1-\sigma_s}}{\sigma_s-\xi_s}\theta_s^{\sigma_s-\xi_s}\Big|_{\bar{\theta}^{p'}_{s,t+1}}^{\bar{\theta}^I_{s,t+1}} + \frac{(\tilde{R}^{p}_s)^{1-\sigma_s}}{\sigma_s-\xi_s}\theta_s^{\sigma_s-\xi_s}\Big|_{\bar{\theta}^I_{s,t+1}}^{\infty}\right]^{\frac{\sigma_s}{\sigma_s-1}} \\
&= (\gamma\gamma_s Y_{t+1})^{\sigma_s}(G^E_{s,t+1})^{1-\sigma_s}(\xi_s {\theta^s_{min}}^{\xi_s})^{\frac{\sigma_s}{\sigma_s-1}}\left[\frac{(\tilde{R}^{p'}_s)^{1-\sigma_s}}{\sigma_s-\xi_s}((\bar{\theta}^I_{s,t+1})^{\sigma_s-\xi_s} - (\bar{\theta}^{p'}_{s,t+1})^{\sigma_s-\xi_s}) - \frac{(\tilde{R}^{p}_s)^{1-\sigma_s}}{\sigma_s-\xi_s}(\bar{\theta}^I_{s,t+1})^{\sigma_s-\xi_s}\right]^{\frac{\sigma_s}{\sigma_s-1}} \\
&= (\gamma\gamma_s Y_{t+1})^{\sigma_s}(G^E_{s,t+1})^{1-\sigma_s}(\frac{\xi_s {\theta^s_{min}}^{\xi_s}}{\xi_s-\sigma_s})^{\frac{\sigma_s}{\sigma_s-1}}\left[((\tilde{R}^{p}_s)^{1-\sigma_s} - (\tilde{R}^{p'}_s)^{1-\sigma_s})(\bar{\theta}^I_{s,t+1})^{\sigma_s-\xi_s} + (\tilde{R}^{p'}_s)^{1-\sigma_s}(\bar{\theta}^{p'}_{s,t+1})^{\sigma_s-\xi_s}\right]^{\frac{\sigma_s}{\sigma_s-1}} \\
&= (\gamma\gamma_s Y_{t+1})^{\frac{\sigma_s(\xi_s-1)}{\sigma_s-1}}(G^E_{s,t+1})^{1-\xi_s}(\sigma_s-1)^{\frac{\sigma_s-\xi_s}{\sigma_s-1}}(\frac{\xi_s {\theta^s_{min}}^{\xi_s}}{\xi_s-\sigma_s})^{\frac{\sigma_s}{\sigma_s-1}} \\
&\quad \times \left[(f^p_s - f^{p'}_s)^{\frac{\sigma_s-\xi_s}{\sigma_s}}((\tilde{R}^{p}_s)^{1-\sigma_s} - (\tilde{R}^{p'}_s)^{1-\sigma_s})^{\frac{\xi_s}{\sigma_s}} + (f^{p'}_s)^{\frac{\sigma_s-\xi_s}{\sigma_s}}(\tilde{R}^{p'}_s)^{\frac{\xi_s(1-\sigma_s)}{\sigma_s}}\right]^{\frac{\sigma_s}{\sigma_s-1}} \\
&= (\gamma\gamma_s Y_{t+1})^{\frac{\sigma_s(\xi_s-1)}{\sigma_s-1}}(G^E_{s,t+1})^{1-\xi_s}(\sigma_s-1)^{\frac{\sigma_s-\xi_s}{\sigma_s-1}}(\frac{\xi_s {\theta^s_{min}}^{\xi_s}}{\xi_s-\sigma_s})^{\frac{\sigma_s}{\sigma_s-1}} \\
&\quad \times \left[f^{p'}_s(\frac{(\tilde{R}^{p'}_s)^{1-\sigma_s}}{f^{p'}_s})^{\frac{\xi_s}{\sigma_s}} + (f^p_s - f^{p'}_s)(\frac{(\tilde{R}^{p}_s)^{1-\sigma_s} - (\tilde{R}^{p'}_s)^{1-\sigma_s}}{f^p_s - f^{p'}_s})^{\frac{\xi_s}{\sigma_s}}\right]^{\frac{\sigma_s}{\sigma_s-1}}
\end{aligned}
$$

Rearranging,

$$
\begin{aligned}
G^E_{s,t+1} = &\left[f^{p'}_s(\frac{(\tilde{R}^{p'}_s)^{1-\sigma_s}}{f^{p'}_s})^{\frac{\xi_s}{\sigma_s}} + (f^p_s - f^{p'}_s)(\frac{(\tilde{R}^{p}_s)^{1-\sigma_s} - (\tilde{R}^{p'}_s)^{1-\sigma_s}}{f^p_s - f^{p'}_s})^{\frac{\xi_s}{\sigma_s}}\right]^{\frac{\sigma_s}{\xi_s(\sigma_s-1)}} \\
&\times (\sigma_s-1)^{\frac{\sigma_s-\xi_s}{\xi_s(\sigma_s-1)}}(\frac{\xi_s {\theta^s_{min}}^{\xi_s}}{\xi_s-\sigma_s})^{\frac{\sigma_s}{\xi_s(\sigma_s-1)}}(\gamma\gamma_s Y_{t+1})^{\frac{\sigma_s(\xi_s-1)}{\xi_s(\sigma_s-1)}}
\end{aligned}
$$

Proposition 2 implies that all sectors fall into one of the two cases. Sectors in $S^D \cup S^{\tilde{D}} \cup S^{\tilde{C}}$ correspond to the first case and sectors in $S^{DC} \cup S^{\tilde{D}C} \cup S^{\tilde{D}\tilde{C}} \cup S^{\tilde{C}\tilde{D}}$ correspond to the second case. Replacing p and p' with D and C accordingly concludes the proof. □

C.8 Proof of Proposition 4

$$
\begin{aligned}
G_t^E &= \prod_{s\in S} (G_{s,t}^E)^{\gamma_s} \\
&= \prod_{s\in S} \left(\mathcal{G}_s^E Y_t^{\frac{\sigma_s(\xi_s-1)}{\xi_s(\sigma_s-1)}}\right)^{\gamma_s} \\
&= \left(\prod_{s\in S} (\mathcal{G}_s^E)^{\gamma_s}\right) Y_t^{\sum_s \frac{\sigma_s(\xi_s-1)}{\xi_s(\sigma_s-1)}\gamma_s} \\
&= \mathcal{G}^E Y_t^{\sum_s \frac{\sigma_s(\xi_s-1)}{\xi_s(\sigma_s-1)}\gamma_s}
\end{aligned}
$$

□

C.9 Proof of Proposition 5

The expected observed size of a project financed by p in sector s is given by:

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

$\mathcal{F}^p_s$ is defined as follows:

- DAC grants

$$\mathcal{F}^p_s = \begin{cases} \tilde{f}^G_s & \text{if } s \in \{S^G, S^{\tilde{G}}\} \\ \frac{(\tilde{f}^G_s)^{\frac{\sigma-\xi_s}{\sigma}} - (f^D_s)^{\frac{\sigma-\xi_s}{\sigma}}}{(\tilde{f}^G_s)^{-\frac{\xi_s}{\sigma}} - (f^D_s)^{-\frac{\xi_s}{\sigma}}} & \text{if } s \in \{S^D, S^{\tilde{D}}, S^{\tilde{C}\tilde{D}}\} \\ \frac{1}{(\tilde{R}^D_s)^{\sigma-1}} \frac{(\tilde{f}^G_s)^{\frac{\sigma-\xi_s}{\sigma}}(\tilde{R}^D_s)^{\frac{(\sigma-\xi_s)(\sigma-1)}{\sigma}} - (f^C_s)^{\frac{\sigma-\xi_s}{\sigma}}(\tilde{R}^C_s)^{\frac{(\sigma-\xi_s)(\sigma-1)}{\sigma}}}{(\tilde{f}^G_s)^{\frac{-\xi_s}{\sigma}}(\tilde{R}^D_s)^{\frac{-\xi_s(\sigma-1)}{\sigma}} - (f^C_s)^{\frac{-\xi_s}{\sigma}}(\tilde{R}^C_s)^{\frac{-\xi_s(\sigma-1)}{\sigma}}} & \text{if } s \in \{S^{\tilde{C}}, S^{\tilde{D}\tilde{C}}, S^{\tilde{D}C}, S^{DC}\} \end{cases}$$

- DAC loans

$$\mathcal{F}^p_s = \begin{cases} f^D_s & \text{if } s \in \{S^D, S^{\tilde{D}}\} \\ \frac{(f^D_s)^{\frac{\sigma-\xi_s}{\sigma}} - (f^C_s - f^D_s)^{\frac{\sigma-\xi_s}{\sigma}}\left(\frac{(\tilde{R}^C_s)^{\sigma-1}}{(\tilde{R}^D_s)^{\sigma-1} - (\tilde{R}^C_s)^{\sigma-1}}\right)^{\frac{\sigma-\xi_s}{\sigma}}}{(f^D_s)^{\frac{-\xi_s}{\sigma}} - (f^C_s - f^D_s)^{\frac{-\xi_s}{\sigma}}\left(\frac{(\tilde{R}^C_s)^{\sigma-1}}{(\tilde{R}^D_s)^{\sigma-1} - (\tilde{R}^C_s)^{\sigma-1}}\right)^{\frac{-\xi_s}{\sigma}}} & \text{if } s \in \{S^{\tilde{C}\tilde{D}}\} \\ (f^D_s - f^C_s)\frac{(\tilde{R}^C_s)^{\sigma-1}}{(\tilde{R}^C_s)^{\sigma-1} - (\tilde{R}^D_s)^{\sigma-1}} & \text{if } s \in \{S^{DC}, S^{\tilde{D}C}, S^{\tilde{D}\tilde{C}}\} \end{cases}$$

- Chinese loans

$$\mathcal{F}^p_s = \begin{cases} f^C_s & \text{if } s \in \{S^C, S^{\tilde{C}}\} \\ \frac{(f^C_s)^{\frac{\sigma-\xi_s}{\sigma}} - (f^D_s - f^C_s)^{\frac{\sigma-\xi_s}{\sigma}}\left(\frac{(\tilde{R}^D_s)^{\sigma-1}}{(\tilde{R}^C_s)^{\sigma-1} - (\tilde{R}^D_s)^{\sigma-1}}\right)^{\frac{\sigma-\xi_s}{\sigma}}}{(f^C_s)^{\frac{-\xi_s}{\sigma}} - (f^D_s - f^C_s)^{\frac{-\xi_s}{\sigma}}\left(\frac{(\tilde{R}^D_s)^{\sigma-1}}{(\tilde{R}^C_s)^{\sigma-1} - (\tilde{R}^D_s)^{\sigma-1}}\right)^{\frac{-\xi_s}{\sigma}}} & \text{if } s \in \{S^{DC}, S^{\tilde{D}C}, S^{\tilde{D}\tilde{C}}\} \\ (f^C_s - f^D_s)\frac{(\tilde{R}^D_s)^{\sigma-1}}{(\tilde{R}^D_s)^{\sigma-1} - (\tilde{R}^C_s)^{\sigma-1}} & \text{if } s \in \{S^{\tilde{C}\tilde{D}}\} \end{cases}$$

C.9.1 DAC grants

(1) If $s \in \{S^G, S^{\tilde{G}}\}$

It is convenient to define $\tilde{f}_s^G \equiv \frac{f_s^G}{1+(\sigma-1)\frac{R_s^D}{\Psi_s^D \tilde{R}_s^D}}$. The expected size of grant-financed projects is

$$
\begin{aligned}
\mathbb{E}\left[g^O_{s,j,t}\middle|\bar{\theta}^G_{s,t} \le \theta_j\right] &= \mathbb{E}\left[\mathbb{E}\left[g^O_{s,j,t}\middle|\bar{\theta}^G_{s,t} \le \theta_j, Y_t, G^E_{s,t}\right]\right] \quad \text{(by Law of Iterated Expectation)} \\
&= \mathbb{E}\left[\mathbb{E}\left[\frac{1}{\Psi_s^D}\left(\frac{\theta_j \gamma\gamma_s Y_t}{\tilde{R}_s^D}\right)^\sigma (G^E_{s,t})^{1-\sigma}\middle|\bar{\theta}^G_{s,t} \le \theta_j, Y_t, G^E_{s,t}\right]\right] \\
&= \mathbb{E}\left[\frac{1}{\Psi_s^D}\left(\frac{\gamma\gamma_s Y_t}{\tilde{R}_s^D}\right)^\sigma (G^E_{s,t})^{1-\sigma}\mathbb{E}\left[\theta^\sigma\middle|\bar{\theta}^G_{s,t} \le \theta_j, Y_t, G^E_{s,t}\right]\right] \\
&= \mathbb{E}\left[\frac{1}{\Psi_s^D}\left(\frac{\gamma\gamma_s Y_t}{\tilde{R}_s^D}\right)^\sigma (G^E_{s,t})^{1-\sigma}\int_{\bar{\theta}^G_{s,t}}^{\infty}\theta^\sigma \frac{h(\theta)}{H(\infty)-H(\bar{\theta}^G_{s,t})}d\theta\right] \\
&= \mathbb{E}\left[\frac{1}{\Psi_s^D}\left(\frac{\gamma\gamma_s Y_t}{\tilde{R}_s^D}\right)^\sigma (G^E_{s,t})^{1-\sigma}\frac{\xi_s \underline{\theta}^{\xi_s}}{\xi_s-\sigma}\frac{(\bar{\theta}^G_{s,t})^{\xi_s}}{\underline{\theta}^{\xi_s}}\left((\bar{\theta}^G_{s,t})^{\sigma-\xi_s}\right)\right] \\
&= \mathbb{E}\left[\frac{1}{\Psi_s^D}\left(\frac{\gamma\gamma_s Y_t}{\tilde{R}_s^D}\right)^\sigma (G^E_{s,t})^{1-\sigma}\frac{\xi_s}{\xi_s-\sigma}\left(\frac{\left((\sigma-1)\tilde{f}_s^G\right)^{1/\sigma}}{\gamma\gamma_s Y_t}(G^E_{s,t}\tilde{R}_s^D)^{\frac{\sigma-1}{\sigma}}\right)^\sigma\right] \\
&= \mathbb{E}\left[\frac{1}{\Psi_s^D}\frac{1}{\tilde{R}_s^D}\frac{\xi_s}{\xi_s-\sigma}(\sigma-1)\tilde{f}_s^G\right] \\
&= \mathbb{E}\left[\frac{\xi_s(\sigma-1)}{\Psi_s^D\tilde{R}_s^D(\xi_s-\sigma)}\tilde{f}_s^G\right] \\
&= \frac{\xi_s(\sigma-1)}{\Psi_s^D\tilde{R}_s^D(\xi_s-\sigma)}\tilde{f}_s^G
\end{aligned}
$$

(2) If $s \in \{S^D, S^{\tilde{D}}, S^{\tilde{C}\tilde{D}}\}$

$$
\begin{aligned}
&\mathbb{E}\bigg[g^O_{s,j,t}\bigg|\bar{\theta}^G_{s,t} \leq \theta_j \leq \bar{\theta}^D_{s,t}\bigg] \\
&\quad = \mathbb{E}\bigg[\mathbb{E}\bigg[g^O_{s,j,t}\bigg|\bar{\theta}^G_{s,t} \leq \theta_j \leq \bar{\theta}^D_{s,t}, Y_t, G^E_{s,t}\bigg]\bigg] \quad \text{(by Law of Iterated Expectation)} \\
&\quad = \mathbb{E}\bigg[\mathbb{E}\bigg[\frac{1}{\Psi^D_s}\Big(\frac{\theta_j\gamma\gamma_s Y_t}{\tilde{R}^D_s}\Big)^\sigma (G^E_{s,t})^{1-\sigma}\bigg|\bar{\theta}^G_{s,t} \leq \theta_j \leq \bar{\theta}^D_{s,t}, Y_t, G^E_{s,t}\bigg]\bigg] \\
&\quad = \mathbb{E}\bigg[\frac{1}{\Psi^D_s}\Big(\frac{\gamma\gamma_s Y_t}{\tilde{R}^D_s}\Big)^\sigma (G^E_{s,t})^{1-\sigma}\mathbb{E}\bigg[\theta^\sigma\bigg|\bar{\theta}^G_{s,t} \leq \theta_j \leq \bar{\theta}^D_{s,t}, Y_t, G^E_{s,t}\bigg]\bigg] \\
&\quad = \mathbb{E}\bigg[\frac{1}{\Psi^D_s}\Big(\frac{\gamma\gamma_s Y_t}{\tilde{R}^D_s}\Big)^\sigma (G^E_{s,t})^{1-\sigma}\int_{\bar{\theta}^G_{s,t}}^{\bar{\theta}^D_{s,t}} \theta^\sigma \frac{h(\theta)}{H(\bar{\theta}^D_{s,t}) - H(\bar{\theta}^G_{s,t})}d\theta\bigg] \\
&\quad = \mathbb{E}\bigg[\frac{1}{\Psi^D_s}\Big(\frac{\gamma\gamma_s Y_t}{\tilde{R}^D_s}\Big)^\sigma (G^E_{s,t})^{1-\sigma}\frac{\xi_s\underline{\theta}^{\xi_s}}{\xi_s-\sigma}\frac{1}{\underline{\theta}^{\xi_s}}\frac{1}{(\bar{\theta}^G_{s,t})^{-\xi_s} - (\bar{\theta}^D_{s,t})^{-\xi_s}}\Big((\bar{\theta}^G_{s,t})^{\sigma-\xi_s} - (\bar{\theta}^D_{s,t})^{\sigma-\xi_s}\Big)\bigg] \\
&\quad = \mathbb{E}\bigg[\frac{1}{\Psi^D_s}\Big(\frac{\gamma\gamma_s Y_t}{\tilde{R}^D_s}\Big)^\sigma (G^E_{s,t})^{1-\sigma}\frac{\xi_s}{\xi_s-\sigma} \\
&\qquad\quad \times \frac{(\sigma-1)^{\frac{\sigma-\xi_s}{\sigma}}(\gamma\gamma_s Y_t)^{\xi_s-\sigma}(G^E_{s,t})^{\frac{(\sigma-\xi_s)(\sigma-1)}{\sigma}}\Big((\tilde{f}^G_s)^{\frac{\sigma-\xi_s}{\sigma}}(\tilde{R}^D_s)^{\frac{(\sigma-\xi_s)(\sigma-1)}{\sigma}} - (f^D_s)^{\frac{\sigma-\xi_s}{\sigma}}(\tilde{R}^D_s)^{\frac{(\sigma-\xi_s)(\sigma-1)}{\sigma}}\Big)}{(\sigma-1)^{\frac{-\xi_s}{\sigma}}(\gamma\gamma_s Y_t)^{\xi_s}(G^E_{s,t})^{-\frac{\xi_s(\sigma-1)}{\sigma}}\Big((\tilde{f}^G_s)^{\frac{-\xi_s}{\sigma}}(\tilde{R}^D_s)^{\frac{-\xi_s(\sigma-1)}{\sigma}} - (f^D_s)^{\frac{-\xi_s}{\sigma}}(\tilde{R}^D_s)^{\frac{-\xi_s(\sigma-1)}{\sigma}}\Big)}\bigg] \\
&\quad = \mathbb{E}\bigg[\frac{1}{\Psi^D_s}\frac{1}{\tilde{R}^D_s}\frac{\xi_s}{\xi_s-\sigma}(\sigma-1)\frac{(\tilde{f}^G_s)^{\frac{\sigma-\xi_s}{\sigma}} - (f^D_s)^{\frac{\sigma-\xi_s}{\sigma}}}{(\tilde{f}^G_s)^{-\frac{\xi_s}{\sigma}} - (f^D_s)^{-\frac{\xi_s}{\sigma}}}\bigg] \\
&\quad = \mathbb{E}\bigg[\frac{\xi_s(\sigma-1)}{\Psi^D_s\tilde{R}^D_s(\xi_s-\sigma)}\frac{(\tilde{f}^G_s)^{\frac{\sigma-\xi_s}{\sigma}} - (f^D_s)^{\frac{\sigma-\xi_s}{\sigma}}}{(\tilde{f}^G_s)^{-\frac{\xi_s}{\sigma}} - (f^D_s)^{-\frac{\xi_s}{\sigma}}}\bigg] \\
&\quad = \frac{\xi_s(\sigma-1)}{\Psi^D_s\tilde{R}^D_s(\xi_s-\sigma)}\frac{(\tilde{f}^G_s)^{\frac{\sigma-\xi_s}{\sigma}} - (f^D_s)^{\frac{\sigma-\xi_s}{\sigma}}}{(\tilde{f}^G_s)^{-\frac{\xi_s}{\sigma}} - (f^D_s)^{-\frac{\xi_s}{\sigma}}}
\end{aligned}
$$

(3) If $s \in \{S^{\tilde{C}}, S^{\tilde{D}\tilde{C}}, S^{\tilde{D}C}, S^{DC}\}$

$$
\begin{aligned}
&\mathbb{E}\left[g^O_{s,j,t}\middle|\bar{\theta}^G_{s,t} \le \theta_j \le \bar{\theta}^C_{s,t}\right] \\
&\quad= \mathbb{E}\left[\mathbb{E}\left[g^O_{s,j,t}\middle|\bar{\theta}^G_{s,t} \le \theta_j \le \bar{\theta}^D_{s,t}, Y_t, G^E_{s,t}\right]\right] \quad \text{(by Law of Iterated Expectation)} \\
&\quad= \mathbb{E}\left[\frac{1}{\Psi^D_s}\big(\frac{\gamma\gamma_s Y_t}{\tilde{R}^D_s}\big)^{\sigma}(G^E_{s,t})^{1-\sigma}\int_{\bar{\theta}^G_{s,t}}^{\bar{\theta}^C_{s,t}} \theta^{\sigma}\frac{h(\theta)}{H(\bar{\theta}^C_{s,t}) - H(\bar{\theta}^G_{s,t})}d\theta\right] \\
&\quad= \mathbb{E}\left[\frac{1}{\Psi^D_s}\big(\frac{\gamma\gamma_s Y_t}{\tilde{R}^D_s}\big)^{\sigma}(G^E_{s,t})^{1-\sigma}\frac{\xi_s\underline{\theta}^{\xi_s}}{\xi_s-\sigma}\frac{1}{\underline{\theta}^{\xi_s}}\frac{1}{(\bar{\theta}^G_{s,t})^{-\xi_s} - (\bar{\theta}^C_{s,t})^{-\xi_s}}\Big((\bar{\theta}^G_{s,t})^{\sigma-\xi_s} - (\bar{\theta}^C_{s,t})^{\sigma-\xi_s}\Big)\right] \\
&\quad= \mathbb{E}\Bigg[\frac{1}{\Psi^D_s}\big(\frac{\gamma\gamma_s Y_t}{\tilde{R}^D_s}\big)^{\sigma}(G^E_{s,t})^{1-\sigma}\frac{\xi_s}{\xi_s-\sigma} \\
&\qquad\times\frac{(\sigma-1)^{\frac{\sigma-\xi_s}{\sigma}}(\gamma\gamma_s Y_t)^{\xi_s-\sigma}(G^E_{s,t})^{\frac{(\sigma-\xi_s)(\sigma-1)}{\sigma}}\big((\tilde{f}^G_s)^{\frac{\sigma-\xi_s}{\sigma}}(\tilde{R}^D_s)^{\frac{(\sigma-\xi_s)(\sigma-1)}{\sigma}} - (f^C_s)^{\frac{\sigma-\xi_s}{\sigma}}(\tilde{R}^C_s)^{\frac{(\sigma-\xi_s)(\sigma-1)}{\sigma}}\big)}{(\sigma-1)^{\frac{-\xi_s}{\sigma}}(\gamma\gamma_s Y_t)^{\xi_s}(G^E_{s,t})^{-\frac{\xi_s(\sigma-1)}{\sigma}}\big((\tilde{f}^G_s)^{\frac{-\xi_s}{\sigma}}(\tilde{R}^D_s)^{\frac{-\xi_s(\sigma-1)}{\sigma}} - (f^C_s)^{\frac{-\xi_s}{\sigma}}(\tilde{R}^C_s)^{\frac{-\xi_s(\sigma-1)}{\sigma}}\big)}\Bigg] \\
&\quad= \mathbb{E}\left[\frac{1}{\Psi^D_s}\frac{1}{\tilde{R}^D_s}\frac{\xi_s}{\xi_s-\sigma}(\sigma-1)\frac{1}{(\tilde{R}^D_s)^{\sigma-1}}\frac{(\tilde{f}^G_s)^{\frac{\sigma-\xi_s}{\sigma}}(\tilde{R}^D_s)^{\frac{(\sigma-\xi_s)(\sigma-1)}{\sigma}} - (f^C_s)^{\frac{\sigma-\xi_s}{\sigma}}(\tilde{R}^C_s)^{\frac{(\sigma-\xi_s)(\sigma-1)}{\sigma}}}{(\tilde{f}^G_s)^{\frac{-\xi_s}{\sigma}}(\tilde{R}^D_s)^{\frac{-\xi_s(\sigma-1)}{\sigma}} - (f^C_s)^{\frac{-\xi_s}{\sigma}}(\tilde{R}^C_s)^{\frac{-\xi_s(\sigma-1)}{\sigma}}}\right] \\
&\quad= \mathbb{E}\left[\frac{\xi_s(\sigma-1)}{\Psi^D_s\tilde{R}^D_s(\xi_s-\sigma)}\frac{1}{(\tilde{R}^D_s)^{\sigma-1}}\frac{(\tilde{f}^G_s)^{\frac{\sigma-\xi_s}{\sigma}}(\tilde{R}^D_s)^{\frac{(\sigma-\xi_s)(\sigma-1)}{\sigma}} - (f^C_s)^{\frac{\sigma-\xi_s}{\sigma}}(\tilde{R}^C_s)^{\frac{(\sigma-\xi_s)(\sigma-1)}{\sigma}}}{(\tilde{f}^G_s)^{\frac{-\xi_s}{\sigma}}(\tilde{R}^D_s)^{\frac{-\xi_s(\sigma-1)}{\sigma}} - (f^C_s)^{\frac{-\xi_s}{\sigma}}(\tilde{R}^C_s)^{\frac{-\xi_s(\sigma-1)}{\sigma}}}\right] \\
&\quad= \frac{\xi_s(\sigma-1)}{\Psi^D_s\tilde{R}^D_s(\xi_s-\sigma)}\frac{1}{(\tilde{R}^D_s)^{\sigma-1}}\frac{(\tilde{f}^G_s)^{\frac{\sigma-\xi_s}{\sigma}}(\tilde{R}^D_s)^{\frac{(\sigma-\xi_s)(\sigma-1)}{\sigma}} - (f^C_s)^{\frac{\sigma-\xi_s}{\sigma}}(\tilde{R}^C_s)^{\frac{(\sigma-\xi_s)(\sigma-1)}{\sigma}}}{(\tilde{f}^G_s)^{\frac{-\xi_s}{\sigma}}(\tilde{R}^D_s)^{\frac{-\xi_s(\sigma-1)}{\sigma}} - (f^C_s)^{\frac{-\xi_s}{\sigma}}(\tilde{R}^C_s)^{\frac{-\xi_s(\sigma-1)}{\sigma}}}
\end{aligned}
$$

C.9.2 DAC loans

(1) If $s \in \{S^D, S^{\tilde{D}}\}$

$$
\begin{aligned}
\mathbb{E}\Big[g^O_{s,j,t}\Big|\bar{\theta}^D_{s,t} \le \theta_j\Big] &= \mathbb{E}\Big[\mathbb{E}\Big[g^O_{s,j,t}\Big|\bar{\theta}^D_{s,t} \le \theta_j, Y_t, G^E_{s,t}\Big]\Big] \quad \text{(by Law of Iterated Expectation)} \\
&= \mathbb{E}\Big[\mathbb{E}\Big[\frac{1}{\Psi^D_s}(\frac{\theta_j \gamma\gamma_s Y_t}{\tilde{R}^D_s})^\sigma (G^E_{s,t})^{1-\sigma}\Big|\bar{\theta}^D_{s,t} \le \theta_j, Y_t, G^E_{s,t}\Big]\Big] \\
&= \mathbb{E}\Big[\frac{1}{\Psi^D_s}(\frac{\gamma\gamma_s Y_t}{\tilde{R}^D_s})^\sigma (G^E_{s,t})^{1-\sigma}\mathbb{E}\Big[\theta^\sigma\Big|\bar{\theta}^D_{s,t} \le \theta_j, Y_t, G^E_{s,t}\Big]\Big] \\
&= \mathbb{E}\Big[\frac{1}{\Psi^D_s}(\frac{\gamma\gamma_s Y_t}{\tilde{R}^D_s})^\sigma (G^E_{s,t})^{1-\sigma}\int_{\bar{\theta}^D_{s,t}}^{\infty}\theta^\sigma \frac{h(\theta)}{H(\infty)-H(\bar{\theta}^D_{s,t})}d\theta\Big] \\
&= \mathbb{E}\Big[\frac{1}{\Psi^D_s}(\frac{\gamma\gamma_s Y_t}{\tilde{R}^D_s})^\sigma (G^E_{s,t})^{1-\sigma}\frac{\xi_s \underline{\theta}^{\xi_s}}{\xi_s-\sigma}\frac{(\bar{\theta}^D_{s,t})^{\xi_s}}{\underline{\theta}^{\xi_s}}\Big((\bar{\theta}^D_{s,t})^{\sigma-\xi_s}\Big)\Big] \\
&= \mathbb{E}\Big[\frac{1}{\Psi^D_s}(\frac{\gamma\gamma_s Y_t}{\tilde{R}^D_s})^\sigma (G^E_{s,t})^{1-\sigma}\frac{\xi_s}{\xi_s-\sigma}\Big(\frac{\big((\sigma-1)f^D_s\big)^{1/\sigma}}{\gamma\gamma_s Y_t}(G^E_{s,t}\tilde{R}^D_s)^{\frac{\sigma-1}{\sigma}}\Big)^\sigma\Big] \\
&= \mathbb{E}\Big[\frac{1}{\Psi^D_s}\frac{1}{\tilde{R}^D_s}\frac{\xi_s}{\xi_s-\sigma}(\sigma-1)f^D_s\Big] \\
&= \mathbb{E}\Big[\frac{\xi_s(\sigma-1)}{\Psi^D_s\tilde{R}^D_s(\xi_s-\sigma)}f^D_s\Big] \\
&= \frac{\xi_s(\sigma-1)}{\Psi^D_s\tilde{R}^D_s(\xi_s-\sigma)}f^D_s
\end{aligned}
$$

(2) If $s \in \{S^{\tilde{C}\tilde{D}}\}$

$$
\begin{aligned}
&\mathbb{E}\Big[g^O_{s,j,t}\Big|\bar{\theta}^D_{s,t} \leq \theta_j \leq \bar{\theta}^I_{s,t}\Big] \\
&\quad = \mathbb{E}\Big[\mathbb{E}\Big[g^O_{s,j,t}\Big|\bar{\theta}^D_{s,t} \leq \theta_j \leq \bar{\theta}^I_{s,t}, Y_t, G^E_{s,t}\Big]\Big] \quad \text{(by Law of Iterated Expectation)} \\
&\quad = \mathbb{E}\Big[\frac{1}{\Psi^D_s}(\frac{\gamma\gamma_s Y_t}{\tilde{R}^D_s})^\sigma (G^E_{s,t})^{1-\sigma}\int_{\bar{\theta}^D_{s,t}}^{\bar{\theta}^I_{s,t}} \theta^\sigma \frac{h(\theta)}{H(\bar{\theta}^I_{s,t}) - H(\bar{\theta}^D_{s,t})} d\theta\Big] \\
&\quad = \mathbb{E}\Big[\frac{1}{\Psi^D_s}(\frac{\gamma\gamma_s Y_t}{\tilde{R}^D_s})^\sigma (G^E_{s,t})^{1-\sigma}\frac{\xi_s \underline{\theta}^{\xi_s}}{\xi_s - \sigma}\frac{1}{\underline{\theta}^{\xi_s}}\frac{1}{(\bar{\theta}^D_{s,t})^{-\xi_s} - (\bar{\theta}^I_{s,t})^{-\xi_s}}\Big((\bar{\theta}^D_{s,t})^{\sigma-\xi_s} - (\bar{\theta}^I_{s,t})^{\sigma-\xi_s}\Big)\Big] \\
&\quad = \mathbb{E}\Big[\frac{1}{\Psi^D_s}(\frac{\gamma\gamma_s Y_t}{\tilde{R}^D_s})^\sigma (G^E_{s,t})^{1-\sigma}\frac{\xi_s}{\xi_s - \sigma}\frac{(\sigma-1)^{\frac{\sigma-\xi_s}{\sigma}}(\gamma\gamma_s Y_t)^{\xi_s-\sigma}(G^E_{s,t})^{\frac{(\sigma-\xi_s)(\sigma-1)}{\sigma}}}{(\sigma-1)^{\frac{-\xi_s}{\sigma}}(\gamma\gamma_s Y_t)^{\xi_s}(G^E_{s,t})^{-\frac{\xi_s(\sigma-1)}{\sigma}}} \\
&\qquad \times \frac{\big((f^D_s)^{\frac{\sigma-\xi_s}{\sigma}}(\tilde{R}^D_s)^{\frac{(\sigma-\xi_s)(\sigma-1)}{\sigma}} - (f^C_s - f^D_s)^{\frac{\sigma-\xi_s}{\sigma}}(\tilde{R}^D_s\tilde{R}^C_s)^{\frac{(\sigma-\xi_s)(\sigma-1)}{\sigma}}(\frac{1}{(\tilde{R}^D_s)^{\sigma-1}-(\tilde{R}^C_s)^{\sigma-1}})^{\frac{\sigma-\xi_s}{\sigma}}\big)}{\big((f^D_s)^{\frac{-\xi_s}{\sigma}}(\tilde{R}^D_s)^{\frac{-\xi_s(\sigma-1)}{\sigma}} - (f^C_s - f^D_s)^{\frac{-\xi_s}{\sigma}}(\tilde{R}^D_s\tilde{R}^C_s)^{\frac{-\xi_s(\sigma-1)}{\sigma}}(\frac{1}{(\tilde{R}^D_s)^{\sigma-1}-(\tilde{R}^C_s)^{\sigma-1}})^{\frac{-\xi_s}{\sigma}}\big)}\Big] \\
&\quad = \mathbb{E}\Big[\frac{1}{\Psi^D_s}\frac{1}{\tilde{R}^D_s}\frac{\xi_s}{\xi_s-\sigma}(\sigma-1)\frac{(f^D_s)^{\frac{\sigma-\xi_s}{\sigma}} - (f^C_s - f^D_s)^{\frac{\sigma-\xi_s}{\sigma}}\left(\frac{(\tilde{R}^C_s)^{\sigma-1}}{(\tilde{R}^D_s)^{\sigma-1}-(\tilde{R}^C_s)^{\sigma-1}}\right)^{\frac{\sigma-\xi_s}{\sigma}}}{(f^D_s)^{\frac{-\xi_s}{\sigma}} - (f^C_s - f^D_s)^{\frac{-\xi_s}{\sigma}}\left(\frac{(\tilde{R}^C_s)^{\sigma-1}}{(\tilde{R}^D_s)^{\sigma-1}-(\tilde{R}^C_s)^{\sigma-1}}\right)^{\frac{-\xi_s}{\sigma}}}\Big] \\
&\quad = \mathbb{E}\Big[\frac{\xi_s(\sigma-1)}{\Psi^D_s\tilde{R}^D_s(\xi_s-\sigma)}\frac{(f^D_s)^{\frac{\sigma-\xi_s}{\sigma}} - (f^C_s - f^D_s)^{\frac{\sigma-\xi_s}{\sigma}}\left(\frac{(\tilde{R}^C_s)^{\sigma-1}}{(\tilde{R}^D_s)^{\sigma-1}-(\tilde{R}^C_s)^{\sigma-1}}\right)^{\frac{\sigma-\xi_s}{\sigma}}}{(f^D_s)^{\frac{-\xi_s}{\sigma}} - (f^C_s - f^D_s)^{\frac{-\xi_s}{\sigma}}\left(\frac{(\tilde{R}^C_s)^{\sigma-1}}{(\tilde{R}^D_s)^{\sigma-1}-(\tilde{R}^C_s)^{\sigma-1}}\right)^{\frac{-\xi_s}{\sigma}}}\Big] \\
&\quad = \frac{\xi_s(\sigma-1)}{\Psi^D_s\tilde{R}^D_s(\xi_s-\sigma)}\frac{(f^D_s)^{\frac{\sigma-\xi_s}{\sigma}} - (f^C_s - f^D_s)^{\frac{\sigma-\xi_s}{\sigma}}\left(\frac{(\tilde{R}^C_s)^{\sigma-1}}{(\tilde{R}^D_s)^{\sigma-1}-(\tilde{R}^C_s)^{\sigma-1}}\right)^{\frac{\sigma-\xi_s}{\sigma}}}{(f^D_s)^{\frac{-\xi_s}{\sigma}} - (f^C_s - f^D_s)^{\frac{-\xi_s}{\sigma}}\left(\frac{(\tilde{R}^C_s)^{\sigma-1}}{(\tilde{R}^D_s)^{\sigma-1}-(\tilde{R}^C_s)^{\sigma-1}}\right)^{\frac{-\xi_s}{\sigma}}}
\end{aligned}
$$

(3) If $s \in \{S^{DC}, S^{\tilde{D}C}, S^{\tilde{D}\tilde{C}}\}$

$$
\begin{aligned}
&\mathbb{E}\left[g^O_{s,j,t}\middle|\bar{\theta}^I_{s,t} \leq \theta_j\right] \\
&\quad = \mathbb{E}\left[\mathbb{E}\left[g^O_{s,j,t}\middle|\bar{\theta}^I_{s,t} \leq \theta_j, Y_t, G^E_{s,t}\right]\right] \quad \text{(by Law of Iterated Expectation)} \\
&\quad = \mathbb{E}\left[\frac{1}{\Psi^D_s}(\frac{\gamma\gamma_s Y_t}{\tilde{R}^D_s})^\sigma (G^E_{s,t})^{1-\sigma} \int_{\bar{\theta}^I_{s,t}}^{\infty} \theta^\sigma \frac{h(\theta)}{H(\infty) - H(\bar{\theta}^I_{s,t})} d\theta\right] \\
&\quad = \mathbb{E}\left[\frac{1}{\Psi^D_s}(\frac{\gamma\gamma_s Y_t}{\tilde{R}^D_s})^\sigma (G^E_{s,t})^{1-\sigma} \frac{\xi_s \underline{\theta}^{\xi_s}}{\xi_s - \sigma} \frac{1}{\underline{\theta}^{\xi_s}} \frac{1}{(\bar{\theta}^I_{s,t})^{-\xi_s}} \left((\bar{\theta}^I_{s,t})^{\sigma - \xi_s}\right)\right] \\
&\quad = \mathbb{E}\left[\frac{1}{\Psi^D_s}(\frac{\gamma\gamma_s Y_t}{\tilde{R}^D_s})^\sigma (G^E_{s,t})^{1-\sigma} \frac{\xi_s}{\xi_s - \sigma} \left(\frac{((\sigma-1)(f^D_s - f^C_s))^{1/\sigma}}{\gamma\gamma_s Y_t} (G^E_{s,t}\tilde{R}^D_s \tilde{R}^C_s)^{\frac{\sigma-1}{\sigma}} (\frac{1}{(\tilde{R}^C_s)^{\sigma-1} - (\tilde{R}^D_s)^{\sigma-1}})^{\frac{1}{\sigma}}\right)^\sigma\right] \\
&\quad = \mathbb{E}\left[\frac{1}{\Psi^D_s} \frac{1}{\tilde{R}^D_s} \frac{\xi_s}{\xi_s - \sigma} (\sigma - 1)(f^D_s - f^C_s) \frac{(\tilde{R}^C_s)^{\sigma-1}}{(\tilde{R}^C_s)^{\sigma-1} - (\tilde{R}^D_s)^{\sigma-1}}\right] \\
&\quad = \mathbb{E}\left[\frac{\xi_s(\sigma-1)}{\Psi^D_s \tilde{R}^D_s (\xi_s - \sigma)} (f^D_s - f^C_s) \frac{(\tilde{R}^C_s)^{\sigma-1}}{(\tilde{R}^C_s)^{\sigma-1} - (\tilde{R}^D_s)^{\sigma-1}}\right] \\
&\quad = \frac{\xi_s(\sigma-1)}{\Psi^D_s \tilde{R}^D_s (\xi_s - \sigma)} (f^D_s - f^C_s) \frac{(\tilde{R}^C_s)^{\sigma-1}}{(\tilde{R}^C_s)^{\sigma-1} - (\tilde{R}^D_s)^{\sigma-1}}
\end{aligned}
$$

C.9.3 Chinese loans

(1) If $s \in \{S^C, S^{\tilde{C}}\}$

$$
\begin{aligned}
\mathbb{E}\left[g^O_{s,j,t}\middle|\bar{\theta}^C_{s,t} \leq \theta_j\right] &= \mathbb{E}\left[\mathbb{E}\left[g^O_{s,j,t}\middle|\bar{\theta}^C_{s,t} \leq \theta_j, Y_t, G^E_{s,t}\right]\right] \quad \text{(by Law of Iterated Expectation)} \\
&= \mathbb{E}\left[\mathbb{E}\left[\frac{1}{\Psi^C_s}(\frac{\theta_j \gamma\gamma_s Y_t}{\tilde{R}^C_s})^\sigma (G^E_{s,t})^{1-\sigma}\middle|\bar{\theta}^C_{s,t} \leq \theta_j, Y_t, G^E_{s,t}\right]\right] \\
&= \mathbb{E}\left[\frac{1}{\Psi^C_s}(\frac{\gamma\gamma_s Y_t}{\tilde{R}^C_s})^\sigma (G^E_{s,t})^{1-\sigma} \mathbb{E}\left[\theta^\sigma\middle|\bar{\theta}^C_{s,t} \leq \theta_j, Y_t, G^E_{s,t}\right]\right] \\
&= \mathbb{E}\left[\frac{1}{\Psi^C_s}(\frac{\gamma\gamma_s Y_t}{\tilde{R}^C_s})^\sigma (G^E_{s,t})^{1-\sigma} \int_{\bar{\theta}^C_{s,t}}^{\infty} \theta^\sigma \frac{h(\theta)}{H(\infty) - H(\bar{\theta}^C_{s,t})} d\theta\right] \\
&= \mathbb{E}\left[\frac{1}{\Psi^C_s}(\frac{\gamma\gamma_s Y_t}{\tilde{R}^C_s})^\sigma (G^E_{s,t})^{1-\sigma} \frac{\xi_s \underline{\theta}^{\xi_s}}{\xi_s - \sigma} \frac{(\bar{\theta}^C_{s,t})^{\xi_s}}{\underline{\theta}^{\xi_s}} \left((\bar{\theta}^C_{s,t})^{\sigma - \xi_s}\right)\right] \\
&= \mathbb{E}\left[\frac{1}{\Psi^C_s}(\frac{\gamma\gamma_s Y_t}{\tilde{R}^C_s})^\sigma (G^E_{s,t})^{1-\sigma} \frac{\xi_s}{\xi_s - \sigma} \left(\frac{\left((\sigma-1)f^C_s\right)^{1/\sigma}}{\gamma\gamma_s Y_t} (G^E_{s,t}\tilde{R}^C_s)^{\frac{\sigma-1}{\sigma}}\right)^\sigma\right] \\
&= \mathbb{E}\left[\frac{1}{\Psi^C_s} \frac{1}{\tilde{R}^C_s} \frac{\xi_s}{\xi_s - \sigma} (\sigma - 1) f^C_s\right] \\
&= \mathbb{E}\left[\frac{\xi_s(\sigma-1)}{\Psi^C_s \tilde{R}^C_s (\xi_s - \sigma)} f^C_s\right] \\
&= \frac{\xi_s(\sigma-1)}{\Psi^C_s \tilde{R}^C_s (\xi_s - \sigma)} f^C_s
\end{aligned}
$$

(2) If $s \in \{S^{DC}, S^{\tilde{D}C}, S^{\tilde{D}\tilde{C}}\}$

$$
\begin{aligned}
&\mathbb{E}\Big[g^O_{s,j,t}\Big|\bar{\theta}^C_{s,t} \leq \theta_j \leq \bar{\theta}^I_{s,t}\Big] \\
&\quad = \mathbb{E}\Big[\mathbb{E}\Big[g^O_{s,j,t}\Big|\bar{\theta}^C_{s,t} \leq \theta_j \leq \bar{\theta}^I_{s,t}, Y_t, G^E_{s,t}\Big]\Big] \quad \text{(by Law of Iterated Expectation)} \\
&\quad = \mathbb{E}\Big[\frac{1}{\Psi^C_s}\big(\frac{\gamma\gamma_s Y_t}{\tilde{R}^C_s}\big)^{\sigma}(G^E_{s,t})^{1-\sigma}\int_{\bar{\theta}^C_{s,t}}^{\bar{\theta}^I_{s,t}} \theta^{\sigma}\frac{h(\theta)}{H(\bar{\theta}^I_{s,t}) - H(\bar{\theta}^C_{s,t})}d\theta\Big] \\
&\quad = \mathbb{E}\Big[\frac{1}{\Psi^C_s}\big(\frac{\gamma\gamma_s Y_t}{\tilde{R}^C_s}\big)^{\sigma}(G^E_{s,t})^{1-\sigma}\frac{\xi_s\underline{\theta}^{\xi_s}}{\xi_s-\sigma}\frac{1}{\underline{\theta}^{\xi_s}}\frac{1}{(\bar{\theta}^C_{s,t})^{-\xi_s} - (\bar{\theta}^I_{s,t})^{-\xi_s}}\Big((\bar{\theta}^C_{s,t})^{\sigma-\xi_s} - (\bar{\theta}^I_{s,t})^{\sigma-\xi_s}\Big)\Big] \\
&\quad = \mathbb{E}\Big[\frac{1}{\Psi^C_s}\big(\frac{\gamma\gamma_s Y_t}{\tilde{R}^C_s}\big)^{\sigma}(G^E_{s,t})^{1-\sigma}\frac{\xi_s}{\xi_s-\sigma}\frac{(\sigma-1)^{\frac{\sigma-\xi_s}{\sigma}}(\gamma\gamma_s Y_t)^{\xi_s-\sigma}(G^E_{s,t})^{\frac{(\sigma-\xi_s)(\sigma-1)}{\sigma}}}{(\sigma-1)^{\frac{-\xi_s}{\sigma}}(\gamma\gamma_s Y_t)^{\xi_s}(G^E_{s,t})^{-\frac{\xi_s(\sigma-1)}{\sigma}}} \\
&\qquad \times \frac{\big((f^C_s)^{\frac{\sigma-\xi_s}{\sigma}}(\tilde{R}^C_s)^{\frac{(\sigma-\xi_s)(\sigma-1)}{\sigma}} - (f^D_s - f^C_s)^{\frac{\sigma-\xi_s}{\sigma}}(\tilde{R}^D_s\tilde{R}^C_s)^{\frac{(\sigma-\xi_s)(\sigma-1)}{\sigma}}\big(\frac{1}{(\tilde{R}^C_s)^{\sigma-1}-(\tilde{R}^D_s)^{\sigma-1}}\big)^{\frac{\sigma-\xi_s}{\sigma}}\big)}{\big((f^C_s)^{\frac{-\xi_s}{\sigma}}(\tilde{R}^C_s)^{\frac{-\xi_s(\sigma-1)}{\sigma}} - (f^D_s - f^C_s)^{\frac{-\xi_s}{\sigma}}(\tilde{R}^D_s\tilde{R}^C_s)^{\frac{-\xi_s(\sigma-1)}{\sigma}}\big(\frac{1}{(\tilde{R}^C_s)^{\sigma-1}-(\tilde{R}^D_s)^{\sigma-1}}\big)^{\frac{-\xi_s}{\sigma}}\big)}\Big] \\
&\quad = \mathbb{E}\Big[\frac{1}{\Psi^C_s}\frac{1}{\tilde{R}^C_s}\frac{\xi_s}{\xi_s-\sigma}(\sigma-1)\frac{(f^C_s)^{\frac{\sigma-\xi_s}{\sigma}} - (f^D_s - f^C_s)^{\frac{\sigma-\xi_s}{\sigma}}\Big(\frac{(\tilde{R}^D_s)^{\sigma-1}}{(\tilde{R}^C_s)^{\sigma-1}-(\tilde{R}^D_s)^{\sigma-1}}\Big)^{\frac{\sigma-\xi_s}{\sigma}}}{(f^C_s)^{\frac{-\xi_s}{\sigma}} - (f^D_s - f^C_s)^{\frac{-\xi_s}{\sigma}}\Big(\frac{(\tilde{R}^D_s)^{\sigma-1}}{(\tilde{R}^C_s)^{\sigma-1}-(\tilde{R}^D_s)^{\sigma-1}}\Big)^{\frac{-\xi_s}{\sigma}}}\Big] \\
&\quad = \mathbb{E}\Big[\frac{\xi_s(\sigma-1)}{\Psi^D_s\tilde{R}^D_s(\xi_s-\sigma)}\frac{(f^C_s)^{\frac{\sigma-\xi_s}{\sigma}} - (f^D_s - f^C_s)^{\frac{\sigma-\xi_s}{\sigma}}\Big(\frac{(\tilde{R}^D_s)^{\sigma-1}}{(\tilde{R}^C_s)^{\sigma-1}-(\tilde{R}^D_s)^{\sigma-1}}\Big)^{\frac{\sigma-\xi_s}{\sigma}}}{(f^C_s)^{\frac{-\xi_s}{\sigma}} - (f^D_s - f^C_s)^{\frac{-\xi_s}{\sigma}}\Big(\frac{(\tilde{R}^D_s)^{\sigma-1}}{(\tilde{R}^C_s)^{\sigma-1}-(\tilde{R}^D_s)^{\sigma-1}}\Big)^{\frac{-\xi_s}{\sigma}}}\Big] \\
&\quad = \frac{\xi_s(\sigma-1)}{\Psi^D_s\tilde{R}^D_s(\xi_s-\sigma)}\frac{(f^C_s)^{\frac{\sigma-\xi_s}{\sigma}} - (f^D_s - f^C_s)^{\frac{\sigma-\xi_s}{\sigma}}\Big(\frac{(\tilde{R}^D_s)^{\sigma-1}}{(\tilde{R}^C_s)^{\sigma-1}-(\tilde{R}^D_s)^{\sigma-1}}\Big)^{\frac{\sigma-\xi_s}{\sigma}}}{(f^C_s)^{\frac{-\xi_s}{\sigma}} - (f^D_s - f^C_s)^{\frac{-\xi_s}{\sigma}}\Big(\frac{(\tilde{R}^D_s)^{\sigma-1}}{(\tilde{R}^C_s)^{\sigma-1}-(\tilde{R}^D_s)^{\sigma-1}}\Big)^{\frac{-\xi_s}{\sigma}}}
\end{aligned}
$$

(3) If $s \in \{S^{\tilde{C}\tilde{D}}\}$

$$
\begin{aligned}
&\mathbb{E}\Big[g^O_{s,j,t}\Big|\bar{\theta}^I_{s,t} \le \theta_j\Big] \\
&\qquad = \mathbb{E}\Big[\mathbb{E}\Big[g^O_{s,j,t}\Big|\bar{\theta}^I_{s,t} \le \theta_j, Y_t, G^E_{s,t}\Big]\Big] \quad \text{(by Law of Iterated Expectation)} \\
&\qquad = \mathbb{E}\Big[\frac{1}{\Psi^C_s}(\frac{\gamma\gamma_s Y_t}{\tilde{R}^C_s})^\sigma (G^E_{s,t})^{1-\sigma}\int_{\bar{\theta}^I_{s,t}}^{\infty}\theta^\sigma \frac{h(\theta)}{H(\infty)-H(\bar{\theta}^I_{s,t})}d\theta\Big] \\
&\qquad = \mathbb{E}\Big[\frac{1}{\Psi^C_s}(\frac{\gamma\gamma_s Y_t}{\tilde{R}^C_s})^\sigma (G^E_{s,t})^{1-\sigma}\frac{\xi_s\underline{\theta}^{\xi_s}}{\xi_s-\sigma}\frac{1}{\underline{\theta}^{\xi_s}}\frac{1}{(\bar{\theta}^I_{s,t})^{-\xi_s}}\Big((\bar{\theta}^I_{s,t})^{\sigma-\xi_s}\Big)\Big] \\
&\qquad = \mathbb{E}\Big[\frac{1}{\Psi^C_s}(\frac{\gamma\gamma_s Y_t}{\tilde{R}^C_s})^\sigma (G^E_{s,t})^{1-\sigma}\frac{\xi_s}{\xi_s-\sigma}\Big(\frac{((\sigma-1)(f^C_s-f^D_s))^{1/\sigma}}{\gamma\gamma_s Y_t}(G^E_{s,t}\tilde{R}^D_s\tilde{R}^C_s)^{\frac{\sigma-1}{\sigma}}(\frac{1}{(\tilde{R}^D_s)^{\sigma-1}-(\tilde{R}^C_s)^{\sigma-1}})^{\frac{1}{\sigma}}\Big)^\sigma\Big] \\
&\qquad = \mathbb{E}\Big[\frac{1}{\Psi^C_s}\frac{1}{\tilde{R}^C_s}\frac{\xi_s}{\xi_s-\sigma}(\sigma-1)(f^C_s-f^D_s)\frac{(\tilde{R}^D_s)^{\sigma-1}}{(\tilde{R}^D_s)^{\sigma-1}-(\tilde{R}^C_s)^{\sigma-1}}\Big] \\
&\qquad = \mathbb{E}\Big[\frac{\xi_s(\sigma-1)}{\Psi^C_s\tilde{R}^C_s(\xi_s-\sigma)}(f^C_s-f^D_s)\frac{(\tilde{R}^D_s)^{\sigma-1}}{(\tilde{R}^D_s)^{\sigma-1}-(\tilde{R}^C_s)^{\sigma-1}}\Big] \\
&\qquad = \frac{\xi_s(\sigma-1)}{\Psi^C_s\tilde{R}^C_s(\xi_s-\sigma)}(f^C_s-f^D_s)\frac{(\tilde{R}^D_s)^{\sigma-1}}{(\tilde{R}^D_s)^{\sigma-1}-(\tilde{R}^C_s)^{\sigma-1}}
\end{aligned}
$$

$\square$

C.10 Extension of Proposition 3

(Extended Aggregation of the Sectoral Effective Public Capital). The effective public capital in sector s for period t is given by:

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

where

$$\mathcal{G}^E_s = \begin{cases} \mathcal{G}^{E,D}_s \cdot \mathcal{G}_s & \text{if } s \in (S^{DG} \cup S^{\tilde{D}\tilde{G}} \cup S^{G} \cup S^{\tilde{G}}) \\ \mathcal{G}^{E,C}_s \cdot \mathcal{G}_s & \text{if } s \in S^{\tilde{C}\tilde{G}} \\ \mathcal{G}^{E,DC}_s \cdot \mathcal{G}_s & \text{if } s \in (S^{DCG} \cup S^{\tilde{D}C\tilde{G}} \cup S^{\tilde{D}\tilde{C}\tilde{G}}) \\ \mathcal{G}^{E,CD}_s \cdot \mathcal{G}_s & \text{if } s \in S^{\tilde{C}\tilde{D}\tilde{G}}. \end{cases}$$

Here, $\mathcal{G}_s$ is a factor not related to the financing choices, defined as:

$$\mathcal{G}_s \equiv \left(\sigma-1\right)^{\frac{\sigma-\xi}{\xi(\sigma-1)}} \left(\gamma\gamma_s\right)^{\frac{\sigma(\xi-1)}{\xi(\sigma-1)}} \left(\frac{\xi {\theta_{min}}^{\xi}}{\xi-\sigma}\right)^{\frac{\sigma}{\xi(\sigma-1)}}$$

and the other financing-specific factors are:

$$\begin{aligned}
\mathcal{G}^{E,D}_s &\equiv (\tilde{R}^D_s)^{-1} (\tilde{f}^G_s)^{\frac{\sigma-\xi}{\xi(\sigma-1)}} \\
\mathcal{G}^{E,C}_s &\equiv \left[(\tilde{f}^G_s)^{\frac{\sigma-\xi}{\sigma}} (\tilde{R}^D_s)^{\frac{(1-\sigma)\xi}{\sigma}} + (1-(\frac{\tilde{R}^C_s}{\tilde{R}^D_s})^{\sigma-1})(f^C_s)^{\frac{\sigma-\xi}{\sigma}} (\tilde{R}^C_s)^{\frac{(1-\sigma)\xi}{\sigma}}\right]^{\frac{\sigma}{\xi(\sigma-1)}} \\
\mathcal{G}^{E,DC}_s &\equiv \left[((\tilde{R}^D_s)^{1-\sigma} - (\tilde{R}^C_s)^{1-\sigma})^{\frac{\xi}{\sigma}} (f^D_s - f^C_s)^{\frac{\sigma-\xi}{\sigma}} + (\tilde{f}^G_s)^{\frac{\sigma-\xi}{\sigma}} (\tilde{R}^D_s)^{\frac{(1-\sigma)\xi}{\sigma}} \right. \\
&\qquad \left. + (1-(\frac{\tilde{R}^C_s}{\tilde{R}^D_s})^{\sigma-1})(f^C_s)^{\frac{\sigma-\xi}{\sigma}} (\tilde{R}^C_s)^{\frac{(1-\sigma)\xi}{\sigma}}\right]^{\frac{\sigma}{\xi(\sigma-1)}} \\
\mathcal{G}^{E,CD}_s &\equiv \left[((\tilde{R}^C_s)^{1-\sigma} - (\tilde{R}^D_s)^{1-\sigma})^{\frac{\xi}{\sigma}} (f^C_s - f^D_s)^{\frac{\sigma-\xi}{\sigma}} + (\tilde{f}^G_s)^{\frac{\sigma-\xi}{\sigma}} (\tilde{R}^D_s)^{\frac{(1-\sigma)\xi}{\sigma}}\right]^{\frac{\sigma}{\xi(\sigma-1)}}.
\end{aligned}$$

The total effective public capital stock in s in t, $G^E_{s,t}$, is

$$\begin{aligned}
\left[\int \theta \cdot (g^E_{s,t}(\theta))^{\frac{\sigma-1}{\sigma}} dH(\theta)\right]^{\frac{\sigma}{\sigma-1}} &= \left[\int \theta \cdot (\frac{\theta\gamma\gamma_s Y_t}{\tilde{R}^p})^{\sigma-1} (G^E_{s,t})^{\frac{(1-\sigma)(\sigma-1)}{\sigma}} \frac{\xi\theta^{\xi}_{min}}{\theta^{\xi+1}} d\theta\right]^{\frac{\sigma}{\sigma-1}} \\
&= (\gamma\gamma_s Y_t)^{\sigma} (G^E_{s,t})^{1-\sigma} (\xi\theta^{\xi}_{min})^{\frac{\sigma}{\sigma-1}} \left[\int (\tilde{R}^p)^{1-\sigma} \theta^{\sigma-\xi-1} d\theta\right]^{\frac{\sigma}{\sigma-1}}
\end{aligned}$$

If $s \in \{S^G, S^{\tilde{G}}\}$,

$$\begin{aligned}
\left[\int (\tilde{R}_s^p)^{1-\sigma}\theta^{\sigma-\xi-1}d\theta\right]^{\frac{\sigma}{\sigma-1}} &= \left[\int_{\bar{\theta}_{s,t}^G}^{\infty} (\tilde{R}_s^D)^{1-\sigma}\theta^{\sigma-\xi-1}d\theta\right]^{\frac{\sigma}{\sigma-1}} \\
&= \left[(\tilde{R}_s^D)^{1-\sigma}\frac{1}{\xi-\sigma}(\bar{\theta}_{s,t}^G)^{\sigma-\xi}\right]^{\frac{\sigma}{\sigma-1}} \\
&= (\tilde{R}^D)^{-\sigma}(\frac{1}{\xi-\sigma})^{\frac{\sigma}{\sigma-1}}\left[\frac{\left((\sigma-1)\tilde{f}_s^G\right)^{\frac{1}{\sigma}}}{\gamma\gamma_s Y_t}(G_{s,t}^E\tilde{R}_s^D)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma(\sigma-\xi)}{\sigma-1}} \\
&= (\tilde{R}^D)^{-\xi}(\frac{1}{\xi-\sigma})^{\frac{\sigma}{\sigma-1}}\left[\frac{\left((\sigma-1)\tilde{f}_s^G\right)^{\frac{1}{\sigma}}}{\gamma\gamma_s Y_t}\right]^{\frac{\sigma(\sigma-\xi)}{\sigma-1}}(G_{s,t}^E)^{\sigma-\xi}
\end{aligned}$$

If $s \in \{S^{DG}, S^{\tilde{D}\tilde{G}}\}$,

$$\begin{aligned}
\left[\int (\tilde{R}_s^p)^{1-\sigma}\theta^{\sigma-\xi-1}d\theta\right]^{\frac{\sigma}{\sigma-1}} &= \left[\int_{\bar{\theta}_{s,t}^D}^{\infty} (\tilde{R}_s^D)^{1-\sigma}\theta^{\sigma-\xi-1}d\theta + \int_{\bar{\theta}_{s,t}^G}^{\bar{\theta}_{s,t}^D} (\tilde{R}_s^D)^{1-\sigma}\theta^{\sigma-\xi-1}d\theta\right]^{\frac{\sigma}{\sigma-1}} \\
&= \left[\int_{\bar{\theta}_{s,t}^G}^{\infty} (\tilde{R}_s^D)^{1-\sigma}\theta^{\sigma-\xi-1}d\theta\right]^{\frac{\sigma}{\sigma-1}} \\
&= (\tilde{R}^D)^{-\xi}(\frac{1}{\xi-\sigma})^{\frac{\sigma}{\sigma-1}}\left[\frac{\left((\sigma-1)\tilde{f}_s^G\right)^{\frac{1}{\sigma}}}{\gamma\gamma_s Y_t}\right]^{\frac{\sigma(\sigma-\xi)}{\sigma-1}}(G_{s,t}^E)^{\sigma-\xi}
\end{aligned}$$

If $s \in \{S^{\tilde{C}\tilde{G}}\}$,

$$\begin{aligned}
\left[\int (\tilde{R}_s^p)^{1-\sigma}\theta^{\sigma-\xi-1}d\theta\right]^{\frac{\sigma}{\sigma-1}} &= \left[\int_{\bar{\theta}_{s,t}^C}^{\infty} (\tilde{R}_s^C)^{1-\sigma}\theta^{\sigma-\xi-1}d\theta + \int_{\bar{\theta}_{s,t}^G}^{\bar{\theta}_{s,t}^C} (\tilde{R}_s^D)^{1-\sigma}\theta^{\sigma-\xi-1}d\theta\right]^{\frac{\sigma}{\sigma-1}} \\
&= \left[(\tilde{R}_s^C)^{1-\sigma}\frac{1}{\xi-\sigma}(\bar{\theta}_s^C)^{\sigma-\xi} + (\tilde{R}_s^D)^{1-\sigma}\frac{1}{\xi-\sigma}((\bar{\theta}_{s,t}^G)^{\sigma-\xi} - (\bar{\theta}_{s,t}^C)^{\sigma-\xi})\right]^{\frac{\sigma}{\sigma-1}} \\
&= (\frac{1}{\xi-\sigma})^{\frac{\sigma}{\sigma-1}}\left[(\tilde{R}_s^D)^{1-\sigma}(\bar{\theta}_{s,t}^G)^{\sigma-\xi} + ((\tilde{R}_s^C)^{1-\sigma} - (\tilde{R}_s^D)^{1-\sigma})(\bar{\theta}_{s,t}^C)^{\sigma-\xi}\right]^{\frac{\sigma}{\sigma-1}} \\
&= (\frac{1}{\xi-\sigma})^{\frac{\sigma}{\sigma-1}}\left[\frac{(\sigma-1)^{\frac{1}{\sigma}}}{\gamma\gamma_s Y_t}\right]^{\frac{\sigma(\sigma-\xi)}{\sigma-1}}(G_{s,t}^E)^{\sigma-\xi} \\
&\quad \cdot \left[(\tilde{R}_s^D)^{1-\sigma}(\tilde{f}_s^G)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}_s^D)^{\frac{(\sigma-1)(\sigma-\xi)}{\sigma}} + ((\tilde{R}_s^C)^{1-\sigma} - (\tilde{R}_s^D)^{1-\sigma})(f_s^C)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}_s^C)^{\frac{(\sigma-1)(\sigma-\xi)}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \\
&= (\frac{1}{\xi-\sigma})^{\frac{\sigma}{\sigma-1}}\left[\frac{(\sigma-1)^{\frac{1}{\sigma}}}{\gamma\gamma_s Y_t}\right]^{\frac{\sigma(\sigma-\xi)}{\sigma-1}}(G_{s,t}^E)^{\sigma-\xi} \\
&\quad \cdot \left[(\tilde{f}_s^G)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}_s^D)^{\frac{(1-\sigma)\xi}{\sigma}} + (1-(\frac{\tilde{R}_s^C}{\tilde{R}_s^D})^{\sigma-1})(f_s^C)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}_s^C)^{\frac{(1-\sigma)\xi}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}
\end{aligned}$$

If $s \in \{S^{DCG}, S^{\tilde{D}\tilde{C}\tilde{G}}\}$,

$$
\begin{aligned}
\left[\int (\tilde{R}_s^p)^{1-\sigma}\theta^{\sigma-\xi-1}d\theta\right]^{\frac{\sigma}{\sigma-1}} &= \left[\int_{\bar{\theta}_{s,t}^I}^{\infty}(\tilde{R}_s^D)^{1-\sigma}\theta^{\sigma-\xi-1}d\theta + \int_{\bar{\theta}_{s,t}^C}^{\bar{\theta}_{s,t}^I}(\tilde{R}_s^C)^{1-\sigma}\theta^{\sigma-\xi-1}d\theta + \int_{\bar{\theta}_{s,t}^G}^{\bar{\theta}_{s,t}^C}(\tilde{R}_s^D)^{1-\sigma}\theta^{\sigma-\xi-1}d\theta\right]^{\frac{\sigma}{\sigma-1}} \\
&= (\frac{1}{\xi-\sigma})^{\frac{\sigma}{\sigma-1}}\left[\frac{(\sigma-1)^{\frac{1}{\sigma}}}{\gamma\gamma_s Y_t}\right]^{\frac{\sigma(\sigma-\xi)}{\sigma-1}}(G_{s,t}^E)^{\sigma-\xi} \\
&\quad \cdot\Bigg[(\tilde{R}_s^D)^{1-\sigma}(f_s^D-f_s^C)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}_s^D\tilde{R}_s^C)^{\frac{(\sigma-1)(\sigma-\xi)}{\sigma}}(\frac{1}{(\tilde{R}_s^C)^{\sigma-1}-(\tilde{R}_s^D)^{\sigma-1}})^{\frac{\sigma-\xi}{\sigma}} \\
&\quad -(\tilde{R}_s^C)^{1-\sigma}(f_s^D-f_s^C)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}_s^D\tilde{R}_s^C)^{\frac{(\sigma-1)(\sigma-\xi)}{\sigma}}(\frac{1}{(\tilde{R}_s^C)^{\sigma-1}-(\tilde{R}_s^D)^{\sigma-1}})^{\frac{\sigma-\xi}{\sigma}} \\
&\quad +(\tilde{R}_s^C)^{1-\sigma}(f_s^C)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}_s^C)^{\frac{(\sigma-1)(\sigma-\xi)}{\sigma}} \\
&\quad -(\tilde{R}_s^D)^{1-\sigma}(f_s^C)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}_s^C)^{\frac{(\sigma-1)(\sigma-\xi)}{\sigma}} \\
&\quad +(\tilde{R}_s^D)^{1-\sigma}(\tilde{f}_s^G)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}_s^D)^{\frac{(\sigma-1)(\sigma-\xi)}{\sigma}}\Bigg]^{\frac{\sigma}{\sigma-1}} \\
&= (\frac{1}{\xi-\sigma})^{\frac{\sigma}{\sigma-1}}\left[\frac{(\sigma-1)^{\frac{1}{\sigma}}}{\gamma\gamma_s Y_t}\right]^{\frac{\sigma(\sigma-\xi)}{\sigma-1}}(G_{s,t}^E)^{\sigma-\xi} \\
&\quad \cdot\Bigg[((\tilde{R}_s^D)^{1-\sigma}-(\tilde{R}_s^C)^{1-\sigma})(f_s^D-f_s^C)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}_s^D\tilde{R}_s^C)^{\frac{(\sigma-1)(\sigma-\xi)}{\sigma}}(\frac{(\tilde{R}_s^D\tilde{R}_s^C)^{1-\sigma}}{(\tilde{R}_s^D)^{1-\sigma}-(\tilde{R}_s^C)^{1-\sigma}})^{\frac{\sigma-\xi}{\sigma}} \\
&\quad +((\tilde{R}_s^C)^{1-\sigma}-(\tilde{R}_s^D)^{1-\sigma})(f_s^C)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}_s^C)^{\frac{(\sigma-1)(\sigma-\xi)}{\sigma}} \\
&\quad +(\tilde{R}_s^D)^{1-\sigma}(\tilde{f}_s^G)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}_s^D)^{\frac{(\sigma-1)(\sigma-\xi)}{\sigma}}\Bigg]^{\frac{\sigma}{\sigma-1}} \\
&= (\frac{1}{\xi-\sigma})^{\frac{\sigma}{\sigma-1}}\left[\frac{(\sigma-1)^{\frac{1}{\sigma}}}{\gamma\gamma_s Y_t}\right]^{\frac{\sigma(\sigma-\xi)}{\sigma-1}}(G_{s,t}^E)^{\sigma-\xi} \\
&\quad \cdot\Bigg[((\tilde{R}_s^D)^{1-\sigma}-(\tilde{R}_s^C)^{1-\sigma})^{\frac{\xi}{\sigma}}(f_s^D-f_s^C)^{\frac{\sigma-\xi}{\sigma}} \\
&\quad +((\tilde{R}_s^C)^{1-\sigma}-(\tilde{R}_s^D)^{1-\sigma})(f_s^C)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}_s^C)^{\frac{(\sigma-1)(\sigma-\xi)}{\sigma}} \\
&\quad +(\tilde{R}_s^D)^{1-\sigma}(\tilde{f}_s^G)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}_s^D)^{\frac{(\sigma-1)(\sigma-\xi)}{\sigma}}\Bigg]^{\frac{\sigma}{\sigma-1}} \\
&= (\frac{1}{\xi-\sigma})^{\frac{\sigma}{\sigma-1}}\left[\frac{(\sigma-1)^{\frac{1}{\sigma}}}{\gamma\gamma_s Y_t}\right]^{\frac{\sigma(\sigma-\xi)}{\sigma-1}}(G_{s,t}^E)^{\sigma-\xi} \\
&\quad \cdot\Bigg[((\tilde{R}_s^D)^{1-\sigma}-(\tilde{R}_s^C)^{1-\sigma})^{\frac{\xi}{\sigma}}(f_s^D-f_s^C)^{\frac{\sigma-\xi}{\sigma}} \\
&\quad +(\tilde{f}_s^G)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}_s^D)^{\frac{(1-\sigma)\xi}{\sigma}}+(1-(\frac{\tilde{R}_s^C}{\tilde{R}_s^D})^{\sigma-1})(f_s^C)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}_s^C)^{\frac{(1-\sigma)\xi}{\sigma}}\Bigg]^{\frac{\sigma}{\sigma-1}}
\end{aligned}
$$

Lastly, if $s \in \{S^{\tilde{C}\tilde{D}\tilde{G}}\}$,

$$\begin{aligned}
\left[\int (\tilde{R}_s^p)^{1-\sigma}\theta^{\sigma-\xi-1}d\theta\right]^{\frac{\sigma}{\sigma-1}} &= \left[\int_{\bar{\theta}_{s,t}^I}^{\infty}(\tilde{R}_s^C)^{1-\sigma}\theta^{\sigma-\xi-1}d\theta + \int_{\bar{\theta}_{s,t}^D}^{\bar{\theta}_{s,t}^I}(\tilde{R}_s^D)^{1-\sigma}\theta^{\sigma-\xi-1}d\theta + \int_{\bar{\theta}_{s,t}^G}^{\bar{\theta}_{s,t}^D}(\tilde{R}_s^D)^{1-\sigma}\theta^{\sigma-\xi-1}d\theta\right]^{\frac{\sigma}{\sigma-1}} \\
&= \left[\int_{\bar{\theta}_{s,t}^I}^{\infty}(\tilde{R}_s^C)^{1-\sigma}\theta^{\sigma-\xi-1}d\theta + \int_{\bar{\theta}_{s,t}^G}^{\bar{\theta}_{s,t}^I}(\tilde{R}_s^D)^{1-\sigma}\theta^{\sigma-\xi-1}d\theta\right]^{\frac{\sigma}{\sigma-1}} \\
&= (\frac{1}{\xi-\sigma})^{\frac{\sigma}{\sigma-1}}\left[\frac{(\sigma-1)^{\frac{1}{\sigma}}}{\gamma\gamma_s Y_t}\right]^{\frac{\sigma(\sigma-\xi)}{\sigma-1}}(G_{s,t}^E)^{\sigma-\xi} \\
&\quad \cdot \left[(\tilde{R}_s^C)^{1-\sigma}(f_s^C - f_s^D)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}_s^D\tilde{R}_s^C)^{\frac{(\sigma-1)(\sigma-\xi)}{\sigma}}(\frac{1}{(\tilde{R}_s^D)^{\sigma-1}-(\tilde{R}_s^C)^{\sigma-1}})^{\frac{\sigma-\xi}{\sigma}}\right. \\
&\quad - (\tilde{R}_s^D)^{1-\sigma}(f_s^C - f_s^D)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}_s^D\tilde{R}_s^C)^{\frac{(\sigma-1)(\sigma-\xi)}{\sigma}}(\frac{1}{(\tilde{R}_s^D)^{\sigma-1}-(\tilde{R}_s^C)^{\sigma-1}})^{\frac{\sigma-\xi}{\sigma}} \\
&\quad \left. + (\tilde{R}_s^D)^{1-\sigma}(f_s^G)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}_s^D)^{\frac{(\sigma-1)(\sigma-\xi)}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \\
&= (\frac{1}{\xi-\sigma})^{\frac{\sigma}{\sigma-1}}\left[\frac{(\sigma-1)^{\frac{1}{\sigma}}}{\gamma\gamma_s Y_t}\right]^{\frac{\sigma(\sigma-\xi)}{\sigma-1}}(G_{s,t}^E)^{\sigma-\xi} \\
&\quad \cdot \left[((\tilde{R}_s^C)^{1-\sigma} - (\tilde{R}_s^D)^{1-\sigma})^{\frac{\xi}{\sigma}}(f_s^C - f_s^D)^{\frac{\sigma-\xi}{\sigma}}\right. \\
&\quad \left. + (f_s^G)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}_s^D)^{\frac{(1-\sigma)\xi}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}
\end{aligned}$$

Note that $(\frac{1}{\xi-\sigma})^{\frac{\sigma}{\sigma-1}}\left[\frac{(\sigma-1)^{\frac{1}{\sigma}}}{\gamma\gamma_s Y_t}\right]^{\frac{\sigma(\sigma-\xi)}{\sigma-1}}(G_{s,t}^E)^{\sigma-\xi}$ is an additional common factor invariant to sectoral financing. Then, the common factor is

$$\begin{aligned}
&(\gamma\gamma_s Y_t)^{\sigma}(G_{s,t}^E)^{1-\sigma}(\xi\theta_{min}^{\xi})^{\frac{\sigma}{\sigma-1}} \times (\frac{1}{\xi-\sigma})^{\frac{\sigma}{\sigma-1}}\left[\frac{(\sigma-1)^{\frac{1}{\sigma}}}{\gamma\gamma_s Y_t}\right]^{\frac{\sigma(\sigma-\xi)}{\sigma-1}}(G_{s,t}^E)^{\sigma-\xi} \\
&= (\frac{\xi\theta_{min}^{\xi}}{\xi-\sigma})^{\frac{\sigma}{\sigma-1}}(\sigma-1)^{\frac{\sigma-\xi}{\sigma-1}}\big(\gamma\gamma_s Y_t\big)^{\frac{\sigma(\xi-1)}{\sigma-1}}(G_{s,t}^E)^{1-\xi}
\end{aligned}$$

Hence,

$$G_{s,t}^E = (\frac{\xi\theta_{min}^{\xi}}{\xi-\sigma})^{\frac{\sigma}{\xi(\sigma-1)}}(\sigma-1)^{\frac{\sigma-\xi}{\xi(\sigma-1)}}\big(\gamma\gamma_s Y_t\big)^{\frac{\sigma(\xi-1)}{\xi(\sigma-1)}}\mathcal{G}_s^E$$

D Additional Theoretical Results

D.1 Effective Public Capital vs Observed Public Capital

$$
\begin{aligned}
g^E_{s,j,t} &= (\frac{\theta_j \gamma\gamma_s}{\tilde{R}^p_s})^{\sigma_s} Y_t^{\sigma_s} (G^E_{st})^{1-\sigma_s} \\
&= (\frac{\theta_j \gamma\gamma_s}{\tilde{R}^p_s})^{\sigma_s} (\mathcal{G}^E_s)^{1-\sigma_s} Y_t^{\frac{\sigma_s}{\xi_s}}
\end{aligned}
$$

Let $g^O_{s,j,t}$ denote the observed size of project j. Then, $g^O_{s,j,t} = o_{s,j} g^E_{s,j,t}$ where $o_{s,j}$ takes the value of 1 if j is not misappropriated and $1/\psi^p_s$ if it is maximally misappropriated. Then,

$$
\begin{aligned}
G^O_{s,j,t} &= \int o_{s,j} g^E_{s,j,t} dj \\
&= \int o_{s,j} g^E_{s,j,t} dj \\
&= \int o_{s,j} (\frac{\theta_j \gamma\gamma_s}{\tilde{R}^p_s})^{\sigma_s} (\mathcal{G}^E_s)^{1-\sigma_s} Y_t^{\frac{\sigma_s}{\xi_s}} dj \\
&= \int o_{s,j} (\frac{\theta \gamma\gamma_s}{\tilde{R}^p_s})^{\sigma_s} (\mathcal{G}^E_s)^{1-\sigma_s} Y_t^{\frac{\sigma_s}{\xi_s}} h(\theta) d\theta \\
&= o_s (\frac{\gamma\gamma_s}{\tilde{R}^p_s})^{\sigma_s} (\mathcal{G}^E_s)^{1-\sigma_s} Y_t^{\frac{\sigma_s}{\xi_s}} \xi_s {\theta^s_{min}}^{\xi_s} \int \theta^{\sigma_s - \xi_s - 1} d\theta \\
&= o_s (\frac{\gamma\gamma_s}{\tilde{R}^p_s})^{\sigma_s} (\mathcal{G}^E_s)^{1-\sigma_s} Y_t^{\frac{\sigma_s}{\xi_s}} \xi_s {\theta^s_{min}}^{\xi_s} \frac{1}{\xi_s - \sigma_s} (\bar{\theta}^p_{s,t})^{\sigma_s - \xi_s} \\
&= o_s (\frac{\gamma\gamma_s}{\tilde{R}^p_s})^{\sigma_s} (\mathcal{G}^E_s)^{1-\sigma_s} Y_t^{\frac{\sigma_s}{\xi_s}} \xi_s {\theta^s_{min}}^{\xi_s} \frac{1}{\xi_s - \sigma_s} (\frac{((\sigma_s - 1) f^p_s)^{\frac{1}{\sigma_s}}}{\gamma\gamma_s Y_t} (\mathcal{G}^E_s \tilde{R}^p_s Y_t^{\frac{\sigma_s(\xi_s - 1)}{\xi_s(\sigma_s - 1)}})^{\frac{\sigma_s - 1}{\sigma_s}})^{\sigma_s - \xi_s} \\
&= o_s (\gamma\gamma_s)^{\xi_s} (\tilde{R}^p_s)^{\frac{-\sigma_s - \xi_s\sigma_s + \xi_s}{\sigma_s}} (\mathcal{G}^E_s)^{\frac{-\xi_s(\sigma_s - 1)}{\sigma_s}} \frac{\xi_s {\theta^s_{min}}^{\xi_s}}{\xi_s - \sigma_s} ((\sigma_s - 1) f^p_s)^{\frac{\sigma_s - \xi_s}{\sigma_s}} Y_t \\
&= o_s (\mathcal{G}^E_s)^{\frac{-\xi_s(\sigma_s - 1)}{\sigma_s}} (\gamma\gamma_s)(\tilde{R}^p_s)^{-1} \left((\gamma\gamma_s)^{\xi_s - 1} (\tilde{R}^p_s)^{\frac{-\xi_s(\sigma_s - 1)}{\sigma_s}} ((\sigma_s - 1) f^p_s)^{\frac{\sigma_s - \xi_s}{\sigma_s}} \frac{\xi_s {\theta^s_{min}}^{\xi_s}}{\xi_s - \sigma_s} \right) Y_t \\
&= o_s (\mathcal{G}^E_s)^{\frac{-\xi_s(\sigma_s - 1)}{\sigma_s}} (\gamma\gamma_s)(\tilde{R}^p_s)^{-1} (\mathcal{G}^E_s)^{\frac{\xi_s(\sigma_s - 1)}{\sigma_s}} Y_t \\
&= o_s \frac{\gamma\gamma_s}{\tilde{R}^p_s} Y_t
\end{aligned}
$$

Meanwhile, $G^E_{s,t} = \mathcal{G}^E_s Y_t^{\frac{\sigma_s(\xi_s - 1)}{\xi_s(\sigma_s - 1)}}$. Then,

$$
\begin{aligned}
G^O_{s,t} &= o_s \frac{\gamma\gamma_s}{\tilde{R}^p_s} \left(\frac{\mathcal{G}^E_s}{\mathcal{G}^E_s} Y_t^{\frac{\sigma_s(\xi_s - 1)}{\xi_s(\sigma_s - 1)}} \right)^{\frac{\xi_s(\sigma_s - 1)}{\sigma_s(\xi_s - 1)}} \\
&= o_s \frac{\gamma\gamma_s}{\tilde{R}^p_s} (\mathcal{G}^E_s)^{-\frac{\xi_s(\sigma_s - 1)}{\sigma_s(\xi_s - 1)}} (G^E_{s,t})^{\frac{\xi_s(\sigma_s - 1)}{\sigma_s(\xi_s - 1)}}
\end{aligned}
$$

Rearranging,

$$
\begin{aligned}
G^E_{s,t} &= \left[\frac{\tilde{R}^p_s}{o_s\gamma\gamma_s}(\mathcal{G}^E_s)^{\frac{\xi_s(\sigma_s-1)}{\sigma_s(\xi_s-1)}} G^O_{s,t}\right]^{\frac{\sigma_s(\xi_s-1)}{\xi_s(\sigma_s-1)}} \\
&= \mathcal{G}^E_s\left(\frac{\tilde{R}^p_s}{o_s\gamma\gamma_s}\right)^{\frac{\sigma_s(\xi_s-1)}{\xi_s(\sigma_s-1)}}(G^O_{s,t})^{\frac{\sigma_s(\xi_s-1)}{\xi_s(\sigma_s-1)}}
\end{aligned}
$$

Then,

$$
\begin{aligned}
g^E_{s,j,t} &= (\frac{\theta_j\gamma\gamma_s}{\tilde{R}^p_s})^{\sigma_s} Y_t^{\sigma_s}(G^E_{st})^{1-\sigma_s} \\
&= (\frac{\theta_j\gamma\gamma_s}{\tilde{R}^p_s})^{\sigma_s} Y_t^{\sigma_s}\left(\mathcal{G}^E_s\left(\frac{\tilde{R}^p_s}{o_s\gamma\gamma_s}\right)^{\frac{\sigma_s(\xi_s-1)}{\xi_s(\sigma_s-1)}}(G^O_{s,t})^{\frac{\sigma_s(\xi_s-1)}{\xi_s(\sigma_s-1)}}\right)^{1-\sigma_s} \\
&= \theta_j^{\sigma_s}(\frac{\gamma\gamma_s}{\tilde{R}^p_s})^{\sigma_s+\frac{\sigma_s(\xi_s-1)}{\xi_s}} o_s^{\frac{\sigma_s(\xi_s-1)}{\xi_s}}(\mathcal{G}^E_s)^{1-\sigma_s}(G^O_{s,t})^{-\frac{\sigma_s(\xi_s-1)}{\xi_s}} Y_t^{\sigma_s}
\end{aligned}
$$

Now suppose a sector that is financed by both providers.

$$
\begin{aligned}
G^O_{s,j,t} &= \int o_{s,j} g^E_{s,j,t} dj \\
&= \int o_{s,j} g^E_{s,j,t} dj \\
&= \int o_{s,j}(\frac{\theta_j\gamma\gamma_s}{\tilde{R}^p_s})^{\sigma_s}(\mathcal{G}^E_s)^{1-\sigma_s} Y_t^{\frac{\sigma_s}{\xi_s}} dj \\
&= \int o_{s,j}(\frac{\theta\gamma\gamma_s}{\tilde{R}^p_s})^{\sigma_s}(\mathcal{G}^E_s)^{1-\sigma_s} Y_t^{\frac{\sigma_s}{\xi_s}} h(\theta) d\theta \\
&= (\gamma\gamma_s)^{\sigma_s}(\mathcal{G}^E_s)^{1-\sigma_s} Y_t^{\frac{\sigma_s}{\xi_s}} \xi_s {\theta^s_{min}}^{\xi_s}\left(o^{p'}_s(\tilde{R}^{p'}_s)^{-\sigma_s}\int_{\bar{\theta}^{p'}_{s,t}}^{\bar{\theta}^I_{s,t}} \theta^{\sigma_s-\xi_s-1} d\theta + o^p_s(\tilde{R}^p_s)^{-\sigma_s}\int_{\bar{\theta}^I_{s,t}}^{\infty} \theta^{\sigma_s-\xi_s-1} d\theta\right) \\
&= (\gamma\gamma_s)^{\sigma_s}(\mathcal{G}^E_s)^{1-\sigma_s} Y_t^{\frac{\sigma_s}{\xi_s}} \xi_s {\theta^s_{min}}^{\xi_s}\left[\frac{o^{p'}_s(\tilde{R}^{p'}_s)^{-\sigma_s}}{\sigma_s-\xi_s}\theta_s^{\sigma_s-\xi_s}\Big|_{\bar{\theta}^{p'}_{s,t+1}}^{\bar{\theta}^I_{s,t+1}} + \frac{o^p_s(\tilde{R}^p_s)^{-\sigma_s}}{\sigma_s-\xi_s}\theta_s^{\sigma_s-\xi_s}\Big|_{\bar{\theta}^I_{s,t+1}}^{\infty}\right] \\
&= (\gamma\gamma_s)^{\sigma_s}(\mathcal{G}^E_s)^{1-\sigma_s} Y_t^{\frac{\sigma_s}{\xi_s}} \xi_s {\theta^s_{min}}^{\xi_s}\left[\frac{o^{p'}_s(\tilde{R}^{p'}_s)^{-\sigma_s}}{\sigma_s-\xi_s}((\bar{\theta}^I_{s,t+1})^{\sigma_s-\xi_s}-(\bar{\theta}^{p'}_{s,t+1})^{\sigma_s-\xi_s}) - \frac{o^p_s(\tilde{R}^p_s)^{-\sigma_s}}{\sigma_s-\xi_s}(\bar{\theta}^I_{s,t+1})^{\sigma_s-\xi_s}\right] \\
&= (\gamma\gamma_s)^{\sigma_s}(\mathcal{G}^E_s)^{1-\sigma_s} Y_t^{\frac{\sigma_s}{\xi_s}} \frac{\xi_s {\theta^s_{min}}^{\xi_s}}{\xi_s-\sigma_s}\left[(o^p_s(\tilde{R}^p_s)^{-\sigma_s} - o^{p'}_s(\tilde{R}^{p'}_s)^{-\sigma_s})(\bar{\theta}^I_{s,t+1})^{\sigma_s-\xi_s} + o^{p'}_s(\tilde{R}^{p'}_s)^{-\sigma_s}(\bar{\theta}^{p'}_{s,t+1})^{\sigma_s-\xi_s}\right] \\
&= \left[(o^p_s(\tilde{R}^p_s)^{-\sigma_s} - o^{p'}_s(\tilde{R}^{p'}_s)^{-\sigma_s})\left(\frac{f^p_s-f^{p'}_s}{(\tilde{R}^p_s)^{1-\sigma_s}-(\tilde{R}^{p'}_s)^{1-\sigma_s}}\right)^{\frac{\sigma_s-\xi_s}{\sigma_s}} + o^{p'}_s(\tilde{R}^{p'}_s)^{-\sigma_s}\left(\frac{f^{p'}_s}{(\tilde{R}^{p'}_s)^{1-\sigma_s}}\right)^{\frac{\sigma_s-\xi_s}{\sigma_s}}\right] \\
&\quad\times(\gamma\gamma_s)^{\xi_s}(\mathcal{G}^E_s)^{-\frac{\xi_s(\sigma_s-1)}{\sigma_s}}\frac{\xi_s {\theta^s_{min}}^{\xi_s}}{\xi_s-\sigma_s}(\sigma_s-1)^{\frac{\sigma_s-\xi_s}{\sigma_s}} Y_t \\
&= \mathcal{Y} Y_t
\end{aligned}
$$

Meanwhile, $G^E_{s,t} = \mathcal{G}^E_s Y_t^{\frac{\sigma_s(\xi_s-1)}{\xi_s(\sigma_s-1)}}$. Then,

$$
\begin{aligned}
G^O_{s,t} &= \mathcal{Y}\left(\frac{\mathcal{G}^E_s}{\mathcal{G}^E_s} Y_t^{\frac{\sigma_s(\xi_s-1)}{\xi_s(\sigma_s-1)}}\right)^{\frac{\xi_s(\sigma_s-1)}{\sigma_s(\xi_s-1)}} \\
&\mathcal{Y}(\mathcal{G}^E_s)^{-\frac{\xi_s(\sigma_s-1)}{\sigma_s(\xi_s-1)}}(G^E_{s,t})^{\frac{\xi_s(\sigma_s-1)}{\sigma_s(\xi_s-1)}}
\end{aligned}
$$

Rearranging,

$$
\begin{aligned}
G^E_{s,t} &= \left[\frac{1}{\mathcal{Y}}(\mathcal{G}^E_s)^{\frac{\xi_s(\sigma_s-1)}{\sigma_s(\xi_s-1)}} G^O_{s,t}\right]^{\frac{\sigma_s(\xi_s-1)}{\xi_s(\sigma_s-1)}} \\
&= \mathcal{G}^E_s \left(\frac{1}{\mathcal{Y}}\right)^{\frac{\sigma_s(\xi_s-1)}{\xi_s(\sigma_s-1)}} (G^O_{s,t})^{\frac{\sigma_s(\xi_s-1)}{\xi_s(\sigma_s-1)}}
\end{aligned}
$$

Then,

$$
\begin{aligned}
g^E_{s,j,t} &= (\frac{\theta_j \gamma \gamma_s}{\tilde{R}^p_s})^{\sigma_s} Y_t^{\sigma_s} (G^E_{st})^{1-\sigma_s} \\
&= (\frac{\theta_j \gamma \gamma_s}{\tilde{R}^p_s})^{\sigma_s} Y_t^{\sigma_s} \left(\mathcal{G}^E_s \left(\frac{1}{\mathcal{Y}}\right)^{\frac{\sigma_s(\xi_s-1)}{\xi_s(\sigma_s-1)}} (G^O_{s,t})^{\frac{\sigma_s(\xi_s-1)}{\xi_s(\sigma_s-1)}}\right)^{1-\sigma_s}
\end{aligned}
$$

Hence, in any case,

$$
\begin{aligned}
g^O_{s,j,t} &= o_s g^E_{s,j,t} \\
&= \theta_j^{\sigma_s} \mathcal{A}_s (G^O_{s,t})^{-\frac{\sigma_s(\xi_s-1)}{\xi_s}} Y_t^{\sigma_s}
\end{aligned}
$$

D.2 Debt Stock to GDP

Proposition 6. (Debt Stock to GDP Ratio). The ratio of debt stock owed to p in sector s in period t to GDP is given by:

$$\frac{D^p_{s,t}}{Y_t} = \frac{\gamma\gamma_s}{\Psi^p_s}\frac{1}{(\tilde{R}^p_s)^\sigma}\mathcal{D}^p_s,$$

and

$$\mathcal{D}^p_s = \begin{cases} (\mathcal{G}^{E,D}_s)^{\frac{\xi(1-\sigma)}{\sigma}}\mathcal{D}^{p,D}_s & \text{if } s \in (S^{DG} \cup S^{\tilde{D}\tilde{G}} \cup S^G \cup S^{\tilde{G}}) \\ (\mathcal{G}^{E,C}_s)^{\frac{\xi(1-\sigma)}{\sigma}}\mathcal{D}^{p,C}_s & \text{if } s \in S^{\tilde{C}\tilde{G}} \\ (\mathcal{G}^{E,DC})^{\frac{\xi(1-\sigma)}{\sigma}}\mathcal{D}^{p,DC}_s & \text{if } s \in (S^{DCG} \cup S^{\tilde{D}C\tilde{G}} \cup S^{\tilde{D}\tilde{C}\tilde{G}}) \\ (\mathcal{G}^{E,CD})^{\frac{\xi(1-\sigma)}{\sigma}}\mathcal{D}^{p,CD}_s & \text{if } s \in S^{\tilde{C}\tilde{D}\tilde{G}}. \end{cases}$$

where

$$\begin{aligned}
\mathcal{D}^{D,D}_s &\equiv (f^D_s)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}^D_s)^{\frac{(\sigma-1)(\sigma-\xi)}{\sigma}} \\
\mathcal{D}^{D,C}_s &\equiv 0 \\
\mathcal{D}^{D,DC}_s &\equiv \left[(f^D_s - f^C_s)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}^D_s\tilde{R}^C_s)^{\frac{(\sigma-1)(\sigma-\xi)}{\sigma}}\left(\frac{1}{(\tilde{R}^C_s)^{\sigma-1} - (\tilde{R}^D_s)^{\sigma-1}}\right)^{\frac{\sigma-\xi}{\sigma}}\right] \\
\mathcal{D}^{D,CD}_s &\equiv \left[(f^D_s)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}^D_s)^{\frac{(\sigma-1)(\sigma-\xi)}{\sigma}} - (f^C_s - f^D_s)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}^D_s\tilde{R}^C_s)^{\frac{(\sigma-1)(\sigma-\xi)}{\sigma}}\left(\frac{1}{(\tilde{R}^D_s)^{\sigma-1} - (\tilde{R}^C_s)^{\sigma-1}}\right)^{\frac{\sigma-\xi}{\sigma}}\right] \\
\mathcal{D}^{C,D}_s &\equiv 0 \\
\mathcal{D}^{C,C}_s &\equiv (f^C_s)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}^C_s)^{\frac{(\sigma-1)(\sigma-\xi)}{\sigma}} \\
\mathcal{D}^{C,DC}_s &\equiv \left[(f^C_s)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}^C_s)^{\frac{(\sigma-1)(\sigma-\xi)}{\sigma}} - (f^D_s - f^C_s)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}^D_s\tilde{R}^C_s)^{\frac{(\sigma-1)(\sigma-\xi)}{\sigma}}\left(\frac{1}{(\tilde{R}^C_s)^{\sigma-1} - (\tilde{R}^D_s)^{\sigma-1}}\right)^{\frac{\sigma-\xi}{\sigma}}\right] \\
\mathcal{D}^{C,CD}_s &\equiv \left[(f^C_s - f^D_s)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}^D_s\tilde{R}^C_s)^{\frac{(\sigma-1)(\sigma-\xi)}{\sigma}}\left(\frac{1}{(\tilde{R}^D_s)^{\sigma-1} - (\tilde{R}^C_s)^{\sigma-1}}\right)^{\frac{\sigma-\xi}{\sigma}}\right]
\end{aligned}$$

First, note that $d^p_{sjt} > 0$ only for projects with productivity $\theta \in [\underline{\theta}, \bar{\theta})$ for some $\underline{\theta}$ and $\bar{\theta}$. Then,

$$\begin{aligned}
D^p_{st} &= \int d^p_{sjt}dj \\
&= \int \frac{1}{\Psi^p_s}g^e_{sjt}dj \\
&= \int \frac{1}{\Psi^p_s}\left(\frac{\theta\gamma\gamma_s}{\tilde{R}^p_s}Y_t\right)^\sigma (G^E_{s,t})^{1-\sigma}\frac{\xi\theta^\xi_{min}}{\theta^{\xi+1}}d\theta \\
&= \frac{1}{\Psi^p_s}\left(\frac{\theta\gamma\gamma_s}{\tilde{R}^p_s}Y_t\right)^\sigma (G^E_{s,t})^{1-\sigma}\frac{\xi\theta^\xi_{min}}{\xi-\sigma}(\underline{\theta}^{\sigma-\xi} - \bar{\theta}^{\sigma-\xi})
\end{aligned}$$

Note that the thresholds $\underline{\theta}$ and $\bar{\theta}$ are either the zero-profit cutoff or financing indifference cutoff. All those cutoffs have $\frac{(\sigma-1)^{\frac{1}{\sigma}}}{\gamma\gamma_s Y_t}(G^E_{st})^{\frac{\sigma-1}{\sigma}}$ as a common factor. Let's denote the remaining factors of $\underline{\theta}$ and $\bar{\theta}$ by $\underline{\theta}_{resid}$

and $\bar{\theta}_{resid}$ respectively. Then,

$$\begin{aligned}
D^p_{st} &= \frac{1}{\Psi^p_s}\big(\frac{\theta\gamma\gamma_s}{\tilde{R}^p_s}Y_t\big)^{\sigma}(G^E_{s,t})^{1-\sigma}\frac{\xi\theta^{\xi}_{min}}{\xi-\sigma}(\underline{\theta}^{\sigma-\xi}-\bar{\theta}^{\sigma-\xi})\\
&= frac1\Psi^p_s\big(\frac{\theta\gamma\gamma_s}{\tilde{R}^p_s}Y_t\big)^{\sigma}(G^E_{s,t})^{1-\sigma}\frac{\xi\theta^{\xi}_{min}}{\xi-\sigma}\big(\frac{(\sigma-1)^{\frac{1}{\sigma}}}{\gamma\gamma_s Y_t}(G^E_{st})^{\frac{\sigma-1}{\sigma}}\big)^{\sigma-\xi}(\underline{\theta}^{\sigma-\xi}_{resid}-\bar{\theta}^{\sigma-\xi}_{resid})\\
&= \frac{1}{\Psi^p_s}(\sigma-1)^{\frac{\sigma-\xi}{\sigma}}(\gamma\gamma_s Y_t)^{\xi}(G^E_{st})^{\frac{\xi(1-\sigma)}{\sigma}}(\tilde{R}^p_s)^{-\sigma}\frac{\xi\theta^{\xi}_{min}}{\xi-\sigma}(\underline{\theta}^{\sigma-\xi}_{resid}-\bar{\theta}^{\sigma-\xi}_{resid})\\
&= \frac{1}{\Psi^p_s}(\sigma-1)^{\frac{\sigma-\xi}{\sigma}}(\gamma\gamma_s Y_t)^{\xi}(\mathcal{G}_s\mathcal{G}^{E,f}_s Y_t^{\frac{\sigma(\xi-1)}{\xi(\sigma-1)}})^{\frac{\xi(1-\sigma)}{\sigma}}(\tilde{R}^p_s)^{-\sigma}\frac{\xi\theta^{\xi}_{min}}{\xi-\sigma}(\underline{\theta}^{\sigma-\xi}_{resid}-\bar{\theta}^{\sigma-\xi}_{resid})\\
&= \frac{1}{\Psi^p_s}\gamma\gamma_s Y_t(\tilde{R}^p_s)^{-\sigma}(\mathcal{G}^{E,f}_s)^{\frac{\xi(1-\sigma)}{\sigma}}(\underline{\theta}^{\sigma-\xi}_{resid}-\bar{\theta}^{\sigma-\xi}_{resid})
\end{aligned}$$

Let $\mathcal{D}^{p,f}$ denote $(\underline{\theta}^{\sigma-\xi}_{resid}-\bar{\theta}^{\sigma-\xi}_{resid})$ for each donor p and financing mode f. Then,

$$\begin{aligned}
\mathcal{D}^{D,D}_s &\equiv (f^D_s)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}^D_s)^{\frac{(\sigma-1)(\sigma-\xi)}{\sigma}}\\
\mathcal{D}^{D,C}_s &\equiv 0\\
\mathcal{D}^{D,DC}_s &\equiv \Big[(f^D_s-f^C_s)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}^D_s\tilde{R}^C_s)^{\frac{(\sigma-1)(\sigma-\xi)}{\sigma}}\big(\frac{1}{(\tilde{R}^C_s)^{\sigma-1}-(\tilde{R}^D_s)^{\sigma-1}}\big)^{\frac{\sigma-\xi}{\sigma}}\Big]\\
\mathcal{D}^{D,CD}_s &\equiv \Big[(f^D_s)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}^D_s)^{\frac{(\sigma-1)(\sigma-\xi)}{\sigma}}-(f^C_s-f^D_s)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}^D_s\tilde{R}^C_s)^{\frac{(\sigma-1)(\sigma-\xi)}{\sigma}}\big(\frac{1}{(\tilde{R}^D_s)^{\sigma-1}-(\tilde{R}^C_s)^{\sigma-1}}\big)^{\frac{\sigma-\xi}{\sigma}}\Big]\\
\mathcal{D}^{C,D}_s &\equiv 0\\
\mathcal{D}^{C,C}_s &\equiv (f^C_s)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}^C_s)^{\frac{(\sigma-1)(\sigma-\xi)}{\sigma}}\\
\mathcal{D}^{C,DC}_s &\equiv \Big[(f^C_s)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}^C_s)^{\frac{(\sigma-1)(\sigma-\xi)}{\sigma}}-(f^D_s-f^C_s)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}^D_s\tilde{R}^C_s)^{\frac{(\sigma-1)(\sigma-\xi)}{\sigma}}\big(\frac{1}{(\tilde{R}^C_s)^{\sigma-1}-(\tilde{R}^D_s)^{\sigma-1}}\big)^{\frac{\sigma-\xi}{\sigma}}\Big]\\
\mathcal{D}^{C,CD}_s &\equiv \Big[(f^C_s-f^D_s)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}^D_s\tilde{R}^C_s)^{\frac{(\sigma-1)(\sigma-\xi)}{\sigma}}\big(\frac{1}{(\tilde{R}^D_s)^{\sigma-1}-(\tilde{R}^C_s)^{\sigma-1}}\big)^{\frac{\sigma-\xi}{\sigma}}\Big].
\end{aligned}$$

E Details for Quantitative Analysis

E.1 Augmentation

DAC grants. As another source of financing, I incorporate the DAC grants. In practice, the DAC grants constitute a significant portion of DF (1.3 million counts) along with the DAC (31,459 counts) and Chinese loans (4,400 counts). The median size of the DAC grants ($53,469) are much smaller than those of the DAC loans ($18.7 million) and Chinese loans ($67million).[9] Since the scale of the DAC grant projects are incomparably small to the loan projects while the count is much higher, I model in such a way that they corresponds to the projects near the bottom of productivity distribution and such a way that the augmentation does not qualitatively affect the main results regarding the loans in previous sections. In reality, the DAC grants are also secured after some negotiation process between the applicant country and the DAC agencies. For tractability, I assume that the DAC evaluates the marginal product of each project and equates it to a shadow cost, which represents the cost the borrower would incur if it were a loan contract. Grants are subject to the same monitoring intensity ψ_s^D as DAC loans. Consequently, the optimal size of a grant-financed project j, evaluated by the DAC, $\bar{g}^{EG}_{s,j,t}$, is determined by the same equation as DAC loans: $mpg^E_{sjt} + 1 - \delta^E_s = \tilde{R}^D_s$. However, there is a limit on project size, and the DAC approves projects only if $\bar{g}^{EG}_{s,j,t} \leq T_s$ for some $T_s > 0$. This reflects the practice of many DAC grant agencies, which set a limit on the amount for each individual call for applications. Additionally, grant-financing incurs a fixed cost denoted by f^G_s. Consequently, the effective profit for the government from a grant-financed project, $\tilde{\pi}^G_{s,j,t}$, is given by:

$$\tilde{\pi}^G_{s,j,t} \equiv \int_0^{\bar{g}^{EG}_{s,j,t}} (mpg^E_{s,j,t} - \tilde{R}^D_s + \frac{R^D_s}{\Psi^D_s}) dg^E_{s,j,t} - f^G_s$$

where Ψ^D_s takes the value of ψ^D_s if $\chi \geq R^D_s$ and 1 otherwise. The zero-profit cutoff, which satisfies $\tilde{\pi}^G_{s,t}(\bar{\theta}^G_{s,t}) = 0$, is obtained as:

$$\bar{\theta}^G_{s,t} = \frac{\left((\sigma_s - 1)\frac{f^G_s}{1+(\sigma_s-1)\frac{R^D_s}{\Psi^D_s \tilde{R}^D_s}}\right)^{\frac{1}{\sigma_s}}}{\gamma\gamma_s Y_t} (G^E_{s,t}\tilde{R}^D_s)^{\frac{\sigma_s-1}{\sigma_s}}.$$

[9] An example of small size grant project is 'Therapy Equipment for Disability and Rehabilitation Centre' in Vietnam to which Australia committed in 2016 to provide $3,640 in 2011 constant dollar term. An example of loan project in the same country and sector is 'Construction of Hai Phong General Hospital' to which South Korea committed in 2017 to provide $87.3 million in 2011 constant USD.

For later convenience, I define $\tilde{f}_s^G \equiv \frac{f_s^G}{1+(\sigma_s-1)\frac{R_s^D}{\Psi_s^D \tilde{R}_s^D}}$. Additionally, I define an extra productivity cutoff, $\bar{\theta}_{s,t}^T$, that equates the optimal project size to the grant size limit, namely $\bar{g}_{s,t}^{EG} = T_s$.

$$\bar{\theta}_{s,t}^T = \frac{\left((\sigma_s - 1)\frac{T_s \cdot (\tilde{R}_s^D)^{1-\sigma_s}}{\sigma_s - 1}\right)^{\frac{1}{\sigma_s}}}{\gamma \gamma_s Y_t} (G_{s,t}^E \tilde{R}_s^D)^{\frac{\sigma_s - 1}{\sigma_s}}.$$

Motivated by the fact that the average size of grant projects is almost ten times smaller than loan projects, I make an additional assumption that in sectors with $T_s < \infty$, the DAC sets the grant size limit T_s such that $\bar{\theta}_{s,t}^T = \min\{\bar{\theta}_{s,t}^D, \bar{\theta}_{s,t}^C\}$. This can be implemented by setting $T_s = \min\{f_s^D \cdot (\tilde{R}_s^D)^{\sigma-1}, f_s^C \cdot (\tilde{R}_s^C)^{\sigma-1}\}$.

This assumption implies that the DAC does not allow borrowing countries to receive grants for projects that are productive enough to make positive effective profits for the government even if they were financed by loans. Suppose that $T_s > \min\{f_s^D \cdot (\tilde{R}_s^D)^{\sigma-1}, f_s^C \cdot (\tilde{R}_s^C)^{\sigma-1}\}$ so that $\bar{\theta}_{s,t}^T > \min\{\bar{\theta}_{s,t}^D, \bar{\theta}_{s,t}^C\}$. In this case, the borrowing country would choose DAC grants for some projects even though it could make positive profits with DAC or Chinese loans. Considering the cost of providing grants without any expected returns, the DAC would not allow this to happen.

It is also unrealistic that $T_s < \min\{f_s^D \cdot (\tilde{R}_s^D)^{\sigma-1}, f_s^C \cdot (\tilde{R}_s^C)^{\sigma-1}\}$, as this would imply that the DAC chooses to finance less productive projects. Therefore, the optimal sectoral financing results in Proposition 2 carry over, except that in each category, projects with productivity $\theta \in [\bar{\theta}_s^G, \min\{\bar{\theta}_{s,t}^D, \bar{\theta}_{s,t}^C\})$ are now financed by DAC grants in addition to the loan-financed projects.

Moreover, allowing for grant-financing potentially gives rise to two additional categories where an entire sector is financed solely by DAC grants, with or without misappropriation. This is possible when $T_s \to \infty$. I denote each category by $S^{\tilde{G}}$ and S^G.

Self-financing. I also allow for self-financing, where the government does not rely on external sources to finance a project. This is because DF is not available in military sector which constitutes a non-trivial portion of public sector. Generally, if DF is available, self-financing is dominated by DF due to the higher fixed costs associated with other financing sources and will not be commonly used. As a result, self-financing is only considered for sectors where DF is not available.

E.2 Sector Classifcation

Table E.1: Sector Classification

Sector name	OECD DAC-5	IMF COFOG
Agriculture, Forestry, Fishing	Agriculture, Forestry, Fishing	Agriculture, Forestry, Fishing, and Hunting
Industry, Mining, Construction	Industry, Mining, Construction	Mining, Manufacturing, Construction
Transport & Storage	Transport & Storage	Transport
Energy	Energy	Fuel and Energy
Communications	Communications	Communication
Health	Health	Health
Education	Education	Education
General Environment Protection	General Environment Protection	Environmental Protection
Water Supply & Sanitation	Water Supply & Sanitation	Housing and Community Amenities
Government & Civil Society	Government & Civil Society; Disaster Prevention & Preparedness	Public Order & Safety
General Budget Support	General Budget Support; Other Multisector	General Public Service; Other Industries
General Economic, Commercial, Labor Affairs	Banking & Financial Services; Business & Other Services; Other Commodity Assistance ; Trade Policies & Regulations	General Economic, Commercial, Labor Affairs; Economic Affairs n.e.c.; Economic affairs R&D
Other Social Infrastructure & Services	Other Social Infrastructure & Services; Population Policies/Programs & Reproductive Health; Development Food Assistance	Recreation Culture Religion; Social Protection
Defense		Defense
	Action Relating to Debt; Emergency Response; Reconstruction Relief & Rehabilitation; Administrative Costs of Donors; Refugees in Donor Countries; Unallocated / Unspecified	

E.3 Estimating public capital sector shares γ_s

The model predicts that if an advanced country self-finances a development project j in sector s without diversion, the optimal project size would be determined by the following first-order condition:

$$mpg^{E}_{s,j,t+1} + 1 - \delta_G = \frac{\tilde{U}'_C(C_t)}{\beta \tilde{U}'_C(C_{t+1})}$$

In steady state, the optimal project size is given by:

$$g^{E*}_{s,j} = \Big(\frac{\theta_j \gamma \gamma_s}{1/\beta - (1-\delta_G)}\Big)^{\sigma} (Y^*)^{\sigma} (G^{E*}_s)^{1-\sigma}$$

Then, the total expenditure on sector s observed in the data, denoted by G^{O*}_s, is obtained as:

$$\begin{aligned} G^{O*}_s &= \int g^{E*}_{s,j} dj \\ &= \frac{\gamma \gamma_s}{1/\beta - (1-\delta_G)} Y^* \end{aligned}$$

Since data on public capital at the sectoral level is not available, while the IMF COFOG provides public expenditure on each sector each year, I target the investment ratios rather than public capital ratios. In the steady state without diversion, total investment in sector s is simply $I^{G*}_s = \delta_G G^{O*}_s$. Therefore, the ratio of I^{G*}_s to GDP in the steady state is characterized as:

$$\frac{I^{G*}_s}{Y^*} = \frac{\delta^E_s \gamma \gamma_s}{1/\beta - (1-\delta^E_s)}$$

It follows that the share of each sector in total public expenditure is γ_s. I estimate γ_s using Sequential Least Squares Programming (SLSQP), which minimizes the squared distance between γ_s and the mean of the corresponding sector share, with the constraint that $\sum_{s \in \mathcal{S}} \gamma_s = 1$. This approach is equivalent to the Generalized Method of Moments (GMM) with the following moment conditions:

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

E.4 Estimating Chinese DF monitoring intensities ψ_s^C

For the quantitative analysis, I focus on the relative monitoring intensities between DAC and Chinese DF, normalizing the monitoring intensities for DAC DF in all sectors to 1 ($\psi_s^D = 1$). There are two reasons for this approach. First, in the empirical analysis, DAC project sizes are not qualitatively correlated with corruption in most sectors. While I find a correlation in sectors that are difficult to monitor, it is much smaller than the correlation observed for Chinese DF. Secondly, it is extremely challenging to estimate the exact values of monitoring intensities for both DAC and Chinese DF across all sectors since there is no cardinal corruption measure that corresponds empirically to the model's corruption parameter, χ_r. However, under certain identifying assumptions, I can estimate the relative monitoring intensity between DAC and Chinese DF for each sector. To estimate monitoring intensities for Chinese DF, I begin with the model equation that determines the optimal size of effective public capital for project j, $g^E_{r,p,s,j,t}$. The actual size of project j observed in the data, $g^O_{r,p,s,j,t}$, is equal to $g^E_{r,p,s,j,t}/\Psi^p_{r,s}$, where $\Psi^p_{r,s}$ is ψ^p_s if country r diverts DF from provider p in sector s, and 1 otherwise. Hence,

$$g^O_{r,p,s,j,t} = \frac{1}{\Psi^p_s}\Big(\frac{\gamma\gamma_s\theta_j}{\tilde{R}^p_{r,s}}\Big)^{\sigma} Y^{\sigma}_{r,t}(G^E_{r,s,t})^{1-\sigma}.$$

Taking the log and approximating $\ln \tilde{R}^p_{r,s} = \ln\Big(\frac{R^p_s-(1-\psi^p_s)\chi_r}{\psi^p_s} - (1-\delta_G)\Big)$ to the first order around $\chi_r = R^p_s$ and $\psi^p_s = 1$, I obtain:

$$\ln g^O_{r,p,s,j,t} \approx -\ln \Psi^p_s + \sigma \ln \theta_j + \sigma \ln \gamma\gamma_s + \sigma \ln Y_{r,t} + (1-\sigma)\ln G^E_{r,s,t} - \sigma \ln(R^p_s - (1-\delta_G)).$$

Note that the equality holds for $p = D$ since $\psi^D_s = 1$. Since $Y_{r,t}$, $G^E_{r,s,t}$, and $\gamma\gamma_s$ are invariant to p, the difference in the log project size between DAC and Chinese DF arises from three components: monitoring intensity, interest rate, and potential selection bias in productivity θ_j. My model predicts that the productivity cutoffs determining the average size of DAC and Chinese DF projects are driven by the borrowing country's corruption, recipient-provider bilateral and sector-specific fixed costs, and interest rates. Based on this, I control for variables that might affect these factors to account for the systemic difference in the productivity of DAC and Chinese projects. Then, with some additional identifying assumptions, the difference in average project size—controlling for all these factors—can be attributed to the difference in monitoring intensity. Consider the following fixed effect regression model. $\mathbf{X}_{r,p,t}$ includes the gravity variables, bilateral political distance, and $\ln(R^p_s - (1-\delta_G))$.

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

I make the following assumptions, where *controls* indicate all the right-hand side variables of the fixed effect 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 states that all countries using Chinese DF during the sample period are corrupt enough to divert the funds. Considering that the majority of Chinese DF is directed toward countries with higher-than-average corruption indices (Malik et al., 2021), this assumption is reasonable. If anything, the bias would lean toward overestimating the monitoring intensity of Chinese DF. Therefore, if there are recipient countries with insufficient corruption in the sample, the actual monitoring intensity should be lower. As a result, the estimate under this assumption should be considered an upper bound of Chinese DF monitoring intensities relative to the DAC.

The second assumption states that I can control for the difference in average productivity between DAC and Chinese DF in a sector by including recipient-time fixed effects, sector fixed effects, and control variables. Under the two assumptions, the expected values of log project size for DAC and Chinese DF in sector s, given control variables, are:

$$
\begin{aligned}
\mathbb{E}\big[\ln g^O_{r,p,s,j,t} | p = D, s, controls\big] \approx & \sigma \ln \gamma\gamma_s - \sigma \ln\big(R_s^D - (1-\delta_G)\big) \\
& + \sigma \ln Y_{r,t} + \mathbb{E}\big[(1-\sigma)\ln G^E_{r,s,t} | s, controls\big] \\
& + \sigma \mathbb{E}\big[\ln \theta_j | p = D, s, controls\big] \\
= & \sigma \ln \gamma\gamma_s - \sigma \ln\big(R_s^D - (1-\delta_G)\big) \\
& + \sigma \ln Y_{r,t} + \mathbb{E}\big[(1-\sigma)\ln G^E_{r,s,t} | s, controls\big] \\
& + \alpha_{rt} + \alpha_s + \mathbf{X}_{r,p=D,t} \cdot \beta \\
\mathbb{E}\big[\ln g^O_{r,p,s,j,t} | p = C, s, controls\big] \approx & \sigma \ln \gamma\gamma_s - \sigma \ln\big(R_s^C - (1-\delta_G)\big) \\
& + \sigma \ln Y_{r,t} + \mathbb{E}\big[(1-\sigma)\ln G^E_{r,s,t} | s, controls\big] \\
& + \sigma \mathbb{E}\big[\ln \theta_j | p = C, s, controls\big] \\
& - \ln \psi_s^C \cdot \mathbb{P}(\chi_r \geq R_s^C | s, p = C) \\
= & \sigma \ln \gamma\gamma_s - \sigma \ln\big(R_s^C - (1-\delta_G)\big) \\
& + \sigma \ln Y_{r,t} + \mathbb{E}\big[(1-\sigma)\ln G^E_{r,s,t} | s, controls\big] \\
& + \alpha_{rt} + \alpha_s + \mathbf{X}_{r,p=D,t} \cdot \beta \\
& - \ln \psi_s^C
\end{aligned}
$$

Then, the difference in sector-provider fixed effects for each sector in the fixed effect regression model is:

$$\begin{aligned} FE_{s,p=C} - FE_{s,p=D} =& \mathbb{E}[\ln g^O_{r,p,s,j,t} | s, p = C, controls] - \mathbf{X}_{r,p=C,t} \cdot \beta \\ & - (\mathbb{E}[\ln g^O_{r,p,s,j,t} | s, p = D, controls] - \mathbf{X}_{r,p=D,t} \cdot \beta) \\ =& - \ln \psi^C_s \end{aligned}$$

Therefore,

$$\psi^C_s = \exp^{FE_{s,p=D} - FE_{s,p=C}}.$$

Based on this, I run the fixed effect regressions and use the estimated sector-provider fixed effects for each sector to estimate Chinese DF monitoring intensities. Note that I include only loan projects and exclude grant projects, as grant projects are systematically smaller than loan projects, reflecting differences in productivity that are not fully controlled for by the control variables. The estimates of ψ^C_s are summarized in Table 9.

E.5 Estimating project productivity distribution ξ_r

I normalize the Pareto scale parameter, $\underline{\theta}_r$, to 1, as this normalization is innocuous for the quantitative results. I estimate the Pareto shape parameter, ξ_r, for each country (r) using the Maximum Likelihood Estimation (MLE) method, exploiting the properties of the mixture of Pareto distributions. In my model, the pool of potential projects is fixed over time, and the government operates all projects with productivity above a certain cutoff in each period. However, in practice, there may be lags between the government's planning and the actual implementation of each project. These delays could be due to various factors, such as lengthy negotiations with DF providers or domestic administrative or legislative lags, which are beyond the scope of this paper.

As a result, in the data, each project appears with some randomness in different years. Moreover, only the information on the initial commitment is fully observable in the project-level data, and each project does not reappear in later years. In other words, projects are sporadically observed in different years regardless of their productivity. To calibrate the distribution of a fixed project pool to the data, I pool all the projects in a way that leverages the unique properties of the mixture of Pareto distributions. It turns out that I can estimate the shape parameter, ξ_r, by simply pooling all the observations.

Suppose there are k distributions with respective probability density functions $f_1(x)$, $f_2(x)$, ..., $f_k(x)$, with supports $\mathbb{S}_1$, $\mathbb{S}_2$, ..., $\mathbb{S}_k$, and positive mixing probabilities p_1, p_2, ..., p_k, where $\sum p_i = 1$. It is well known that a random variable X from the mixture distribution has a pdf $f(x) = \sum_{i=1}^{k} p_i f_i(x)$, with support $x \in \cup_i \mathbb{S}_i$ (Hogg et al., 2013).

Recall that the size of project i financed by provider p observed in year t is determined by the following equation:

$$g^{O}_{r,p,s,j,t} = \frac{1}{\Psi^p_s}\left(\frac{\theta_j \gamma \gamma_s}{\tilde{R}^p_s}\right)^{\sigma} Y_t^{\sigma} (G^E_{s,t})^{1-\sigma}.$$

If θ_j follows a Pareto distribution with shape parameter ξ_r and scale parameter $\underline{\theta}_r$, then the distribution of project sizes financed by p in year t in sector s also follows a Pareto distribution but with shape parameter $\frac{\xi_r}{\sigma}$ and scale parameter $\underline{\theta}_{r,s,p,t} \equiv \frac{1}{\Psi^p_s}\left(\frac{\gamma\gamma_s}{\tilde{R}^p_s}\right)^{\sigma} Y_t^{\sigma}(G^E_{s,t})^{1-\sigma}\underline{\theta}^{\sigma}_{r,s}$. Let $f_{r,s,p,t}(x; \frac{\xi_r}{\sigma}, \underline{\theta}_{r,s,p,t})$ denote the corresponding pdf for all p and t. Also, let $N_{r,s,p,t}$ denote the number of projects observed in year t for provider p in sector s, and define $w_{r,s,p,t} \equiv N_{r,s,p,t}/\sum_{p,t} N_{r,s,p,t}$. Then, the pdf of project size from the pooled sample can be written as:

$$f_r(x) = \sum_{p,t,s} w_{r,s,p,t} \cdot f_{r,s,p,t}(x; \frac{\xi_r}{\sigma}, \underline{\theta}_{r,s,p,t})$$

Note that all $f_{r,s,p,t}$ share the same shape parameter $\frac{\xi_r}{\sigma}$. As a result, the closed-form expression for f_r is:

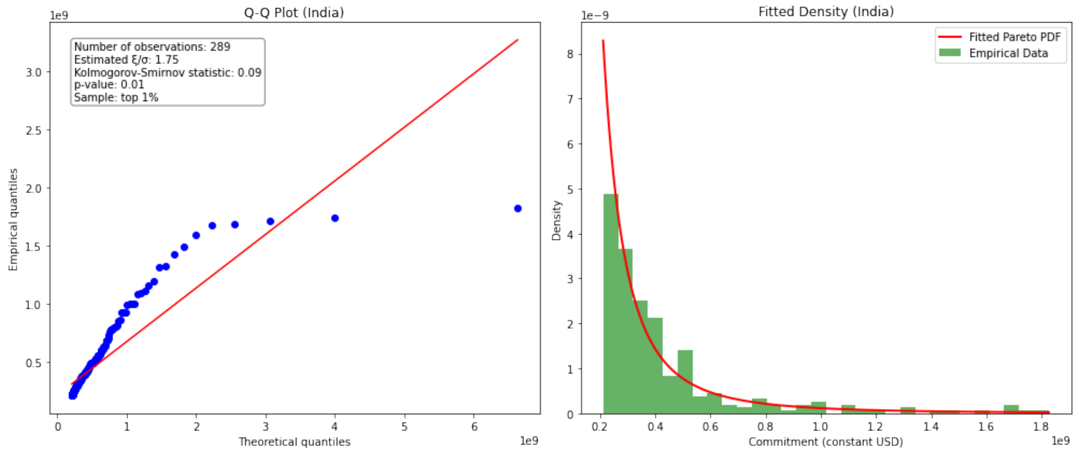
$$f_r(x) = \frac{\frac{\xi_r}{\sigma}\left(\left[\sum_{p,s,t} w_{r,s,p,t} \cdot \underline{\theta}_{r,s,p,t}\right]^{\frac{\sigma}{\xi_r}}\right)^{\frac{\xi_r}{\sigma}}}{x^{\frac{\xi_r}{\sigma}+1}},$$

which is in the same form as a Pareto distribution with shape parameter $\frac{\xi_r}{\sigma}$ and scale parameter $\tilde{\theta}_r \equiv \left[\sum_{p,s,t} w_{r,s,p,t} \cdot \underline{\theta}_{r,s,p,t}\right]^{\frac{\sigma}{\xi_r}}$. Based on this result, I fit the right tail of the pooled sample using the Pareto distribution and estimate $\frac{\xi_r}{\sigma}$. In doing so, I maximize the following log-likelihood function:

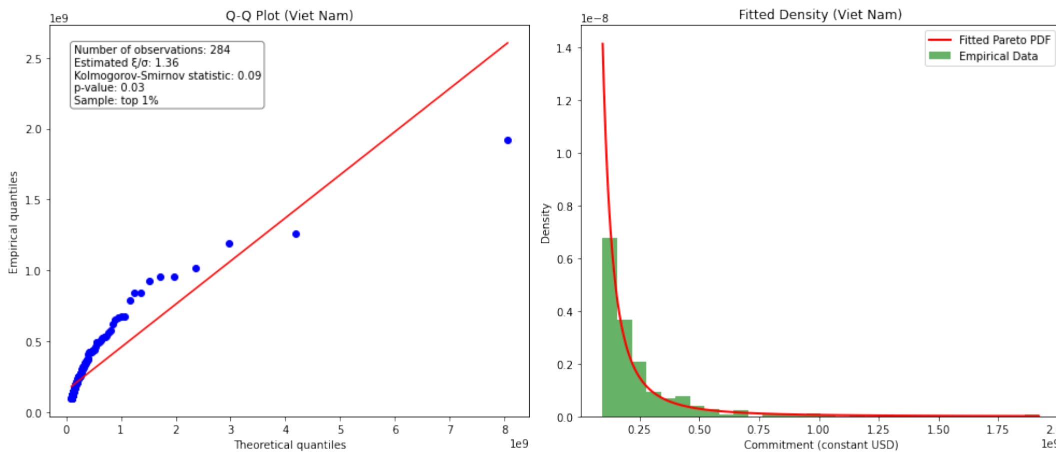
$$log\mathcal{L}(\frac{\xi_r}{\sigma}, \tilde{\theta}_r) = \sum_{i=1}^{N_r} log f_r(x_i; \frac{\xi_r}{\sigma}, \tilde{\theta}_r).$$

I focus on fitting the right tail rather than using all observations, following the literature that utilizes the Pareto distribution. In the firm dynamics and trade literature studying the distribution of firm sizes, the Pareto distribution is widely adopted not only for its analytical convenience but also for its ability to approximate the right tail of the distribution (Arkolakis et al., 2012). Similarly, the assumption of a Pareto distribution provides analytical convenience for aggregation in my model and empirically explains the right tail of the distribution of public project sizes. However, it is well known that the Pareto distribution may not provide a good fit for the entire distribution. More importantly, when estimating the shape parameter using the full sample, the estimated value often fails to meet theoretical requirements (Head et al., 2014).

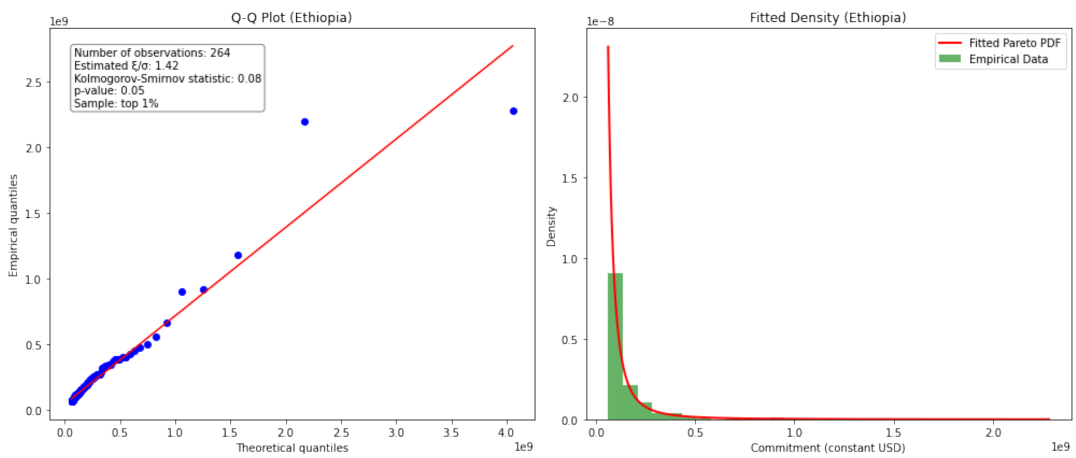
My model faces the same issue, as it requires $\xi_r > \sigma$ and that the estimated value for $\xi_r > \sigma$ be greater than 1. Therefore, I take a similar approach to Head et al. (2014) by fitting the right tail of the distribution. For each recipient, I fit the top 1 percent of samples and estimate the shape parameter. Among 112 countries with enough sample sizes (> 30), all except for 17 have estimates of ξ_r/σ greater than 1. For those with estimates lower than 1 and those with less than 30 projects at the top 1%, I set the value to 1.014, which is the lowest estimate among those greater than 1. Figure E.2 shows the histogram of estimated ξ_r/σ. Figure E.1 shows the QQ plot and fitted density of the projects with summary statistics for three selected countries with the most sample size.



(a) Optimal financing in Kenya



(b) Optimal financing in Vietnam



(c) Optimal financing in Ethiopia

Figure E.1: Optimal financing of each sector

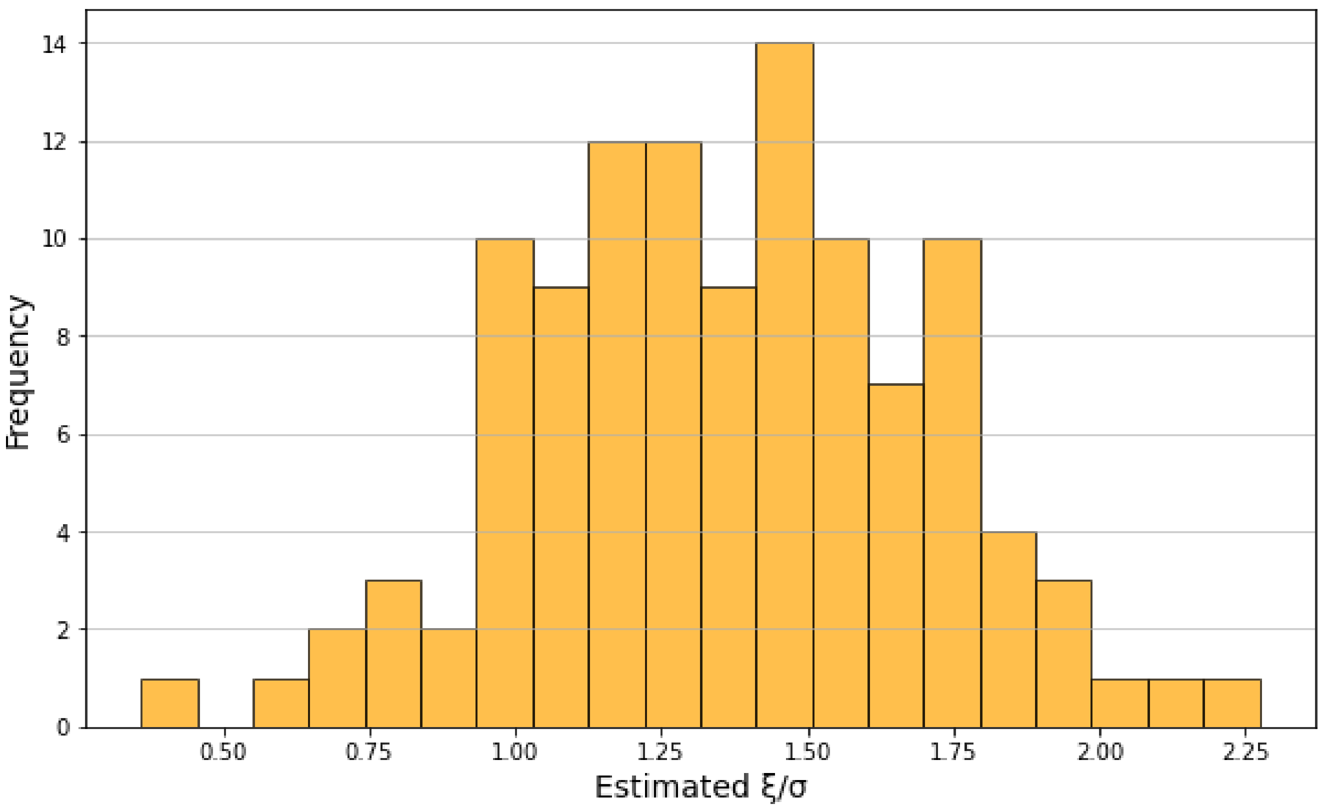


Figure E.2: Welfare effect of Chinese DF by recipient countries

E.6 Estimating DF fixed costs f_S^G, f_s^D, and f_s^C