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. And China emerged as a new significant DF provider with distinct lending practices in the past two decades. I present 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 110 countries (2000-2021), I establish four new stylized facts: (1) more corrupt countries rely more heavily on Chinese DF at the aggregate level; (2) Chinese project sizes are positively correlated with corruption, unlike DAC projects; (3) the count of Chinese projects is positively correlated with corruption, while DAC projects show a negative correlation; and (4) project sizes in hard-to-monitor sectors are more strongly positively correlated with corruption. To explain these findings and conduct welfare analysis, I develop a neoclassical growth model where a potentially corrupt government invests in public projects across multiple sectors, securing DF from the DAC and China. In doing so, the government can divert the DF, depending on heterogeneous monitoring intensity across sectors and DF sources. The model suggests a dual impact of Chinese DF: it can fill funding gaps left by the DAC but also exacerbate inefficiencies due to lax monitoring, with the aggregate impact depending on the government's level of corruption. Finally, a quantitative analysis estimates the impact of the presence of Chinese DF on the representative household's welfare in steady state across 108 developing economies, finding that roughly 15% experience welfare improvements, 17% negligible effects, 12% ambiguous effects, and 55% potentially large welfare reductions due to Chinese DF.

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1 Introduction

Capital is the cornerstone of economic growth, particularly in early stages of development. Since the early 1960s, developed countries represented by the Development Assistance Committee (DAC) have channeled substantial capital into developing countries through government-to-government official development finance (DF) to stimulate public expenditure and economic growth. Although extensive research has explored the socioeconomic impacts of this capital infusion, often with mixed results, several critical questions remain underexplored: How much DF do developing countries choose to use? How is this capital allocated across sectors? Furthermore, the recent emergence of nontraditional DF providers like China poses an additional question: From which providers do countries prefer to secure DF? Understanding these dynamics clarifies global capital allocation patterns, illuminates the effects of DF inflows on economies, and provides policy implications for DF providers seeking to maximize effectiveness.

These questions have been relatively less explored in the literature for both conceptual and practical reasons. Conceptually, traditional DF, primarily driven by DAC countries, has mostly been concessional and often includes substantial grant components. Consequently, DF has been narrowly viewed as foreign aid—a form of lump-sum transfer from developed to developing countries, largely determined by donor countries. However, developing countries are not obligated to use DF; rather, they actively seek different types of DF, including grants and loans. The emergence of nontraditional DF providers like China, offering distinct and often non-concessional terms, underscores the need to understand demand-side decisions by recipient governments. Practically, detailed project-level data encompassing DF projects from both traditional providers and China has only recently become available.

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 neoclassical growth model in which a potentially corrupt government makes public investment decisions across different sectors. This model incorporates DF from both traditional providers (the DAC) and China, each with distinct attributes. Third, using this model, I provide theoretical insights on how corruption can undermine the efficient use of DF, how Chinese DF can be both a boon and bane for households, how DF affects the efficiency of public capital, and how corruption and DF inflows exhibit two-way feedback. Lastly, by calibrating the model for 108 developing countries, I conduct quantitative analyses to explore the welfare implications and identify in which countries households are better or worse off due to the presence of Chinese DF.

To investigate the pattern of global DF flows, I first establish four new stylized facts, using project-level datasets encompassing DF projects from over 110 developing countries, financed by more than 30 official providers between 2000 and 2021. First, at the country level, I find that higher public sector corruption in the recipient country, as measured by the widely used Corruption Perception Index, is associated with a greater total value of Chinese DF inflows and a smaller total value of DAC DF inflows, resulting in a heavier reliance on Chinese DF relative to DAC DF. Specifically, a one-standard-deviation increase in corruption is associated with a 7.9%p increase in China's share of total DF inflows over 2000-2021.

Second, in the project-level analysis, I find that the size of Chinese projects is positively correlated with corruption, whereas DAC projects are not. Third, the count of DAC projects is negatively correlated with corruption, while the count of Chinese projects is positively correlated with corruption.

Fourth, at the cross-sectoral level, I classify sectors as either hard-to-monitor or easy-to-monitor, based on sectoral differences in average ratings from a recently released project-level evaluation dataset covering more than 20,000 projects by 12 aid agencies across 183 recipient countries. I find that project sizes are disproportionately positively correlated with corruption in hard-to-monitor sectors, with the total effect of corruption on project size being significant even for DAC projects. Additionally, the count of projects is more strongly positively correlated with corruption in these sectors, especially for DAC projects.

To understand the stylized facts and conduct quantitative analysis on the welfare implications of government DF decisions, I develop a novel variant of neoclassical growth model that integrates public sector corruption, project-level public investment, and the endogenous use of DF from both the DAC and China. The model features two sectors: a standard private sector, characterized by representative households, accumulation of private capital, and production of a final good, and a public sector managed by a potentially corrupt government. Within the public sector, the government invests in a continuum of differentiated public projects across various subsectors, each with heterogeneous project-specific productivity levels. Public investment forms public capital, which enters the production function of the final good as an additional input alongside private capital and labor.

The government finances each project by securing DF from the DAC and China. In doing so, it has the opportunity to divert a portion of the DF for its own benefit, embedding a corruption dynamic into the investment process. DAC DF offers lower interest rates and higher monitoring intensity than Chinese DF, presenting a crucial tradeoff for the government: while DAC DF is less costly, it provides fewer opportunities for diversion compared to Chinese DF. Additionally, financing each project with either type of DF incurs distinct fixed costs, reflecting the difficulty of securing DF for each project. These DF characteristics also 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 DF. Corruption is modeled through a parameter that quantifies the government's relative valuation of diverted DF versus household consumption. I characterize the government's optimal financing decisions regarding the amount and source of DF at the project, sectoral, and aggregate levels.

The model provides four key insights. First, it identifies three channels through which corruption and the motive for diversion distort efficient DF choices: (1) the government overinvests in each project and undertakes more projects due to the diversion motive; (2) resources are misallocated to sectors with lower monitoring intensity; and (3) Chinese DF, despite its higher interest rates, is preferred over DAC DF due to its lower monitoring. These channels explain the observed stylized facts: the positive correlation between project sizes and corruption, the positive correlation between project counts and corruption, the disproportionately larger correlations in hard-to-monitor sectors, and the positive relationship between corruption and relative reliance on Chinese DF.

Second, 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 benefit borrowing countries by providing alternative financing options, especially when the fixed costs of using DAC DF are prohibitively high for certain sectors. On the other hand, in highly corrupt environments, the availability of Chinese DF may increase inefficiencies through the three channels described above. The aggregate impact depends on the government's level of corruption.

Third, the model suggests that the efficiency of public capital, often modeled as a fixed external parameter in existing literature, may actually emerge from the complex endogenous interplay between public sector corruption and the characteristics of DF. I theoretically derive an expression that mirrors the traditional efficiency parameter form found in literature, but which is functionally dependent on the corruption parameter and DF characteristics. This insight indicates that for developing countries reliant on DF, international DF providers can potentially affect the efficiency of public capital.

Fourth, my model suggests a possibility of two-way feedback where corruption influences DF inflows, and DF inflows, in turn, affect corruption. It suggests two definitions of corruption: (1) as fundamental corruption, represented by the corruption parameter χ, which reflects the government's preference for diversion over household consumption, and (2) as the amount of actual diversion, aligning with empirical indices typically based on surveys about resource diversion in the public sector. Thus, the correlation between corruption and Chinese DF inflows may reflect both forces: higher fundamental corruption attracts more Chinese DF due to lower monitoring, which then increases diversion and, consequently, measured corruption.

In the quantitative analyses, I calibrate the model for each of 108 developing countries, estimating parameters using both micro and macro data. With the calibrated model, I conduct counterfactual analysis to identify countries where households are better or worse off in steady state due to the presence of Chinese DF compared to a scenario without it. For each country, I provide a range of potential welfare changes, with the actual welfare impact depending on the level of corruption, which I can only bound using available data.

Among the 108 economies, roughly 15% experience unambiguous welfare improvements, 17% experience negligible effects, 12% experience ambiguous effects depending on the actual level of corruption, and 55% experience potentially large welfare reductions due to the presence of Chinese DF. To understand the root of this cross-country heterogeneity, I conduct case studies, finding that welfare outcomes depend on which sectors are financed by Chinese DF. If Chinese DF is used in sectors with monitoring intensity comparable to DAC DF and with sufficiently lower fixed costs, it yields positive effects by filling the funding gap left by DAC DF. However, if Chinese DF is allocated to sectors with significantly lower monitoring than the DAC and without much lower fixed costs, it is likely to only have adverse impacts. My data and model are sufficiently rich to identify these sector-specific impacts and draw aggregate-level welfare implications for households.

Related literature. First, this research intersects with the literature on global capital allocation, particularly within two emerging and fast-growing subfields. The first concerns the rising interest in official capital flows. Horn et al. (2020) and Avdjiev et al. (2022) note that while literature traditionally emphasizes cross-border flows of private capital, it often overlooks official capital flows despite their comparable scale. The second subfield explores China's increasing influence on 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). In particular, Dreher et al. (2021) introduces a novel dataset on Chinese overseas DF activities, which has catalyzed research into the allocations of Chinese DF projects and their impacts on various socioeconomic outcomes (Isaksson and Kotsadam, 2018; Knutsen and Kotsadam, 2020; Mueller, 2022).

I make significant contributions to these areas. First, I establish new stylized facts regarding a key category of official capital flows—development finance—and provide theoretical explanations. Second, I am the first to propose a macro-development model that incorporates the role of Chinese DF, exploring its interactions with corruption, DAC DF, and public investment and conduct quantitative welfare analysis.

Second, this study engages with the literature on the impact of public sector corruption on economic growth. Early empirical works (Acemoglu et al., 2001; Keefer and Knack, 2007; Mauro, 1996, 1995, 1998; Tanzi and Davoodi, 1998) demonstrate that corruption and poor institutional quality hinder economic growth by distorting efficient public investment. On the theoretical side, Acharya et al. (2020); De la Croix and Delavallade (2009); Robinson and Torvik (2005); Svensson (2000) provide microfoundations for the relationship between rent-seeking and public investment. Within macroeconomic growth frameworks, Aguiar and Amador (2011); Chakraborty and Dabla-Norris (2011) examine how political frictions can shape growth outcomes.

My contributions to this field are twofold. First, using project-level data, I provide evidence that public sector corruption and diversion motives significantly influence public investment decisions at the project level. Second, I theoretically outline multiple mechanisms through which corruption and DF interact to affect economic growth, and I perform quantitative welfare analysis on the impact of corruption.

Third, I contribute to the literature on the impact of public expenditure on economic growth. Early empirical research (Aschauer, 1989) demonstrates that public capital significantly contributes to output growth, a finding reinforced 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 studies 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 weak institutions, with subsequent research (Dabla-Norris et al., 2012; Gupta et al., 2014; Herrera and Ouedraogo, 2018) attempting to quantify such inefficiencies.

My contributions to this literature are primarily theoretical. First, my model diverges from prior models that assume tax financing for public investments by examining an environment where the government relies on international DF—an increasingly realistic scenario. Second, rather than treating public capital as a monolithic input, I model it as comprising numerous differentiated projects across multiple sectors. Third, while previous models assume an exogenous fraction of public investment is lost due to inefficiencies, I offer a framework linking corruption and endogenous DF choices, thus determining aggregate efficiency loss.

Lastly, I contribute to the literature on DF allocation and impact. Early studies 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 employ instruments to identify exogenous changes in DF flows (Galiani et al., 2017; Temple and Van de Sijpe, 2017), though these empirical efforts are typically conducted at the aggregate level. Theoretically, most research models foreign aid as an exogenous lump-sum transfer from abroad (Adam and Bevan, 2006; Chatterjee and Turnovsky, 2007), with one 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 global DF allocation patterns, providing evidence that the diversion motives of recipient governments significantly influence DF allocation, in interaction with heterogeneous monitoring across DF sources and sectors. Theoretically, this study is the first to propose a growth model that integrates the endogenous use of DF—not as exogenous transfers—examining its interactions with corruption.

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 calibrates the model parameters for 108 economies. Section 7 conducts counterfactual analyses. Finally, Section 8 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 feature interest rates 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.

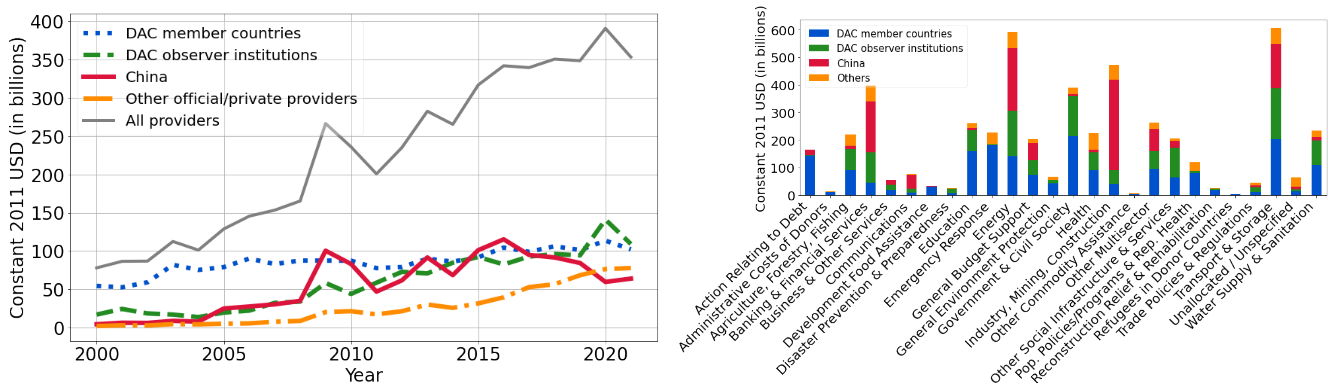
Chinese development finance. In the last two decades, China has emerged as a significant provider of DF, adhering to the traditional objective of promoting economic growth and development in developing countries. However, China's DF model exhibits unique features that distinguish it from the DAC approach. 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. Second, 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). Third, 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, it can be harder to secure the concessional DAC DF, particularly in specific sectors and for high-risk countries (Brautigam, 2011; Dreher et al., 2022). 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 corrupt governments. 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 become comparable to 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 great 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.

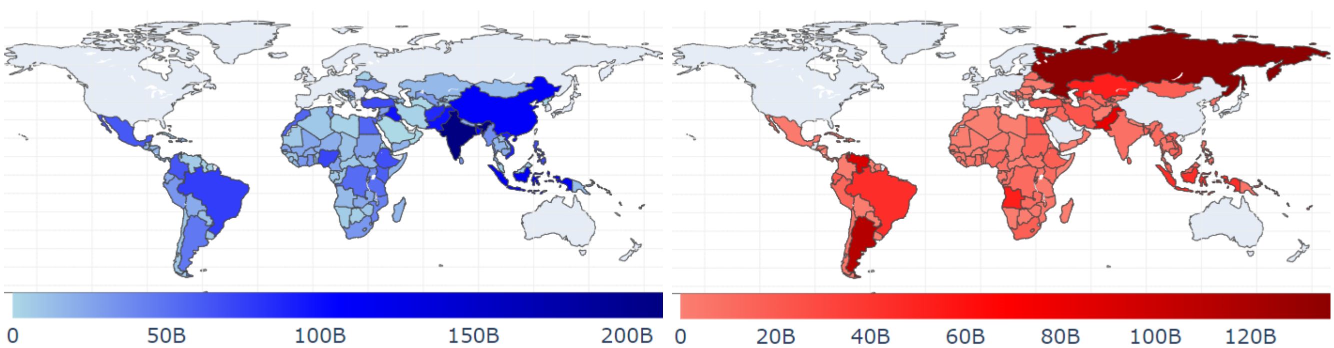
[1] Historically, DAC countries have been referred to as "donors" since most DF was concessional. However, the term "donor" is too narrow to encompass different types of DF providers, especially considering the non-concessional nature of Chinese DF. Hereinafter, I use "DF provider" and "donor" interchangeably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



(a) 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.



(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

Throughout the paper, I rely on detailed project-level DF data. The use of this granular data enables a cleaner analysis by facilitating the inclusion of rich fixed effects and control variables at more aggregate levels.

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 the 109 countries used in the empirical analysis, the mean is 34.1 and standard deviation is 10.9. 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

Motivation. Recent findings show that public sector corruption significantly affects the global allocation of development finance (DF). Andersen et al. (2022) report increased capital flows to tax havens from developing countries following World Bank DF disbursements. Some governments with high levels of corruption prefer Chinese DF because of its lenient oversight, which increases the risk of fund diversion (Bunte, 2019).

Isaksson and Kotsadam (2018) note increased regional corruption associated with Chinese DF projects in Africa, and Malik et al. (2021) find that a significant portion of Chinese DF goes to countries with higher-than-average levels of corruption. Although there is both anecdotal and aggregate evidence, the relationship between a recipient country's public sector corruption and global DF allocation at the sectoral and project levels, particularly when considering comprehensive samples of recipients and providers, still remains an uncharted area. By analyzing project-level data from 2000 to 2021 across over 110 recipient countries and more than 30 official DF providers, I investigate how a recipient country's corruption influences DF usage.

Outline and key results. I establish four stylized facts, providing suggestive evidence that public sector corruption is crucial in shaping global DF allocation, with the monitoring of DF playing a central role, and that Chinese DF is monitored less strictly than DAC DF. First, at the aggregate level, more corrupt countries are more dependent on Chinese DF than on DAC DF. Second, at the project level, more corrupt countries tend to exhibit larger Chinese project sizes, a pattern not observed with DAC projects. Third, the number of DAC projects is negatively correlated with corruption, whereas the number of Chinese projects shows a marginally positive correlation. Finally, in a cross-sectoral analysis using project evaluation data to rank sectors by monitoring difficulty, I discover that the positive correlation between corruption and project size is disproportionately stronger in sectors that are more challenging to monitor. I then connect these findings to the corrupt governments' motives for diverting less strictly monitored DF, discussing their validity against alternative explanations. Lastly, I summarize the robustness tests conducted. Throughout this section, "corruption" refers to public sector corruption in the recipient country as measured by the Corruption Perception Index. It reflects the overall institutional quality of a country. To address any potential omitted variable bias, I include a host of control variables throughout the main analysis. Note that, although I often refer to the correlation between corruption and the dependent variable as the "corruption effect" in this section for ease of exposition, I am reporting correlation results and do not claim causality. The empirical findings in this section do not rule out the possibility of two-way feedback, where corruption affects DF inflows, and DF inflows, in turn, affect corruption. In the model section, I show that my model is able to provide insights into the potential for both directions (Section 5).

3.1 Which Countries Rely on DAC vs. Chinese DF? (Aggregate-Level Analysis)

FACT 1: *More corrupt countries rely more on Chinese DF relative to the DAC DF.*

As a first step, I examine which countries have relied on DAC and Chinese DF at the aggregate level over the past two decades (2000-2021). I find strong evidence that more corrupt countries are more dependent on Chinese DF compared to DAC DF. I establish this by first analyzing the correlation between China's share in total DF and the level of public sector corruption at the cross-country level. Then, I confirm these findings by analyzing the correlations between corruption and the total values of both DAC DF and Chinese DF separately, using bilateral panel data with Ordinary Least Squares (OLS) and Poisson Pseudo Maximum Likelihood (PPML) methods. In this section (Section 3.1), I present results regarding DF flows at the country level. In robustness checks (Appendix B.3), I repeat the analysis at the sectoral level, with the dependent variables aggregated at the sectoral level, and confirm that the main results hold consistently across different sectors, indicating they are not driven by specific sectors.

3.1.1 Corruption and China's Share of the Total Value of DF

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

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

$SHARE_r^{CHN}$ denotes the proportion (%) of Chinese Development Finance (DF) utilized by recipient country r from 2000 to 2021, relative to the total value of DF from all donors over the same period. The corruption measure, $CORRUPT_r$, is obtained by subtracting the average Corruption Perception Index (CPI) over the same period from 100, with 0 indicating minimal and 100 maximal corruption. $\mathbf{X}_r$ represents a vector of control variables that include characteristics of the recipient country as well as specific political, social, and economic factors between the recipient and China.[2] β captures the correlation between corruption and a country's reliance on Chinese DF relative to DAC DF.

The regression clearly demonstrates a significant positive relationship between corruption and the proportion of Chinese DF at the country level. Figure 3 presents a partial regression plot of China's share versus corruption, using data from the regression. Each circle represents a recipient country, with the size of the circles indicating 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, suggesting that, after controlling for other variables, countries with one standard deviation (10.9) higher in the corruption index relied 7.9%p more on Chinese DF at the country level over the last two decades. In Appendix B.3, I confirm the result with panel regressions.

[2] **Recipient characteristics:** log initial GDP per capita in 2000, average GDP per capita growth, average log population, average external debt stock to GDP, average Public and Publicly Guaranteed (PPG) debt stock to GDP, average net FDI inflows to GDP, average inflation, and dummies for regions, oil producer, English as official language, GATT, and WTO. **Recipient×donor bilateral characteristics:** average ideal point distance, average log total value of bilateral trade, distance, and dummies for being contiguous, common legal origins, common language, common colony, common religion, sibling, colonial relation, and FTA.

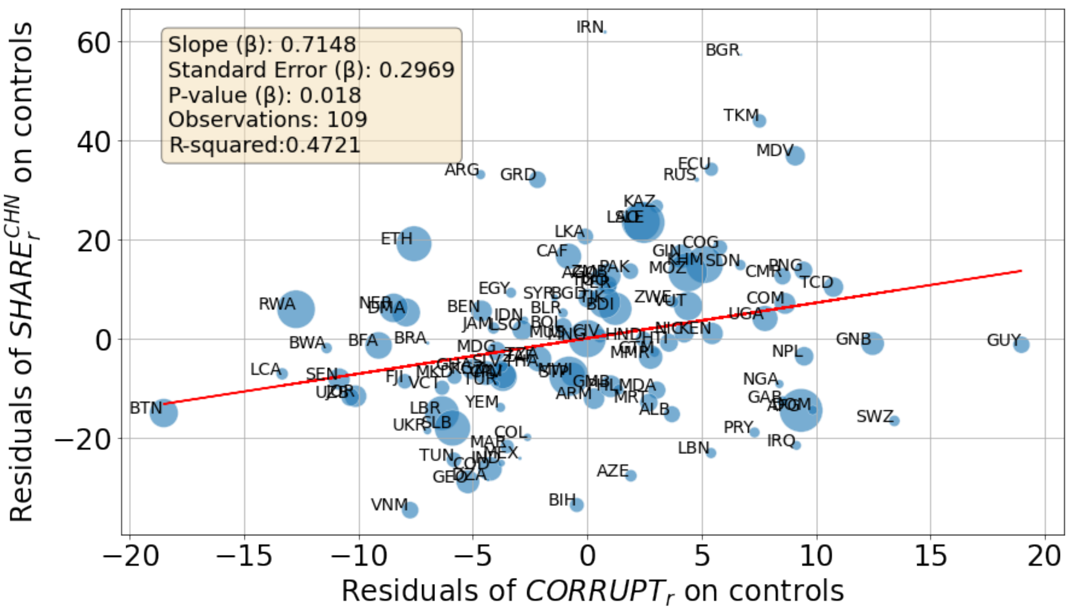


Figure 3: China's Share in Total DF Amount and Recipient Corruption

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.

3.1.2 Corruption and the Inflows of the DAC and Chinese DF

As additional diagnostics, I examine the differential correlations between recipient corruption and inflows of DAC and Chinese DF, using bilateral panel analysis on DF flows. I find that the value of DAC DF inflows is negatively correlated with corruption, whereas that of Chinese DF is positively correlated. These relationships hold at both the country and sectoral levels.

Unlike data focused on single countries, panel data on bilateral DF flows with many recipients and donors often contain many zeros, reflecting years in which specific bilateral flows do not occur. This poses a challenge when taking the log of dependent variables, as zeros must be dropped. To address this, I use OLS with a log transformation of 1 plus the value of DF, and the Poisson Pseudo Maximum Likelihood (PPML) method. This approach follows practices common in international trade literature that encounters similar issues with bilateral trade data. I first explain all the specifications and then discuss the results.

OLS. I first use OLS to investigate the correlation between corruption and bilateral DF inflows at the country level, conducting separate regressions for DAC DF and Chinese DF. For each recipient country r receiving DF from donor d in year t, I estimate:

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

Here, DF_{rdt} represents the total committed amounts in constant 2011 USD by donor d, for recipient r

in year t. Like the regression with China's share, the corruption measure, $CORRUPT_r$, is averaged over the sample period.[3] I use the log of $CORRUPT_r$ as the main independent variable, which allows the coefficients to be interpreted as elasticities, facilitating a straightforward comparison between coefficients estimated using OLS and PPML. The log transformation does not qualitatively affect the main findings. The vector $\mathbf{X}_{rdt}$ includes the same recipient- and bilateral-level control variables as in previous regressions. FE_{dt} represents donor×year fixed effects. ϵ_{rdt} is the error term. I run the regression separately for the DAC and Chinese projects. Note that in the regression with Chinese projects, the donor dimension becomes redundant as China is the only donor in the sample. The coefficients β from each regression reflect the elasticity of DAC and Chinese DF inflows with respect to changes in corruption, as measured by the Corruption Perception Index, and I refer to this as the "corruption effect."

PPML. As an alternative specification to address the many zero values in bilateral DF flows, I estimate the corruption effect using the Poisson Pseudo Maximum Likelihood (PPML) method following Silva and Tenreyro (2006). I estimate:

$$\mathbb{E}\left[DF_{rdt}\middle|\mathbf{X}\right] = exp\Big(FE_{dt} + \beta \cdot \ln CORRUPT_r + \mathbf{X}_{rdt} \cdot \gamma + constant\Big) \tag{2}$$

where $\mathbf{X}$ represents the vector of all predictor variables on the right-hand side of each equation. The exponents on the right-hand side correspond to the right-hand sides of the OLS regressions in equations (1). One advantage of PPML is that the estimated corruption effect β can be interpreted in the same way as the estimates from their OLS counterparts.

Results. Panel (a) of Table 1 shows that the value of DAC DF inflows and that of Chinese DF inflows are negatively and positively correlated with the recipient's corruption, respectively. Columns (1) through (4) suggest that a 1% increase in the corruption measure is associated with a reduction in the DAC DF inflows by 0.86-1.52%, depending on the specifications. Note that the reduction in sample size when including recipient-donor controls is due to the unavailability of these variables for multinational donors like the World Bank and the IMF. Conversely, columns (5) through (8) indicate that Chinese DF inflows are positively correlated with corruption. Although the OLS estimates are not statistically significant, the PPML estimates are statistically significant, with all point estimates being positive, contrasting the effects seen with DAC DF. The PPML estimates indicate that a 1% increase in corruption is associated with a 2.35-3.2% increase in Chinese DF inflows.

[3] Variance decomposition shows that within-country variation accounts for only 2% of the variance in the Corruption Perception Index (CPI), justifying the use of the average CPI. It can also alleviate potential measurement error.

Table 1: Aggregate Effect of Corruption on Total DF Inflows

	DAC DF				Chinese DF			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln $CORRUPT_r$	-1.442**	-1.524*	-0.860*	-0.871	4.187	4.161	2.345**	3.195***
	(0.634)	(0.781)	(0.442)	(0.568)	(3.855)	(3.947)	(1.137)	(1.059)
Observations	88768	53704	74916	47878	2134	1964	2134	1964
R^2	0.572	0.633	0.6243	0.6887	0.338	0.460	0.4613	0.5299
Specification	OLS	OLS	PPML	PPML	OLS	OLS	PPML	PPML
Donor×Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Recipient controls	✓	✓	✓	✓	✓	✓	✓	✓
Recipient×Donor controls		✓		✓		✓		✓

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), (2), (5) and (6), and total DF amount for columns (3), (4), (7) and (8). DAC institutions are excluded in the sample for columns (2) and (4) due to the lack of recipient×donor controls. For PPML estimations, the pseudo R^2 is reported.

3.2 Effect of Corruption on the Size and Count of Projects (Project-Level Analysis)

It is widely recognized in the literature that elevated levels of corruption within the public sector lead to increased public expenditures at both the micro and macro levels (Mauro, 1996, 1995; Tanzi and Davoodi, 1998). This increase is often attributed to cost exaggeration and inefficient resource allocation, driven by the diversion motives of public sector agents. Similarly, more corrupt governments might have an incentive to inflate the costs of DF projects, resulting in larger project sizes.

Exploiting the granularity of the DF data, I conduct a project-level analysis to test this hypothesis. This analysis also clarifies whether the aggregate-level correlation between corruption and DF inflows is primarily influenced by the average project size or the number of projects. I first investigate how the project sizes of the DAC and Chinese DF correlate with corruption, followed by an analysis of how the counts of these projects correlate. I find that Chinese project sizes are positively correlated with corruption, whereas DAC project sizes show no correlation. Meanwhile, the count of DAC projects is negatively correlated, and that of Chinese projects is positively correlated with corruption.

3.2.1 Corruption Effect on Project Sizes

FACT 2: *The size of Chinese DF projects is positively correlated with the recipient country's corruption. Such effect is not observed for the DAC DF projects.*

I find that the sizes of Chinese DF projects are significantly larger in countries with higher levels of corruption, a pattern not observed with DAC projects. I begin by comparing the effect of corruption on the sizes of Chinese DF projects to that on DAC DF projects on average in a pooled regression. This is followed by an estimation of the corruption effect on project sizes for each DAC member country and institution.

Chinese DF vs. DAC DF on average. I first test how corruption affects the project sizes of Chinese DF and DAC projects on average by running project-level regressions:

$$\ln SIZE_i = FE_{d(i)s(i)t(i)} + \beta \cdot \ln CORRUPT_{r(i)} + \mathbf{X}_{r(i)d(i)t(i)} \cdot \gamma + constant + \epsilon_i \tag{3}$$

SIZE_i represents the value of 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 recipient-specific and recipient-donor-specific control variables as used in the country-level analysis, supplemented by a dummy variable indicating whether the project is financed by a loan or a grant. This dummy helps control for the tendency that grant projects are generally smaller than loan projects. ϵ_i represents the error term. I run the regression separately for the DAC projects and Chinese projects, and the estimated β captures the corruption effect on the DAC project sizes and Chinese project sizes respectively.

Table 2 demonstrates that the sizes of Chinese DF projects are statistically significantly positively correlated with recipient corruption. Columns (3) and (4) indicate that a 1% increase in the corruption index is associated with an increase in Chinese project sizes by 0.96-1.46%. In contrast, columns (1) and (2) reveal that the estimates of the corruption effect on DAC project sizes are neither significant in magnitude nor in statistical significance.

Table 2: Corruption Effect on DF Project Sizes

	DAC projects		Chinese projects	
	(1)	(2)	(3)	(4)
$\ln CORRUPT_{r(i)}$	0.211	0.098	0.960**	1.460***
	(0.167)	(0.144)	(0.395)	(0.490)
Observations	1160794	1025229	7559	7559
R^2	0.351	0.263	0.657	0.662
Donor×Sector×Year FE	✓	✓	✓	✓
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×donor controls. Standard errors are clustered at the recipient level.

Chinese DF vs. Each DAC Donor. To further explore the differential impact of recipient countries' corruption on projects by various donors, I conduct a regression for each donor similar to equation (4), instead of pooling projects from all DAC donors as in equation (3). For country donors, all control variables are included, whereas recipient-donor-specific controls are omitted for institutional donors due to lack of data.

Figure 4 confirms that the corruption effect on the sizes of Chinese DF projects is significantly larger than those on projects financed by other donors. 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 relative size of the circles reflecting the total amount provided by the donor during the same period. 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 public sector corruption in recipient countries. The estimated corruption effect on Chinese projects is in even more stark contrast with those of the most significant DAC contributors, including the US, EU, Japan, Germany, France, and the World Bank. The figure also reveals that China is one of the most significant DF providers in terms of both the total amount and the number of recipient countries.

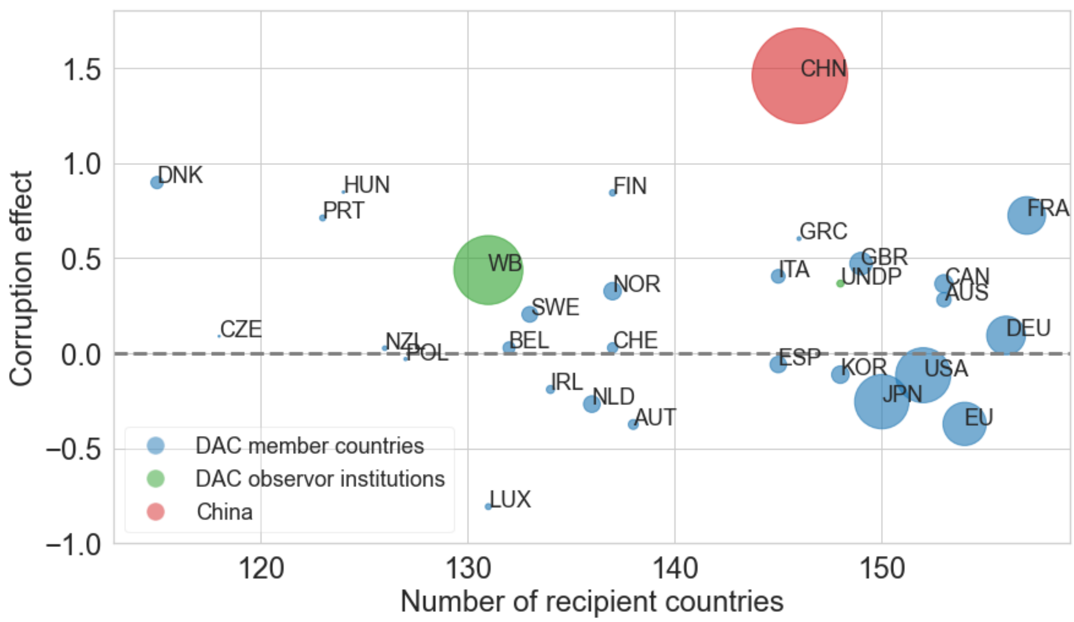


Figure 4: Corruption Effect on the Relative Importance of Each Donor

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

3.2.2 Corruption Effect on the Count of Projects

FACT 3: *The count of DAC DF projects is significantly negatively correlated with the recipient country's corruption, whereas the count of Chinese DF projects is marginally positively correlated with corruption.*

To investigate the corruption effect on the count of DF projects, I replace the log of total DF value with the total count of DF projects by each donor in each year as the dependent variable in the country-level OLS regressions (Equations (1) in Section 3.1.2). Table 3 shows that higher corruption is significantly negatively correlated with the count of DAC projects, while it is marginally positively correlated with Chinese projects. Columns (1) and (2) reveal that a 1% increase in the corruption index is associated with approximately 9.4 fewer DAC projects. Conversely, columns (3) and (4) suggest that a 1% increase in corruption leads to roughly 1.5 to 3.1 additional Chinese projects, although these results lack statistical significance. Given that many Chinese projects are not reported in international statistics, and considering that more corrupt countries are less likely to transparently disclose their projects, the estimates are likely biased downward.

Table 3: Corruption Effect on DF Project Counts

	DAC projects		Chinese projects	
	(1)	(2)	(3)	(4)
ln $CORRUPT_{r(i)}$	-9.722***	-9.345**	3.109	1.549
	(2.515)	(4.252)	(2.132)	(1.767)
Observations	88768	53704	2336	2149
R^2	0.385	0.462	0.323	0.387
Donor×Year FE	✓	✓	✓	✓
Loan dummy & recipient controls	✓	✓	✓	✓
Recipient×Donor controls		✓		✓

Note: The dependent variables are the count of projects. Projects from DAC institutions are excluded in column (2) due to the lack of recipient×donor controls. Standard errors are clustered at the recipient level.

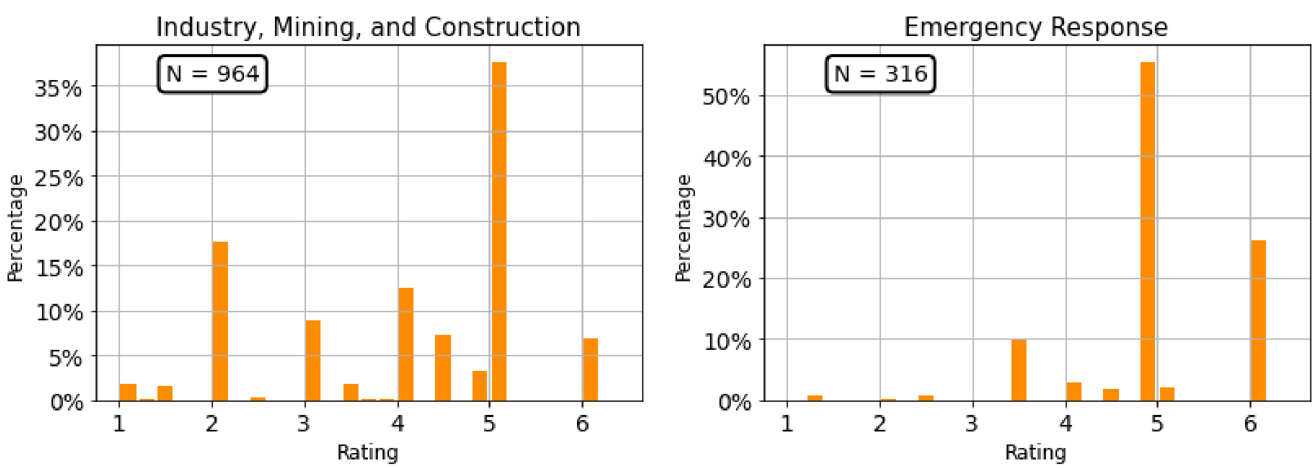
3.3 Corruption Effect in Hard-to-Monitor Sectors (Cross-Sectoral Analysis)

FACT 4: *Project sizes are disproportionately more positively correlated with corruption in sectors that are difficult to monitor. Higher corruption is also associated with an increased count of projects in those sectors.*

To further investigate the mechanism behind the corruption effect on project sizes, I exploit the varying levels of monitoring difficulty across different sectors. If the motive of public sector agents to divert DF plays a significant role, a stronger correlation between corruption and project size would be anticipated in sectors that are more difficult for DF providers to monitor. I first classify sectors into easier-to-monitor and harder-to-monitor categories using DF project evaluation data. Subsequently, I estimate the corruption effect on project sizes and the count of projects within these two groups. I find that the corruption effect on project sizes is disproportionately larger in sectors that are more difficult to monitor, with the net effect being statistically significant even for DAC projects. I also find that higher corruption is associated with more projects in hard-to-monitor sectors than in other sectors. Finally, I analyze the corruption effects on project sizes and their interaction with monitoring across different corruption quartiles. I discover that the level effect of corruption is linear across quartiles for Chinese projects, while the interaction effect through monitoring displays a nonlinear pattern for Chinese projects but a linear pattern for DAC DF.

3.3.1 Classifying Sectors by Monitoring Difficulty

I rank sectors based on the difficulty of monitoring using the AidData Project Performance Data (PPD), which evaluates more than 20,000 DF projects from 12 DF agencies from 1956 to 2016 across 183 recipient countries. The evaluations are rated on a 6-point scale, with 1 indicating highly unsatisfactory performance and 6 indicating highly satisfactory performance. Although these ratings assess holistic project performance and the detailed criteria vary by agency and evaluator, key criteria often include the efficiency of project implementation and the quality of supervision or monitoring. I note that average ratings vary significantly by sector. For instance, Figure 5 shows that in the Emergency Response sector, 80 percent of projects are rated almost 5 and above, whereas in the Industry, Mining, and Construction sector, the ratings are more evenly distributed. I interpret these differences as indicative of the relative difficulty in monitoring each sector and rank the sectors accordingly based on their average ratings.



(a) Industry, Mining, and Construction

(b) Emergency Response

Figure 5: Average Ratings by Sectors

Source: AidData Project Performance Dataset (PPD) 2. The ratings are on six-point scale, 1 indicating highly unsatisfactory performance and 6 indicating highly satisfactory performance.

In doing so, I calculate the average ratings after controlling for potential confounding factors by running the following regression:

$$RATINGS_i = FE_{r(i)d(i)t(i)} + \gamma_{s(i)} + \mathbf{X}_{r(i)d(i)s(i)t(i)} \cdot \beta + constant + \epsilon_i.$$

$RATINGS_i$ represents the six-point scale rating of DF project i. $FE_{r(i)d(i)t(i)}$ denotes recipient×donor×year fixed effects, which capture both time-varying and invariant characteristics of recipient countries and donors, such as institutional quality, geography, economic or political relationships, and year-specific effects. $\mathbf{X}_{r(i)d(i)s(i)t(i)}$ includes the log of the total project amount for the recipient country in each sector, reflecting recipient-sector-specific effects related to sector size. This vector also includes dummy variables for evaluator type to control for potential biases by evaluating agencies, as well as the log of project size. The sector fixed effect, $\gamma_{s(i)}$, captures the average ratings of projects for each sector, adjusted for other effects specific to the recipient, donor, year, evaluator, project size, and sector size.

Table B.1 presents the estimation results for the control variables along with the F-test results. These tests evaluate the null hypothesis that the sector fixed effects are jointly zero. The results allow me to reject this null hypothesis, with standard error clustering at various levels demonstrating that average project ratings differ significantly across sectors. See Appendix B.2 for the OLS estimates of sector fixed effects and further discussion.

3.3.2 Estimating Corruption Effect in Hard-to-Monitor Sectors

Using the average ratings by sectors, I examine whether the effect of corruption on project size and count of projects varies across sectors based on monitoring difficulty. For ease of exposition, I refer to these sectoral average ratings as "monitoring difficulty" henceforth. To facilitate clearer interpretation, I employ a binary version of monitoring difficulty, classifying sectors into "low" and "high" monitoring categories based on the 1st quartile of the estimated average ratings. Five sectors—Industry, Mining, and Construction; Disaster Prevention and Preparation; Water Supply and Sanitation; Agriculture, Forestry, and Fishing; and Government and Civil Society—fall into the low monitoring category. In the robustness checks (Section 3.5), I verify the qualitative results using alternative versions of sectoral monitoring difficulty. I exclude the Emergency Response and Reconstruction, and Relief & Rehabilitation sectors due to the distinct nature of their projects, which are often initiated by donor countries in response to disasters. Additionally, I exclude the Action Relating to Debt sector, as it is not relevant to new development projects. I first outline the specification for the project size regressions and project count regressions, and then discuss the results together.

Project sizes. I conduct the following regression, first for DAC projects and then for Chinese projects:

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

$LowMonitor_{s(i)}$ is a dummy variable that takes the value of 1 if project i belongs to one of the harder-to-monitor sectors and 0 otherwise. Its level effect is absorbed by the donor×sector×year fixed effects, $FE_{d(i)s(i)t(i)}$, and it is included in the model as an interaction term with the corruption index. The coefficient δ captures the "interaction effect" between corruption and the presence in harder-to-monitor sectors.

Hereinafter, I will refer to β as the "level effect" of corruption to distinguish it from the interaction effect. Note that when analyzing only Chinese projects, the donor dimension becomes redundant.

Project counts. I run the following regression to estimate the level and interaction effects of corruption on the count of projects:

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

where N_{rdst} is the number of projects for recipient r by donor d in sector s in year t. The right-hand-side variables are identical to those in the project size regression, except that the control variables $\mathbf{X}_{rdt}$ do not include the loan vs. grant dummy.

Results. Panel (a) of Table 4 demonstrates that the effect of corruption on project sizes is disproportionately larger in sectors that are harder to monitor. The estimated level effect of corruption is consistent with the previous regression that does not include an interaction term. Meanwhile, the coefficient of the interaction term is significantly positive for both DAC and Chinese DF across all specifications, supporting the hypothesis that in sectors with high monitoring difficulty, higher corruption leads to a greater increase in 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 surpasses 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. In columns (3) and (6), I additionally include recipient fixed effects as a robustness check, and the results concerning the interaction effect remain qualitatively unchanged.

Panel (b) reveals that in hard-to-monitor sectors, higher corruption is associated with an increased count of projects, particularly for DAC projects. Specifically, a 1% increase in corruption leads to an increase of 0.62 DAC projects in hard-to-monitor sectors compared to other sectors. While the estimated interaction effects for Chinese project counts are positive, they are not statistically significant. The estimates of the level effects are consistent with those from the regressions without the interaction term.

3.3.3 Corruption Effect by Corruption Quartiles

As an additional exercise, I estimate the level effect and the interaction effect of corruption on project sizes across different corruption quartiles. This approach offers two significant advantages. First, it reveals whether these effects are consistently present across various corruption quartiles or if the estimates are predominantly driven by countries within specific quartiles. Second, it provides an alternative quantitative interpretation, allowing me to quantify how much larger project sizes are in countries within different

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

Panel (a) Project sizes						
	DAC projects			Chinese projects		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln CORRUPT_{r(i)}$	0.087	-0.020		0.879**	1.376***	
	(0.143)	(0.131)		(0.375)	(0.459)	
$\ln CORRUPT_{r(i)} \times LowMonitor_{s(i)}$	0.347**	0.328**	0.225**	0.466	0.449	0.592
	(0.146)	(0.163)	(0.101)	(0.706)	(0.708)	(0.649)
Observations	1133308	1002107	1133308	7439	7439	7439
R^2	0.352	0.263	0.358	0.658	0.662	0.675
Donor×Sector×Year FE	✓	✓	✓	✓	✓	✓
Loan dummy & recipient controls	✓	✓	✓	✓	✓	✓
Recipient×Donor controls		✓	✓		✓	✓
Recipient FE			✓			✓

Panel (b) Project counts						
	DAC projects			Chinese projects		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln CORRUPT_r$	-0.649***	-0.599***		0.124	0.048	
	(0.142)	(0.205)		(0.105)	(0.090)	
$\ln CORRUPT_r \times LowMonitor_s$	0.477***	0.619***	0.619***	0.111	0.111	0.111
	(0.140)	(0.194)	(0.194)	(0.074)	(0.081)	(0.081)
Observations	1495040	1074080	1074080	46720	42980	42980
R^2	0.261	0.288	0.294	0.300	0.314	0.327
Donor×Sector×Year FE	✓	✓	✓	✓	✓	✓
Recipient controls	✓	✓	✓	✓	✓	✓
Recipient×Donor controls		✓	✓		✓	✓
Recipient FE			✓			✓

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

corruption quartiles. This contrasts with the elasticity interpretation used previously, which focuses on how sensitively project size responds to changes in corruption.

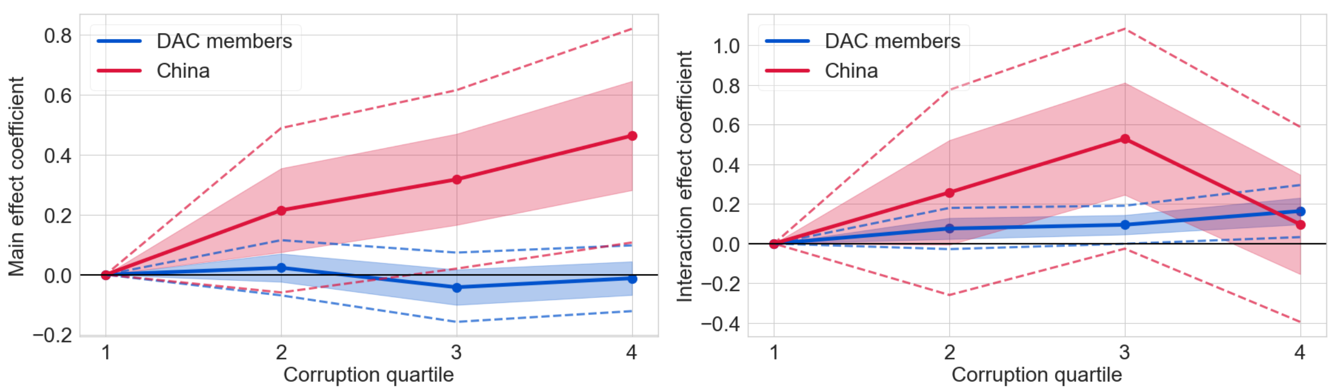
I use OLS to estimate:

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

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 in previous specifications. The coefficient β_q measures the percentage increase in project sizes for countries in the qth quartile of corruption compared to those in the least corrupt quartile (level effect). The coefficient δ_q captures the additional effect of corruption on project sizes in sectors characterized by low monitoring intensity (interaction effect). I estimate the level and interaction effects for DAC projects and Chinese projects by running the regression separately.

Figure 6 illustrates that the positive level effect of corruption on project size linearly strengthens across corruption quartiles for Chinese projects, while DAC projects exhibit no significant level effects in any quartile. The figure displays the point estimates along with 68% and 90% confidence intervals for both the level effects (β_q) and interaction effects (δ_q). Panel (a) reveals that in countries within the most corrupt quartile, project sizes are, on average, greater by 0.46%, and by 0.32% for countries in the third quartile—both statistically significant. Although the effect for the second quartile is not statistically significant at the 10% level, the estimates indicate a linear increase in the level effect of corruption on Chinese projects across all quartiles. Conversely, the level effect of corruption for DAC projects is not significantly different from zero across all quartiles, consistent with the qualitative findings from previous regressions.

Panel (b) shows that the interaction effect of monitoring difficulty and corruption on project sizes is linear across corruption quartiles for DAC DF, but nonlinear for Chinese projects. In sectors that are harder to monitor, DAC projects in the 2nd, 3rd, and 4th corruption quartiles exhibit statistically significantly larger project sizes compared to those in the least corrupt quartile, with a weak linear trend across these quartiles. However, the interaction effect for Chinese projects is statistically significant only in the third quartile, without exhibiting a linear pattern across quartiles.



(a) Level 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.

3.4 Taking Stock and Potential Explanation

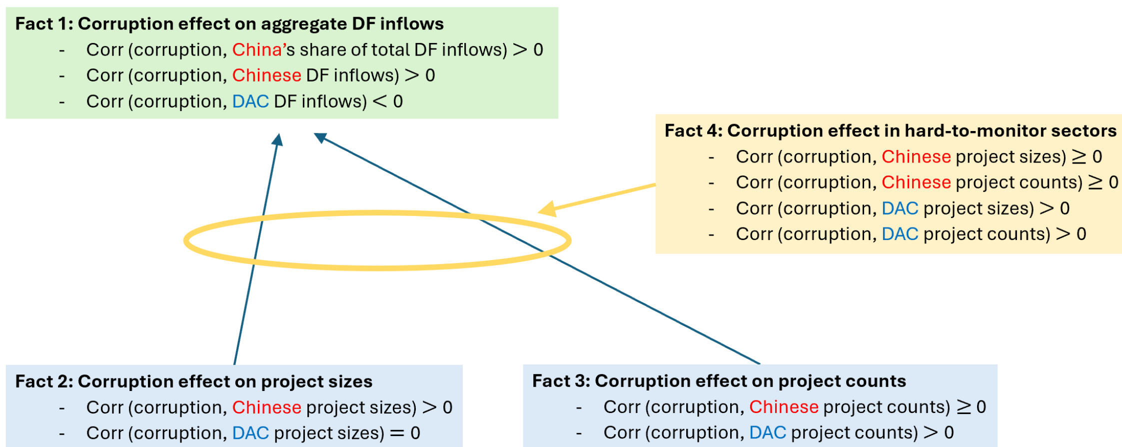


Figure 7: Stylized Facts on the Effect of Corruption on DF Flows

Rationalizing the facts. The stylized facts, summarized in Figure 7, suggest that public sector corruption and the diversion motives of recipient governments play a significant role in shaping global DF flows and that Chinese DF is relatively less strictly monitored compared to the DAC DF. The facts can be rationalized if we consider that Chinese DF is indeed subject to less stringent monitoring. When a government with diversion motives faces a choice between two sources of DF, it would naturally prefer the one with less stringent monitoring. Consequently, more corrupt countries are likely to have a greater number of projects from the more lenient donor, China, and fewer projects from the stricter donors, the DAC (Fact 3). This indicates that projects from strict DAC donors are more likely to be allocated to cleaner countries with weaker diversion motives. The tendency of countries with stronger diversion motives to select lenient monitoring conditions, coupled with the tendency to inflate project sizes due to less stringent oversight, leads to a significantly positive correlation between Chinese project sizes and corruption. In contrast, the opposite effects result in an insignificant correlation between DAC project sizes and corruption (Fact 2). With these forces at play, at the aggregate level, more corrupt countries would rely more heavily on Chinese DF relative to DAC DF (Fact 1).

Meanwhile, although DAC projects are generally strictly monitored, certain sectors inherently difficult to monitor might still provide lucrative opportunities for diversion. In these sectors, corruption could be disproportionately more correlated with project sizes, and this effect might be significant even for DAC projects, leading to a higher count of projects in these sectors (Fact 4). This additional corruption effect may also manifest in Chinese projects. However, because Chinese projects are generally subject to more lenient monitoring, variations in sectoral monitoring might not significantly influence the overall pattern in Chinese projects. This scenario is reflected in the data, which shows a significant interaction effect between corruption and monitoring difficulty on both project size and count for DAC, where this interaction effect dominates the level effect. Conversely, for Chinese projects, the level effect of corruption on project size and count is much stronger than the interaction effect.

Other forces. There is a narrative that explains the reliance of developing countries on Chinese DF as a supply-side issue, where DAC DF may be insufficient due to rationing of certain countries or neglect of specific sectors, or because it is harder to secure (Brautigam, 2011; Dreher et al., 2022). Since the stylized facts I establish represent equilibrium outcomes of both demand and supply dynamics, they do not dismiss the supply narrative. However, the supply-side story alone cannot account for all the empirical findings. While it might explain the aggregate-level observation that corruption is positively correlated with reliance on Chinese DF (Fact 1)—suggesting that more corrupt countries are possibly rationed by the DAC—it is insufficient to explain the project- and cross-sectoral findings (Facts 2-4).

Another potential explanation could be the significance of bilateral political or economic ties between donors and recipients (Alesina and Dollar, 2000; Kuziemko and Werker, 2006). Although this perspective might account for Fact 1, it falls short of explaining Facts 2-4. Importantly, in all analyses, I control for these factors by including a host of bilateral control variables and the main findings concerning the relationship between corruption and DF flows remain robust.

Comprehensive modeling approach. While the empirical findings provide suggestive evidence of corruption and diversion motives, they do not exclude other narratives, such as the supply-side story and the importance of bilateral ties. These explanations are not necessarily mutually exclusive, and it is likely that all these forces concurrently influence DF allocation. In the model section, I account for all these factors. The government decides on DF usage from the DAC and China, with diversion motives, while considering the given DF characteristics, including interest rates, monitoring intensities, and fixed costs to secure each project. Additionally, other forces, including supply-side factors and bilateral ties, are embedded on these DF characteristics. While the model does not theoretically explore how these supply-side characteristics are determined, I estimate them using data in the quantitative analysis and examine the welfare implications, taking into account all these forces.

3.5 Robustness Checks

I conduct several robustness checks that largely confirm the qualitative results, detailed in Appendix B.3. These include: instrumenting the corruption index using settler mortality following Acemoglu et al. (2001); sectoral-level panel analysis on China's share and the value and count of the DAC and Chinese DF; alternative outlier treatments of dependent variables; different transformations of the corruption measure; various versions of sectoral monitoring difficulty; placebo tests with interaction terms between corruption and other recipient characteristics; replacing the corruption index with a more direct index of diversion risk; and controlling for capital openness, public capital stock, and degree of democracy.

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 log utility function $U(C) = \ln C$, 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):

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

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 (Hulten, 1996), 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 government runs the public sector. It accumulates and provides public capital to the private sector. It also has enough instruments to affect private agents' decisions as it desires. As a result, the government solves a planning problem in which it directly chooses household consumption and saving as well as public capital accumulation.

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 $g^E_{s,j,t}$ denote effective public capital stock in project j in sector s in period t. It follows the law of motion: $g^E_{s,j,t+1} = (1-\delta_G)\cdot g^E_{s,j,t} + I^E_{s,j,t}$ where δ_G is depreciation rate of public capital and $I^E_{s,j,t}$ 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 public capital in each subsector, $G^E_{s,t}$, 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,

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

where $\sigma > 1$ is the elasticity of substitution between various projects within a sector, and θ_j denotes project-specific productivity. Second, the effective final public capital G^E_t, which enters the firm's production function, is a Cobb-Douglas composite of $G^E_{s,t}$:

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

where γ_s denotes the sector s share within the public sector ($\sum_{s\in\mathcal{S}} \gamma_s = 1$). My modeling approach of public capital at the project- and sectoral level extends the existing works that usually treat public capital as a monolithic input.

Financing of public capital. In addition to domestic savings, the government can fund its public projects through international development finance (DF) loans.[4] 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 benefit. 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. Note that $g_{s,j,t}^E$ is a stock variable, with an undepreciated fraction $(1-\delta_G)$ remaining after being used for production in each period. In contrast, $g_{s,j,t}^X$ does not accumulate and is fully consumed by the government immediately in each period.[5] 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 consumption or private investment. Hence, the government faces the "non-fungibility constraint" for j:

$$g_{s,j,t}^E + g_{s,j,t}^X \geq d_{s,j,t}^D + d_{s,j,t}^C. \tag{4}$$

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 $\psi_s^D \in (0,1]$ and $\psi_s^C \in (0,1]$ fractions, respectively, of their DF contract go into $g_{s,j,t}^E$. ψ_s^D and ψ_s^C reflect the sector-specific monitoring intensities of each provider. Hence, the government faces an additional "monitoring constraint" for j:

$$g_{s,j,t}^E \geq \psi_s^D d_{s,j,t}^D + \psi_s^C d_{s,j,t}^C. \tag{5}$$

In other words, it can divert only up to $1-\psi_s^D$ and $1-\psi_s^C$ fractions of a DAC and a Chinese DF contract, respectively. I assume $\psi_s^D \geq \psi_s^C$ for all $s \in \mathcal{S}$.

[4] 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.

[5] For example, suppose the government borrows capital worth \$100 to finance one of its public projects from the DAC, allocating \$90 to effective public capital and \$10 to diversion. After production, the government retains $(1-\delta_G) \times \$90$ in effective public capital but fully consumes the \$10 allocated to diversion. In the next period, the government must repay $(1+R_s^D) \times \$100$ out of the retained effective public capital and the output.

In addition, issuing new DF debt each period for each project incurs fixed costs f_s^D and f_s^C 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 $\tilde{U}(C, G^X; \chi) = \ln\big(C + \chi \cdot G^X\big)$, which takes a Greenwood-Hercowitz-Huffman (GHH, Greenwood et al. (1988)) form. C is the representative household's consumption, and G^X is the total amount of diverted funds, defined as $G_t^X \equiv \sum_{s\in\mathcal{S}} \int_{j\in\mathcal{J}_s} g_{s,j,t}^X dj$. 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. Note that if $\chi = 0$, the government's period utility is the same as the household's. 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.

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 are competed 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 representative 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 interest payments 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 for 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 decisions 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:

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

$$\text{subject to} \quad \text{(RC): } C_t + I^K_t + \sum_{s\in\mathcal{S}} \int_{j\in\mathcal{J}_s} (I^E_{s,j,t} + g^X_{s,j,t+1} + R^D_s d^D_{s,j,t} + R^C_s d^C_{s,j,t} + \mathbb{I}^D_{s,j,t} f^D_s + \mathbb{I}^C_{s,j,t} f^C_s) dj$$

$$= Y_t + \sum_{s\in\mathcal{S}} \int_{j\in\mathcal{J}_s} (d^D_{s,j,t+1} + d^C_{s,j,t+1}) dj,$$

$$\text{(NF): } g^E_{s,j,t} + g^X_{s,j,t} \geq d^D_{s,j,t} + d^C_{s,j,t},$$

$$\text{(MC): } g^E_{s,j,t+1} \geq \psi^D_s d^D_{s,j,t+1} + \psi^C_s d^C_{s,j,t+1},$$

$$\text{(NX), (ND), (NC): } g^X_{s,j,t+1} \geq 0,\ d^D_{s,j,t+1} \geq 0,\ d^C_{s,j,t+1} \geq 0,$$

$$\text{for all } t, s \in \mathcal{S}, j \in \mathcal{J}_s, \text{ given } k_0, \mathbf{g}^E_0, \mathbf{g}^X_0, \mathbf{d}^D_0, \mathbf{d}^C_0,$$

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

(RC) is the economy-wide resource constraint 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 (Eq. 4.1.2) and monitoring constraints (Eq. 4.1.2). (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

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. A sufficient condition for such allocations is $f^S_s \geq \min\{f^D_s, f^C_s\}$ where f^S_s denotes fixed cost for operating a project in sector s with self-financing. Intuitively, together with $R^D_s < R^C_s < 1/\beta$, it implies that self-financing is costlier than DF-financing both in terms of fixed cost and marginal cost. In the quantitative analysis (Section 7), 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 $p \in \{D, C\}$:

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

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

$$\begin{aligned} mpg_{s,j,t+1}^E + 1 - \delta_s^E &= R_s^p \qquad \text{if } \chi < R_s^p \\ \psi_s^p \cdot (mpg_{s,j,t+1}^E + 1 - \delta_s^E) + (1 - \psi_s^p) \cdot \chi &= R_s^p \qquad \text{if } \chi \geq R_s^p \end{aligned}$$

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

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 ($\chi < R_s^p$), the optimal project size is determined by equating the total return on project j to the interest rate. If the government is sufficiently corrupt ($\chi \geq R_s^p$), the marginal benefit consists of two components: ψ_s^p fraction from total return on the project, and $1 - \psi_s^p$ 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, $\tilde{R}_s^p$, is defined as the interest rate adjusted for capital retention after depreciation and the marginal utility of diversion:

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

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: $mpg_{s,j,t+1}^E = \tilde{R}_s^p$.

Note that $mpg_{s,j,t+1}^E$ is the same for all projects with the same productivity within the same sector. Hence, I define $mpg_{s,t+1}^E(\theta)$ 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, $\tilde{\pi}_{s,t+1}^p(\theta)$, is the total increase in final output due to the project net of the effective marginal cost and the fixed cost:

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

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

Note that the effective profit depends on which provider finances the project 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). Zero profit cutoffs serve as thresholds that determine whether projects are operating or non-operating by distinguishing between projects that generate sufficient revenue to cover costs and those that do not.

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

The financing indifference cutoff determines which source of funding, DAC or China, renders projects more profitable for the government.

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: $\tilde{\pi}^C_{s,t}(\bar{\theta}^I_{s,t}) = \tilde{\pi}^D_{s,t}(\bar{\theta}^I_{s,t})$.

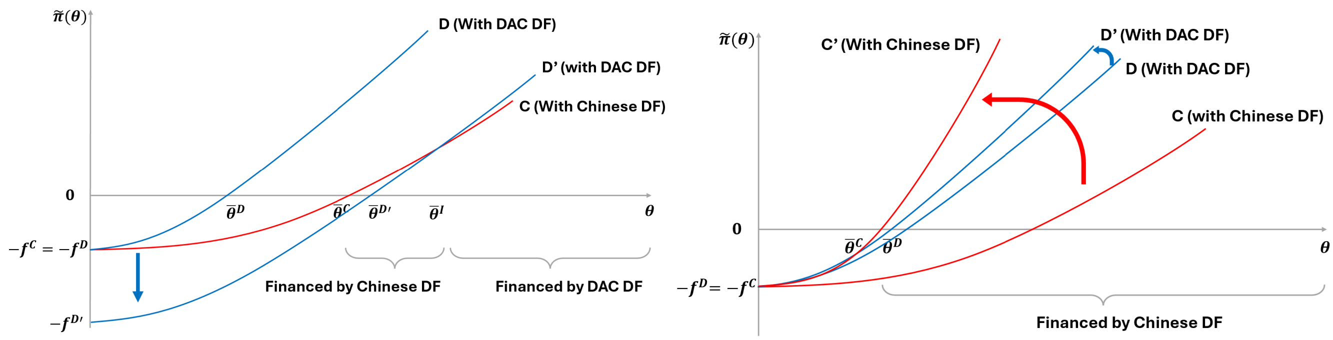
Figure 8 illustrates optimal financing of projects with different productivity θ within a sector in some examples. First, suppose that the government chooses zero diversion both with the DAC and Chinese DF and that the fixed costs are the same for the two providers. Then, since the interest rate for 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 8a. 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. It creates a hierarchy where more productive and hence larger projects are financed by the DAC, while relatively less productive and smaller projects are financed by China.

Figure 8b 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 a 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. Intuitively, higher corruption χ favors providers with less monitoring, which I link to the stylized facts later in Section 5. 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.

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.



(a) Zero diversion and different fixed costs

(b) Maximal diversion and the same fixed costs

Figure 8: Optimal financing of each project

Lemma 4. For sector s, suppose $\tilde{R}_s^p < \tilde{R}_s^q$. If $f_s^p \leq (\tilde{R}_s^q/\tilde{R}_s^p)^{\sigma_s - 1} \cdot f_s^q$, all operating projects in sector s are financed by p, with only those with productivity $\theta \geq \bar{\theta}_{s,t}^p$ operating. If $f_s^p > (\tilde{R}_s^q/\tilde{R}_s^p)^{\sigma_s-1} \cdot f_s^q$, only projects with $\theta_s \geq \bar{\theta}_{s,t}^q$ operate. In this case, projects with $\theta_s \in [\bar{\theta}_{s,t}^q, \bar{\theta}_{s,t}^I]$ are financed by q, while those with $\theta \in [\bar{\theta}_{s,t}^I, \infty)$ 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. Recall that the corruption χ and monitoring intensities enter the effective marginal costs. If p features a lower effective marginal cost ($\tilde{R}_s^p < \tilde{R}_s^q$) and its fixed cost is also not too high relative to q'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 q, 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, $\theta_{s,t}^I$) are financed by p, while those below this threshold are financed by q.

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

Proposition 2. (Optimal Financing at the Sectoral Level). Let $\mathcal{S}^{pq}$ denote the set of sectors where projects with $\theta \in [\bar{\theta}^I, \infty)$ are financed by p, and projects with $\theta \in [\bar{\theta}^q, \bar{\theta}^I)$ are financed by q. 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. Then, 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 9 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. Note that in $\mathcal{S}^{\tilde{D}C}$, corruption χ affects only the DAC projects, not Chinese projects.

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 ($\mathcal{S}^{\tilde{C}\tilde{D}}$).

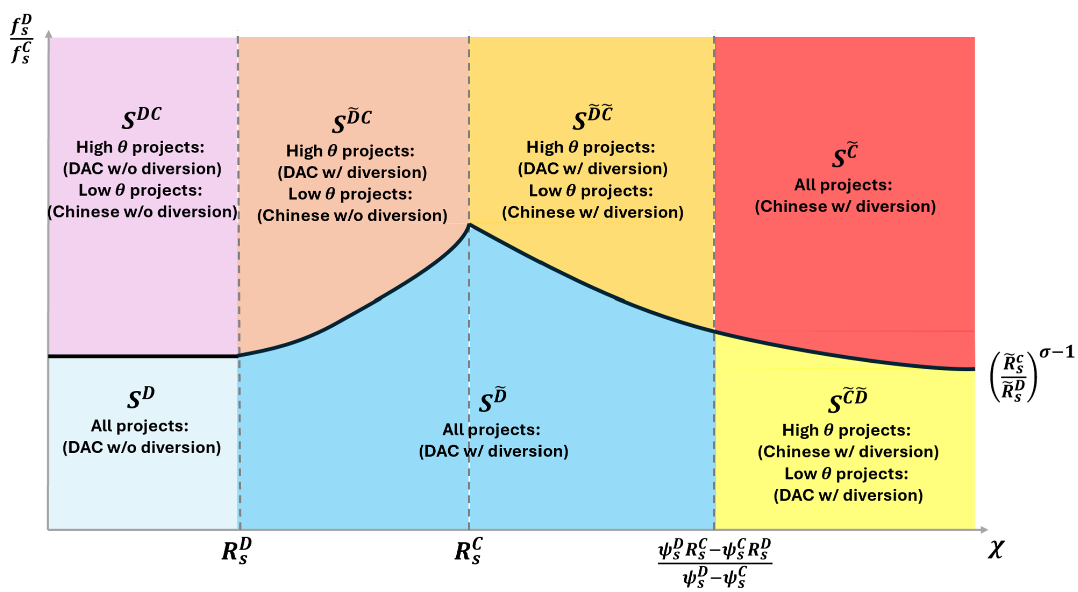


Figure 9: Optimal financing of each sector

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 depending on 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 four insights: First, I show that the model accounts for 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. Fourth, I show the possibility of two-way feedback between corruption and the use of DF.

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 a deviation from the benevolent allocation through three channels: overinvestment, sectoral misallocation, and financing inefficiency.

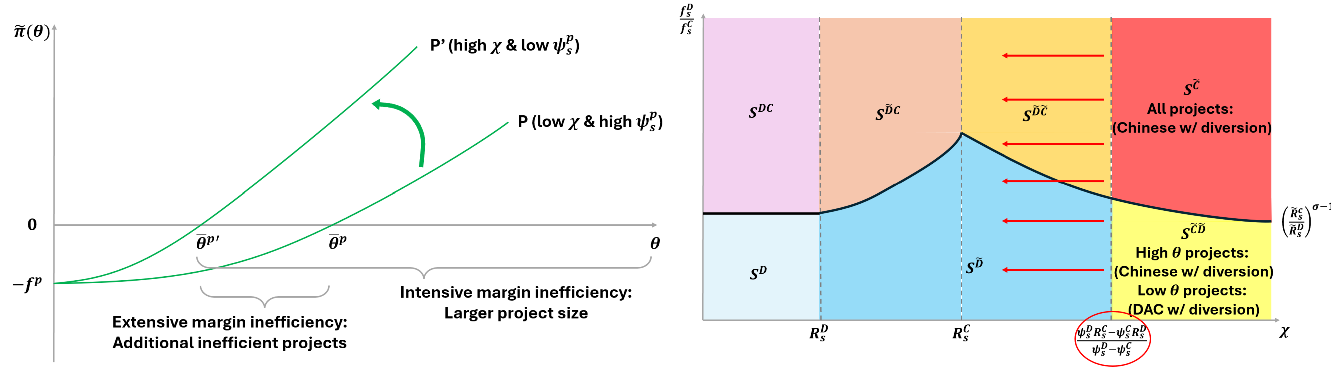
5.1.1 Overinvestment Channel

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 and corruption parameter exceeds the interest rate ($\chi > R_s^p$), $\tilde{R}_s^p = \frac{R_s^p - (1-\psi_s^p)\cdot\chi}{\psi_s^p} - (1 - \delta_s^E)$, 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 10a. 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 when $\chi > R_s^p$. This channel explains cases where some governments invest in large public projects that appear unprofitable.



(a) Overinvestment Channel

(b) Financing Inefficiency Channel

Figure 10: 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:

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

In a benevolent allocation, the effective marginal cost is simply $R_s^p - (1-\delta)$. Hence, the optimal ratio would be determined by each sector's contribution to final output, accounting for relative interest rates and fixed costs. However, a distortion arises if the government is sufficiently corrupt and the monitoring intensity differs between sectors. If sector s has more intense monitoring ($\psi_s^p > \psi_{s'}^p$), 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 $\tilde{\pi}_{s,j,t+1}^p$. For simplicity, suppose both DAC and Chinese DF feature identical fixed costs. Then, the decision depends solely on the effective marginal costs, $\tilde{R}_s^p$. In a benevolent allocation, $\tilde{R}_s^p$ 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 $\tilde{R}_s^C < \tilde{R}_s^D$ and Chinese DF is chosen despite its higher interest rate. This is if and only if $\chi > \frac{\psi_s^D R_s^C - \psi_s^C R_s^D}{\psi_s^D - \psi_s^C}$. 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 10b. 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 expands the 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 DAC DF, particularly when DAC DF entails very high fixed costs. Such costs may reflect the challenges of securing DAC DF for projects, potentially due to harsh negotiation processes, demands for abrupt policy reforms, sector de-emphasis, or even rationing some countries in specific sectors. These conditions may restrict DAC DF to a few highly productive projects. In contrast, if Chinese DF has lower fixed costs, its availability can foster public investment, thereby 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 discussed above. 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 11. If $\chi < R_s^C$, the government does not divert any Chinese 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 fills the funding gap or exacerbate inefficiencies can vary across sectors and whether Chinese DF is a boon or a bane to the household at the aggregate level is a quantitative question, which I explore in Section 7.

5.3 Implication on the Efficiency of Public Capital and TFP

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 (Hulten, 1992). Subsequent studies (Dabla-Norris et al., 2012; Gupta et al., 2014)

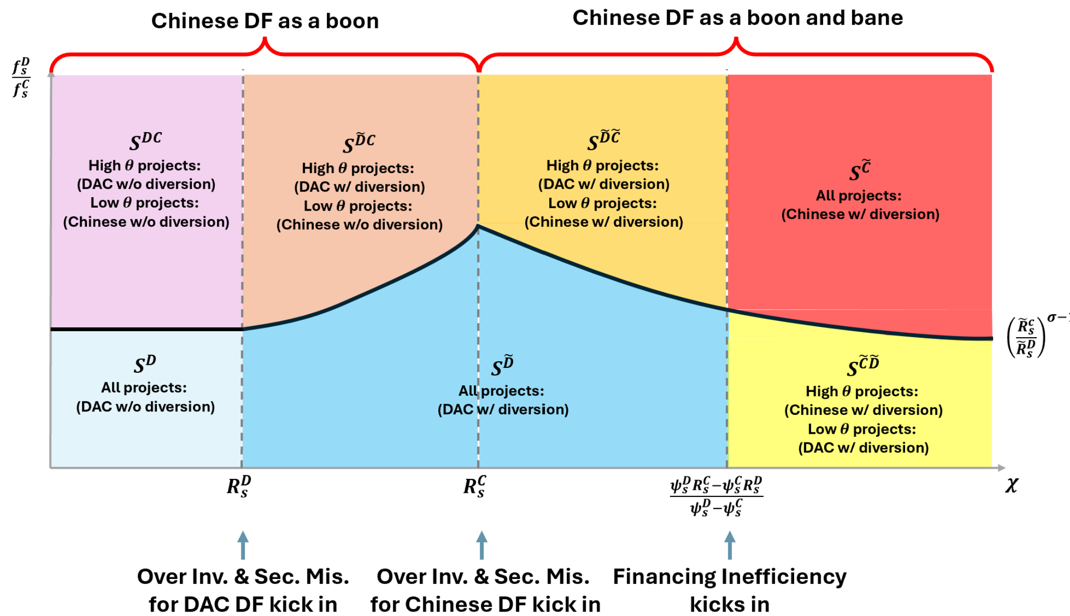


Figure 11: Boon and Bane effects of Chinese DF

quantify public capital efficiency across countries, often assuming that public capital G enters production function with a constant efficiency term, Θ, multiplied to it: $Y = A \cdot (\Theta G)^{\gamma} K^{\alpha} L^{\lambda}$. 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.

My model also has implications for Total Factor Productivity (TFP). Viewed through the lens of more traditional models that assume a production technology with two inputs, $Y = A \cdot K^{\alpha} L^{1-\alpha}$, my model facilitates the decomposition of TFP, A. Specifically, it is useful for determining how much of a change in TFP can be attributed to variations in public capital and its efficiency shaped by corruption and global DF environments.

5.4 Two-Way Feedback between Corruption and DF Inflows

My model suggests the possibility of two-way feedback, where corruption affects DF inflows, and DF inflows, in turn, affect corruption. My model proposes two definitions of corruption. The first is fundamental corruption, represented by the corruption parameter χ, which reflects the extent to which the government values diversion relative to household consumption. The second definition measures corruption by the actual amount of diversion, which aligns more closely with empirical corruption indices, as these are typically based on surveys regarding the diversion or expropriation of resources in public sector. In this sense, my model suggests that the correlation between corruption and Chinese DF inflows may reflect both forces: first, higher fundamental corruption leads to increased Chinese DF inflows due to less stringent monitoring and diversion incentives. Subsequently, this increase in DF inflows results in greater diversion, leading to higher levels of corruption as measured by diversion.

6 Calibration

In this section, I apply the model to data from each developing country and calibrate it accordingly for later steady state welfare analysis in Section 7. As preliminary steps, I incorporate two additional sources of financing public projects, DAC grants and self-financing, and classify sectors into 14 categories. Then, I calibrate the model parameters.

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).[6]

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. See Appendix E.1 for the implication of the setup and additional details.

[6] 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 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.

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 of Parameters

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 5 summarizes the calibration strategy.

6.2.1 Common Macro Parameters

Standard parameters. I externally calibrate the standard macro parameters that are common across all borrower countries. A period is a year. 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

Table 5: Calibration

Parameter	Description	Values	Method	Source/Target moment
Common Macro parameters				
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.	Benchmark
γ_s	Pub. sector share	0.0004 - 0.3588	GMM	$\mathbb{E}$[sector share in pub. inv.]
L	Labor supply	1	Normalization	Normalization
A	TFP	1	Normalization	Normalization
DF characteristics				
R_s^D	DAC interest rate	1.009 - 1.015	Data	Mean interest rates
R_s^C	China interest rate	1.018 - 1.045	Data	Mean interest rates
ψ_s^D	DAC monitoring	1	Normalization	Normalization
ψ_s^C	China monitoring	0.42 - 1	FE Regression	$\mathbb{E}[\frac{\text{CHN proj. size}}{\text{DAC proj. size}}]$
Recipient country characteristics				
χ_r	Corruption	0 - 1.3	Upper bound	Marginal cost of DF
ξ_r	Pareto shape	2.2 - 4.95	MLE	Upper tail of proj. size dist.
$\underline{\theta}_r$	Pareto scale	1	Normalization	Normalization
Recipient $\times$ sector $\times$ DF provider characteristics				
$f_{r,s}^G$	Grant fixed cost	varies by $r \times s$	GMM	$\mathbb{E}$[DAC grant proj. size]
$f_{r,s}^D$	DAC loan fixed cost	varies by $r \times s$	GMM	$\mathbb{E}$[DAC loan proj. size]
$f_{r,s}^C$	Chinese loan fixed cost	varies by $r \times s$	GMM	$\mathbb{E}$[CHN loan proj. size]
$f_{r,s}^S$	Self-financing fixed cost	1	Normalization	Normalization

rate, δ_K, and the public capital depreciation rate, δ_G, are both set to 0.05. The aggregate public capital share parameter, γ, is set to 0.106, following Bom and Ligthart (2014). I normalize the labor supply L and the TFP A to 1.

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).[7]

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

[7]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:[8]

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

The estimates are summarized in Table E.2.

6.2.2 DF Provider Characteristics

Interest rates. I set the interest rates for each provider-sector pair to the average interest rates of all the projects within the pair observed in the data, as summarized in Table 6. 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

[8] 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.

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.

Consider the following fixed effect regression model. $g^O_{r,p,s,j,t}$ is the observed project size. $\mathbf{X}_{r,p,t}$ 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 6.

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 6: 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. The scale parameter governs the level of output but does not affect the government's optimal DF decisions. I estimate the Pareto shape parameter, ξ_r, for each country (r) using 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 (Hogg et al., 2013). It turns out that the pdf of a pooled sample of project sizes resembles the pdf of Pareto distribution with shape parameter ξ_r/σ. 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 $\bar{\theta}_r$. See Appendix E.5 for the details and results.

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

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

Note that I subtract a small value $\epsilon > 0$ to ensure that $\tilde{R}^C_{r,s}$ 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: $f^G_{r,s}$, $f^D_{r,s}$, and $f^C_{r,s}$ 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:

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

$\mathcal{F}^p_{r,s}$ 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 $m(\Xi_r)$, and let $\bar{m}_r$ represent the empirical moments, where $\Xi_r \equiv \{\{f^G_{r,s}, f^D_{r,s}, f^C_{r,s}\}_{s\in\mathcal{S}}\}$. I estimate Ξ_r by minimizing the following objective function:

$$(m(\Xi_r) - \bar{m}_r)' \cdot \mathcal{W} \cdot (m(\Xi_r) - \bar{m}_r)$$

where $\mathcal{W}$ is a weighting matrix. The choice of a weighting matrix is inconsequential, as the fixed costs are exactly identified.

7 Quantitative Analysis

7.1 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 12. 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. Among the 108 economies, roughly 15% experience unambiguous welfare improvements, 17% experience negligible effects, 12% experience ambiguous effects depending on the actual level of corruption, and 55% experience potentially large welfare reductions due to the presence of Chinese DF. First, note that in all countries, Chinese DF is welfare-improving if the government is benevolent. This is because Chinese DF is used only in the sectors in which its fixed costs are lower than those of the DAC DF. 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.

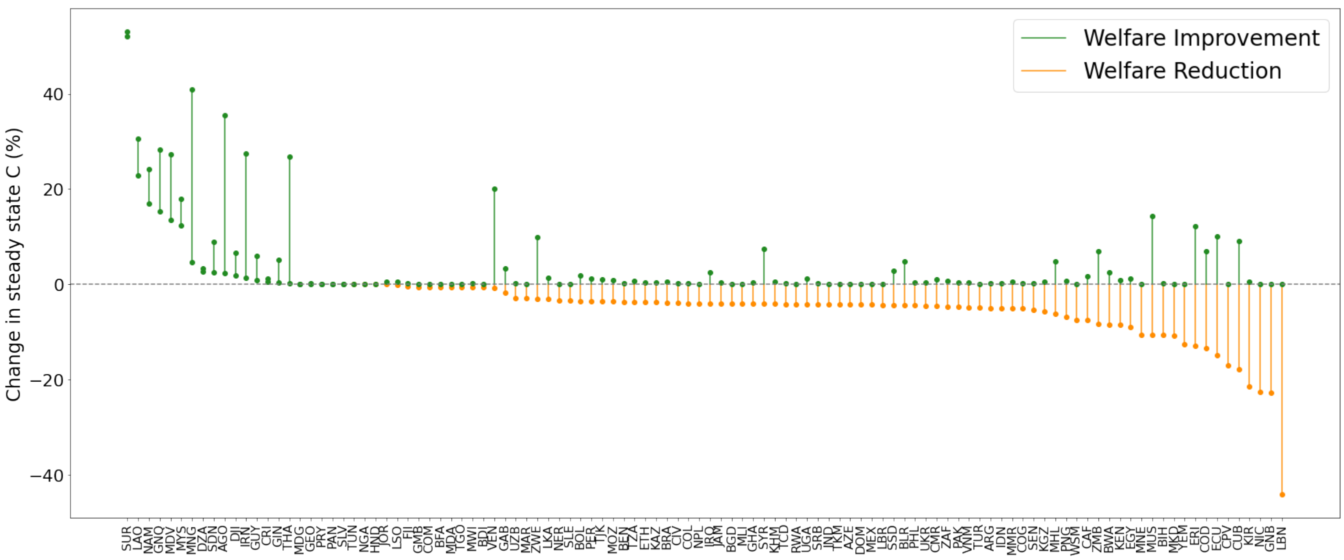


Figure 12: Welfare effect of Chinese DF on households

7.2 Case Studies

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 13 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.

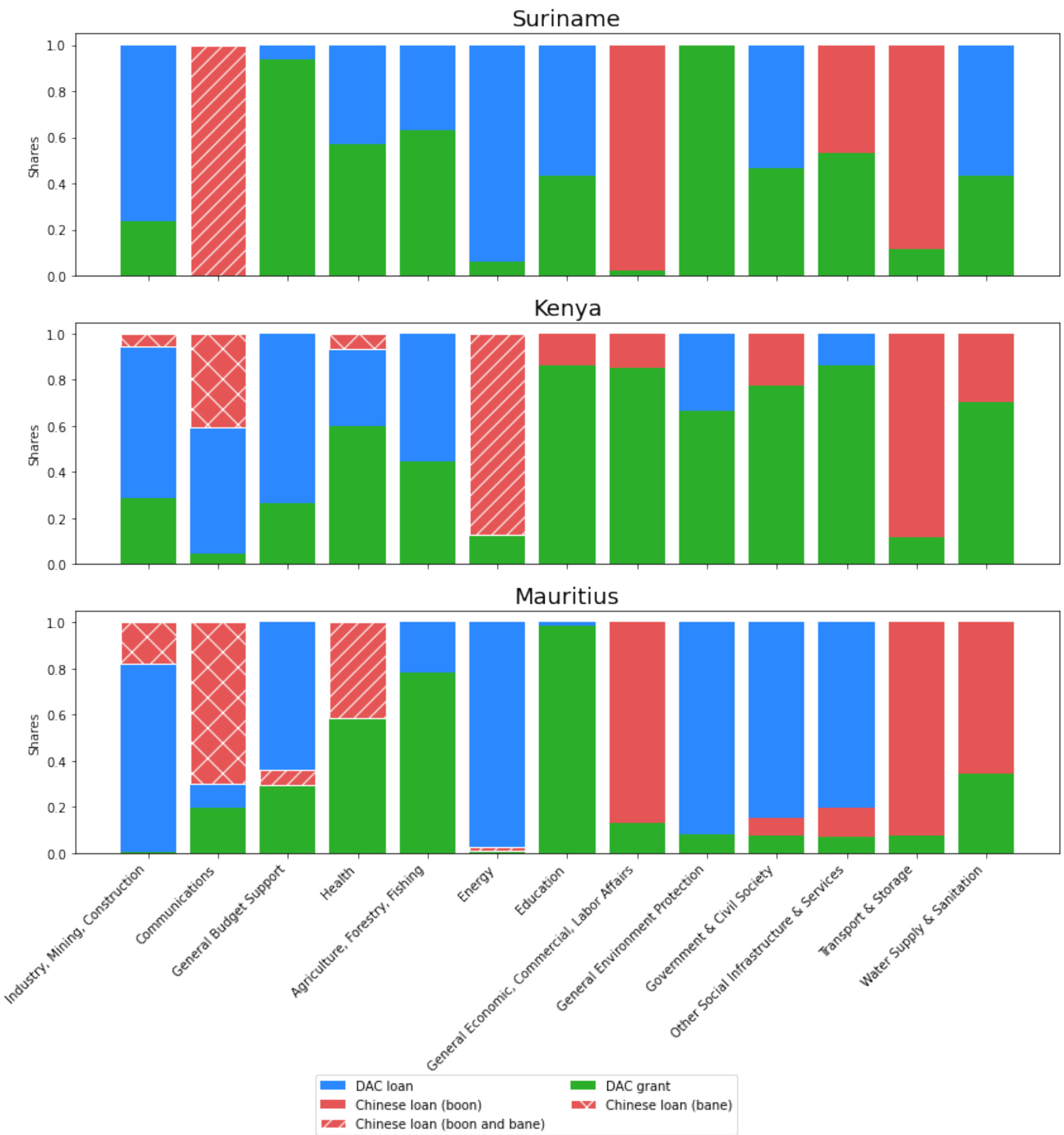


Figure 13: DF composition by sectors in Suriname, Kenya, and Mauritius

Case 1 (boon): Suriname. Figure 12 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 13 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 12.

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 12 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.

8 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.

References

Acemoglu, D., Johnson, S., and Robinson, J. A. (2001). The colonial origins of comparative development: An empirical investigation. *American economic review*, 91(5):1369–1401.

Acharya, V. V., Parlatore, C., and Sundaresan, S. M. (2020). Financing infrastructure in the shadow of expropriation. *Available at SSRN 3689262*.

Adam, C. S. and Bevan, D. L. (2006). Aid and the supply side: Public investment, export performance, and dutch disease in low-income countries. *The World Bank Economic Review*, 20(2):261–290.

Agénor, P.-R. (2010). A theory of infrastructure-led development. *Journal of Economic Dynamics and Control*, 34(5):932–950.

Aguiar, M. and Amador, M. (2011). Growth in the shadow of expropriation. *The Quarterly Journal of Economics*, 126(2):651–697.

Aguiar, M. and Gopinath, G. (2007). Emerging market business cycles: The cycle is the trend. *Journal of political Economy*, 115(1):69–102.

AidData (2017). Aiddatacore_researchrelease_level1_v3. 1 research releases dataset.

Alesina, A. and Dollar, D. (2000). Who gives foreign aid to whom and why? *Journal of economic growth*, 5(1):33–63.

Alesina, A. and Passalacqua, A. (2016). The political economy of government debt. *Handbook of macroeconomics*, 2:2599–2651.

Andersen, J. J., Johannesen, N., and Rijkers, B. (2022). Elite capture of foreign aid: Evidence from offshore bank accounts. *Journal of Political Economy*, 130(2):388–425.

Arkolakis, C., Costinot, A., and Rodríguez-Clare, A. (2012). New trade models, same old gains? *American Economic Review*, 102(1):94–130.

Aschauer, D. A. (1989). Is public expenditure productive? *Journal of monetary economics*, 23(2):177–200.

Avdjiev, S., Hardy, B., Kalemli-Özcan, Ş., and Servén, L. (2022). Gross capital flows by banks, corporates, and sovereigns. *Journal of the European Economic Association*, 20(5):2098–2135.

Bailey, M. A., Strezhnev, A., and Voeten, E. (2017). Estimating dynamic state preferences from united nations voting data. *Journal of Conflict Resolution*, 61(2):430–456.

Baqaee, D. R. and Farhi, E. (2019). The macroeconomic impact of microeconomic shocks: Beyond hulten's theorem. *Econometrica*, 87(4):1155–1203.

Barro, R. J. (1990). Government spending in a simple model of endogeneous growth. *Journal of political economy*, 98(5, Part 2):S103–S125.

Berg, A., Buffie, E. F., Pattillo, C., Portillo, R., Presbitero, A. F., and Zanna, L.-F. (2019). Some misconceptions about public investment efficiency and growth. *Economica*, 86(342):409–430.

Berg, M. A., Portillo, R., Buffie, M. E. F., Pattillo, M. C. A., and Zanna, L.-F. (2012). *Public investment, growth, and debt sustainability: Putting together the pieces*. International Monetary Fund.

Bom, P. R. and Ligthart, J. E. (2014). What have we learned from three decades of research on the productivity of public capital? *Journal of economic surveys*, 28(5):889–916.

Boone, P. (1996). Politics and the effectiveness of foreign aid. *European economic review*, 40(2):289–329.

Brautigam, D. (2011). *The dragon's gift: the real story of China in Africa*. oUP oxford.

Broda, C. and Weinstein, D. E. (2006). Globalization and the gains from variety. *The Quarterly journal of economics*, 121(2):541–585.

Bunte, J. B. (2019). *Raise the debt: How developing countries choose their creditors*. Oxford University Press.

Burnside, A. C. and Dollar, D. (2004). Aid, policies, and growth: revisiting the evidence. *Policies, and Growth: Revisiting the Evidence (March 18, 2004)*.

Calderón, C., Moral-Benito, E., and Servén, L. (2015). Is infrastructure capital productive? a dynamic heterogeneous approach. *Journal of Applied Econometrics*, 30(2):177–198.

Chakraborty, S. and Dabla-Norris, E. (2011). The quality of public investment. *The BE Journal of Macroeconomics*, 11(1).

Chatterjee, S. and Turnovsky, S. J. (2007). Foreign aid and economic growth: The role of flexible labor supply. *Journal of Development economics*, 84(1):507–533.

Chinn, M. D. and Ito, H. (2008). A new measure of financial openness. *Journal of comparative policy analysis*, 10(3):309–322.

Clayton, C., Maggiori, M., and Schreger, J. (2023). A framework for geoeconomics. Technical report, National Bureau of Economic Research.

Conte, M., Cotterlaz, P., Mayer, T., et al. (2022). *The CEPII gravity database*. CEPII.

Coppola, A., Maggiori, M., Neiman, B., and Schreger, J. (2021). Redrawing the map of global capital flows: The role of cross-border financing and tax havens. *The Quarterly Journal of Economics*, 136(3):1499–1556.

Custer, S., Dreher, A., Elston, T.-B., Escobar, B., Fedorochko, A. F., Ghose, S., Lin, J. J., Malik, A. A., Parks, B. C., Solomon, K., et al. (2023). *Tracking Chinese Development Finance: An Application of AidData's TUFF 3.0 Methodology*. AidData at William & Mary Williamsburg, VA.

Dabla-Norris, E., Brumby, J., Kyobe, A., Mills, Z., and Papageorgiou, C. (2012). Investing in public investment: an index of public investment efficiency. *Journal of Economic Growth*, 17(3):235–266.

De Clerck, M. S. and Wickens, T. (2015). *Government Finance Statistics Manual 2014: Manual*. International Monetary Fund.

De la Croix, D. and Delavallade, C. (2009). Growth, public investment and corruption with failing institutions. *Economics of Governance*, 10(3):187–219.

Dreher, A., Fuchs, A., Parks, B., Strange, A., and Tierney, M. J. (2021). Aid, china, and growth: Evidence from a new global development finance dataset. *American Economic Journal: Economic Policy*, 13(2):135–74.

Dreher, A., Fuchs, A., Parks, B., Strange, A., and Tierney, M. J. (2022). *Banking on Beijing: The Aims and Impacts of China's Overseas Development Program*. Cambridge University Press.

Florez-Orrego, S., Maggiori, M., Schreger, J., Sun, Z., and Tinda, S. (2023). Global capital allocation.

Franco-Rodriguez, S., Morrissey, O., and McGillivray, M. (1998). Aid and the public sector in pakistan: evidence with endogenous aid. *World Development*, 26(7):1241–1250.

Futagami, K., Morita, Y., and Shibata, A. (1993). Dynamic analysis of an endogenous growth model with public capital. *The Scandinavian Journal of Economics*, pages 607–625.

Galiani, S., Knack, S., Xu, L. C., and Zou, B. (2017). The effect of aid on growth: Evidence from a quasi-experiment. *Journal of Economic Growth*, 22(1):1–33.

Gelpern, A., Horn, S., Morris, S., Parks, B., and Trebesch, C. (2021). How china lends: A rare look into 100 debt contracts with foreign governments.

Glomm, G. and Ravikumar, B. (1994). Public investment in infrastructure in a simple growth model. *Journal of Economic Dynamics and Control*, 18(6):1173–1187.

Greenwood, J., Hercowitz, Z., and Huffman, G. W. (1988). Investment, capacity utilization, and the real business cycle. *The American Economic Review*, pages 402–417.

Gupta, S., Kangur, A., Papageorgiou, C., and Wane, A. (2014). Efficiency-adjusted public capital and growth. *World development*, 57:164–178.

Hansen, H. and Tarp, F. (2001). Aid and growth regressions. *Journal of development Economics*, 64(2):547–570.

Head, K., Mayer, T., and Thoenig, M. (2014). Welfare and trade without pareto. *American Economic Review*, 104(5):310–316.

Herrera, S. and Ouedraogo, A. (2018). Efficiency of public spending in education, health, and infrastructure: an international benchmarking exercise. *World Bank Policy Research Working Paper*, (8586).

Hogg, R. V., McKean, J. W., Craig, A. T., et al. (2013). *Introduction to mathematical statistics*. Pearson Education India.

Honig, D., Lall, R., and Parks, B. C. (2022). When does transparency improve institutional performance? evidence from 20,000 projects in 183 countries. *American Journal of Political Science*.

Horn, S., Reinhart, C. M., and Trebesch, C. (2020). Coping with disasters: two centuries of international official lending.

Horn, S., Reinhart, C. M., and Trebesch, C. (2021). China's overseas lending. *Journal of International Economics*, 133:103539.

Hulten, C. R. (1992). Growth accounting when technical change is embodied in capital.

Hulten, C. R. (1996). Infrastructure capital and economic growth: How well you use it may be more important than how much you have.

Isaksson, A.-S. and Kotsadam, A. (2018). Chinese aid and local corruption. *Journal of Public Economics*, 159:146–159.

Keefer, P. and Knack, S. (2007). Boondoggles, rent-seeking, and political checks and balances: public investment under unaccountable governments. *The Review of Economics and Statistics*, 89(3):566–572.

Knutsen, T. and Kotsadam, A. (2020). The political economy of aid allocation: Aid and incumbency at the local level in sub saharan africa. *World Development*, 127:104729.

Kuziemko, I. and Werker, E. (2006). How much is a seat on the security council worth? foreign aid and bribery at the united nations. *Journal of political economy*, 114(5):905–930.

Malik, A., Parks, B., Russell, B., Lin, J. J., Walsh, K., Solomon, K., Zhang, S., Elston, T.-B., and Goodman, S. (2021). Banking on the belt and road: Insights from a new global dataset of 13,427 chinese development projects. *Williamsburg, VA: AidData at William & Mary*, pages 23–36.

Mauro, M. P. (1996). *The effects of corruptionon growth, investment, and government expenditure*. International Monetary Fund.

Mauro, P. (1995). Corruption and growth. *The quarterly journal of economics*, 110(3):681–712.

Mauro, P. (1998). Corruption and the composition of government expenditure. *Journal of Public economics*, 69(2):263–279.

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *econometrica*, 71(6):1695–1725.

Mueller, J. (2022). China's foreign aid: Political determinants and economic effects.

OECD (2024). DAC List of ODA Recipients – Purpose Codes: Sector Classification. https://www.oecd.org/dac/thedevelopmentassistancecommitteesmandate.htm. Accessed: 2024-06-22.

Rajan, R. G. and Subramanian, A. (2008). Aid and growth: What does the cross-country evidence really show? *The Review of economics and Statistics*, 90(4):643–665.

Robinson, J. A. and Torvik, R. (2005). White elephants. *Journal of public economics*, 89(2-3):197–210.

Silva, J. S. and Tenreyro, S. (2006). The log of gravity. *The Review of Economics and statistics*, 88(4):641–658.

Svensson, J. (2000). Foreign aid and rent-seeking. *Journal of international economics*, 51(2):437–461.

Tanzi, V. and Davoodi, H. (1998). Corruption, public investment, and growth. In *The welfare state, public investment, and growth*, pages 41–60. Springer.

Temple, J. and Van de Sijpe, N. (2017). Foreign aid and domestic absorption. *Journal of International Economics*, 108:431–443.

Tierney, M. J., Nielson, D. L., Hawkins, D. G., Roberts, J. T., Findley, M. G., Powers, R. M., Parks, B., Wilson, S. E., and Hicks, R. L. (2011). More dollars than sense: Refining our knowledge of development finance using aiddata. *World Development*, 39(11):1891–1906.

Appendix

A Data Cleaning (to be updated)

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*, 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 Supplementary Material for Empirical Analysis

B.1 Corruption Effect on Project Sizes by DF Providers

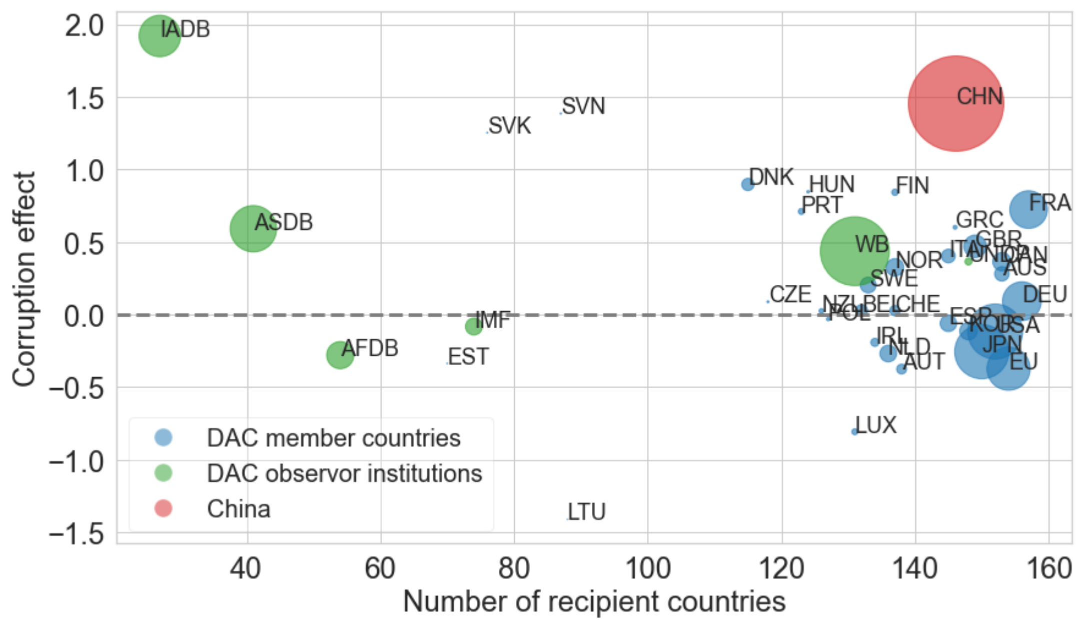


Figure B.1

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.

B.2 Sectoral Monitoring Difficulty

B.2.1 Estimation of Sectoral Monitoring Difficulty

I calculate the average ratings after controlling for potential confounding factors by running the following regression:

$$RATINGS_i = FE_{r(i)d(i)t(i)} + \gamma_{s(i)} + \mathbf{X}_{r(i)d(i)s(i)t(i)} \cdot \beta + constant + \epsilon_i.$$

$RATINGS_i$ represents the six-point scale rating of DF project i. $FE_{r(i)d(i)t(i)}$ denotes recipient×donor×year fixed effects, which capture both time-varying and invariant characteristics of recipient countries and donors, such as institutional quality, geography, economic or political relationships, and year-specific effects. $\mathbf{X}_{r(i)d(i)s(i)t(i)}$ includes the log of the total project amount for the recipient country in each sector, reflecting recipient-sector-specific effects related to sector size. This vector also includes dummy variables for evaluator type to control for potential biases by evaluating agencies, as well as the log of project size. The sector fixed effect, $\gamma_{s(i)}$, captures the average ratings of projects for each sector, adjusted for other effects specific to the recipient, donor, year, evaluator, project size, and sector size.

Table B.1 presents the estimation results for the control variables along with the F-test results. These tests evaluate the null hypothesis that the sector fixed effects are jointly zero. The results allow me to reject this null hypothesis, with standard error clustering at various levels demonstrating that average project ratings differ significantly across sectors. See Appendix B.2 for the OLS estimates of sector fixed effects and further discussion.

Figure B.2 depicts the OLS estimates of sector fixed effects alongside the distribution of bootstrapped estimates, illustrating the heterogeneity in average ratings across sectors. It is evident that 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 with relatively small standard errors. Conversely, sectors associated with unexpected and unplanned humanitarian projects, in-kind transfers, or short-term projects, such as Emergency Response, Reconstructive Relief & Rehabilitation, Development Food Assistance, and Other Commodity Assistance, rank highly, albeit with larger standard errors. This pattern supports the conventional wisdom that managing and monitoring long-term, large-scale projects with complex structures and financial transfers is more challenging, while it is relatively easier to monitor emergency and short-term, in-kind projects. Additionally, Health and Education sectors also rank highly. This observation corroborates findings from previous literature suggesting 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).

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.

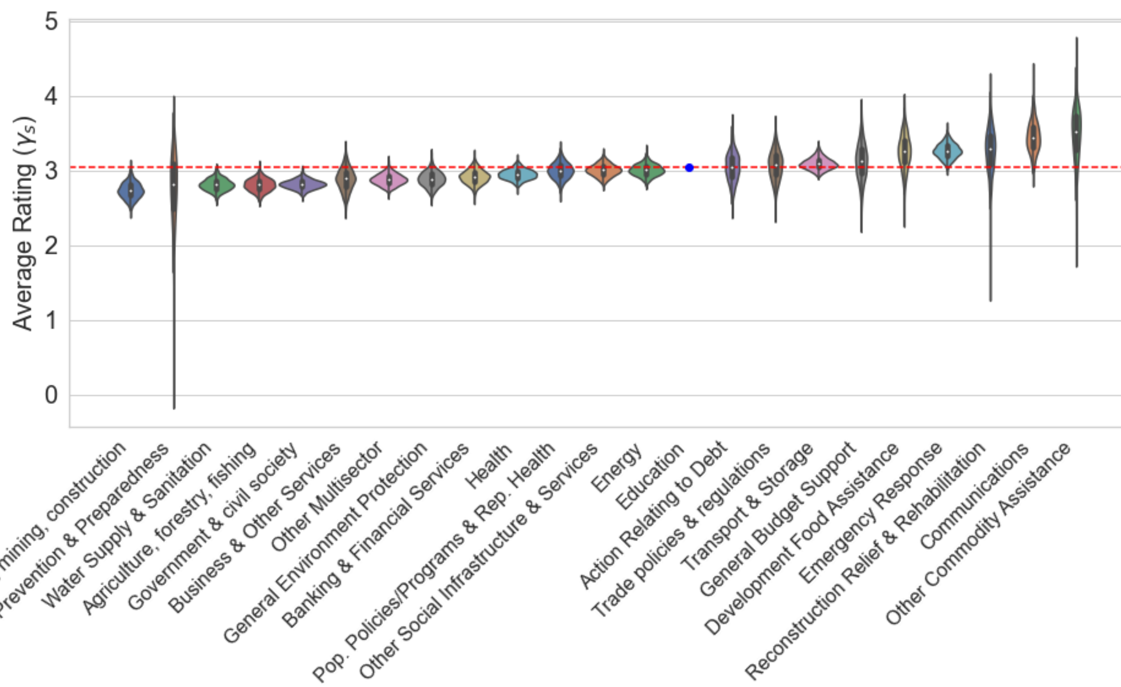


Figure B.2: Bootstrapped Estimates of Sectoral Monitoring Intensity

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.

B.2.2 Regression with Sectoral Monitoring Difficulty

I use OLS to estimate:

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

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.

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.

B.3 Robustness checks

B.3.1 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. 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 observed for DAC projects. For detailed methodology and estimation results, see Table B.3.

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.

The second-stage regression is the same as in the main text. In the first stage, I run the following regression:[9]

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

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:

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

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.

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.

B.3.2 Country- and Sectoral Level Panel Regression with China's share of DF inflows

Panel regression (country-level). Through panel regressions, I confirm that the positive correlation between China's share and recipient's corruption is not driven by specific years but consistent over time. 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 the percentage share of the value of Chinese DF used by recipient country r in year t. Like the cross-section regression, the corruption measure, $CORRUPT_r$, is averaged over the sample period.[10] FE_t denotes time fixed effects, and $\mathbf{X}_{rt}$ includes the same control variables as in the cross-country regression, measured annually instead of being averaged over the sample period.

Estimates in columns (1) and (2) of Panel (a) of Table B.4 show that a standard deviation increase in the corruption index is associated with a 6.3%p increase in the share of Chinese DF, slightly smaller than the cross-country estimate of 7.9%p. In columns (3) and (4), where the dependent variable is trimmed at 5% to exclude observations that heavily rely on either the DAC or Chinese DF, the results are qualitatively similar. The effect of a one standard deviation increase in corruption ranges from 8.6%p to 9.5%p, suggesting that the results are not driven by outliers where a recipient country relies exclusively on either Chinese or DAC DF.

Panel regression (sectoral level). To examine whether the country-level results are influenced by some sector-specific characteristics potentially correlated with corruption, I conduct a sectoral-level regression incorporating sector-year fixed effects. This approach helps isolate the relationship between corruption and China's share of total DF value at the sectoral level. I estimate the following panel regression:

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

$SHARE_{rst}^{CHN}$ represents China's percentage share of the total DF value used by recipient r in sector s in year t. FE_{st} is sector×year fixed effects that absorb any sector-year-specific effects on China's share. $\mathbf{X}_{rt}$ includes the same control variables as in the country-level regression. β quantifies the correlation between corruption and China's share at the sectoral level.

The results indicate a positive correlation between corruption and reliance on Chinese DF at the sectoral level. In columns (1) and (2) of Table B.4, I include all observations, while in columns (4) and (5) I trim the sample at the 5% level to exclude outliers. The findings suggest that a one standard deviation increase in corruption is associated with an approximate 1.1%p increase in China's share, varying slightly by specification. Although trimming the sample reduces its statistical significance due to a smaller sample size, the magnitude of the estimates remains consistent with the full sample. Despite the smaller effect sizes relative to the country-level estimates, these results confirm that the correlation between reliance on Chinese DF and corruption is pervasive across different sectors and not confined to a few.

B.3.3 Sectoral-level Regression with the DAC and Chinese DF Inflows

OLS and PPML (sectoral level) To confirm that the results at the country-level are not driven by certain sectors, I run OLS and PPML at the sectoral level, including sector fixed effects. The OLS

[10] Variance decomposition shows that within-country variation accounts for only 2% of the variance in the Corruption Perception Index (CPI), justifying the use of the average CPI.

Table B.4: Sectoral Corruption Effect on China's Share of Total DF Inflows

Panel (a) Country-level panel regression				
	Full sample		If $SHARE^{CHN}_{rt} \in (0,100)$	
	(1)	(2)	(3)	(4)
$CORRUPT_r$	0.575***	0.562***	0.778***	0.864***
	(0.157)	(0.154)	(0.177)	(0.182)
	(0.157)	(0.154)	(0.188)	(0.179)
Observations	1960	1960	939	939
R^2	0.184	0.234	0.219	0.247
Year FE & Recipient controls	✓	✓	✓	✓
Recipient×Donor controls		✓		✓

Panel (b) Sectoral level panel regression				
	Full sample		If $SHARE^{CHN}_{rt} \in (0,100)$	
	(1)	(2)	(3)	(4)
$CORRUPT_r$	0.130***	0.108**	0.093	0.137
	(0.048)	(0.041)	(0.106)	(0.090)
Observations	34548	34548	2064	2064
R^2	0.022	0.027	0.035	0.045
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.

specifications are:

$$\ln(1 + DF_{rdst}) = FE_{dst} + \beta_{DAC} \cdot \ln CORRUPT_r + \mathbf{X}_{rdt} \cdot \gamma_{DAC} + constant_{DAC} + \epsilon_{rdst} \tag{6}$$

$$\ln(1 + DF_{rCst}) = FE_{st} + \beta_{CHN} \cdot \ln CORRUPT_r + \mathbf{X}_{rt} \cdot \gamma_{CHN} + constant_{CHN} + \epsilon_{rCst}. \tag{7}$$

DF_{rdst} represents the value of total commitment for recipient country r by donor d in sector s for year t. FE_{dst} is donor×sector×year fixed effects, and the other predictors are the same as in the country-level regressions. The PPML counterparts are similarly defined, with the right-hand sides of the OLS specifications being the exponent of e.

Panel (b) of Table B.5 shows that the country-level results are confirmed at the sectoral level, both qualitatively and quantitatively. Columns (1)-(4) indicate that the estimates of the corruption effect on the DAC DF are similar to those at the country level, both in terms of signs and magnitudes. Columns (5)-(8) report the estimates for Chinese DF. The PPML estimates are consistent with those at the country level, with values ranging from 2.28 to 3.13. Although the OLS estimates are smaller in magnitude than those at the country level, they are still positively estimated.

Table B.5: Aggregate Effect of Corruption on Total DF Inflows

Panel (a) Country-level analysis								
	DAC DF				Chinese DF			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln $CORRUPT_r$	-1.442**	-1.524*	-0.860*	-0.871	4.187	4.161	2.345**	3.195***
	(0.634)	(0.781)	(0.442)	(0.568)	(3.855)	(3.947)	(1.137)	(1.059)
Observations	88768	53704	74916	47878	2134	1964	2134	1964
R^2	0.572	0.633	0.6243	0.6887	0.338	0.460	0.4613	0.5299
Model	OLS	OLS	PPML	PPML	OLS	OLS	PPML	PPML
Donor×Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Recipient controls	✓	✓	✓	✓	✓	✓	✓	✓
Recipient×Donor controls		✓		✓		✓		✓
Panel (b) Sectoral level analysis								
	DAC DF				Chinese DF			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln $CORRUPT_r$	-1.035***	-1.024***	-0.893	-0.890	1.013	0.733	2.267*	3.131***
	(0.247)	(0.301)	(0.612)	(0.570)	(0.612)	(0.560)	(1.223)	(1.099)
Observations	1495040	1074080	1028826	788023	44472	40890	38271	34988
R^2	0.412	0.460	0.5150	0.5726	0.154	0.162	0.4597	0.4949
Model	OLS	OLS	PPML	PPML	OLS	OLS	PPML	PPML
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.

B.3.4 Count Regression at the Sectoral Level

Count of DF projects. To investigate the corruption effect on the count of DF projects, I replace the log of total DF value with the total count of DF projects by each donor in each year as the dependent variable in the country- and sectoral-level OLS regressions (Equations (1), (2), (5), and (6) in Section 3.1.2). Table B.6 shows that higher corruption is significantly negatively correlated with the count of DAC projects at both the country and sectoral levels, while it is marginally positively correlated with Chinese projects. Columns (1) and (2) in Panels (a) and (b) reveal that a 1% increase in the corruption index is associated with approximately 9.4 fewer DAC projects at the country level and 0.45 fewer projects at the sectoral level. Conversely, columns (3) and (4) in Panels (a) and (b) suggest that a 1% increase in corruption leads to roughly 1.5 to 3.1 additional Chinese projects at the country level, and 0.08 to 0.15 more projects at the sectoral level, although these results lack statistical significance. Given that many Chinese projects are not reported in international statistics, and considering that more corrupt countries are less likely to transparently disclose their projects, the estimates are likely biased downward.

Table B.6: Corruption Effect on DF Project Sizes

(a) Country-level regressions				
	DAC projects		Chinese projects	
	(1)	(2)	(3)	(4)
ln $CORRUPT_{r(i)}$	-9.722***	-9.345**	3.109	1.549
	(2.515)	(4.252)	(2.132)	(1.767)
Observations	88768	53704	2336	2149
R^2	0.385	0.462	0.323	0.387
Fixed Effects	Donor×Sector×Year	Donor×Sector×Year	Sector×Year	Sector×Year
Loan dummy & recipient controls	✓	✓	✓	✓
Recipient×Donor controls		✓		✓

(b) Sectoral level regressions				
	DAC projects		Chinese projects	
	(1)	(2)	(3)	(4)
ln $CORRUPT_{r(i)}$	-0.530***	-0.445**	0.152	0.076
	(0.144)	(0.209)	(0.105)	(0.088)
Observations	1495040	1074080	46720	42980
R^2	0.261	0.288	0.300	0.314
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.

B.3.5 Additional Robustness Checks

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.7 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.8 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 difficulty for straightforward interpretation. Table B.9 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 difficulty for DAC projects might be capturing the interaction effects of sectoral monitoring difficulty 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.10 shows that in all specifications, the interaction effect of corruption is significantly positive. Table B.11 reports the coefficients of all placebo interaction terms.

Direct measure of diversion 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 diversion motives play a significant role, I use the Public Corruption Index and the Executive Corruption Index from V-Democracy. These indices specifically measure the prevalence of expropriation 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.12 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.13 reports the results, indicating that the main findings are qualitatively unaffected.

Table B.7

	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.8

	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.9

	Binary (=1 if ≤ Q1)	Binary (=1 if ≤ Q2)	Continuous (-1 × 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.10

	(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.11

	(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.12

	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.13

	(1)	(2)	(3)	(4)
	Log project size	$SHARE_{rst}^{CHN}$	Total amount	$SHARE_{rt}^{CHN}$
(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.

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

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. □

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. □

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 $\tilde{\pi}^p_{s,j,t}$. □

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 $s \in S^{\tilde{C}\tilde{D}}$. $\square$

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:

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

where

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

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

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

and the other financing-specific factors are:

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

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

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 $g^{E*}_{s,j,t+1} = (\theta_{s,j}\gamma\gamma_s Y_{t+1}/\tilde{R}^p_s)^{\sigma_s}(G^E_{s,t+1})^{1-\sigma_s}$. 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. $\square$

C.8 Proof of Proposition 4

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

□

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 $\tilde{f}^G_s \equiv \frac{f^G_s}{1+(\sigma-1)\frac{R^D_s}{\Psi^D_s \tilde{R}^D_s}}$. The expected size of grant-financed projects is

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

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

$$
\begin{aligned}
&\mathbb{E}\Big[g^O_{s,j,t}\Big|\bar{\theta}^G_{s,t} \le \theta_j \le \bar{\theta}^D_{s,t}\Big] \\
&\quad = \mathbb{E}\Big[\mathbb{E}\Big[g^O_{s,j,t}\Big|\bar{\theta}^G_{s,t} \le \theta_j \le \bar{\theta}^D_{s,t}, Y_t, G^E_{s,t}\Big]\Big] \quad \text{(by Law of Iterated Expectation)} \\
&\quad = \mathbb{E}\Big[\mathbb{E}\Big[\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}\Big|\bar{\theta}^G_{s,t} \le \theta_j \le \bar{\theta}^D_{s,t}, Y_t, G^E_{s,t}\Big]\Big] \\
&\quad = \mathbb{E}\Big[\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}\Big[\theta^\sigma\Big|\bar{\theta}^G_{s,t} \le \theta_j \le \bar{\theta}^D_{s,t}, Y_t, G^E_{s,t}\Big]\Big] \\
&\quad = \mathbb{E}\Big[\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\Big] \\
&\quad = \mathbb{E}\Big[\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)\Big] \\
&\quad = \mathbb{E}\Big[\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^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)}\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{(\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}}}\Big] \\
&\quad = \mathbb{E}\Big[\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}}}\Big] \\
&\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 $s \in \{S^D, S^{\tilde{D}}\}$

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

(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} \le \theta_j \le \bar{\theta}^I_{s,t}\Big] \\
&\quad= \mathbb{E}\Big[\mathbb{E}\Big[g^O_{s,j,t}\Big|\bar{\theta}^D_{s,t} \le \theta_j \le \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}}\Big(\frac{(\tilde{R}^C_s)^{\sigma-1}}{(\tilde{R}^D_s)^{\sigma-1}-(\tilde{R}^C_s)^{\sigma-1}}\Big)^{\frac{\sigma-\xi_s}{\sigma}}}{(f^D_s)^{\frac{-\xi_s}{\sigma}} - (f^C_s - f^D_s)^{\frac{-\xi_s}{\sigma}}\Big(\frac{(\tilde{R}^C_s)^{\sigma-1}}{(\tilde{R}^D_s)^{\sigma-1}-(\tilde{R}^C_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^D_s)^{\frac{\sigma-\xi_s}{\sigma}} - (f^C_s - f^D_s)^{\frac{\sigma-\xi_s}{\sigma}}\Big(\frac{(\tilde{R}^C_s)^{\sigma-1}}{(\tilde{R}^D_s)^{\sigma-1}-(\tilde{R}^C_s)^{\sigma-1}}\Big)^{\frac{\sigma-\xi_s}{\sigma}}}{(f^D_s)^{\frac{-\xi_s}{\sigma}} - (f^C_s - f^D_s)^{\frac{-\xi_s}{\sigma}}\Big(\frac{(\tilde{R}^C_s)^{\sigma-1}}{(\tilde{R}^D_s)^{\sigma-1}-(\tilde{R}^C_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^D_s)^{\frac{\sigma-\xi_s}{\sigma}} - (f^C_s - f^D_s)^{\frac{\sigma-\xi_s}{\sigma}}\Big(\frac{(\tilde{R}^C_s)^{\sigma-1}}{(\tilde{R}^D_s)^{\sigma-1}-(\tilde{R}^C_s)^{\sigma-1}}\Big)^{\frac{\sigma-\xi_s}{\sigma}}}{(f^D_s)^{\frac{-\xi_s}{\sigma}} - (f^C_s - f^D_s)^{\frac{-\xi_s}{\sigma}}\Big(\frac{(\tilde{R}^C_s)^{\sigma-1}}{(\tilde{R}^D_s)^{\sigma-1}-(\tilde{R}^C_s)^{\sigma-1}}\Big)^{\frac{-\xi_s}{\sigma}}}
\end{aligned}
$$

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

$$\mathbb{E}\left[g^O_{s,j,t}\middle|\bar{\theta}^I_{s,t} \le \theta_j\right]$$

$$= \mathbb{E}\left[\mathbb{E}\left[g^O_{s,j,t}\middle|\bar{\theta}^I_{s,t} \le \theta_j, Y_t, G^E_{s,t}\right]\right] \quad \text{(by Law of Iterated Expectation)}$$

$$= \mathbb{E}\left[\frac{1}{\Psi^D_s}(\frac{\gamma\gamma_s Y_t}{\tilde{R}^D_s})^\sigma (G^E_{s,t})^{1-\sigma}\int_{\bar{\theta}^I_{s,t}}^\infty \theta^\sigma \frac{h(\theta)}{H(\infty) - H(\bar{\theta}^I_{s,t})}d\theta\right]$$

$$= \mathbb{E}\left[\frac{1}{\Psi^D_s}(\frac{\gamma\gamma_s Y_t}{\tilde{R}^D_s})^\sigma (G^E_{s,t})^{1-\sigma}\frac{\xi_s \underline{\theta}^{\xi_s}}{\xi_s - \sigma}\frac{1}{\underline{\theta}^{\xi_s}}\frac{1}{(\bar{\theta}^I_{s,t})^{-\xi_s}}\left((\bar{\theta}^I_{s,t})^{\sigma-\xi_s}\right)\right]$$

$$= \mathbb{E}\left[\frac{1}{\Psi^D_s}(\frac{\gamma\gamma_s Y_t}{\tilde{R}^D_s})^\sigma (G^E_{s,t})^{1-\sigma}\frac{\xi_s}{\xi_s - \sigma}\left(\frac{((\sigma-1)(f^D_s - f^C_s))^{1/\sigma}}{\gamma\gamma_s Y_t}(G^E_{s,t}\tilde{R}^D_s \tilde{R}^C_s)^{\frac{\sigma-1}{\sigma}}(\frac{1}{(\tilde{R}^C_s)^{\sigma-1} - (\tilde{R}^D_s)^{\sigma-1}})^{\frac{1}{\sigma}}\right)^\sigma\right]$$

$$= \mathbb{E}\left[\frac{1}{\Psi^D_s}\frac{1}{\tilde{R}^D_s}\frac{\xi_s}{\xi_s - \sigma}(\sigma-1)(f^D_s - f^C_s)\frac{(\tilde{R}^C_s)^{\sigma-1}}{(\tilde{R}^C_s)^{\sigma-1} - (\tilde{R}^D_s)^{\sigma-1}}\right]$$

$$= \mathbb{E}\left[\frac{\xi_s(\sigma-1)}{\Psi^D_s \tilde{R}^D_s(\xi_s - \sigma)}(f^D_s - f^C_s)\frac{(\tilde{R}^C_s)^{\sigma-1}}{(\tilde{R}^C_s)^{\sigma-1} - (\tilde{R}^D_s)^{\sigma-1}}\right]$$

$$= \frac{\xi_s(\sigma-1)}{\Psi^D_s \tilde{R}^D_s(\xi_s - \sigma)}(f^D_s - f^C_s)\frac{(\tilde{R}^C_s)^{\sigma-1}}{(\tilde{R}^C_s)^{\sigma-1} - (\tilde{R}^D_s)^{\sigma-1}}$$

C.9.3 Chinese loans

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

$$\mathbb{E}\left[g^O_{s,j,t}\middle|\bar{\theta}^C_{s,t} \le \theta_j\right] = \mathbb{E}\left[\mathbb{E}\left[g^O_{s,j,t}\middle|\bar{\theta}^C_{s,t} \le \theta_j, Y_t, G^E_{s,t}\right]\right] \quad \text{(by Law of Iterated Expectation)}$$

$$= \mathbb{E}\left[\mathbb{E}\left[\frac{1}{\Psi^C_s}(\frac{\theta_j\gamma\gamma_s Y_t}{\tilde{R}^C_s})^\sigma (G^E_{s,t})^{1-\sigma}\middle|\bar{\theta}^C_{s,t} \le \theta_j, Y_t, G^E_{s,t}\right]\right]$$

$$= \mathbb{E}\left[\frac{1}{\Psi^C_s}(\frac{\gamma\gamma_s Y_t}{\tilde{R}^C_s})^\sigma (G^E_{s,t})^{1-\sigma}\mathbb{E}\left[\theta^\sigma\middle|\bar{\theta}^C_{s,t} \le \theta_j, Y_t, G^E_{s,t}\right]\right]$$

$$= \mathbb{E}\left[\frac{1}{\Psi^C_s}(\frac{\gamma\gamma_s Y_t}{\tilde{R}^C_s})^\sigma (G^E_{s,t})^{1-\sigma}\int_{\bar{\theta}^C_{s,t}}^\infty \theta^\sigma \frac{h(\theta)}{H(\infty) - H(\bar{\theta}^C_{s,t})}d\theta\right]$$

$$= \mathbb{E}\left[\frac{1}{\Psi^C_s}(\frac{\gamma\gamma_s Y_t}{\tilde{R}^C_s})^\sigma (G^E_{s,t})^{1-\sigma}\frac{\xi_s \underline{\theta}^{\xi_s}}{\xi_s - \sigma}\frac{(\bar{\theta}^C_{s,t})^{\xi_s}}{\underline{\theta}^{\xi_s}}\left((\bar{\theta}^C_{s,t})^{\sigma-\xi_s}\right)\right]$$

$$= \mathbb{E}\left[\frac{1}{\Psi^C_s}(\frac{\gamma\gamma_s Y_t}{\tilde{R}^C_s})^\sigma (G^E_{s,t})^{1-\sigma}\frac{\xi_s}{\xi_s - \sigma}\left(\frac{\left((\sigma-1)f^C_s\right)^{1/\sigma}}{\gamma\gamma_s Y_t}(G^E_{s,t}\tilde{R}^C_s)^{\frac{\sigma-1}{\sigma}}\right)^\sigma\right]$$

$$= \mathbb{E}\left[\frac{1}{\Psi^C_s}\frac{1}{\tilde{R}^C_s}\frac{\xi_s}{\xi_s - \sigma}(\sigma-1)f^C_s\right]$$

$$= \mathbb{E}\left[\frac{\xi_s(\sigma-1)}{\Psi^C_s \tilde{R}^C_s(\xi_s - \sigma)}f^C_s\right]$$

$$= \frac{\xi_s(\sigma-1)}{\Psi^C_s \tilde{R}^C_s(\xi_s - \sigma)}f^C_s$$

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

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

□

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:

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

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} \\
&\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}} \\
&- (\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}} \\
&+ (\tilde{R}_s^C)^{1-\sigma}(f_s^C)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}_s^C)^{\frac{(\sigma-1)(\sigma-\xi)}{\sigma}} \\
&- (\tilde{R}_s^D)^{1-\sigma}(f_s^C)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}_s^C)^{\frac{(\sigma-1)(\sigma-\xi)}{\sigma}} \\
&+ (\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} \\
&\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}} \\
&+ ((\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}} \\
&+ (\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} \\
&\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}} \\
&+ ((\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}} \\
&+ (\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} \\
&\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}} \\
&+ (\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}
\Big[\int (\tilde{R}_s^p)^{1-\sigma}\theta^{\sigma-\xi-1}d\theta\Big]^{\frac{\sigma}{\sigma-1}} &= \Big[\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\Big]^{\frac{\sigma}{\sigma-1}} \\
&= \Big[\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\Big]^{\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^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}} \\
&\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 + (\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^C)^{1-\sigma}-(\tilde{R}_s^D)^{1-\sigma})^{\frac{\xi}{\sigma}}(f_s^C-f_s^D)^{\frac{\sigma-\xi}{\sigma}} \\
&\quad + (\tilde{f}_s^G)^{\frac{\sigma-\xi}{\sigma}}(\tilde{R}_s^D)^{\frac{(1-\sigma)\xi}{\sigma}}\Bigg]^{\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,

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

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,

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

E Supplementary Material 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).[11] 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:

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

[11] 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 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.

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:

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

Table E.2: 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**

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,

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

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 6.

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:

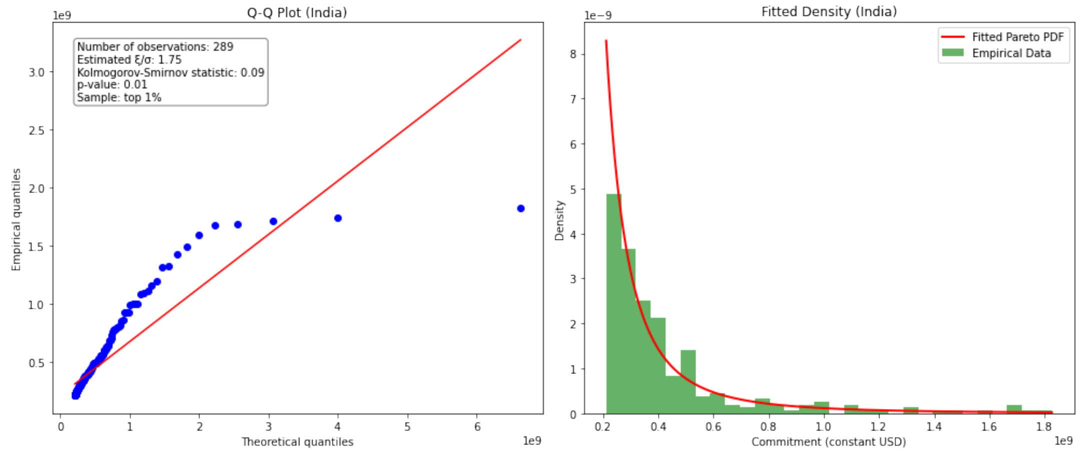
$$f_r(x) = \frac{\frac{\xi_r}{\sigma}\left(\left[\sum_{p,s,t} w_{r,s,p,t} \cdot \underline{\theta}_{r,s,p,t}\right]^{\frac{\sigma}{\xi_r}}\right)^{\frac{\xi_r}{\sigma}}}{x^{\frac{\xi_r}{\sigma}+1}},$$

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:

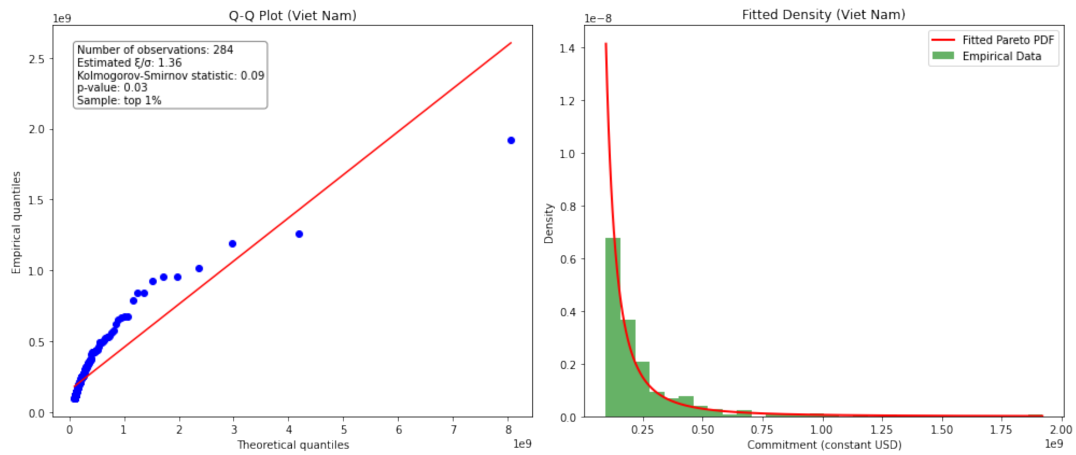
$$log\mathcal{L}(\frac{\xi_r}{\sigma}, \tilde{\theta}_r) = \sum_{i=1}^{N_r} log f_r(x_i; \frac{\xi_r}{\sigma}, \tilde{\theta}_r).$$

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).

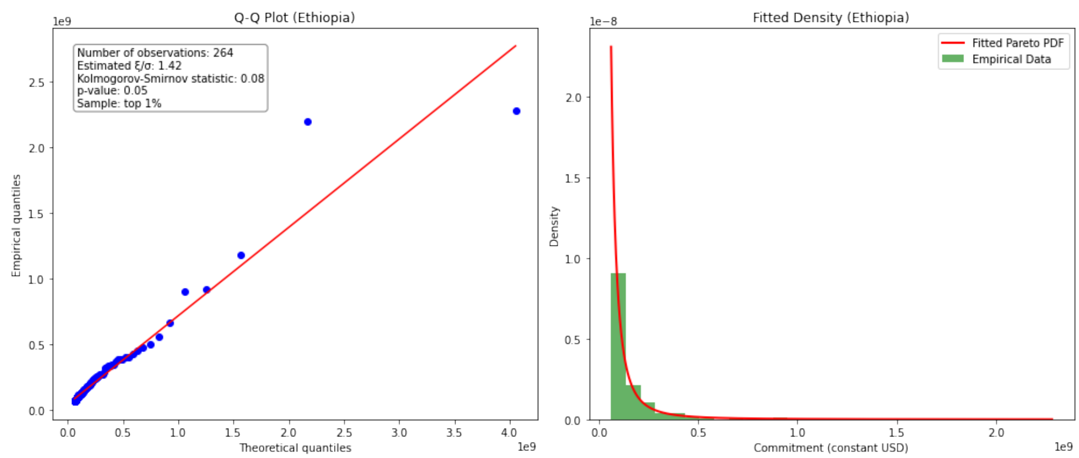
My model faces the same issue, as it requires $\xi_r > \sigma$ and that the estimated value for $\xi_r > \sigma$ be greater than 1. Therefore, I take a similar approach to Head et al. (2014) by fitting the right tail of the distribution. For each recipient, I fit the top 1 percent of samples and estimate 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: QQ Plot and Fitted Density of Selected Economies

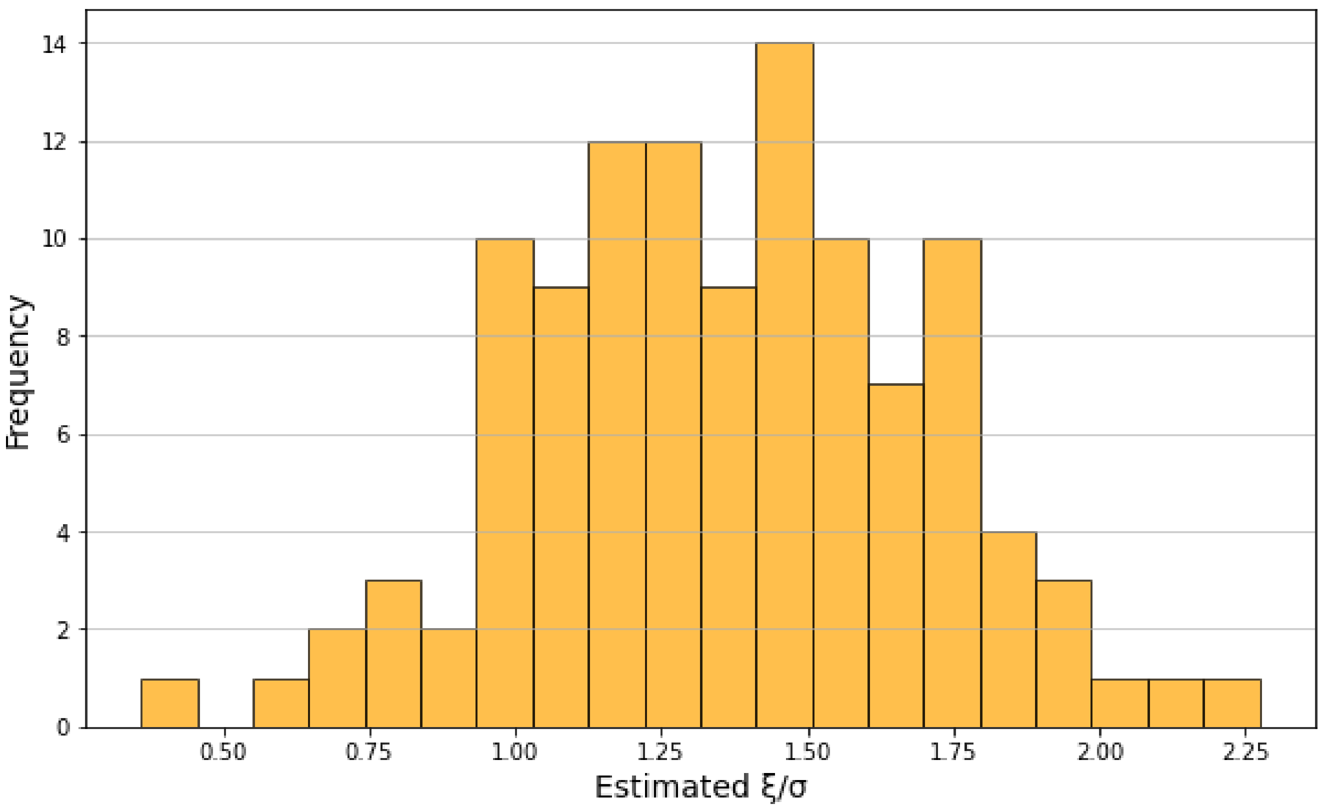


Figure E.2: Histogram of Estimated ξ/σ