The Geopolitics of Debt Sustainability Analysis

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Abstract

Debt crises in developing countries are becoming increasingly prominent. To promote sustainable sovereign borrowing and lending, the International Monetary Fund and the World Bank jointly assess countries' debt risks and issue Debt Sustainability Analysis (DSA). Since its introduction in 2005, the DSA framework has become a cornerstone of sovereign lending and borrowing, guiding both public and private lending practices. Although the DSA's stated goal is to provide technical assessments, we find that geopolitical dynamics systematically influence the content of DSA reports. Using an original dataset of over 1,013 DSAs for low-income countries from 2005 to 2024, we show that countries politically aligned with the United States tend to receive more favorable risk ratings, more positive text, and more optimistic debt forecasts, relative to their economic fundamentals. In contrast, countries aligned with China receive less favorable risk ratings and more pessimistic debt forecasts. Our findings highlight the geopolitical influence on international financial institutions and the tensions between great powers in sovereign financing.

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1 Introduction

A developing country debt crisis is looming. According to the International Monetary Fund (IMF), 56% of low-income countries and 25% of emerging markets are “in or at high levels of debt distress”[1]. Low-income countries (LICs) paid $443.5 billion in debt interest and principal in 2022; that amount is expected to rise by 40% in 2024, reaching above 95% of global GDP[2]. Debt crises impose severe costs on domestic societies. As governments redirect resources toward debt repayment, spending on health, education, and other public services is curtailed. Economic activity contracts, unemployment rises, and vulnerable populations disproportionately shoulder the burden of adjustment, thereby exacerbating existing inequalities.

International financial institutions (IFIs) – mainly the IMF and the Word Bank – play an important role in the resolution of debt crises. They analyze a country’s macroeconomic conditions and assess debt sustainability, offer additional funds to borrowers facing liquidity crises, help creditors coordinate, and catalyze further lending[3]. Some observers view these IFIs as largely independent agents, attempting to solve technocratic problems of macroeconomic balance and debt sustainability. Others, however, find that their major shareholders (the U.S., Western European countries, Japan, and now rising China) significantly influence their decisions, leading to differences in treatment of debtor countries .[4]

This study investigates the ways in which the IMF and World Bank’s debt sustainability analysis (DSA) is the result of politics as well as economics. Since its introduction in 2005, the DSA framework has become a cornerstone of sovereign lending and borrowing; the risk assessment from the DSA informs the IMF’s lending policies, as well as shapes broader international efforts for debt restructuring. The DSAs aim to provide technical assistance

[1] International Monetary Fund, 2023.
[2] World Bank, 2023.
[3] Asonuma and Trebesch, 2016.
[4] Clark and Dolan, 2021; Copelovitch, 2010; Dreher et al., 2022; Lang and Presbitero, 2018; Stone, 2011.

to low- and middle-income countries, helping countries align their need for funds with their current and prospective ability to service their debt. However, using an original dataset of over 1,013 DSAs for LICs between 2005 and 2024, we find that geopolitical dynamics around the U.S. and China exert systemic bias on the contents of DSAs: Countries that are politically aligned with the U.S. tend to receive more favorable risk ratings, more positive text, and more optimistic debt forecasts, relative to their economic fundamentals. In contrast, countries aligned with China receive less favorable risk ratings and more pessimistic debt forecasts, relative to their fundamentals.

This study makes three contributions to important literatures. First, it offers both theoretical and empirical contributions to the sovereign debt literature. By examining the political influence in the construction of DSAs through a new dataset, the study not only highlights geopolitical factors but also identifies potential bottlenecks and challenges that emerge during debt restructuring and resolution. Second, it contributes to the political economy of international organizations by demonstrating the influence of major powers over IFIs' ostensibly technocratic tasks. While geopolitical influence on IFIs' loan programs is widely recognized, there has been less attention to potential bias in the regular reports IFIs publish. Our findings reveal systemic political bias even in these routine reports filled with technocratic tasks, further demonstrating the geopolitical influence at play. Lastly, while previous studies have primarily focused on how IFIs extend favorable treatment to countries aligned with traditional Western powers, our analysis shows that IFIs also systematically disadvantage countries that are closer to China, highlighting how emerging geopolitical rivalries shape the behavior of international organizations.

2 DSAs: What are they? How are they produced?

Debt crises often come in waves, driven not only by earlier decisions to borrow, but also by external factors such as rising global interest rates or falling commodity prices – phenomena beyond the control of LIC[5]. LICs are often unable to escape the cycle of borrowing, distress, crisis, restructuring, and borrowing again. To help low- and middle-income countries be on more sustainable debt cycles, the IMF and the World Bank jointly introduced a DSA framework in 2005. Country team staff from the IMF and the World Bank jointly conduct DSA under this framework, which requires approval from the executive boards from both organizations. The stated aim of the framework is to "to guide the borrowing decisions of low-income countries in a way that matches their financing needs with their ability to repay now and in the future"[6]

Since its introduction, the DSF has gone through several revisions but follows a common approach. First, countries are classified as having weak, medium, or strong "debt-carrying capacity" based on their macroeconomic prospects. Next, IMF and World Bank staff forecast debt levels and economic growth, and assess whether the present value of debt (as a share of GDP) exceeds pre-set thresholds tied to the country's debt-carrying capacity. For example, the benchmark is 55% debt to GDP ratio for "strong" countries and 30% for "weak" countries. Because future growth is uncertain, staff run tests under both optimistic and pessimistic scenarios. Based on these exercises, each country is assigned one of four debt risk ratings: (1) low risk (no thresholds breached), (2) moderate risk (thresholds breached only under stress scenarios), (3) high risk (thresholds breached even in the baseline), or (4) in debt distress (arrears or restructuring has occurred or is imminent).[7] Because debt sustainability forecasts inherently rely on assumptions and are subject to uncertainty, IMF and World Bank staff retain discretion to adjust the final risk classification, particularly when threshold breaches are minor or borderline.[8] While DSAs are not directly tied to staff career incentives, this discretionary space nonetheless creates the potential for unconscious bias or subjective judgment to shape outcomes.

[5]Reinhart et al., 2016; Rey, 2013.

[6]IMF official website. Accessible at: https://www.imf.org/en/About/Factsheets/Sheets/2023/imf-world-bank-debt-sustainability-framework-for-low-income-countries.

[7]The latest version of DSF methodology is available here (*Last accessed on Sep 26, 2025*).

[8]IMF, 2013; Lang and Presbitero, 2018.

Debt sustainability analyses (DSAs) serve three main audiences: IMF and World Bank staff, donors and creditors including multilateral agencies and private investors, and the authorities of LICs themselves. The IMF and World Bank use DSAs as an "early warning system" to signal any debt distress risks, and to provide policy advice on preventative actions.[9] They are also integral to IMF program evaluation. For example, every Article IV evaluations require a DSA, and DSAs are central to the debt relief efforts under the Highly Indebted Poor Countries (HIPC) program. Furthermore, DSAs inform policies at the Fund and IDA that may limit a country's debt accumulation. The IDA, for instance, allocates grants and credits based on DSA results to mitigate the risk of distress. Other multilateral creditors, such as the African Development Bank, the Asian Development Bank and the Inter-American Development Bank adopt similar approaches based on DSAs. DSAs also guide private creditor's lending behavior. When DSAs flag high risk, sovereign bond spreads widen, implying that investors adjust pricing or demand higher risk premia.[10] Credit rating agencies such as Moody's frequently cite and incorporate DSA ratings as justification for downgrades or outlook changes. In recent years, the DSA for LICs has become even more significant due to rising financing needs driven by geopolitical instability and uncertainties, as well as an increased dependence on non-traditional official creditors and international private capital markets, exposing countries to new risks.

The central role of DSAs in shaping both public and private lending decisions creates strong incentives for low-income country (LIC) authorities to influence their outcomes. Although the IMF and World Bank conduct DSA analyses, they rely heavily on national authorities for macroeconomic statistics, including government revenue and growth. Evidence suggests that LIC governments sometimes conceal debt in order to secure more favorable DSA assessments.[11] The effectiveness of such efforts, however, may vary: some LICs are better positioned to obtain favorable DSAs, particularly when they enjoy close ties with

[9]IMF, 2013.
[10]Lang and Presbitero, 2018.
[11]Brown, 2025.

IFI's major shareholders.

There is emerging scholarly interest in DSAs, mostly focusing on whether the DSAs are accurately reflective of the country's economic fundamentals. Mooney and De Soyres (2017), published by the IMF, provides the first assessment of the DSA's performance. Using DSAs for LICs from 2005 to 2015, it reports that countries with high incomes, good prospects for market access and at 'moderate' risk of debt distress face systematic higher levels of optimism, mostly driven by favorable fiscal projections. Gaudin et al. (2024) focuses on recent 605 DSAs from 2013 to 2024 to find forecast errors in DSAs. They report that larger economies get positive bias, mostly due to underestimation of primary deficits. Also, the study identifies institutional and structural factors influencing biases. For instance, countries with fragile governance or in conflict get more pessimistic forecasts for primary deficits and external debt, but overly optimistic growth projections.

In sum, previous studies overall find that DSAs do enjoy significant discretion from the IMF and WB staff despite their technical nature. Moreover, the bias not only stems from the country's economic structure or global economic conditions, but also the country's political institutions. We aim to extend the burgeoning literature by bringing in geopolitical dynamics.

3 Geopolitics of DSAs

Traditionally, delegation to a multilateral organizations has been thought to keep their staff insulated from the (geo-)political objectives of the member governments.[12] The influence of powerful states on lending practices of the various lending institutions is however abundant.[13] States receive more aid from the World Bank,[14] with fewer conditions,[15] and are

[12] Milner, 2006.

[13] Clark and Dolan, 2021; Copelovitch, 2010; Stone, 2008, 2011; J. Vreeland and Dreher, 2014; J. R. Vreeland, 2019.

[14] Andersen et al., 2006.

[15] Clark and Dolan, 2021.

disbursed faster,[16] if they are aligned with the U.S., or when they hold a temporary seat at, or vote with the U.S. on, the United Nations Security Council.[17][18] Similarly, Lim and Vreeland (2013) offer evidence of Japan's influence over the Asian Development Bank, while China's influence on the Asian Infrastructure and Investment Bank is explored in Kaya et al. (2021).

Geopolitical rivalry is reflected in sovereign debt landscape. Debt resolution for countries in distress is slowed when both western and Chinese lenders must agree on restructuring terms, each often insisting that the other bear the burden of haircuts for fear that any bailout will be used to finance outstanding obligations to their rival. China's presence as a creditor slows negotiations with the IMF over loan packages,[19] while Paris Club agreements are less likely when the debtor holds more Chinese-sourced debt.[20]

Pressure by geopolitical principals on the IO agents may not be explicit. Staff design programs – often implicitly – that are consistent with hegemonic preferences, whether because they wish to please their principals,[21] have bureaucratic incentives to maximize budgets (and not get overturned),[22] or they may have simply internalized a similar set of norms and views.[23]

The DSF combines an algorithmic process for establishing a rating for risk distress with the scope for staff judgment when country-specific circumstances warrant adjustment. Lang and Presbitero (2018) finds evidence of bureaucratic biases in this ratings, aligned with the geopolitical interests of the institutions' major shareholders. This dynamic reflects what Stone (2011) terms "informal governance." While the DSA process operates through formal channels, informal pressures permit the staff to, on occasion, shade their findings in the

[16] Kersting and Kilby, 2016.
[17] Dreher et al., 2015, 2022.
[18] For a recent challenge to this conventional wisdom, see (Copelovitch and Powers, 2021).
[19] Ferry and Zeitz, 2024.
[20] Ballard-Rosa et al., 2024.
[21] Clark and Dolan, 2021.
[22] Malis et al., 2023.
[23] Barnett and Finnemore, 1999.

interest of major players. Such influence, however, can only be exerted selectively – overuse will undermine the legitimacy of the IO, gained largely from its multilateral character.[24]

We build on Lang and Presbitero (2018) which analyzed 377 DSAs between 2006 and 2015, and employed the statistical models used at the time to recompute the technical risk rating and compared this with the actual rating reported; they find that countries aligned with major shareholders receive better ratings relative to the mechanical model predictions, especially in election years. We extend this analysis to the full set of over 1,000 DSAs between 2005 and 2024, and we additionally explore the effect of geopolitical alignment on the sentiment expressed in the text of the DSAs, as well as the effect on the predictions made in the DSAs on GDP and the debt to GDP ratios. Like Gaudin et al. (2024) we find frequent over-optimism in the forecasts; here we show that the degree of optimism is correlated with a country's geopolitical alignment.

Hypothesis 1: Countries politically aligned with the U.S. receive more favorable DSAs (relative to fundamentals).

Hypothesis 2: Countries politically aligned with China receive less favorable DSAs (relative to fundamentals).

4 Empirical Strategy

To investigate the effect of major power's influence on DSA contents, we construct an original dataset of 1,013 DSAs for 78 LICs between 2005 and 2024.[25] We have scraped all the DSAs publicly available on the IMF website using a combination of ChatGPT and manual quality assurance. We focus exclusively on DSAs for LICs to ensure comparability across cases and to concentrate on instances where DSAs are particularly critical to borrowing and lending decisions.

[24] Lang and Presbitero, 2018; Malis et al., 2023; Stone, 2011.

[25] The data construction is still on-going. As of this writing, approximately 100 DSAs remain to be coded (2014-2021).

The sample is unbalanced panel: Most countries get one DSA per one year, but some get multiple DSAs in one year, especially when they are under an IMF program which has to go through program reviews including DSAs every three months. Conversely, some countries may drop out of the sample in certain years due to disruptions in IMF engagement or when they graduate out of the LICs category. For instance, Lebanon did not have DSA in 2024 because the war in Israel and Gaza delayed the IMF engagement. To our knowledge, this is the most comprehensive dataset of DSAs assembled to date.

4.1 Dependent Variables: Ratings, Sentiment, and Forecasts

We measure bias in DSA contents in three ways: (1) risk rating, (2) text sentiment, and (3) forecast errors. First, we focus on the overall risk rating reported in the DSA, arguably the most important and visible outcome from DSA. Every DSA presents a debt risk rating prominently on the first page of the report. The DSA categorizes countries into four levels of debt distress, to which we assign numerical values for analysis: 'in distress' (4), 'high risk' (3), 'moderate risk' (2), and 'low risk' (1). Figure 1 shows the distribution of each rating across DSAs over time.

To complement the categorical measure of rating, we introduce a second measure of bias based on the text sentiment of DSA reports. IMF and World Bank staff typically write tens of pages interpreting the technical outputs from statistical models, incorporating their own judgment and discretion. We analyze the overall sentiment of the text to capture potential biases that may not be fully reflected in the formal risk rating alone.

We measure the textual tone using FinBERT model, an adaption of the Bidirectional Encoder Representations from Transformers (BERT) architecture, specifically trained on financial text[26]. FinBERT is pre-trained using large amounts of financial texts, including earning conference call transcripts, analyst reports, and corporate statistics. Like other

[26] Yang et al., 2020.

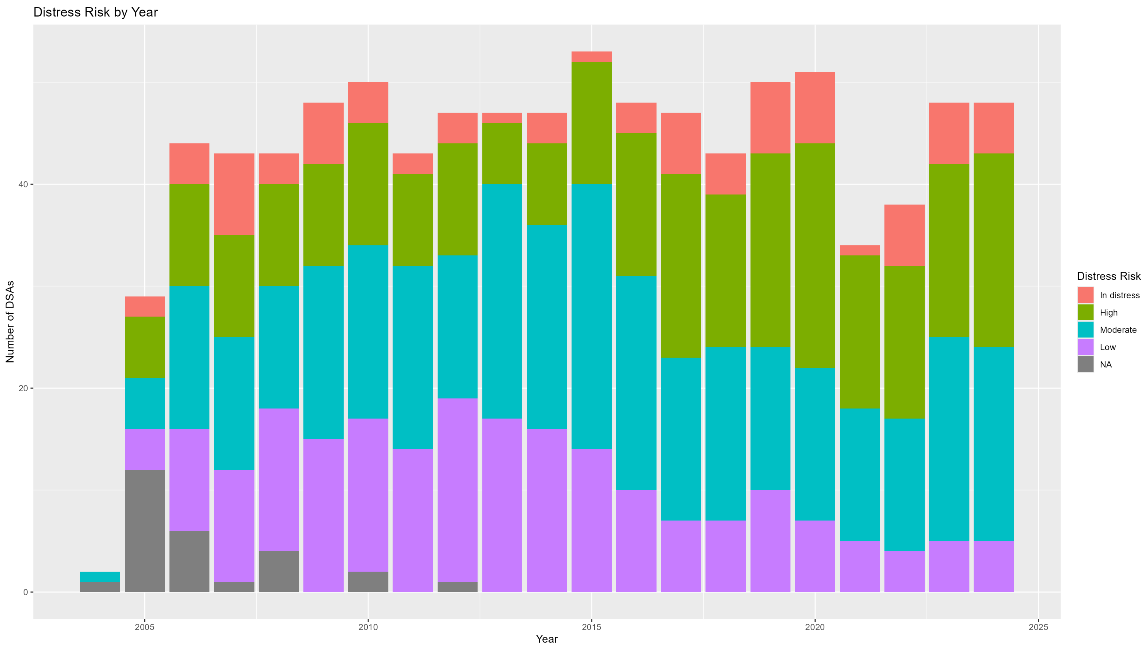

Figure 1: DSA ratings by year, 78 countries, 2005-2024

BERT models, it processes entire sentences simultaneously, rather than either left-to-right or right-to-left, allowing it to understand each word in relation to its surroundings. For example, instead of invariably taking 'debt' as a negative word, BERT models analyze surrounding words, such as 'decreasing levels', and generate a sentiment measure of the text as a whole. FinBERT can analyze upto 512-token (approximately 400 words) at once, an inherent limit to every BERT model. We employ FinBERT to measure an executive summary in each DSA report, most of which contain less than 512-token. Using FinBERT, we classify each DSA summary into one of three sentiment categories: positive, neutral, or negative.[27] In our dataset, 264 summaries (26%) are coded as positive, 401 summaries (39%) as neutral, and 348 summaries (34%) as negative. Figure 2 shows the overall text sentiment in DSA summaries over years. As expected, DSA texts tend to be more neutral and negative during global crises, including the 2007-08 Global Financial Crisis, and the 2020 Pandemic crisis.

Lastly, we operationalize bias in DSAs by calculating forecast errors. The categorical

[27]See examples of FinBERT coding in Appendix.

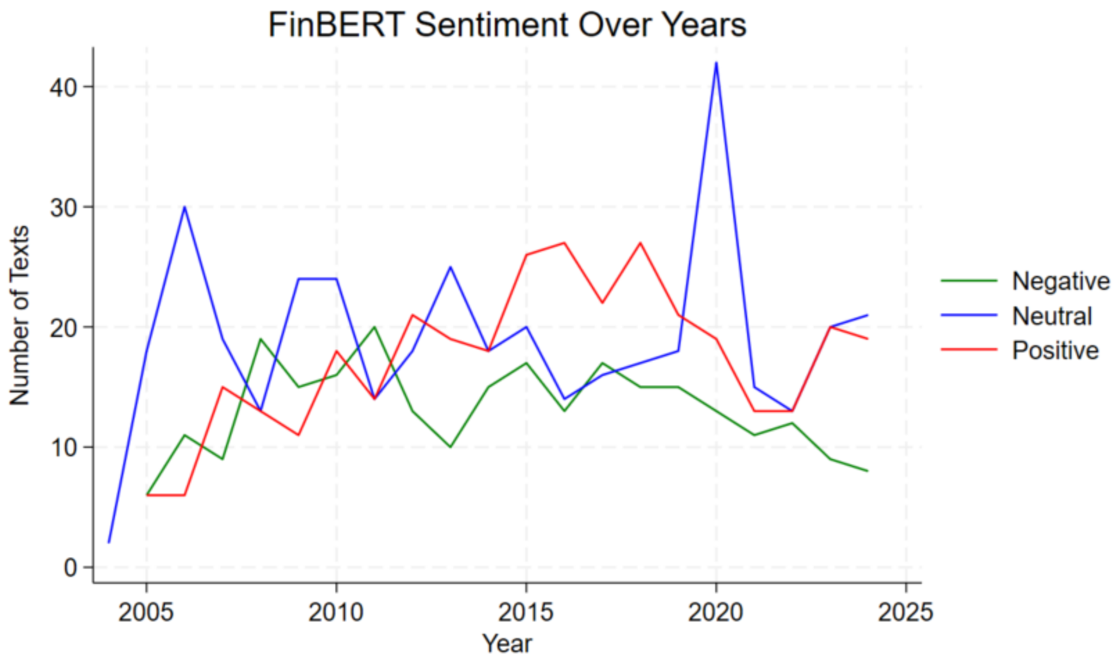

Figure 2: Text sentiment in DSAs, 78 countries, 2005-2024

debt risk evaluation is drawn from *predictions* of countries' fiscal sustainability based on their past performance. We scrape tables in DSAs which include detailed information on the predictions of each parameter and examine where the bias may arise by comparing the predicted values and realized values. Because each DSA predicts fiscal performance in future years, the unit of analysis is DSA-year. Calculation of forecast errors, however, is not as straightforward because economic indicators in LICs are prone to revisions when updated statistics become available or definitions/coverage changes.[28] This suggests that the difference between predicted values and realized values can be driven by both bias and the fact that they used different methods or data. Given that it is impossible to identify whether and when such revisions were made, we adopt two additional methods to tease out forecast bias following approaches by Mooney and De Soyres (2017). The following

[28] Mooney and De Soyres, 2017.

equations show how three methods calculate forecast errors (FE) for an indicator X:

$$
\begin{aligned}
FE_A =& X_t - X'_t \\
FE_B =& (X_t - X_D) - \left(X'_t - X'_D\right) \\
FE_C =& \frac{X_t - X_D}{X_D} - \frac{X'_t - X'_D}{X'_D}
\end{aligned}
$$

where X_t denotes predicted value for year t published in the DSA and X'_t denotes the realized value for year t. D denotes the vantage point which is the publication year of DSA. X_D denotes the realized value for year D published in the DSA. X'_D denotes the realized value for year D published in the same year as X'_t. X_t and X_D are sourced from the DSAs while X'_t and X'_D are sourced from World Economic Outlook (WEO) or World Development Indicators (WDI). Method B is well-positioned to account for static revisions such as corrections of economic statistics of certain years, while Method C accounts for dynamic revisions such as coverage or calculation methods that could affect the following years. Both Method B and C address the revision concerns under the assumption that data published in the same source and year incorporates the same revisions. We show empirical results using all three methods for transparency.

4.2 Explanatory Variables: Geopolitical Alignment

Following the literature, we adopt two primary measures for a country's political alignment with great powers. First, we use United Nations General Assembly (UNGA) voting records to assess the similarity between a country's voting behavior and that of the United States (or China).[29] Second, we measure the (logged) amount of foreign aid a country receives from the US, assuming that countries systematically important to the US tends to receive more foreign aid from the US. The data for US foreign aid comes from the OECD's Creditor Reporting System (CRS). Similarly, to measure a country's importance to China, we use

[29] Bailey et al., 2017.

the (logged) amount of total aid projects from China in the country in a given year. The data for Chinese aid projects is from GODAD project.[30] All the explanatory variables are lagged by one year to account for reverse causality.

4.3 Control Variables

We control for different factors that might confound the relationship between our key explanatory variables and outcome measures. First, we control for a country's macroeconomic conditions that are important for debt sustainability analysis and that could potentially affect a country's relations with great powers. We include lagged measures of current account balance, external debt (% GDP), FDI inflows (% GDP), GDP growth rates, and total reserve (% external debt). These are the variables that go into the statistical models the IMF and the World Bank use to generate DSAs. Additionally, we control for a country's eligibility for the HIPC (Enhanced Heavily Indebted Poor Countries) initiatives as HIPC countries, by definition, have unsustainable levels of debt and may receive special attention from the WB and the IMF for their DSAs.

Second, we control for institutional-level reforms conducted on DSAs. The IMF and WB occasionally updated the DSA framework for better performance. By 2012, country authorities, donors, and staff within the IMF and World Bank had raised concerns about overly mechanical application of thresholds and limited flexibility in judgments about country-specific risks. Thus, the IMF and WB executed an overall reform for DSA framework in 2013 for more nuanced and flexibility. We control for the institutional changes by including a binary measure of reforms which take 1 for DSAs post-2013 and 0 otherwise. Similarly, in 2017, the IMF and WB responded to the evolving financing patterns for LICs — including increased reliance on non-concessional borrowing, market financing, and new creditors like China — by having a major overhaul of the DSA framework. The 2017 reform introduced a country-specific, risk-based approach, allowing for more flexibility and nuance. We include

[30] Bomprezzi et al., 2024.

another binary measure of reform which takes 1 for DSAs conducted in post-2017 period and 0 otherwise.

Lastly, we control for different regions, as previous studies identify systematic bias across regions. For example, Gaudin et al. (2024) finds that small islands suffer from a more pessimistic outlook compared to larger countries, while countries in the Sub-Saharan Africa region tend to be assessed with more optimism. We include regional fixed effects to capture such regional-level heterogeneity.

5 Results

Overall, our results provide robust evidence of geopolitical influence on DSAs. As we use three different outcome measures, we present the results for each in turn.

5.1 Risk rating analysis

Table 1 presents the results from ordinal logit regressions on DSA risk ratings. The unit of analysis is DSA-level. Recall that a higher rating indicates a less favorable assessment (i.e., 4 corresponds to "In Distress," while 1 corresponds to "Low Risk"). As expected, countries that are ideologically more distant from the U.S. receive higher (less favorable) risk ratings. Conversely, countries receiving greater amounts of U.S. foreign aid are associated with lower (more favorable) risk ratings. The pattern is reversed with respect to China: countries ideologically distant from China receive more favorable DSA ratings, while those receiving larger Chinese foreign aid receive less favorable risk assessments. The findings on Chinese aid are particularly interesting as they show that not all foreign assistance is treated equally in IMF/WB debt sustainability evaluations. Contrary to the common idea that larger aid flows improve debt outlook, greater Chinese aid is seen as a risk. These results suggest that the Bank and the Fund respond not only to a country's alignment with their major shareholder, the U.S., but also to its positioning in the broader geopolitical rivalry involving China.

All the controls show expected results: countries with positive current account balance, more FDI inflows, and higher GDP growth rates, and larger foreign reserve tend to get more favorable ratings, while countries with larger external debt get less favorable ratings. The 2017 reform appears to be critical as post-2017 DSAs are much more likely to include unfavorable risk ratings.

The results remain robust across a few robustness checks. First, we note that some countries may have multiple DSAs in a given year due to their participation in the IMF, which generates clustering. In such cases, the content of the DSAs produced within a year is largely repetitive. To avoid unnecessary clustering, we collapse multiple DSAs within the same year into a single observation by taking their average. In addition, we take into account a country's engagement with the World Bank and IMF programs. The Bank and the Fund might have institutional incentives to provide systematically different DSAs when a country is participating in their programs, while at the same time, taking part in these programs could reflect the country's relations with the U.S. and China. We include a (logged) amount of total World Bank commitments in a country in a given year as well as a binary measure of IMF participation. The results indicate that increased amount of World Bank financing is associated with better DSA ratings, while IMF program participation is linked with worse DSA ratings. All of the results regarding geopolitical relations remain substantively the same with countries politically closer to the U.S. and recipients of U.S. foreign aid get better DSA ratings, while increased Chinese financing is associated with worse ratings (See Table 9 in Appendix.).

Table 1: Geopolitical bias and risk ratings in DSAs

DV: Distress risk (1 low, 2 moderate, 3 high, 4 in distress)	(1)	(2)	(3)	(4)
l. Current account balance	-0.0335***	-0.0227***	-0.0323***	-0.0349**
	(0.00853)	(0.00877)	(0.00819)	(0.0160)
l. External debt (% GDP)	0.0105***	0.0105***	0.0111***	0.0146***
	(0.00297)	(0.00288)	(0.00287)	(0.00386)
l. FDI inflow (% GDP)	-0.0447***	-0.0519***	-0.0467***	-0.0658***
	(0.0112)	(0.0120)	(0.0113)	(0.0242)
l. GDP growth rate	-0.0366**	-0.0252*	-0.0345**	-0.0985***
	(0.0158)	(0.0130)	(0.0155)	(0.0360)
l. Total reserve (% Debt)	-0.00250	-0.00237	-0.00281*	-0.0119***
	(0.00168)	(0.00204)	(0.00168)	(0.00341)
HIPC decision	2.347**	2.447***	2.308**	1.976
	(0.986)	(0.773)	(0.932)	(2.329)
2017 Reform	1.187***	1.151***	1.099***	1.034***
	(0.195)	(0.189)	(0.192)	(0.332)
2013 Reform	-0.153	-0.190	-0.149	-0.440*
	(0.193)	(0.195)	(0.192)	(0.245)
l. Policy distance from US	0.614**			
	(0.268)			
l. (log) US foreign aid		-0.236***		
		(0.0380)		
l. Policy distance from China			-0.680**	
			(0.310)	
l. (log) Chinese aid (% GDP)				0.0503**
				(0.0202)
N	663	636	663	352

Region fixed effects included. Robust standard errors in parentheses.* p <.1, ** p <.05, *** p<.01

5.2 Text sentiment analysis

Using sentiment scores generated by FinBERT, we code DSA summaries classified as *positive* as 1, *neutral* as 0.5, and *negative* as 0, and estimate fractional logit models with regional fixed effects.[31] The unit of analysis is the DSA-level. Table 2 presents the results from our regressions. Our results from text analysis are consistent with the earlier results on rating analysis: Countries that are politically less aligned with the U.S. are less likely to get positive DSA summaries, whereas countries that receive U.S. foreign aid are more likely to get positive ones. Unlike our ratings analysis, a country's relations with China are not linked with their DSA text sentiments.

As a robustness check, we employ an alternative measure of bias in text sentiment. In some cases, DSAs contain relatively negative language despite concluding with a favorable risk rating, while others contain relatively positive language despite unfavorable ratings. To capture this discrepancy, we construct two binary variables: (1) Unfavorable bias, coded as 1 if a DSA concludes "Low Risk" but the overall sentiment of the first two pages is classified as negative by ChatGPT, and 0 otherwise; and (2) Favorable bias, coded as 1 if a DSA concludes "Moderate Risk," "High Risk," or "In Distress" but the sentiment of the first two pages is classified as positive by ChatGPT, and 0 otherwise. There are 19 DSAs with "unfavorable bias", and 78 DSAs with "favorable bias" (See Table 10 in Appendix). Again, we find that DSA text sentiment systematically varies with U.S. foreign aid: countries receiving more U.S. aid are more likely to exhibit favorable bias and less likely to show unfavorable bias in DSA texts. We also find that countries ideologically distant from China are less likely to experience unfavorable bias. Overall, our results confirm that DSA texts are under the influence of geopolitical dynamics around the U.S. and China.

[31] Ordered logit models yield substantively similar results.

Table 2: Geopolitical bias and text sentiments in DSAs

DV: Text sentiments	(1)	(2)	(3)	(4)
l. Current account balance	-0.00369	-0.00759	-0.00456	-0.00544
	(0.00562)	(0.00613)	(0.00565)	(0.0121)
l. External Debt (%GDP)	-0.000682	-0.000701	-0.000948	0.000502
	(0.00124)	(0.00127)	(0.00125)	(0.00157)
l. FDI inflow (%GDP)	0.0101	0.0101	0.0106	0.00494
	(0.00759)	(0.00791)	(0.00765)	(0.00998)
l. GDP growth rate	-0.00720	-0.0160	-0.00822	-0.0262
	(0.0124)	(0.0120)	(0.0123)	(0.0189)
l. Total reserve (% debt)	-0.000859	-0.000788	-0.000680	0.00192
	(0.00112)	(0.00117)	(0.00112)	(0.00262)
HIPC decision	0.102	0.121	0.141	0.0364
	(0.614)	(0.592)	(0.609)	(0.792)
2017 Reform	-0.0109	-0.0201	0.0270	0.267
	(0.164)	(0.168)	(0.163)	(0.369)
2013 Reform	-0.176	-0.245	-0.174	-0.299
	(0.159)	(0.162)	(0.157)	(0.192)
l. Policy distance from US	-0.315**			
	(0.150)			
l. (log) US foreign aid		0.0460*		
		(0.0268)		
l. Policy distance from China			0.173	
			(0.190)	
l. (log) Chinese aid (% GDP)				-0.00234
				(0.0139)
_cons	0.879*	-0.0922	-0.163	-0.0314
	(0.504)	(0.224)	(0.253)	(0.358)
N	682	653	682	366

Region fixed effects included. Standard errors in parentheses.* p <.1, ** p <.05, *** p<.01

5.3 Forecast errors analysis

Because each DSA predicts fiscal performance in future years, the unit of analysis is DSA-year. We start the analysis on forecast errors with the most fundamental assumption in DSAs – GDP growth rate. The dependent variable is the difference between the predicted values and the realized values calculated using different methods. Method A takes simple difference without adjusting for revisions. Methods B and C account for revisions of economic statistics in different ways - Method B adjusts for static revisions, while Method C accounts for dynamic revisions. When GDP growth is the outcome of interest, a higher value suggests optimism while a lower value implies pessimism. Recall that we expect alignment with the U.S. introduces optimistic predictions and alignment with China may have the opposite effect. Table 3 shows preliminary results on the relationship between GDP growth forecast errors and political alignment with the U.S. The coefficients on U.S. foreign aid are consistently positive but not significant, which provides suggestive evidence for our hypothesis of optimism in GDP growth rate among countries receive more foreign aid from the U.S. But the relationship does not hold when we measure alignment using ideological distance with the U.S. Similarly, Table 4 show mixed evidence of relationship between GDP growth rate and political distance with China. In general, there is no consistent evidence that political alignment with either country is associated with optimism in GDP growth rate predictions.

We turn to the errors in external debt and GDP ratio, another important fiscal indicator in the DSAs. When using external debt (% GDP) as the outcome of interest, a higher value suggests pessimism while a lower value implies optimism. Tables 5 and 6 show coefficient estimates on the relationship between alignment and forecast errors in external debt (%GDP). Columns (3)–(6) suggest that after accounting for debt to GDP ratio revisions, DSAs still show more optimism when countries receive more foreign aid from the U.S. or when they are politically close with the U.S. The results further suggest that DSAs are more pessimistic in their forecasts for debt (%GDP) for countries with greater Chinese financing

Table 3: GDP Growth Rate Prediction Error and Alignment with US

	GDP Growth Rate Error					
	Method A		Method B		Method C	
	(1)	(2)	(3)	(4)	(5)	(6)
(Log) US Foreign Aid	0.201		0.107		0.373	
	(0.180)		(0.205)		(0.289)	
Policy Distance w/ US		0.550		0.406		1.071
		(0.545)		(0.698)		(0.955)
Prediction Length (# of years)	0.204***	0.200***	0.216***	0.214***	0.015	0.021
	(0.052)	(0.051)	(0.053)	(0.052)	(0.024)	(0.024)
IMF Program	0.057	0.068	−0.181	−0.154	−1.199	−1.148
	(0.235)	(0.234)	(0.299)	(0.304)	(0.772)	(0.774)
HIPC	0.928	0.912	0.900	0.922	0.015	−0.025
	(1.260)	(1.293)	(1.362)	(1.402)	(0.708)	(0.788)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,712	4,850	4,693	4,825	4,693	4,825
R^2	0.101	0.100	0.088	0.088	0.084	0.084
Adjusted R^2	0.083	0.083	0.070	0.070	0.065	0.066

Note: All specifications control for participation in IMF program and HIPC participation. Standard errors are clustered at country level. *p<0.1; **p<0.05; ***p<0.01

Table 4: GDP Growth Rate Prediction Error and Alignment with China

	GDP Growth Rate Error					
	Method A		Method B		Method C	
	(1)	(2)	(3)	(4)	(5)	(6)
(Log) Chinese Debt	0.008		0.074***		−0.030	
	(0.015)		(0.026)		(0.035)	
Policy Distance w/ China		0.349		0.011		0.127
		(0.395)		(0.664)		(1.084)
Prediction Length (# of years)	0.194***	0.201***	0.204***	0.211***	0.024	0.023
	(0.051)	(0.051)	(0.052)	(0.052)	(0.025)	(0.024)
IMF Program	0.041	0.094	−0.146		−1.127	−1.119
	(0.233)	(0.236)	(0.290)		(0.774)	(0.757)
HIPC	0.995	0.966	1.097		−0.003	0.077
	(1.279)	(1.274)	(1.391)		(0.770)	(0.727)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,754	4,850	4,735	5,320	4,735	4,825
R^2	0.101	0.100	0.093	0.090	0.082	0.083
Adjusted R^2	0.084	0.083	0.075	0.073	0.065	0.065

Note: All specifications control for participation in IMF program and HIPC participation. Standard errors are clustered at country level. *p<0.1; **p<0.05; ***p<0.01

or close to China.

Table 5: External Debt GDP Ratio Prediction Error and Alignment with US

	External Debt Percentage of GDP					
	Method A		Method B		Method C	
	(1)	(2)	(3)	(4)	(5)	(6)
(Log) US Foreign Aid	1.159		−0.520		−0.022	
	(2.115)		(1.239)		(0.032)	
Policy Distance w US		12.525*		5.747		0.054
		(6.985)		(3.946)		(0.085)
Prediction Length (# of years)	−2.656***	−2.663***	−2.588***	−2.573***	−0.067***	−0.066***
	(0.524)	(0.512)	(0.529)	(0.520)	(0.010)	(0.010)
IMF Program	−1.432	−1.357	−0.440	−0.368	0.104***	0.103***
	(4.721)	(4.567)	(2.798)	(2.729)	(0.038)	(0.038)
HIPC	22.629***	21.792***	−9.821	−10.340	0.244***	0.238***
	(7.699)	(7.872)	(9.797)	(9.801)	(0.073)	(0.072)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,459	4,544	4,418	4,503	4,418	4,503
R^2	0.549	0.553	0.379	0.380	0.395	0.395
Adjusted R^2	0.540	0.544	0.367	0.368	0.383	0.383

Note: All specifications control for participation in IMF program and HIPC participation. Standard errors are clustered at country level. *p<0.1; **p<0.05; ***p<0.01

We theorize that political alignment leads to bias in the process of debt risk evaluations in DSAs. One may argue that the relationship we find is driven by omitted variable bias. For example, less transparent countries may see more pessimism in their debt risk evaluations while also prefer to borrow from less transparent creditors such as China.[32] Furthermore, countries that receive negative evaluations may have trouble securing support from the U.S. and have no choice but to resort to China for help, suggesting the possibility of reserve causality.

We leverage a quota reform at the IMF in 2010 to demonstrate that the bias is driven

[32]Mosley and Rosendorff, 2023.

Table 6: External Debt GDP Ratio Prediction Error and Alignment with China

	External Debt Percentage of GDP					
	Method A		Method B		Method C	
	(1)	(2)	(3)	(4)	(5)	(6)
(Log) Chinese Debt	0.091		0.063		0.002	
	(0.111)		(0.136)		(0.003)	
Policy Distance w/ China		-12.160^{***}		-11.329^{**}		-0.094
		(4.514)		(4.799)		(0.086)
Prediction Length (# of years)	-2.650^{***}	-2.642^{***}	-2.570^{***}	-2.563^{***}	-0.066^{***}	-0.066^{***}
	(0.514)	(0.512)	(0.519)	(0.518)	(0.010)	(0.010)
IMF Program	-1.883	-1.580	-0.890	-0.690	0.092^{**}	0.100^{***}
	(4.523)	(4.521)	(2.752)	(2.778)	(0.036)	(0.037)
HIPC	23.388^{***}	22.911^{***}	-9.491	-9.880	0.249^{***}	0.242^{***}
	(7.989)	(7.937)	(9.609)	(9.688)	(0.073)	(0.073)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,513	4,544	4,472	4,503	4,472	4,503
R^2	0.553	0.553	0.382	0.384	0.399	0.396
Adjusted R^2	0.544	0.544	0.370	0.371	0.387	0.384

Note: All specifications control for participation in IMF program and HIPC participation. Standard errors are clustered at country level. *p<0.1; **p<0.05; ***p<0.01

by the voting power of US and China at the IMF,[33] rather than the omitted variable bias or self-selection. In 2010, the Board of Governors of the IMF approved a proposal to update members' voting power. The biggest winner in this reform is China who gained an additional 2.3 percentage points in its voting power while the U.S. lost 0.24 percentage points of its vote share[34]. If the bias in DSAs is driven by omitted variables or country self-selection, the relationship should be consistent regardless of the reform at the IMF. However, if the bias in DSAs comes from political alignment with major IMF shareholders, we should expect the bias to attenuate when China receives more voting power and the U.S. loses some of its voting power.

Coefficients in Table 7 show the change of bias in GDP growth rate before and after the 2010 reform. Columns (1), (3) and (5) show limited evidence of bias when countries are politically distant from the U.S. before 2010 but some evidence of increasing optimism among countries distant from the U.S. after 2010. Columns (2), (4) and (6) present stronger evidence that geopolitical relations play a role in growth forecasts: countries politically distant from China receive a more optimistic growth prediction before the quota reform (when China had less voting power at the IMF) but such bias attenuates after the reform (when China gained more formal power at the IMF).

Recall that the bias is more salient in the forecast error of external debt to GDP ratio. Table 8 shows how bias in debt to GDP ratio changes after the quota reform in 2010. Coefficients in columns (1), (3) and (5) suggest that countries politically distant from the U.S. receive more pessimistic debt(% GDP) forecasts before 2010 but the pessimism shrinks after the reform in 2010. In other words, a country's relations with the U.S. become becomes a less influential factor for DSA debt forecasts after the U.S. lost some of its formal voting power through the 2010 governance reform. Similarly, columns (2), (4) and (6) show that countries distant from China receive more optimistic debt forecast before 2010, but the bias

[33] Noh, 2025.

[34] See IMF reform document and press release for details

Table 7: GDP Growth Prediction Error and IMF Quota Reform

	GDP Growth Rate Error					
	Method A		Method B		Method C	
	(1)	(2)	(3)	(4)	(5)	(6)
Distance w/ US	−0.074		−1.231		0.662	
	(0.773)		(0.951)		(1.025)	
Distance w/ US X Post2010	0.835		2.199***		0.550	
	(0.589)		(0.711)		(0.913)	
Distance w China		1.307**		0.819		0.425
		(0.578)		(0.891)		(1.117)
Distance w China X Post2010		−1.227**		−1.480*		−0.382
		(0.538)		(0.773)		(0.858)
Prediction length (# of years)	0.200***	0.201***	0.214***	0.215***	0.021	0.023
	(0.051)	(0.051)	(0.052)	(0.052)	(0.024)	(0.024)
IMF Program	0.047	0.069	−0.211	−0.192	−1.162	−1.127
	(0.227)	(0.231)	(0.292)	(0.307)	(0.785)	(0.756)
HIPC	0.908	1.016	0.913	1.020	−0.027	0.092
	(1.293)	(1.268)	(1.403)	(1.369)	(0.789)	(0.718)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,850	4,850	4,825	4,825	4,825	4,825
R^2	0.101	0.101	0.091	0.089	0.085	0.083
Adjusted R^2	0.083	0.083	0.073	0.071	0.066	0.065

Note: All specifications control for participation in IMF program and HIPC participation. Standard errors are clustered at country level. *p<0.1; **p<0.05; ***p<0.01

attenuates after the reform. These results suggest that major stakeholders at the IMF play a role in the biases in DSAs.

Table 8: External Debt Prediction Error and IMF Quota Reform

	External Debt Percentage of GDP Error					
	Method A		Method B		Method C	
	(1)	(2)	(3)	(4)	(5)	(6)
Distance w/ US	16.913**		13.839*		0.157*	
	(7.843)		(7.250)		(0.093)	
Distance w/ US X Post2010	−6.124		−11.289		−0.143*	
	(9.005)		(7.994)		(0.072)	
Distance w/ China		−26.592**		−19.322*		−0.208*
		(10.195)		(10.638)		(0.110)
Distance w/ China X Post2010		19.005*		10.527		0.151
		(9.800)		(8.851)		(0.098)
Prediction Length (# of years)	−2.661***	−2.641***	−2.571***	−2.562***	−0.066***	−0.066***
	(0.512)	(0.511)	(0.521)	(0.517)	(0.010)	(0.010)
IMF Program	−1.203	−1.235	−0.085	−0.495	0.106***	0.103***
	(4.532)	(4.346)	(2.623)	(2.648)	(0.038)	(0.037)
HIPC	21.807***	22.094***	−10.320	−10.342	0.238***	0.235***
	(7.865)	(7.720)	(9.618)	(9.783)	(0.071)	(0.071)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,544	4,544	4,503	4,503	4,503	4,503
R^2	0.553	0.557	0.383	0.385	0.397	0.397
Adjusted R^2	0.544	0.548	0.371	0.373	0.385	0.385

Note: All specifications control for participation in IMF program and HIPC participation. Standard errors are clustered at country level. *p<0.1; **p<0.05; ***p<0.01

6 Conclusion

We have collected the most comprehensive dataset of the LIC-DSAs, and coded the risk ratings, text sentiment and the forecast errors. Preliminary results offer evidence that geopolitical concerns of the U.S. are correlated with these measures. A state's DSA provides the Bank and Fund's assessment of its ability to manage its debt burden; the staff appear to shade their findings in favor of geopolitical allies of the hegemonic power, and against those more closely allied with China, the U.S.'s major geopolitical rival.

The international financial institutions preserve their legitimacy by offering its evaluations and its advice in an impartial technocratic manner. Yet hegemonic influence often appears when geopolitical interests are salient. The staff within these organizations are not immune from these concerns, and their advice often reflects these geopolitical realities. By demonstrating that geopolitical bias plays a role even in technical tasks, this paper highlights the power of major shareholders in shaping IFI behavior.

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Appendix A FinBERT coding of DSA text sentiments

FinBERT is a language model specifically trained for financial texts.[35] Unlike many other language models that analyze sentences in isolation, FinBERT accounts for the surrounding textual context when assessing sentiment. To illustrate, Ethiopia's 2010 and 2016 DSAs are classified by FinBERT as positive and negative, respectively.

> Ethipoia 2010: Based on the joint World Bank-IMF debt sustainability framework for low-income countries, Ethiopia's debt distress rating has fallen to low risk. The introduction of gross workers' remittances as a source of enhanced repayment capacity and the resilience of the Ethiopian economy to the global economic crisis have contributed to this improvement. Notwithstanding this development, the debt ratio continues to rise and liquidity risks are prevalent, underscoring the need to closely monitor borrowing of the largest public enterprises, develop an integrated debt strategy for the entire public sector, and invigorate structural reforms to attract foreign direct investment (FDI) and stimulate growth of exports.

> Ethiopia 2016: Ethiopia's risk of external debt distress remains moderate, although external vulnerabilities have increased. Exports underperformed relative to projections, owing to a weak external environment; and the supply shock from the drought required scaled-up food imports. Despite strong remittances and curtailed public sector imports of investment goods, the current account deficit remains high. Reflecting higher indebtedness and low exports, indicators based on debt-to-exports ratios have deteriorated and (as in the 2015 DSA) breach one standard threshold in the baseline. Key considerations in maintain-

[35] Yang et al., 2020.

> ing the moderate rating are: (i) the envisaged investment-based expansion in re-payment capacity financed by the external borrowing; and (ii) special factors that mitigate the risk of debt/currency distress episodes including capital controls, the large share of debt with official creditors with a significant concessional component, virtual absence of tradeable debt instruments, and limited integration in global markets. The main risks are a potential continuation of export underperformance and failure to rein in project-related imports and refrain from associated new non-concessional borrowing. Should these risks materialize, debt sustainability prospects would deteriorate materially. The projected baseline path of total public sector debt-to-GDP (external plus domestic debt) does not result in additional risks beyond those discussed for the external debt above.

These examples highlight FinBERT's ability to capture nuanced differences in tone. The 2010 DSA emphasizes positive developments—such as improved repayment capacity and resilience to external shocks—whereas the 2016 DSA underscores mounting risks, with detailed discussion of export underperformance, external vulnerabilities, and potential debt distress.

Appendix B Robustness checks

B.1 DSA Risk Rating Analysis

B.2 Text Sentiment Analysis

Table 9: Geopolitical bias and risk ratings in DSAs in collapsed sample

	(1)	(2)	(3)	(4)
l. Current account balance	-0.0528***	-0.0450***	-0.0498***	-0.0517***
	(0.0112)	(0.0117)	(0.0111)	(0.0200)
l. External debt (% GDP)	0.0154***	0.0159***	0.0161***	0.0202***
	(0.00327)	(0.00322)	(0.00322)	(0.00474)
l. FDI inflow (% GDP)	-0.0802***	-0.0809***	-0.0806***	-0.0940***
	(0.0182)	(0.0186)	(0.0181)	(0.0303)
l. GDP growth rate	-0.0519*	-0.0367	-0.0447	-0.0752*
	(0.0301)	(0.0305)	(0.0303)	(0.0408)
l. Total reserve (% Debt)	-0.000840	-0.000771	-0.00103	-0.00880**
	(0.00204)	(0.00234)	(0.00208)	(0.00361)
HIPC decision	3.662***	3.626***	3.529***	25.05***
	(0.799)	(0.604)	(0.749)	(1.096)
l. (log) WB financing	-0.0623***	-0.0463***	-0.0610***	-0.0819***
	(0.0126)	(0.0153)	(0.0132)	(0.0203)
l. IMF participation	0.605***	0.480**	0.558***	0.186
	(0.212)	(0.219)	(0.215)	(0.292)
2017 Reform	1.287***	1.225***	1.166***	1.006***
	(0.238)	(0.235)	(0.234)	(0.387)
2013 Reform	-0.166	-0.214	-0.149	-0.349
	(0.221)	(0.224)	(0.219)	(0.276)
l. Policy distance from US	0.862***			
	(0.289)			
l. (log) US foreign aid		-0.128***		
		(0.0493)		
l. Policy distance from China			-0.592	
			(0.416)	
l. (log) Chinese aid (% GDP)				0.0572*
				(0.0318)
N	469	450	469	288

Region fixed effects included. Robust standard errors in parentheses.* p <.1, ** p <.05, *** p<.01

Table 10: Geopolitical bias and text sentiments in DSAs: Binary measure of text bias

	Favorable bias				Unfavorable bias			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
l. Policy distance w US	0.00841				-0.0306			
	(0.303)				(0.660)			
l. (log) US foreign aid		0.369***				-0.178*		
		(0.0930)				(0.0936)		
l. Policy distance w China			0.0814				-1.950*	
			(0.376)				(1.143)	
l. (log) Chinese debt (% GDP)				0.0542				0.179
				(0.0408)				(0.181)
N	701	672	701	381	701	672	701	308

All of the controls and region fixed effects included. Standard errors in parentheses, * p <.1, ** p <.05, *** p<.01

B.3 Forecast Optimism

Table 11: GDP Growth Rate Prediction Error and Alignment with US

	GDP Growth Optimism (Binary)					
	Method A		Method B		Method C	
	(1)	(2)	(3)	(4)	(5)	(6)
(Log) US Foreign Aid	0.040***		0.013		0.022*	
	(0.012)		(0.013)		(0.013)	
Policy Distance w US		−0.051		−0.033		0.073*
		(0.037)		(0.038)		(0.038)
Prediction length (years)	0.020***	0.019***	0.021***	0.020***	0.014***	0.014***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,641	4,744	4,622	4,719	4,622	4,719
R^2	0.149	0.148	0.107	0.107	0.098	0.096

Note: *p<0.1; **p<0.05; ***p<0.01

Table 12: GDP Growth Rate Prediction Error and Alignment with China

	GDP Growth Optimism (Binary)					
	Method A		Method B		Method C	
	(1)	(2)	(3)	(4)	(5)	(6)
(Log) Chinese Debt	−0.001		0.005***		0.004***	
	(0.001)		(0.001)		(0.001)	
Policy Distance w China		0.037		−0.017		−0.010
		(0.034)		(0.035)		(0.035)
Prediction length (years)	0.019***	0.019***	0.019***	0.020***	0.014***	0.014***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,654	4,744	4,635	4,719	4,635	4,719
R^2	0.141	0.148	0.108	0.107	0.094	0.095
Adjusted R^2	0.123	0.130	0.090	0.088	0.076	0.077
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 13: External Debt GDP Ratio Prediction Error and Alignment with US

	External Debt Percentage of GDP Optimism (Binary)					
	Method A		Method B		Method C	
	(1)	(2)	(3)	(4)	(5)	(6)
(Log) US Foreign Aid	0.005		−0.024*		0.002	
	(0.011)		(0.012)		(0.012)	
Policy Distance w US		−0.149***		−0.010		−0.053
		(0.034)		(0.039)		(0.039)
Prediction length (years)	0.027***	0.028***	0.029***	0.028***	0.029***	0.029***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,322	4,374	4,266	4,318	4,259	4,311
R^2	0.400	0.405	0.205	0.207	0.218	0.220
Adjusted R^2	0.388	0.392	0.188	0.190	0.201	0.204
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 14: External Debt GDP Ratio Prediction Error and Alignment with China

	External Debt Percentage of GDP Optimism (Binary)					
	Method A		Method B		Method C	
	(1)	(2)	(3)	(4)	(5)	(6)
(Log) Chinese Debt	0.002**		0.001		−0.001	
	(0.001)		(0.001)		(0.001)	
Policy Distance w China		0.192***		0.125***		0.095***
		(0.032)		(0.036)		(0.036)
Prediction length (years)	0.027***	0.027***	0.028***	0.028***	0.029***	0.029***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,349	4,374	4,293	4,318	4,286	4,311
R^2	0.404	0.407	0.206	0.209	0.219	0.221
Adjusted R^2	0.391	0.395	0.189	0.192	0.202	0.204

Note: *p<0.1; **p<0.05; ***p<0.01