Hidden Debt Revelations[*]

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Abstract

How reliable are public debt statistics? This paper quantifies the magnitude, characteristics, and timing of hidden debt by tracking ex post data revisions across a comprehensive new database of more than 50 vintages of World Bank debt statistics. In a sample of debt data covering 146 countries and 53 years, we establish three new stylized facts about hidden debt: (i) hidden debt is large and common; (ii) hidden debt accumulates in boom years and tends to be revealed in bad times, often during IMF programs and sovereign defaults; and (iii) in debt restructurings, higher hidden debt is associated with larger creditor losses. We use these novel data to numerically discipline a quantitative sovereign debt model with hidden debt accumulation and an endogenous monitoring decision that triggers revelations. We use this model to study the effects of hidden debt on sovereign default risk, asset pricing, and welfare. Our model simulations show that hidden debt increases default incentives and borrowing costs and is therefore welfare detrimental.

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1 Introduction

Public debt statistics are a cornerstone of macroeconomic analysis. Investors, taxpayers, and academic researchers all have a keen interest in the level and composition of a country's public debt. However, these statistics are subject to major limitations and incomplete reporting (World Bank, 2021). Notably, half the lending from China, now the world's largest official creditor, has been missing from World Bank debt statistics (Horn et al., 2021). When Zambia and Chad sought debt restructurings in 2021, it took them more than six months to assemble comprehensive debt data and reconcile it with the records of their creditors (Estevão, 2021). Most famously perhaps, large revelations of previously unreported debts triggered major debt crises in Greece and Mozambique (Reinhart and Rogoff, 2011a,b; IMF, 2018). Despite the importance of hidden debt, there is little research that systematically measures its magnitude, characteristics, and effects.

We fill this gap by quantifying hidden debt by systematically tracking ex post revisions of debt figures across different editions ("vintages") of the most widely used international debt statistics. The key idea is as follows: when previously unreported loans are reported, past debt statistics need to be revised. Tracking these revisions allows us to quantify the scale, characteristics, and timing of hidden debt accumulation and revelation. We apply this approach to a new and comprehensive dataset of the past 51 vintages of the World Bank's International Debt Statistics that we digitize all the way back to the 1970s. Our new approach and data allow us to systematically document the degree of under-reporting for more than 50 years of data and for up to 146 developing and emerging market countries.

Our empirical analysis makes three novel contributions to our understanding of hidden debt. First and foremost, we document that there is a pervasive under-reporting of public debts. We show that debt data revisions are systematically upward biased for almost all debtor regions and income groups. Across all countries and years, we identify USD 1 trillion in "hidden" sovereign borrowing that is added to debt statistics only in hindsight, more than twelve percent of total sovereign borrowing by all countries in our sample. This amount is a lower bound for the true magnitude of hidden debt since not all unreported debt is eventually revealed. In the cross-section of countries, hidden debt levels are highest in countries with weak institutions and low capacity, however, even the countries with the strongest institutions in our sample exhibit systematic downward bias in their debt reporting. Comparing across creditor groups, we document that non-bond private loans and bilateral loan instruments are the most prone to under-reporting.

Second, we show that hidden debt tends to accumulate when growth is strong and be revealed in economic downturns. For example, the COVID-19 recession was followed by the largest hidden debt revelation in 50 years. We document that the procyclicality of hidden debt accumulation and revelation is mainly driven by time-varying monitoring efforts. In our data, hidden debt revelations are particularly sizeable during sovereign default episodes and IMF programs, when the sovereign's books come under close scrutiny.[1]

[1] In contrast, we do not find evidence that governments strategically disclose hidden debts for political gains.

Third, we use our new data to shed light on the role of hidden debts during sovereign default episodes and the debt resolution process. One key concern among bondholders during sovereign restructurings is that hidden debt can dilute the recovery value of their own marketable claims. During recent debt restructuring episodes, for example in Zambia, such concerns amplified coordination issues and led to substantial delays in debt resolution, with potentially severe costs for debtors and creditors alike.[2] To systematically analyze the role of hidden debt in default episodes we combine our data on debt under-reporting with data on the outcomes of all sovereign restructurings with private creditors since 1970. We find that higher hidden debt at the onset of a restructuring is associated with both longer restructuring episodes and larger creditor losses, which suggests that high hidden debts do indeed dilute the recovery value of market investors.

Motivated by these findings, we develop a quantitative sovereign debt and default model (in the tradition of Eaton and Gersovitz, 1981, Arellano, 2008, and Aguiar and Gopinath, 2006) with hidden debt, asymmetric information and an endogenous information acquisition problem that generates hidden debt revelations. The sovereign debtor in the model faces an exogenous hidden debt accumulation process that is not observed by investors in the country's market debt. Each period, however, the investors need to decide whether to monitor the sovereign's books. In line with our empirical evidence, the model features a recovery rate for market debt that is diluted by undisclosed hidden debts of the sovereign. This aspect gives bond investors further incentives to monitor the sovereign, therefore triggering revelations of hidden debt, particularly during bad times when sovereign default risk is high, just as we observe in the data.

We calibrate this model with our new data and analyze the effects of both hidden debt and its revelation. We show that asymmetric information about the true level of indebtedness has sizeable effects on equilibrium outcomes: The existence of hidden debt increases default incentives and depresses sovereign bond prices. To compensate investors for the uncertainty about true debt levels, sovereign borrowers need to pay higher spreads for given levels of market debt. On the other hand, monitoring-induced revelations of hidden debt are uncertainty reducing and therefore decrease the sovereign's borrowing costs for a given level of overall debt. If the revealed amount of hidden debt is large, however, the increase in overall debt leads to an increase in spreads that outweighs the spread compression from reduced uncertainty. Thus, our model predicts that the spread response to a revelation increases with the amount of hidden debt that is revealed. We corroborate this finding empirically by running panel regressions of bond price reactions on our new measures of hidden debt revelations.

Overall, hidden debt is welfare detrimental because it worsens the borrowing opportunities of the debtor country. Eliminating the uncertainty associated with hidden debt (by making it public information) allows the economy to sustain higher debt at lower spreads, delivering

[2]Zambia's bondholders rejected the government's first debt relief request citing debt transparency concerns in 2020. The following year the government conceded that debt to Chinese creditors had been under-reported. See Financial Times (2020, November 13) *"Zambia on brink of default after lenders reject debt relief request"* and Financial Times (2020, September 30) *"Bondholders balk at Zambia's plan to delay debt payments"*.

large average welfare gains of 5.5 percent of permanent income. Our model also allows us to analyze the welfare effects of increased oversight in a world with asymmetric information and hidden debt. We find that only countries with strong fundamentals and low hidden debt levels benefit from increased transparency. In contrast, countries with high levels of hidden debt are likely to find exposure to greater scrutiny to be costly. This finding suggests that transparency policies are best implemented during good times to avoid the negative welfare effects of exposing hidden debts during times of crisis.

Related literature. Our findings and data shed new light on several well-documented empirical patterns in sovereign debt markets. One long-standing puzzle in the academic literature is why developing and emerging market countries have repeatedly entered default and debt distress at seemingly manageable levels of public debt, i.e., the widespread phenomenon of "debt intolerance" (Reinhart et al., 2003; Reinhart and Rogoff, 2009). The frequent and sizeable ex post upward revisions that we document here may help to rationalize the strong crisis susceptibility of debt-intolerant countries even at low levels of *reported* debt. Relatedly, high uncertainty over the true value of developing country indebtedness may contribute to the high levels of consumption volatility in developing countries (Aguiar and Gopinath, 2007; Alvarez-Parra et al., 2013) and to the remarkably low cross-border capital inflows that these countries have been able to attract (Lucas, 1990; Alfaro et al., 2008; Greenwood et al., 2010). Our findings also add to a large and influential literature on the procyclicality of macroeconomic variables and policies in developing and emerging market countries (see, e.g., Kaminsky et al., 2004; Reinhart and Reinhart, 2008; Alesina et al., 2008; Bianchi et al., 2023; Azzimonti and Mitra, 2023). We show that the procyclical accumulation and revelation of hidden debt can amplify boom-bust patterns by increasing resources in good times and generating additional bad news during economic downturns. Finally, our finding that the instruments of different creditors differ systematically in their propensity to be under-reported contributes to a nascent literature on the importance of investor composition in sovereign debt and other asset markets (Fang et al., 2023; Coppola, 2024; Agarwal et al., 2024; Graf von Luckner and Horn, 2024).

Our paper also contributes to a large literature that studies the implications of asymmetric information and investor attention on asset prices and financial crises (for overviews see, e.g., Brunnermeier, 2001; Gorton and Ordonez, 2023; Veldkamp, 2023). In particular, our paper is closely related to a growing body of theoretical work that analyzes sovereign debt markets with asymmetric information and opaque borrowing (Kletzer, 1984; Alfaro and Kanczuk, 2022; Guler et al., 2022; Gamboa, 2023; Kondo et al., 2024; Gu and Stangebye, 2023), often with a focus on government reputation (D'Erasmo, 2011; Fourakis, 2021; Morelli and Moretti, 2023).[3] Our finding that hidden debt tends to be revealed during episodes of sovereign distress further informs and is consistent with theories that link financial crises to state-contingent information acquisition (Gorton and Ordonez, 2014; Cole et al., 2022, 2024; Gu and Stangebye, 2023). We contribute to this literature by compiling rich new data and by integrating a simple information acquisition problem with a quantitative sovereign debt

[3] Related papers on unsecured consumer credit, default and asymmetric information include Chatterjee et al. (2023), Athreya et al. (2012), and Sanchez (2018).

and default model that features asymmetric information about the sovereign's true debt level.

Our findings have important implications for empirical research more broadly, as debt statistics are essential input variables for a large variety of research designs. Researchers should be wary of the fact that data downloads from different vintages of debt statistics can lead to significantly different results and can therefore complicate the replication and updating of empirical work (also see Aruoba, 2008; Christensen and Miguel, 2018; Goes, 2024). Empirical applications in macroeconomic forecasting or asset pricing, in particular, need to take into account that debt figures tend to get upward revised after their initial publication (Frankel, 2011; Beaudry and Willems, 2022; Akey et al., 2023; Estefania-Flores et al., 2023).

The rest of this paper is structured as follows: Section 2 motivates our approach by presenting two recent case studies. Section 3 introduces our new database of debt data revisions and our measure of hidden debt revelations. We explain in detail how our measure of hidden debt should be interpreted and point out important caveats. Section 4 presents the main statistical properties of debt data revisions, and it documents new stylized facts about the size, characteristics, and timing of hidden debt and its revelation. Section 5 presents our quantitative model of sovereign debt and default with hidden debt and an endogenous monitoring decision. Section 6 uses our new data to numerically discipline the model: we measure the impact of hidden debt on equilibrium default incentives, sovereign spreads, and welfare. Section 7 concludes.

2 Case studies

In this section, we present two recent case studies to motivate our approach and to illustrate the main idea of using debt data revisions as a measure of hidden debt.

2.1 Mozambique's hidden debt scandal

In 2016, Mozambique made international headlines when an international audit discovered USD 2 billion in unreported sovereign debt liabilities. During the early 2010s, Mozambique was considered a development success story. The discovery of large natural gas deposits off the country's northern coastline was followed by a surge in foreign direct investment and years of high real GDP growth. In 2013, at the height of the boom, the country managed to issue sovereign bonds worth USD 850 million in international capital markets to fund investments in a tuna boat fleet. In the same year, state-owned enterprises used government guarantees to borrow nearly USD 2 billion from international banks Credit Suisse and VTB without disclosing these additional liabilities to bond investors and the public.[4]

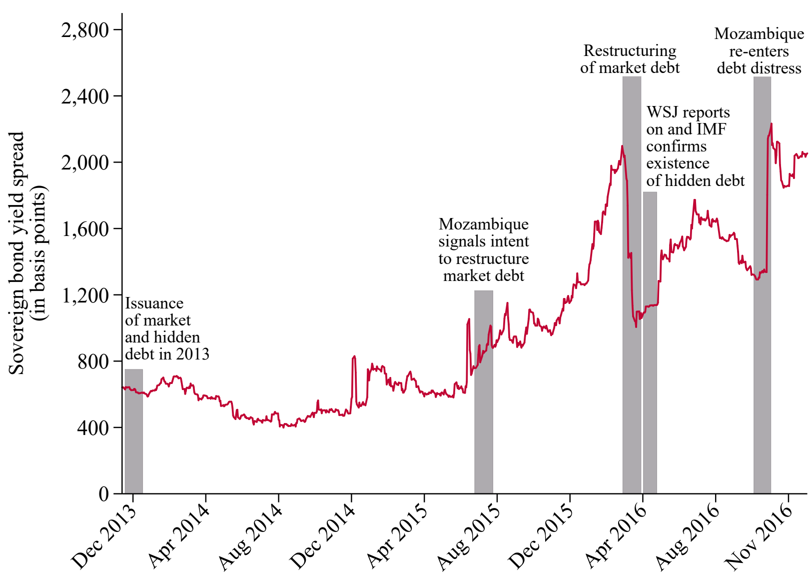
Two years later, in 2015, Mozambique first started to experience debt servicing difficulties. The tuna fleet, funded with the USD 850 million bond issuance, pulled in less than 5% of the tuna that it had expected, and the government approached bondholders with a plan to

[4] See Financial Times (2017, June 25) *"State loans at heart of Mozambique debt scandal"*.

restructure the bond. After most bondholders had agreed to the restructuring in early 2016, rumors about large hidden debts started to emerge. In April 2016, the Wall Street Journal first reported about the additional and previously undisclosed bank loans that Mozambican state-owned enterprises had borrowed and the state guarantees that they carried.[5]

The rumors about hidden debt led to a surge in Mozambique's bond spreads (see Figure 1), with bond investors expressing concerns that the existence of undisclosed, additional liabilities would dilute the recovery value of their bonds in the event of a default, which ultimately happened in January 2017. Audits of Mozambique's debt through the IMF and international accounting firms followed.[6] They confirmed the existence of nearly USD 2 billion in hidden liabilities (Cortez et al., 2021). Ultimately, it took 4 years to settle renegotiations with bondholders and the country has been unable to access the international bond market ever since.

Figure 1: Sovereign bond yields during Mozambique's hidden debt scandal



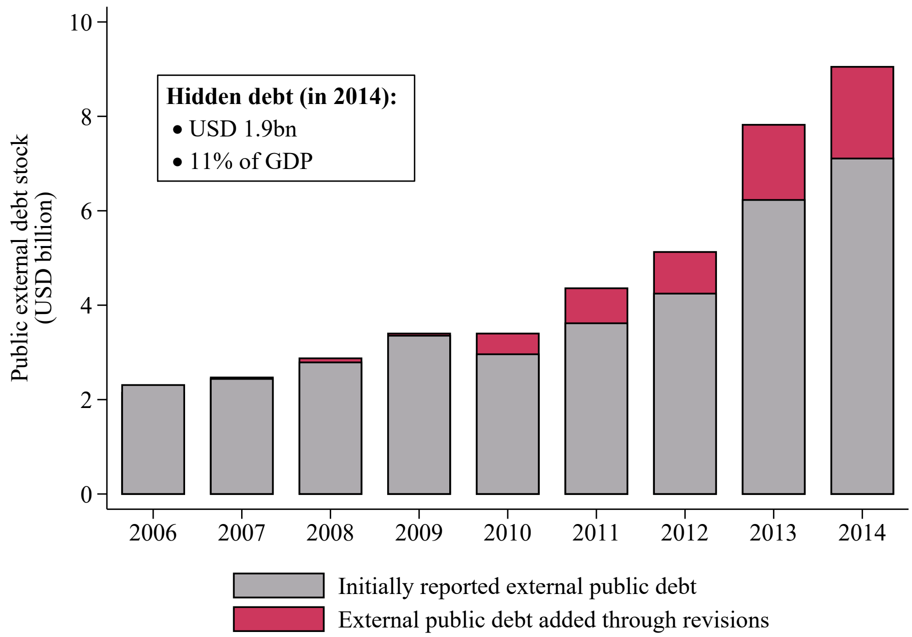
Sources: Wall Street Journal (2016, April 3) *"Tuna and Gunships: How \$850 Million in Bonds Went Bad in Mozambique"*, Reuters (2016, April 23) *"IMF says Mozambique has over \$1 bln of hidden debt"*, J.P. Morgan (2024).
Notes: The figure plots the EMBI+ spread for Mozambique from December 2013 until December 2016. EMBI+ spread in basis points.

Mozambique's hidden debts and their revelation can be quantified by comparing the country's debt reports across different vintages of the World Bank's International Debt Statistics. When initially reported, the 2014 debt figure for Mozambique was USD 7.1 billion (see Figure 2). This figure was strongly upward revised in subsequent vintages as the previously

[5]See Wall Street Journal (2016, April 3) *"Tuna and Gunships: How \$850 Million in Bonds Went Bad in Mozambique"*.

[6]See Reuters (2017, May 13) *"Mozambique receives Kroll audit into hidden debts"* and Reuters (2017, July 11) *"IMF team visits Mozambique after damning debt audit"*.

Figure 2: Mozambique's hidden debt scandal, 2006 – 2014



Notes: The figure shows the initially and most recently reported public and publicly guaranteed debt stocks for Mozambique between 2006 and 2014 in billion USD. The grey bars show the initially reported debt stocks. The red bars show additional debt stocks added through revisions in subsequent reporting. The data is from our new database (see Section 3 and Appendix A).

undisclosed loans became public knowledge. The latest debt figure for year 2014 is USD 9.1 billion, an increase of USD 1.9 billion or 11% of GDP).

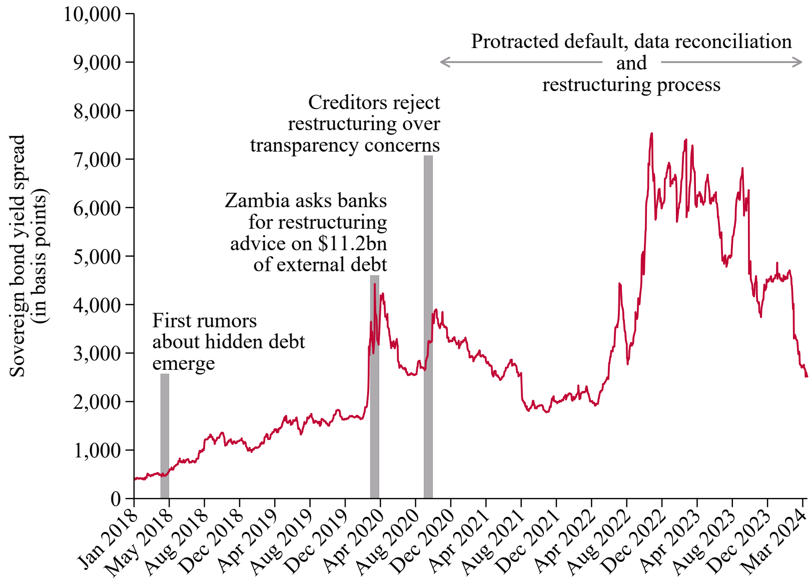
2.2 Zambia's opaque external debts

During the 2010s, Zambia went on an international borrowing spree. Supported by high commodity prices, the country contracted liabilities with myriad external creditors, including bondholders, Chinese and Western commercial banks, export credit agencies and dozens of different suppliers. Debt issuance was carried out not only by the central government but also by a range of state-owned enterprises and special purpose vehicles that accumulated debt to finance infrastructure and energy projects (Brautigam, 2022). Whereas the country had contracted only five new loans in 2011, it contracted at least thirty new loans at the height of the boom in 2016 (Smith et al., 2017).

As the complexity of Zambia's public debt portfolio increased, uncertainty over the true extent of the country's indebtedness emerged. Zambia's borrowing costs started to increase in April 2018, when the international press and major investors openly questioned the accuracy of the country's debt statistics (see Figure 3).[7] At the beginning of 2020, the onset of

[7]See Africa Confidential (2018, April 6) *"Into the valley of debt"* and Bloomberg (2018, April 8) *"Zambia's bonds plummet on concern it's pulling a Mozambique"*.

Figure 3: Sovereign bond yields during Zambia's hidden debt saga



Sources: Financial Times (2020, April 1) *"Zambia's bonds drop on expected restructuring"*, Financial Times (2020, September 30) *"Bondholders balk at Zambia's plan to delay debt payments"*, Financial Times (2021, November 10) *"Zambia's new president tackles debt mountain and empty treasury"* and J.P. Morgan (2024).
Notes: The figure plots the EMBI+ spread for Zambia from January 2018 until April 2024.

COVID-19 and the accompanying capital outflows from emerging markets exacerbated the country's debt challenges. In March 2020, Zambia's ministry of finance sought advice from banks on the restructuring of USD 11.2 billion of foreign debt.[8] The news sent Zambia's bond spread surging and ultimately pushed the country into default when the government missed a USD 42.5 million coupon payment on one of its Eurobonds in October 2020.

The uncertainty over the true scale of Zambia's debt stock caused long delays in the ensuing debt resolution process. Creditor committees declined Zambian requests for a debt standstill and a restructuring proposal over concerns about the "lack of transparency regarding the country's other external debts".[9] After several months of data reconciliation, Zambian authorities eventually published revised debt statistics that confirmed investor concerns and led Zambia's new president to admit that the "hole is bigger than expected".[10] Four years later, as of June 2024, the restructuring had not yet concluded.[11]

Our measurement approach allows to quantify Zambia's hidden debts by comparing debt figures across different vintages of the World Bank International Debt Statistics (see Figure 4). The reported stock of Zambia's external public and publicly guaranteed debt for 2021

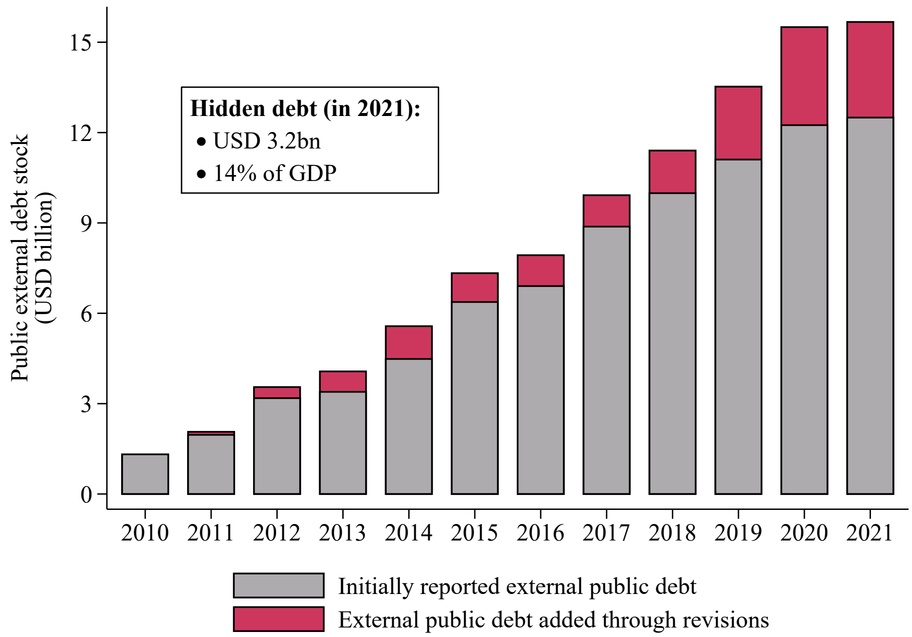
[8]See Financial Times (2020, April 1) *"Zambia's bonds drop on expected restructuring"*.

[9]See Financial Times (2020, November 13) *"Zambia on brink of default after lenders reject debt relief request"* and Financial Times (2020, September 30) *"Bondholders balk at Zambia's plan to delay debt payments"*.

[10]BBC (2021, September 1) *"Zambian President Hichilema inherits 'empty treasury'"*.

[11]Negotiations are still ongoing with suppliers and Chinese creditors deemed private representing a quarter of the country's external debt.

Figure 4: Zambia's opaque external debts, 2010 – 2021



Notes: The figure shows the initially and most recently reported public and publicly guaranteed debt stocks for Zambia between 2010 and 2021 in billion USD. The gray bars show the initially reported debt stocks. The red bars show additional debt stocks added through revisions in subsequent reporting. The data is from our new database (see Section 3 and Appendix A).

amounted to USD 12.5 billion when it was initially published in the World Bank's International Debt Report 2022. In the latest vintage, the same figure is given as USD 15.7 billion, indicating an upward revision of USD 3.2 billion or 14% of GDP.

3 Data, measurement and interpretation

In this section, we introduce our new dataset of debt data revisions and explain how we quantify hidden debt and hidden debt revelations. Throughout this section, we focus on the main principles of data construction and measurement and refer interested readers to Appendix A for further details.

3.1 A new database of debt data revisions

To systematically quantify hidden debt and its revelation, we construct a new and comprehensive database of all editions (i.e., "vintages") of the World Bank's International Debt Statistics (IDS) and its predecessor publications. This subsection explains why we focus on the World Bank debt statistics and how we compile our new database.

Why focus on the World Bank IDS? The World Bank's International Debt Statistics is uniquely suited for the purpose of our measurement approach. First, it is the most widely used source for developing and emerging market country external debt data and frequently cited by researchers, investors, rating agencies and market commentators. Reporting is mandatory for all countries with outstanding liabilities to the World Bank and debtor countries that violate their reporting obligations risk losing eligibility for financial support (World Bank, 2017). These conditions ensure high coverage across countries and time.

Second, the IDS has numerous desirable features that facilitate the interpretation of debt data revisions as a measure of hidden debt:

- The International Debt Statistics and its predecessor publications are based on direct debtor reporting. While the World Bank compiles the annual statistical report and performs consistency checks, all underlying data on debt instruments are reported by national debt management offices. Omissions and revisions of debt data can therefore be traced back to the reporting decisions of sovereign debtor countries.[12] An upward revision implies that a sovereign debtor now reports a liability to the World Bank that it had not previously reported.

- All debt instruments enter the World Bank's debt statistics with their nominal or face value. They are not adjusted for fluctuations in their market value. This implies that ex post data revisions do not reflect valuation changes; rather, they indicate changes in the underlying debt reporting.[13]

- Since the first publication of the World Debt Tables in 1973, the World Bank's reporting guidelines have essentially remained unchanged. Section B.1 in the appendix provides a systematic comparison of the Debtor Reporting System (DRS) reporting manual over time and confirms that only minimal refinements have occurred over the past four decades.[14] This finding ensures that ex post data revisions do not reflect the evolution of reporting guidelines; rather, they can be traced back to changes in compliance with a stable set of rules over time.

Sources and digitization: Our new database combines more than 50 different editions ("vintages") of the World Bank's International Debt Statistics (2013–2023) and its predecessor publications, the Global Development Finance reports (1997–2012) and the World Debt Tables (1973–1996). While the name of the publication has changed over the recent decades, all reports build on the same underlying data series from the World Bank's DRS and on highly similar variable definitions (see Appendix B.1 for details).

The latest vintages of the debt statistics are readily available in machine-readable format on the World Bank's website. For the majority of vintages, however, we need to digitize

[12] As explained in greater detail in Appendix Section A.2, the World Bank occasionally provides debt estimates if a reporting country does not fulfill its reporting obligations, but we exclude these estimates from our analysis.

[13] See Appendix Section B.2 below for a discussion of ex post foreign exchange rate revisions. We show that they are minuscule in size and cannot explain the revision patterns that we document.

[14] Appendix Section B.1 documents these minor refinements. Our results remain unchanged when eliminating vintages that introduced changes to the reporting guidelines.

the data from PDFs or hard-copy reports. Specifically, we download all vintages of the International Debt Statistics (2013–2023) and eight vintages of the Global Development Finance reports (2005–2012) from the World Bank website. For all editions prior to 2005, we obtain PDFs or hard copies from different libraries and rely on a combination of optical character recognition (OCR) software and manual coding to render reports into machine-readable formats. Finally, we verify and reconcile the consistency of the data series and merge the data from all vintages into a single dataset (see Appendix A.2 for details).

Scope of database: Our new database covers debt statistics for an unbalanced sample of 146 developing and emerging market countries covering 53 years of data from 1970 to 2022. Appendix Table C6 provides a full list of all countries in our sample. For each country, the database combines the full reporting history with up to 51 different vintages so that each statistic can be compared across dozens of different debt reports.

Table 1: New database of debt data revisions: Scope and coverage

Number of vintages	51
Number of variables	49
Number of countries	146
Time coverage	1970–2022
Number of observations	3,315,950

Notes: This table provides details on the scope and coverage of our new database on debt data revisions. See Appendix Table C6 for a full list of all countries in our sample.

Key variables of interest: Our dataset includes 49 debt-related indicators that the World Bank has published consistently over recent decades (see Appendix A.3 for details). In our core analysis presented in Section 4, we focus on the following key debt measures and concepts:[15]

- **Debt stocks:** Our key measure for the debt stock is the series on external, public and publicly guaranteed debt disbursed and outstanding (series code "DT.DOD.DPPG.CD" in the most recent vintage). It captures all external, long-term obligations of the general government and state-owned corporations and liabilities of private debtors that have been guaranteed by a public entity.

- **Debt flows:** Our key measure for debt flows (or borrowing) is commitments to public and publicly guaranteed borrowers (series code "DT.COM.DPPG.CD" in the most recent vintage), where public and publicly guaranteed borrowers are defined as above and commitments refer to the total amount of long-term external loans for which contracts were signed in a given year.

[15] Note that our analysis focuses on under-reporting of *external* public debt only since no comparably systematic source exists for *domestic* government debt. For a discussion of domestic debt as a source of hidden debt and rich historical case evidence, see Reinhart and Rogoff (2009) and Reinhart and Rogoff (2011b).

3.2 Measurement and interpretation

By comparing debt statistics across different vintages in our database, we can measure both the amount of unreported debt in any given year and the timing of discovery or revelation of previously unreported debt. More formally, we rely on the following two measures that we construct for both the debt stock and debt flow series.

$$HiddenDebt_{i,t} = Debt_{i,t}^{V} - Debt_{i,t}^{v_0} \tag{1}$$

where *Debt* is either the debt stock or flow value, reported in vintages V and v_0, with V being the most recent vintage and v_0 being the first vintage with a value for country i and year t. In other words, the amount of unreported or hidden debt in a given year is defined as the difference between the debt value when first published and the debt value in the most recently published vintage.

We define hidden debt revelations as the amount of hidden debt uncovered in a given vintage and derive it as the difference in debt values in vintage v and vintage $v-1$, summed across all past years for which both vintages report a value for $Debt_{i,t}$.

$$HiddenDebtRevelations_i^v = \sum_{t=t_0}^{T} \left(Debt_{i,t}^{v} - Debt_{i,t}^{v-1} \right) \tag{2}$$

where $Debt_{i,t}$ is defined as above, with t_0 being the first year available in both vintages v and $v-1$, and T being the most recent year available in the same two vintages.[16]

By definition, the total amount of hidden debt equals the total amount of hidden debt revelations for any particular country.

$$\sum_{t=t_0}^{T} HiddenDebt_i^t = \sum_{v=v_0}^{V} HiddenDebtRevelations_i^v \,. \tag{3}$$

Interpretation: As explained above, the data from the World Bank International Debt Statistics that we analyze is exclusively based on debtor reporting. It is not subject to valuation changes and is compiled according to reporting rules that have been remarkably stable across 50 years. Therefore, revisions should be exclusively caused by changes in information about the underlying loans and bonds portfolio.[17] These properties of the World Bank's debt statistics ensure that ex post upward revisions are associated with the debtor country reporting additional, previously unreported loans to the World Bank retrospectively.

[16] Note that equation (2) has a clearer interpretation for the flow measure than for the stock measure of debt. The reason is that an ex post addition of a single *loan* leads to revisions of debt *stocks* across all years until final repayment and therefore involves double-counting. The same issue does not exist for the flow measure.

[17] This stands in contrast with real GDP growth and other macro variables that are also subject to frequent revisions (see, e.g., Aruoba, 2008; Johnson et al., 2013; Goes, 2024). Since these variables need to be estimated or can be revised in response to methodological refinements or updated assumptions, the nature of revisions in these variables is different from that of revisions in debt data reporting that we document here.

As the reporting guidelines are stable over time, any previously unreported loan should have been reported in the previous vintage and thus constitutes a violation of World Bank reporting guidelines. Our measure of hidden debt can therefore be summarized as initially under-reported debt in violation of prevailing reporting standards that is only revealed ex post.

Distinction from contingent liability realizations: The debt data revisions that we document are *not* driven by contingent liability realizations, i.e., the government's assumption of private sector liabilities. In contrast to hidden debt as defined here, contingent liability realizations do not require ex post revisions to previously published debt data; rather, they only lead to increases in subsequent annual public debt burden indicators (see Appendix Section B.3 for a detailed discussion and an empirical analysis of this proposition). Nevertheless, contingent liability realizations share several of the properties of hidden debt revelations that we document in this paper. The government's assumption of private sector liabilities, most notably in the form of bailouts of domestic banks, tends to occur during times of distress and can lead to unanticipated jumps in the government's debt burden (Diaz-Alejandro, 1983; Campos et al., 2006; Reinhart and Rogoff, 2011b; Bova et al., 2016; Hur et al., 2024). In this sense, our measure of under-reporting is a lower bound for the overall magnitude of "debt revelations" that bond investors endure in financial crises.

Validation and robustness: In Appendix Section B, we conduct several robustness and validation exercises to rule out the possibility that the debt data revisions that we observe are driven by alternative mechanisms. In particular, we verify that our revision patterns are not driven by changes in reporting rules (Section B.1), ex post revisions to exchange rates (Section B.2), contingent liability realizations (Section B.3), the reclassification of liabilities (Section C.1), by mere reporting lags (Section B.4) or revisions of dated debt figures (Section B.5), among others. We also verify that cases of reporting rule violations documented by the IMF Board align with the debt data revisions in our dataset (Section B.6).

Limitations: We emphasize two distinct limitations to our measure. First, loans that are initially missing from the IDS may have been reported in other debt databases. Such instances would still constitute a violation of World Bank reporting requirements but would imply less secrecy. Similarly, revelations within the IDS may follow revelations through other sources with a lag (see, e.g., the Mozambique case study in Section 2, where the hidden loans were added to the IDS after being revealed by an international audit). This issue warrants caution in regard to treating our debt data revisions as pure "news shocks" (Arezki et al., 2017).

Finally, our measure of hidden debt is a lower bound for the true level of unreported or hidden debt. Our revision-based measure of hidden debt captures only instances in which initially unreported debt is revealed at a later point in time. By definition, our measure does not capture the possibly large amount of unreported debt that remains unreported and that is never incorporated into debt statistics.

4 Main empirical findings

In this section, we present the key statistical properties of debt data revisions and discuss the magnitude, characteristics and timing of hidden debt and its revelation. Our analysis reveals three key stylized facts about hidden debt.

- **Stylized fact 1: The size and characteristics of hidden debt**
  Hidden debt is large and common. Debt data revisions are systematically upward biased with a statistically significant mean revision of approximately 1% of GDP. Under-reporting of debt has occurred persistently across all decades, debtor regions and income groups, particularly in countries with weak institutions. On the creditor side, under-reporting is most severe for bilateral and non-bond commercial lending.

- **Stylized fact 2: The timing of hidden debt revelations**
  Hidden debt tends to be accumulated during boom years and is revealed during bad years, often in the context of IMF programs and external sovereign defaults.

- **Stylized fact 3: Hidden debt and sovereign defaults**
  During default episodes, hidden debt is associated with larger creditor losses (haircuts) and longer default spells.

The following subsections discuss in turn each of these findings.

4.1 Hidden debt is large and common

Figure 5 shows the distribution of hidden debt, as measured by data revisions to external public and publicly guaranteed debt across all vintages, years, and countries in our database. Panel A focuses on debt stocks, while Panel B focuses on debt flows. Revisions are scaled by debtor country GDP, which is taken from the latest World Bank data release and not subject to revisions.

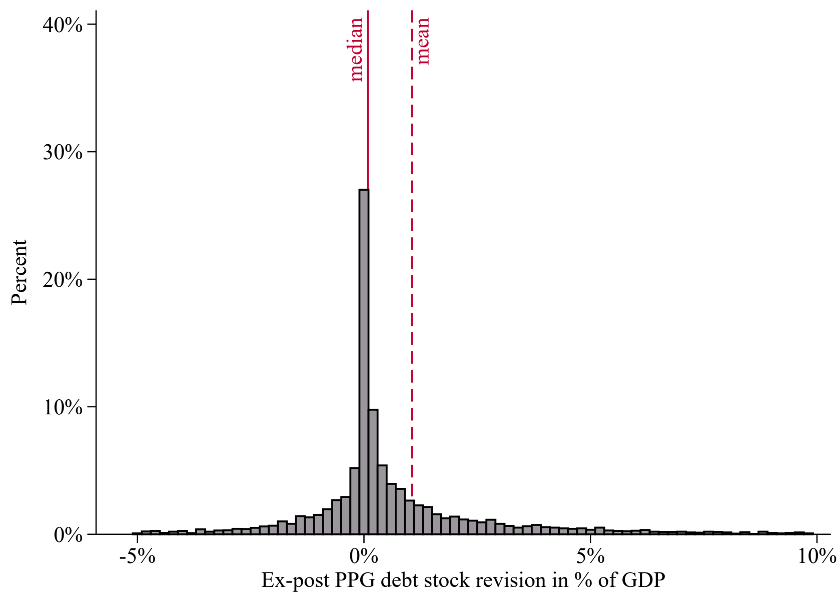
Two results stand out. First, Figure 5 reveals the large degree of uncertainty around the true level of indebtedness of developing and emerging market countries. Debt data revisions exhibit large dispersion, with frequent upward and downward revisions.[18] Approximately 70 percent of all debt stock statistics and 50 percent of all debt flow statistics published through the World Bank International Debt Statistics are revised at least once after their initial publication. This result is also reflected by the large standard deviation of 5.76 percent of GDP for stock revisions and 4.17 percent of GDP for flow revisions.

Second, the figure shows that debt data is systematically under-reported. If data revisions were the result of a well-behaved statistical process, one akin to noise or accidental misreporting, then we would expect the mean of the distribution to not be significantly different

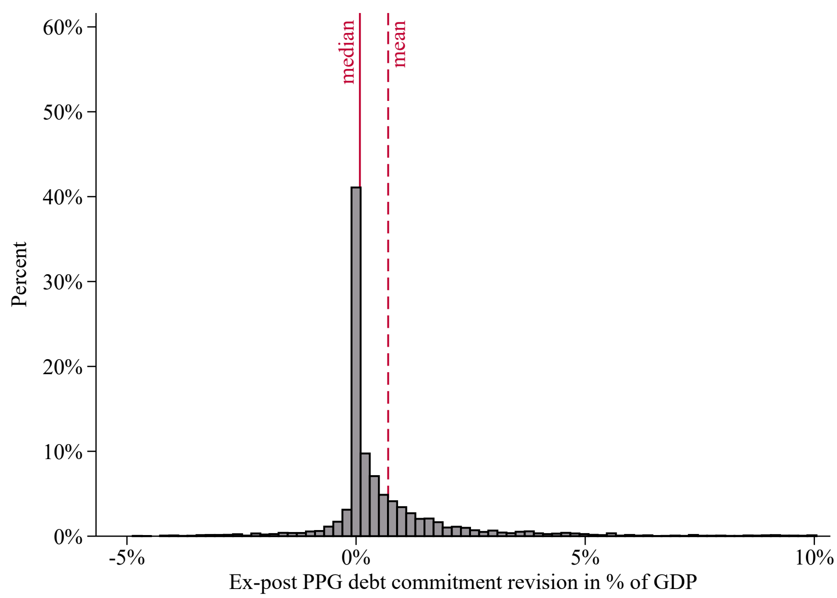
[18] For the flow measures, ex post upward revisions are four times as likely as downward revisions. For stock revisions, the same metric is not as insightful, since a single flow revision (e.g. a missing borrowing) may lead to persistent debt stock revisions until loans are repaid. Downward revisions can be caused by outright measurement error (e.g. typos) or by under-reporting of repayment flows (see Appendix Section C.3).

Figure 5: The distribution of debt stock and flow revisions

Panel A: Revisions to debt stocks in percent of GDP



Panel B: Revisions to debt flows in percent of GDP



Notes: The figure shows the percentage distribution of data revisions to debt stocks and debt flows (i.e. commitments) as defined in equation (1), in percent of GDP. Solid lines show the median, dashed lines show the mean. GDP data is taken from World Bank (2022) and not subject to revisions.

from zero (Aruoba, 2008). Figure 5 reveals that this is not the case. The distribution of both debt stock and debt flow revisions are heavily skewed to the right. While the median debt stock revision is close to zero, the average revision is positive and large at approxi-

Table 2: Summary statistics of debt data revisions

	N	Mean	Median	Std. Dev.	p-value
As a percentage of GDP					
Debt stock (DOD)	5,702	1.06	0.09	5.76	0.000
Commitments (COM)	5,695	0.70	0.08	4.17	0.000
In million USD					
Debt stock (DOD)	5,702	159.22	5.00	1,909.90	0.000
Commitments (COM)	5,695	148.60	6.00	1,169.82	0.000

Notes: The table reports summary statistics and p-values for data revisions to debt stocks and debt commitments as defined in equation (1), both in percent of GDP and in millions of nominal USD. GDP data is taken from World Bank (2022) and not subject to revisions. P-values are obtained from testing the null hypothesis that revisions have a mean of zero. We use Newey-West heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987).

mately 1 percent of GDP. Likewise, yearly undisclosed new borrowing has a mean of 0.7 percent of GDP. Table 2 combines the mean and median debt revisions with the standard deviation and shows that the mean revision as a percentage of GDP is positive and statistically different from zero at the 1% significance level. This result is incompatible with the notion of a purely noisy revision process and indicates systematic under-reporting of initial debt stocks and flows.[19] In Appendix Table C4 we show that this result is not driven by a specific subgroup but holds across all decades and almost all creditor types, debtor regions and income groups.

Our data also allows us to understand the determinants of under-reporting across debtors and creditors. To test for the role of debtor country institutions, Panel A of Figure 6 depicts the distribution of debt data revisions across country groups with different levels of institutional strength, as measured by their average score in the Polity V dataset. Figure 6 shows that reporting noise - as measured by the dispersion of the revision distribution - is substantially higher in countries with weak institutional strength, more limited checks and balances and low capacity. Notably, however, even the countries with the strongest institutions in our sample systematically under-report their debt, with a significant mean revision of 0.5 percent of GDP.

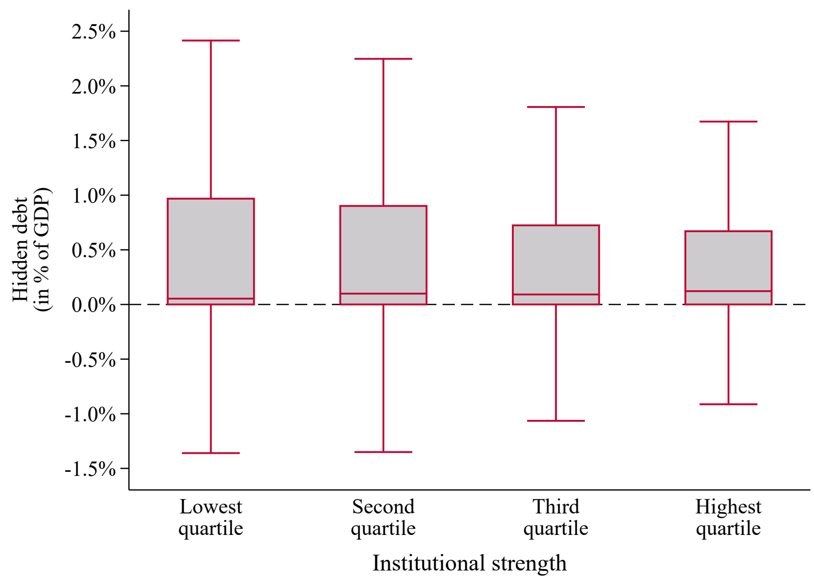
We next disaggregate debt data revisions by creditor group and find striking differences in the propensity of different instruments to be under-reported.[20] Panel B of Figure 6 reveals that the upward bias in revisions is largest in debt to bilateral and non-bond private creditors. However, for debt owed to the World Bank and for debt owed to private bondholders, the figure shows only very small revisions. This result is not surprising, given that data on (publicly traded) bonds is generally widely available and the World Bank can readily

[19] Another way of assessing the magnitude of hidden debt and borrowing is to measure how much borrowing remained undisclosed in the initial reporting and was revealed only in subsequent vintages. Our data shows that 12.6 percent of all lending is only revealed retrospectively. Over the entire history of the World Bank's debt report publications, USD 1 trillion in loans was initially unreported and revealed only in subsequent vintages.

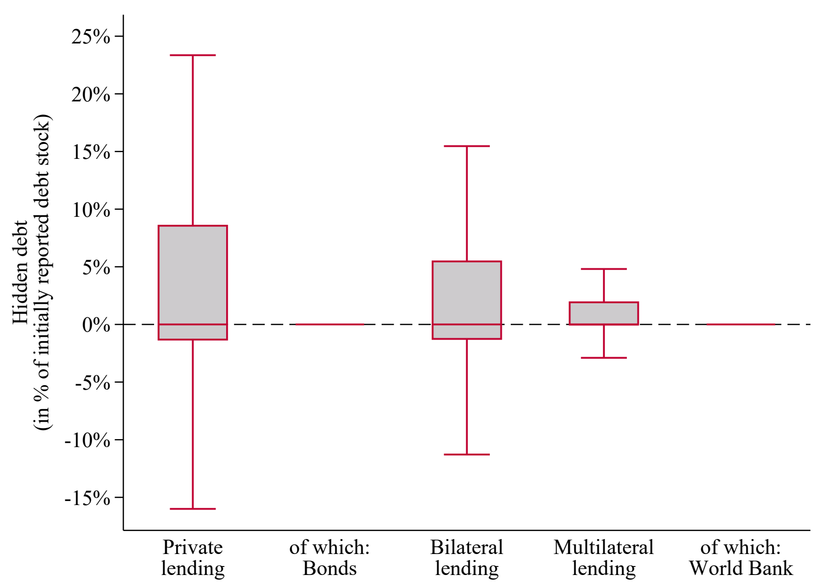
[20] Since the size of outstanding debt differs greatly across lender groups, we scale revisions by initial debt rather than GDP. See Appendix Table C3 for alternative scaling.

Figure 6: Where is hidden debt the largest?

Panel A: In borrower countries with weaker institutions



Panel B: In loans from bilateral and private creditors



Notes: This boxplot shows the distribution of hidden debt, as defined in equation (1), across debtor (Panel A) and creditor (Panel B) groups. Panel A splits the observations into quartiles of borrowing country institutional strength, as measured by average Polity V scores between 1970-2020 (Marshall and Gurr, 2020) . Panel B splits observations by creditor groups as defined by the World Bank. GDP data is taken from World Bank (2022) and is not subject to revisions.

monitor its own lending activities and ensure that they are accurately reflected in borrower reporting. Lending by bilateral and other private creditors, on the other hand, is not traded in secondary markets and is often shielded from public scrutiny through non-disclosure clauses (Gelpern et al., 2023; Mosley and Rosendorff, 2023).

4.2 Hidden debt accumulates in boom years and is revealed during busts

This section analyzes the cyclical patterns of hidden debt accumulation and revelation. We start by documenting that hidden debt tends to accumulate during boom years and be revealed during bust years. Figure 7 presents this key result in the form of binned scatter plots, following the optimal binning approach developed by Cattaneo et al. (2024).

Panel A shows the association between hidden debt and real GDP growth *in the year that is being revised*. The figure shows that boom year data points are subject to higher upward revisions, implying that more unreported borrowing occurs during good times. Panel B shows the association between hidden debt *revelations* and real GDP growth. That is, we focus on those years (vintages) in which hidden debt is revealed and added to the statistics. The negative association shows that previously unreported borrowing is more likely to be revealed during economic downturns. Hidden debt accumulation is markedly procyclical.

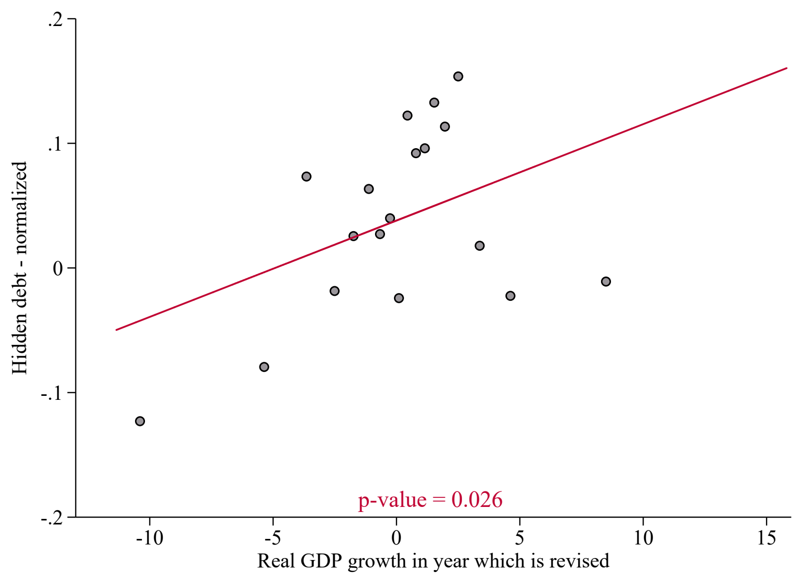
Table 3 sheds further light on the mechanisms that underlie hidden debt revelations in bad times. Specifically, in a fixed effects panel regression, we show that IMF programs and external sovereign defaults are associated with larger revelations of previously unreported debt, even when controlling for the business cycle, and for country and vintage fixed effects. While the variables explain only a small share of the overall variation in our noisy revision data, they are associated with economically sizeable effects. Both new IMF programs and sovereign default episodes are associated with an increase in hidden debt revelations of 12 percent of the standard deviation of hidden debt revelations. This result corresponds to approximately USD 200 million in newly revealed loans during the first year of the average IMF program or while a country is experiencing a sovereign default episode.

These findings confirm existing anecdotal evidence on the repeated discovery of hidden debts during crises and point to outside monitoring as a key driver of greater debt transparency.[21] Both IMF programs and external sovereign defaults are times of intense external scrutiny of a country's debt statistics. In exchange for a lending program, the IMF requires detailed access to a country's debt statistics to assess debt sustainability and calibrate program parameters and objectives. Similarly, during a sovereign default, a country's creditors come together to reconcile their data with the debtor's records as part of the debt restructuring process. In this context, the sovereign's debt records are vetted by sovereign advisors and may be subject to additional checks by international audit firms working on behalf of creditors concerned about the dilution of their claims (see the Mozambique case study in Section 2 and the next subsection).

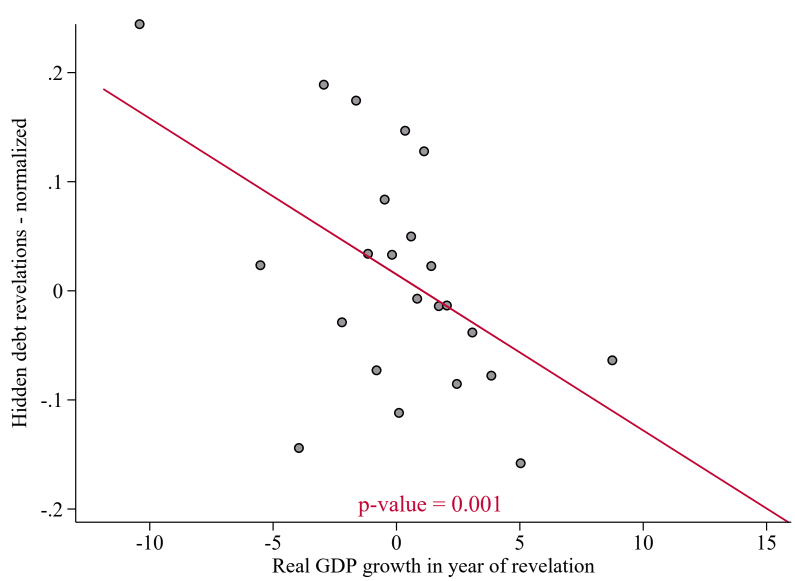
[21] An alternative hypothesis is that governments strategically reveal hidden debts for political gain, for example after coming to power or after elections. In Appendix Section C.2, we test whether domestic political factors can explain revelations of hidden debt. We do not find any evidence that governments strategically reveal previously unreported debt or that hidden debt revelations vary systematically across the political cycle.

Figure 7: The procyclical nature of hidden debt

Panel A: Which years are being revised?



Panel B: When do revelations happen?



Notes: Panel A shows the association between hidden debt and GDP growth in the year that is being revised. Panel B shows the association between hidden debt revelations and GDP growth in the vintage of the revision. The vertical axes show normalized hidden debt flows and their revelations, as defined in equations (1) and (2) respectively, standardized to account for outliers and to ease interpretation. Horizontal axes show detrended growth rates, winsorized at the 1st and 99th percentile. Trends were computed using the Hodrick-Prescott filter with a smoothing parameter of 100. Bins are constructed following the approach of Cattaneo et al. (2024). P-values and regression lines were obtained from panel regression in which we control for country fixed effects and the creditor composition of borrowing.

Table 3: Drivers of hidden debt revelations

	Dep. variable: Hidden debt revelations, 1975-2020			
	(1)	(2)	(3)	(4)
Real GDP growth (WDI)	-0.03**			-0.03**
	(0.01)			(0.01)
External sov. default		0.14***		0.12**
		(0.05)		(0.05)
IMF program			0.13***	0.12**
			(0.04)	(0.05)
Observations	3,914	4,069	4,069	3,892
R-squared	0.049	0.047	0.048	0.053
Country FE	✓	✓	✓	✓
Vintage FE	✓	✓	✓	✓

Notes: This table shows regression results from a fixed effects panel regression of hidden debt revelations on real GDP growth, the occurrence of a sovereign default, and IMF programs. The dependent variable is the sum of all previously unreported loan commitments of a country as revealed by a new vintage (see Section 3.2 and equation (2) for details). Real GDP growth is detrended and winsorized at the 1^{st} and 99^{th} percentiles. Trends were computed using the Hodrick-Prescott filter with a smoothing parameter of 100. To account for outliers and to facilitate interpretation, real GDP growth and the dependent variable are standardized. IMF program measures the first year of a program and is from Horn et al. (2020). External sovereign defaults data is from Asonuma and Trebesch (2016) and refers to all years in which a country is in default. All regressions include country and vintage fixed effects. In regression (4) we additionally control for the creditor composition of external borrowing. Robust standard errors are shown in parentheses.

4.3 Hidden debt is associated with larger creditor losses and longer default spells

The previous subsection showed that revelations of hidden debt are particularly common during external sovereign default episodes. In this context, international market creditors are often concerned about the existence of hidden debt that may dilute the recovery value of their claims. In several recent debt distress episodes, uncertainty over the true level of indebtedness has been a key obstacle to distress resolution that delayed the restructuring process and exacerbated the coordination issues among creditors (see Section 2 for anecdotal evidence).

Our newly collected data allows to empirically test, whether high hidden debts (as measured by subsequent upward revisions) are systematically correlated with longer and costlier debt restructuring processes. To test this hypothesis, we merge our hidden debt measures with the datasets on external sovereign defaults and restructurings compiled by Cruces and Trebesch (2013), Asonuma and Trebesch (2016) and Asonuma et al. (2023). Their combined data captures sovereign debt restructurings with external, private creditors between 1970 and 2020 and measures both net present value creditor losses ("haircuts") and the length of each default episode (defined by the time between the initial missed payment and the resolution through a debt restructuring). This data allows to test whether high hidden debts at the onset of a default episode are associated with (i) larger haircuts and (ii) longer resolution processes.

Table 4: Hidden debt and default spells

	Haircut		Duration of spell	
	(1)	(2)	(3)	(4)
Hidden debt	1.23***	1.03**	2.04**	1.94**
	(0.45)	(0.41)	(0.83)	(0.83)
Real GDP growth		-0.49		-0.47
		(0.37)		(0.74)
Debt to GDP ratio		0.25***		0.22**
		(0.05)		(0.10)
Real GDP p.c.		-0.76		-0.48
		(0.59)		(1.19)
Institutional strength		-0.55*		-0.99*
		(0.29)		(0.59)
Share of bond debt		-0.00		-0.24
		(0.18)		(0.36)
Share of debt to WB		0.41*		0.20
		(0.24)		(0.49)
Constant	33.78***	18.24***	36.83***	26.13*
	(2.24)	(6.76)	(4.07)	(13.59)
Observations	148	140	148	140
R-squared	0.048	0.314	0.040	0.138

Notes: This table shows the results of OLS regressions of two outcome measures of sovereign defaults on our measure of hidden debt in a cross-section of external sovereign default episodes in 1970-2020. The dependent variable in columns (1) and (2) is the net present value loss suffered by creditors as a percentage ("haircut"). The dependent variable in columns (3) and (4) is the duration of the default spell in months, measured as the time between the default event and the restructuring. Data is from Cruces and Trebesch (2013), Asonuma and Trebesch (2016) and Asonuma et al. (2023). The hidden debt variable measures the share of unreported debt at the onset of the default episode as percentage of GDP and is constructed as defined by equation (1) in Section 3.2. Standard errors are reported in parentheses. See Appendix Section A.4 and text for details on and sources of the control variables included.

Table 4 shows the results from this exercise. Columns (1) and (2) show that higher unreported debts are indeed associated with higher creditor losses in statistically and economically meaningful ways. A one percentage point increase in the amount of unreported debt (as a percentage of GDP) is associated with an increase in the haircut of 1.23 percentage points. This correlation remains strongly significant and similar in size when we control for other common predictors of creditor losses and restructuring outcomes (Graf von Luckner et al., 2023; Bai and Zhang, 2012). Columns (3) and (4) repeat the exercise but focus on the duration of the default episode. We find a strong positive correlation between hidden debt and the length of the default spell in the cross-section of external sovereign debt crises since 1970. A one percentage point increase in the amount of unreported debt is associated with an increase in the default spell by approximately two months. Again, this result holds when controlling for other common determinants of restructuring outcomes.

5 Model

To quantify the effects of hidden debt and its revelation on default risk and asset prices and to explore the welfare implications of transparency policies, we develop a quantitative model that builds on the traditional framework of the sovereign debt and default literature (following Eaton and Gersovitz, 1981, Arellano, 2008, and Aguiar and Gopinath, 2006) with long-term debt and positive recovery rates (as in Hatchondo et al., 2016 and Hatchondo et al., 2021). Our main modifications to this framework are motivated by the insights derived from our new data, particularly the stylized facts presented in Section 4. Our model features a hidden debt accumulation process and allows for international lenders to monitor the country's accounts, thereby triggering endogenous revelations of hidden debt. In the model, monitoring is costly, but investors have an incentive to monitor because hidden debt reduces their claims in the case of default through a diluting effect on their recovery rate. Our new data is used to inform the statistical properties of all of these model innovations.

To keep the framework tractable and to be able to make full use of our rich new dataset, our model abstracts from other potentially important features of hidden debt. Most notably, in the model, hidden debt accumulates exogenously and is not driven by a strategic borrower decision.[22] In this sense, our model economy is best understood as an economy in which the government has limited control over the borrowing decisions of the broader public sector, e.g. the country's state-owned enterprises. Therefore, the model primarily reflects the case of countries with weak institutions and large uncertainty about the true level of indebtedness (see Figure 6).

Furthermore, our model features international lenders who form expectations about the level of hidden debt, and these expectations depend on the time that has passed since the last revelation. However, we abstract from investors learning from the country's actions by assuming that investors arrive in overlapping generations. In addition to helping to keep the model tractable and allowing us to use the rich new data, the idea of having different generations of investors without learning is consistent with the "this time is different" narratives of past crisis episodes (Reinhart and Rogoff, 2009, 2011b). New generations of investors often repeat past mistakes by believing that financial crises are a phenomenon of the past.

5.1 Environment

Preferences and income process. The representative agent in the borrowing economy has preferences given by

$$E_t \sum_{j=t}^{\infty} \beta^{j-t} u\left(c_j\right),$$

[22]For work on the strategic use of hidden debt, see Alfaro and Kanczuk (2022), Gamboa (2023) or Guler et al. (2022).

where E denotes the expectation operator of domestic agents, β denotes the subjective discount factor, and c_t represents consumption. The utility function is strictly increasing and concave. The government cannot commit to future (default and borrowing) decisions.[23]

The economy's endowment of the single tradable good is denoted by $y \in Y \subset \mathbb{R}_{++}$. This endowment follows a Markov process.

Market debt. The small open economy borrows from a large pool of international investors by issuing long-duration bonds, b. As in Hatchondo and Martinez (2009), a bond issued in period t promises an infinite stream of coupons that decreases at a constant rate δ.[24] In particular, a bond issued in period t promises to pay $\kappa\,(1-\delta)^{j-1}$ units of the tradable good in period $t+j$, for all $j \geq 1$. The advantage of this payment structure is that it enables us to condense all future payment obligations derived from past debt issuances into a one-dimensional state variable: the payment obligations that mature in the current period.

Hidden debt. We assume that in addition to market debt, the country also faces an exogenous process for hidden debt. Provided that there has not been a revelation in the previous period (more details on the revelation below), the country starts period t with a level of hidden debt, h, which has the same coupon structure as the market debt. Absent a default in period t, the country needs to service the initial hidden debt (i.e., it pays the coupons due), and it draws a "hidden-debt issuance" realization ε from a probability distribution $G(\varepsilon)$. We assume that ε is *iid* and that $G(\varepsilon)$ is common knowledge, and we will use our novel dataset to parameterize it. The hidden debt issuance shock ε delivers new flows in period t, and it is added to the stock of hidden debt.

Monitoring. While the probability distribution for ε is common knowledge, we assume that the level of h is not. Only the country knows its true level of hidden debt, and the lenders (who are risk averse) need to form expectations about this level. Every period, before deciding how many bonds to buy, lenders have an option to "monitor" the country's statistics: they have to pay a monitoring fee f to trigger a hidden debt revelation (i.e., they learn the true level of hidden debt). If they decide to not exercise this option, they can still buy government bonds but they need to take into account the additional uncertainty of not knowing the true indebtedness of the country. Throughout the paper, we maintain the assumption that this monitoring is the only way (apart from a default) in which lenders

[23] Thus, one may interpret this environment as a game in which the government making decisions in period t is a player who takes as given the (default and borrowing) strategies of other players (governments) who will decide after t.

[24] Arellano and Ramanarayanan (2012) and Hatchondo et al. (2016) allow the government to issue both short-term and long-term debt, and they study optimal maturity and the effects of debt dilution, respectively. Hatchondo et al. (2017) allow the government to issue both defaultable and non-defaultable debt. Roch and Roldán (2023) and Sosa-Padilla and Sturzenegger (2022) allow the government to issue debt with payments contingent on the level of income.

can know the true level of hidden debt.[25] This assumption is consistent with our empirical results showing that revelations happen in times of high scrutiny (Table 3).

Defaults and recovery rates. When the government defaults, it does so on all (reported and hidden) current and future debt obligations. This is consistent with the observed behavior of defaulting governments, and it is a standard assumption in the literature.[26] Following the empirical evidence on hidden debt revelations (especially Table 3 above), we assume that a default triggers a hidden debt revelation.

A default event also triggers exclusion from the debt market for a stochastic number of periods. Furthermore, income is given by $y - \phi(y)$ in every period in which the government is excluded from debt markets. Starting the first period after the default period, with a constant probability $\theta \in [0, 1]$, the government may regain access to debt markets. We assume that to emerge from a default episode the country exchanges its defaulted bonds for new bonds. That is, the country reenters markets with a non-negative amount of debt. We call this amount, b_D and assume the following regarding b_D:

$$b_D(b, h, y) = \min\left\{\alpha(y), b + \tilde{h}\right\} , \tag{4}$$

where $\tilde{h} = \max\{0, h\}$ and $\alpha(y)$ is a non-decreasing function of the income level realized upon reentry. These new bonds b_D are divided among holders of the previously issued market and hidden debt as follows. Holders of hidden debt (which was revealed at the default event) obtain $\chi\tilde{h}$, with $\chi \in [0, 1]$.[27] Holders of the previously issued market debt obtain the remainder, $b_D - \chi\tilde{h}$. This implies the following recovery rate for market debt:

$$\omega^b(b, h, y) = \frac{b_D(b, h, y) - \chi\tilde{h}}{b} . \tag{5}$$

From equation (5) it is clear how hidden debt can dilute the recovery rate for market lenders, which further justifies their potential decision to monitor the country's accounts.

Timing. For a country that ended period $t - 1$ in good financial standing, the timing of events within period t is as follows:

0. The levels of market debt and of hidden debt $\{b, h\}$ are known to the government. Lenders know b and how many periods have passed since the last hidden debt revelation, τ.

[25] For example, one can think of uncertain and/or opaque items in the government's budget constraint such that even after factoring in all the observables (coupon payments on market debt, issuances, consumption, etc.) lenders are still unable to perfectly infer the level of hidden debt. See Gamboa (2023) for empirical support in favor of this assumption.

[26] Sovereign debt contracts often contain an acceleration clause and a cross-default clause. The first clause allows creditors to call the full value of the debt that they hold in case the government defaults on a single payment. The cross-default clause states that a default on any government obligation constitutes a default on all the other contracts containing such a clause. As a result of these two clauses, after a default event, all future debt obligations become current.

[27] We assume that debt that is hidden at the time of default is excluded from the regular restructuring process. This hidden debt has an effective recovery rate of χ.

1. y and ε are realized. All agents observe y, but only the government observes ε.
2. Lenders use their information to post (i) a monitoring rule, $m \in \{0, 1\}$, and (ii) price schedules q_{M} and q_{NM} for the cases of monitoring and non-monitoring, respectively.
3. The government observes all states and lenders policy functions, and it makes a default decision: $d \in \{0, 1\}$
   - If default ($d = 1$): no coupons are paid, all hidden debt is revealed, the country does not obtain any flows from ε, and it suffers from income losses and exclusion while the default status persists.
   - If repay ($d = 0$): the government can borrow again by choosing b'. When it evaluates possible values for b' it takes into account the fact that different borrowing levels imply different prices and different monitoring policies from lenders.
     - If there is monitoring ($m = 1$), all discovered debt is added to b, and the hidden debt going forward is zero ($h' = 0$).
     - If there is no monitoring ($m = 0$), hidden debt is $h' = h\,(1 - \delta) + \varepsilon$.
4. Consumption and coupon payments (if relevant) take place.

For a country that ended period $t - 1$ in financial exclusion, the first event that occurs is a realization of a reentry shock. With probability $1 - \theta$ the country remains excluded and has no decision in the period (it consumes its reduced income level). If reentry occurs (with probability θ), then the country receives a realization of ε, its initial debt level gets reduced to b_D (according to equation 4), and its initial hidden debt is set to zero (since it had been revealed in the prior default event). The country then finds itself at step 2 above, and the timing of events continues as specified there.[28]

5.2 Foreign lenders

We follow the modeling of lenders presented in Gu and Stangebye (2023); however, to use the full extent of our novel dataset of hidden debt revelations and to retain tractability, we simplify the information acquisition problem. We assume that foreign lenders are risk averse and that they arrive in overlapping generations, each with wealth W. They have access to a risk-free asset that yields a net return of r. When the sovereign starts the period in good standing and has not defaulted, the problem for a foreign lender is to decide whether to monitor the country's debt: $m = 1$ denotes monitoring, and $m = 0$ denotes not monitoring. Monitoring is the only way in which lenders can acquire information about the true debt level of the country and it is costly: lenders have to pay a fee of f.

When they make this decision they know b, y, and the number of periods since the last revelation (τ), and they evaluate their value under monitoring or no monitoring for different candidate levels of B'. After this decision is made, hidden debt either continues to be

[28]Implicit in our timing is the assumption that when the government makes decisions (d and b'), lenders cannot change their monitoring policies or pricing schedules.

unknown to lenders or is fully revealed, and lenders then have to choose how many bonds to buy.[29] In the exposition of the lenders' problem, we use b' to denote the borrowing choice of the government and B' to denote lenders' investment in government bonds.[30]

The lenders' problem can be written as

$$V^{\ell}(b', y, \tau) = \max_{m \in \{0,1\}} \left\{ m\, V_M^{\ell}(b', y) + (1-m)\, V_{NM}^{\ell}(b', y, \tau) \right\} . \tag{6}$$

In turn, their value under monitoring is given by

$$V_M^{\ell}(b', y) = \max_{B'} \; E^{\ell}\left[u_{\ell}\left(C'_{\ell}\right)\right] \tag{7}$$

subject to

$$C'_{\ell}\left(B', h', y', \varepsilon', \tau'\right) = (W - f - q_{\text{M}} B')(1+r) + B'\mathcal{R}' \tag{8}$$

$$\mathcal{R}'(b', h', y', \varepsilon', \tau') \equiv d'\, q_D(b', h', y') + (1-d') \times \Big[\kappa + (1-\delta)\Big(m^*(b'', y', \tau')\, q_{\text{M}}(b'', y') + (1 - m^*(b'', y', \tau'))\, q_{\text{NM}}(b'', y', \tau')\Big)\Big] \tag{9}$$

where $\tau' = 1$, $h' = 0$, q_D denotes the price of a bond in default, $b'' = \hat{b}(b', h', y', \varepsilon', \tau')$, and $d' = \hat{d}(b', h', y', \varepsilon', \tau')$, with $\hat{b}$ and $\hat{d}$ denoting the optimal borrowing and default policies that lenders expect the government to follow, respectively. $m^*(b'', y', \tau')$ is the monitoring policy that current lenders expect the future generation of lenders will follow, and E^{ℓ} denotes the expectation operator of lenders in the case of monitoring.[31]

The solution to this problem features a demand schedule for sovereign bonds given by

$$q_{\text{M}}(b', y) = \frac{E^{\ell}\left\{u'_{\ell}\left(C'_{\ell}\left(B', h', y', \varepsilon', \tau'\right)\right) \times \mathcal{R}'(b', h', y', \varepsilon', \tau')\right\}}{E^{\ell}\left[u'_{\ell}\left(C'_{\ell}\left(B', h', y', \varepsilon', \tau'\right)\right)(1+r)\right]} . \tag{10}$$

The value of not monitoring is similar to that above, with two exceptions: (i) there is no monitoring fee (f) to be paid, and (ii) there is no revelation of hidden debt, which implies that the information set in this case is different (and, hence, the subjective expectations are different). In this case, we use E_{τ}^{ℓ} to denote the expectation operator of lenders, where the sub-index τ indicates that the lenders' expectations about h' vary with the time since the last revelation. Therefore, the value under no monitoring can be written as follows:

$$V_{NM}^{\ell}(b', y, \tau) = \max_{B'} \; E_{\tau}^{\ell}\left[u_{\ell}\left(C'_{\ell}\right)\right] \tag{11}$$

[29] Note that in this framework, different from Gu and Stangebye (2023), the government has an informational advantage over lenders (it knows h and ε), but we assume that it has no credible way of communicating the true level of hidden debt. This modeling approach is consistent with our finding that governments do not strategically reveal hidden debt for political gain (see C.2). Moreover, we assume that there is no communication between the different overlapping generations of lenders. These assumptions combined with the fact that the monitoring rule and pricing schedules cannot be changed after observing government actions imply that lenders do not learn from the country's actions.

[30] In equilibrium, we will naturally have $b' = B'$.

[31] In the case of monitoring, τ becomes zero (i.e. the last revelation of debt occurred in the current period), and lenders know for certain that $h' = 0$.

subject to

$$C'_\ell\left(B', h', y', \varepsilon', \tau'\right) = (W - q_{\text{NM}} B')(1+r) + B'\mathcal{R}' \tag{12}$$

where $\mathcal{R}'$ is given by equation (9) evaluated at $\tau' = \tau + 1$. Lenders view h' as a random variable drawn from a distribution that depends on (i) $G(\varepsilon)$ (the distribution of innovations to hidden debt, which is known) and (ii) the time since the last hidden debt revelation, τ.

The solution to lenders' problem under no monitoring features a demand schedule for sovereign bonds given by

$$q_{\text{NM}}(b', y, \tau) = \frac{E^\ell_\tau\left\{u'_\ell\left(C'_\ell\left(B', h', y', \varepsilon', \tau'\right)\right) \times \mathcal{R}'(b', h', y', \varepsilon', \tau')\right\}}{E^\ell_\tau\left[u'_\ell\left(C'_\ell\left(B', h', y', \varepsilon', \tau'\right)\right)(1+r)\right]}, \tag{13}$$

where C'_ℓ is given by equation (12) and $\tau' = \tau + 1$.

Finally, a foreign lender who arrives in a state in which the government is in default faces a similar problem but with a different set of returns. Debt is not serviced in default; however, in every period, there is a constant probability of reentry, in which case the government exchanges its defaulted bonds for new bonds, as specified above. This implies the following problem for foreign lenders in default:

$$V^\ell_D(b, h, y) = \max_B \; E^\ell\left[u_\ell(C'_\ell)\right] \tag{14}$$

subject to

$$C'_\ell(B, h, y', \varepsilon', \tau') = (W - q_D(b, \tilde{h}, y')B)(1+r) + B\mathcal{R}'_{\mathcal{D}}, \tag{15}$$

$$\begin{aligned}\mathcal{R}'_{\mathcal{D}}(b, h, y', \varepsilon', \tau') = (1-\theta)q_D(b, \tilde{h}, y') + \theta\,\omega(b, h, y')\Bigg[&\hat{d}(b_D, 0, y', \varepsilon', \tau')\,q_D(b_D, 0, y') + \\ &(1 - \hat{d}(b_D, 0, y', \varepsilon', \tau'))\Big[\kappa + (1-\delta)\Big(m^*(b'', y', \tau')q_{\text{M}}(b'', y') + \\ &(1 - m^*(b'', y', \tau'))\,q_{\text{NM}}(b'', y', \tau')\Big)\Big]\Bigg]\end{aligned} \tag{16}$$

where $\theta \in (0,1)$ is the probability of reentry to financial markets, $\tilde{h} = \max\{h, 0\}$ and $\tau' = 1$. As before, $\hat{d}$ represents the expected default policy, $b'' = \hat{b}(b_D, 0, y', \varepsilon', \tau')$ is the expected borrowing policy, and $m^*(b'', y', \tau')$ is the expected monitoring policy. b_D and $\omega(b, h, y')$ are given by equations (4) and (5), respectively. Therefore, the price of a bond in default is given by

$$q_D(b, h, y) = \frac{E^\ell\left\{u'_\ell(C'_\ell) \times \mathcal{R}'_{\mathcal{D}}(b, h, y', \varepsilon', \tau')\right\}}{E^\ell\left[u'_\ell(C'_\ell)(1+r)\right]}. \tag{17}$$

Note that in this case, the correct expectation operator is E^{ℓ}, the same as under monitoring. The reason is our assumption that a default triggers a revelation of hidden debt and therefore lowers uncertainty.[32]

5.3 The government's problem

A government that starts the period in good standing has the option to default on its debt. Therefore,

$$V(b,h,y,\varepsilon,\tau) = \max_{d\in\{0,1\}} \Big\{ d\, V_1(b,h,y) + (1-d)\, V_0(b,h,y,\varepsilon,\tau) \Big\} \tag{18}$$

As described above, a government default triggers (i) the revelation of all hidden debt and (ii) temporary market exclusion and income costs. We also assume there are no further additions to hidden debt during exclusion. Thus, the value under default is given by

$$V_1(b,h,y) \quad = \quad u(c_D) + \beta E_{y',\varepsilon'|y} \Big[(1-\theta)\, V_1(b,\tilde{h},y') + \theta\, V(b_D,h',y',\varepsilon',\tau') \Big] \tag{19}$$

subject to

$$c_D = y - \phi(y) + \left(\tilde{h} - h\right) \tag{20}$$

where $\tilde{h} = \max\{h,0\}$, $h' = 0$, $\tau' = 1$, and $b_D(b,h,y')$ is given by equation (4). The function $\phi(y)$ captures the income cost of defaults.

If the government decides to repay, then the problem is more involved, as it depends on the monitoring decision of lenders. The value of repayment is

$$V_0(b,h,y,\varepsilon,\tau) = m^*\, V_0^M(b,h,y,\varepsilon) + (1-m^*)\, V_0^{NM}(b,h,y,\varepsilon,\tau)$$

where $m^*(b',y,\tau)$ denotes the optimal monitoring policy, which the government takes as given (understanding how it depends on the level of b'). In the case of monitoring ($m^* = 1$), hidden debt is revealed and is added to the existing market debt, and the end-of-period level of hidden debt is zero ($h' = 0$). In this case, the problem of the government is

$$V_0^M(b,h,y,\varepsilon) = \max_{b'} \big\{ u(c) + \beta E_{y',\varepsilon'|y}\, V(b',h',y',\varepsilon',\tau') \big\} \tag{21}$$

subject to

$$\begin{aligned} c &= y - \kappa(b+h) + q_{\mathrm{M}}(b',y)\iota + q_h\varepsilon \\ \iota &= b' - [(1-\delta)b + (1-\delta)h + \varepsilon] \\ h' &= 0, \qquad \tau' = 1, \\ \iota &> 0, \quad \text{only if} \quad q_{\mathrm{M}}(b',y) > \underline{q}, \end{aligned}$$

[32]This assumption is consistent with the evidence in our new dataset, in which we observe that revelations are high in default episodes. The uncertainty reduction effect of defaults has also been highlighted in recent work by Gutkowski (2022).

where ι represents the issuance of new market debt and $q_{\text{M}}(b', y)$ is the per-bond price of this new debt. The last constraint is the "price-floor" constraint, which is typically used in models of sovereign default with long-term debt to avoid "infinite dilution" in the period prior to a default (see Hatchondo et al., 2016). To simplify the analysis, we treat q_h as a parameter.

In the case of no monitoring ($m^* = 0$), hidden debt continues to be hidden to lenders, and its end-of-period level is $h' = (1-\delta)h + \varepsilon$. In this case, the problem of the government is

$$V_0^{NM}(b, y, h, \varepsilon; \tau) = \max_{b'} \left\{ u(c) + \beta E_{y', \varepsilon' | y} V(b', y', h', \varepsilon', \tau') \right\} \tag{22}$$

subject to

$$\begin{aligned}
c &= y - \kappa(b+h) + q_{\text{NM}}(b', y, \tau)\iota + q_h \varepsilon \\
\iota &= b' - (1-\delta)b \\
h' &= (1-\delta)h + \varepsilon \\
\tau' &= \tau + 1 \\
\iota &> 0 \quad \text{only if} \quad q_{\text{NM}}(b', y, \tau) > \underline{q}\,.
\end{aligned}$$

5.4 Equilibrium definition

A Markov perfect equilibrium is defined by value functions $\{V(b, h, y, \varepsilon, \tau), V_0^M(b, h, y, \varepsilon), V_0^{NM}(b, h, y, \varepsilon, \tau), V_1(b, h, y)\}$, policy functions $\left\{\hat{d}(b, h, y, \varepsilon, \tau), \hat{b}_M(b, h, y, \varepsilon), \hat{b}_{NM}(b, h, y, \varepsilon, \tau)\right\}$, a monitoring rule $m^*(b', y, \tau)$, and bond price schedules $\{q_{\text{M}}(b', y), q_{\text{NM}}(b', y, \tau), q_D(b, h, y)\}$ such that: **(i)** given the bond price schedules and monitoring rule, government policies and value functions solve the dynamic programming problem defined by equations (18)–(22); **(ii)** given the bond price schedules and government policies, the monitoring rule solves the problem in equation (6); **(iii)** given government and lender policies, the price functions satisfy equations (10), (13), and (17); and **(iv)** the market for government debt clears.

6 Quantitative analysis

In this section, we present the results from the quantitative model. First, we discuss the calibration strategy for our benchmark model and how the results fit the novel database described in Sections 3 and 4. Second, we examine the properties of the model regarding default incentives, monitoring policies, and borrowing terms for the government. Third, we study the relationship between revelations and equilibrium spreads, both in the model and in our novel database. Finally, we present the welfare implications of hidden debt by comparing the benchmark model results with an otherwise identical model where monitoring by creditors is cheaper and another model with full information on debt accumulation.

6.1 Calibration

Functional forms and stochastic processes. The utility function of the representative agent in a small open economy displays a constant coefficient of relative risk aversion, i.e.,

$$u(c) = \frac{c^{1-\gamma}}{1-\gamma}, \text{ with } \gamma \neq 1\,.$$

We assume that lenders have a utility function of the same form, with a coefficient of relative risk aversion given by γ_ℓ.

The endowment process for the borrowing country follows:

$$\log(y_t) = (1-\rho)\mu + \rho \log(y_{t-1}) + \nu_t,$$

where $|\rho| < 1$ and $\nu_t \sim N\left(0, \sigma_\nu^2\right)$. As in Chatterjee and Eyigungor (2012), we assume a quadratic loss function for income during a default episode $\phi(y) = \max\{y[\lambda_0 + \lambda_1[y - \mathbb{E}(y)]], 0\}$. The function controlling the minimum level of debt upon reentry is parametrized as $\alpha(y) = \overline{\alpha}$.

We assume that innovations to (i.e., 'issuances' of) hidden debt ε are *iid* and follow a normal distribution with mean μ_ε and variance σ_ε^2. Importantly, while lenders know the distribution of ε, they can observe ε and h only upon a revelation. Knowing this distribution, how many periods have passed since the last revelation (τ), and the law of motion for hidden debt conditional on no revelation (i.e. $h' = (1-\delta)h + \varepsilon$), lenders understand that h' is distributed as follows:[33]

$$h' \sim N\left(\mu_\varepsilon \frac{1-(1-\delta)^\tau}{\delta}, \sigma_\varepsilon^2 \frac{1-(1-\delta)^\tau}{\delta}\right). \tag{23}$$

Equation (23) makes it clear that as time passes since the last hidden debt revelation, lenders' expectations of the future levels of hidden debt feature a higher mean and a higher variance.

Parameter values. Table 5 presents the benchmark values assigned to all parameters in the model. A period in the model refers to a year. The coefficient of relative risk aversion for the borrowing country, risk-free interest rate, and discount factor β take standard values.

The parameters that govern the endowment process are estimated from our dataset. These values, $\rho = 0.6$ and $\sigma_\nu = 3\%$, are close to those typically found in studies of emerging and low-income countries.[34] We assume an average duration of sovereign default events of three years ($\theta = 0.33$), following Dias and Richmond (2007). We set $\delta = 0.31$; with this value, sovereign debt has an average risk-free duration of 5 years in the simulations, which is close to the average duration found in the previous literature.[35] The coupon is normalized to

[33] The distribution of h', conditional on τ, is a straightforward consequence of the properties of the normal distribution. See Appendix D for more details.

[34] Note that the income autocorrelation is somewhat lower than the values estimated for countries with continuous market access (e.g. Mexico).

[35] We use the Macaulay definition of duration, which, with the coupon structure in this paper, is given by $D = (1+r)/(\delta + r)$, where r denotes the risk-free rate. Cruces et al. (2002), using a sample of 27 emerging

$\kappa = (r+\delta)/(1+r)$, which ensures that a default-free bond (with the same coupon structure as our sovereign bonds) trades at a price of $1/(1+r)$. The price floor $\underline{q}$ is set to 70% of the risk-free price, which is never binding in the simulations.

Table 5: Benchmark parameter values.

Borrower's risk aversion	γ	2.0	Standard
Risk-free rate	r	0.04	Standard
Discount factor	β	0.90	Standard
Income autocorrelation coefficient	ρ	0.6	Estimated
Standard deviation of innovations	σ_ν	0.03	Estimated
Probability exclusion ends	θ	0.33	Mean exclusion = 3 years
Debt duration	δ	0.31	Debt duration = 5 years
Bond coupon	κ	$(r+\delta)/(1+r)$	Risk-free bond price = $1/(1+r)$
Price floor	$\underline{q}$	$0.7/(1+r)$	Never binding
Lender's risk aversion	γ_ℓ	2.0	Aguiar et al. (2016)
Lender's wealth	W	2.5	Aguiar et al. (2016)
Hidden debt price	q_h	$1/(1+r)$	Normalization
Hidden debt recovery	χ	1.0	Normalization
Mean of ε	μ_ε	1%	Our dataset
Standard deviation of ε	σ_ε	2%	Our dataset
Income cost of defaulting	λ_0	0.07	Avg. market debt = 26%
Income cost of defaulting	λ_1	1.75	Avg. spread = 3.0%
Monitoring fee	f	0.03%	Freq. of monitoring = 7.1%
Recovery rate parameter	$\overline{\alpha}$	0.15	Mean recovery rate = 55%

Notes: Mean and standard deviation of ε and the monitoring fee are expressed in percent of GDP.

The second part of Table 5 details our parametrization of the lender's side of the model and the properties of hidden debt. We follow Aguiar et al. (2016) in setting the risk aversion coefficient of lenders to the same value as that for the borrower ($\gamma_\ell = \gamma = 2$). The lender's wealth W is set to 2.5 (i.e., 250% of the mean income in the borrowing country), which is in line with the parameter value used in Aguiar et al. (2016). The price of hidden debt q_h is normalized to the risk-free price and the effective recovery rate on hidden debt χ is normalized to one. The mean and variance of innovations to hidden debt are set using the values found in our dataset.[36]

The last part of Table 5 has the remaining parameters. We calibrate the default cost parameters (λ_0 and λ_1), the monitoring fee (f), and recovery rate parameter ($\overline{\alpha}$) to target four moments from the data: (i) an average debt-to-GDP ratio of 26%, (ii) a mean spread of 3.0%, (iii) a frequency of monitoring of 7.1%, and (iv) a recovery rate of 55%. The first three moments are computed directly from our dataset. The recovery rate is taken from Graf von Luckner et al. (2023) and corresponds to the mean recovery rate obtained by bondholders in the modern era of sovereign bond financing. We solve the model using value function iteration and interpolation (Hatchondo et al., 2010).

economies, find an average duration of 4.77 years, with a standard deviation of 1.52 years. In a panel of 11 emerging economies, Bai et al. (2017) report an average debt duration of 6.7 years.

[36] We obtain μ_ε of 1% and σ_ε of 2% after winsorizing our revelations data at the 1st and 99th percentiles.

Model fit. The moments reported in Table 6 are chosen to illustrate the ability of the model to replicate distinctive business cycle properties of economies with sovereign risk as well as the hidden debt revelation patterns that we observe in the data.

Table 6: Model fit

	Data	Model
Targeted moments		
Mean debt-to-GDP	26	24
Mean spread (r_s)	3.0	3.0
Mean recovery rate	55	56
Freq. of revelations	7.1	7.2
Non-targeted moments		
a) Business cycle statistics		
$\sigma(c)/\sigma(y)$	1.1	1.3
$\rho\,(c, y)$	0.9	0.8
$\rho\,(r_s, y)$	-0.3	-0.4
$\sigma\,(r_s)$	2.8	1.8
b) Hidden debt revelation patterns		
Mean Revelation$/y$	0.94	0.88
$\rho(\text{Revelation}/y, b/y)$	0.10	0.03
$\rho(\text{Revelation}/y, y)$	-0.06	-0.18
$\rho(\text{Hidden debt}, \text{HC})$	0.17	0.13

Notes: The standard deviation of x is denoted by $\sigma\,(x)$. The coefficient of correlation between x and z is denoted by $\rho\,(x, z)$. HC is the debt haircut and is defined as one minus the recovery rate. Moments are computed using log-detrended series. Trends are computed using the Hodrick-Prescott filter with a smoothing parameter of 100. In the simulations, moments correspond to the mean value of each moment in 500 simulation samples, with each sample including 500 periods. To compute the frequency of monitoring in the data we condition on revelations outside of default years and on revelations that amount to at least 1% of GDP.

Table 6 shows that our model well approximates the moments used as targets and is broadly consistent with non-targeted moments in the data. In both the model and data, consumption is procyclical and more volatile than income and the sovereign spreads are volatile and countercyclical.

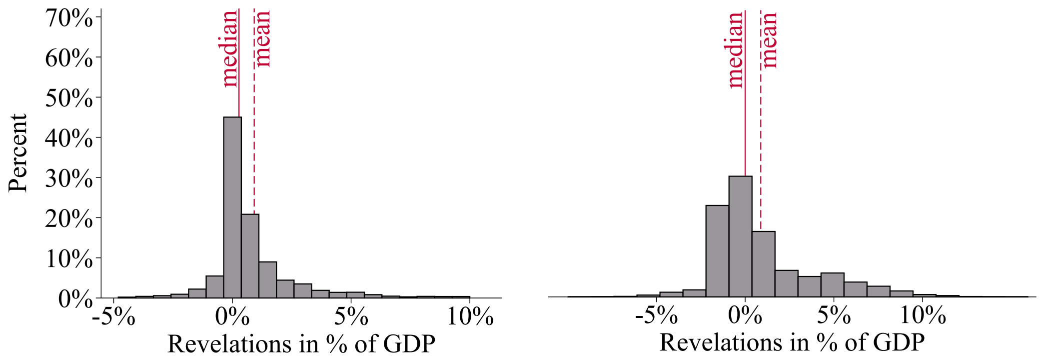
The model further produces hidden debt revelation patterns that closely match those observed in our novel dataset. Revelations are highly similar in (mean) size, and they are negatively correlated with income and positively correlated with the debt-to-income ratio. Finally, in the event of default, the stock of hidden debt is associated with higher net present value losses (haircuts) for market creditors, as observed in the data (see Section 4.3).

This ability of our model to replicate the revelations observed in the data also becomes evident when observing the full distribution of revelations in the data and the model output, presented in Figure 8. Both distributions exhibit a right skew, positive means and near-zero medians.

Figure 8: Hidden debt revelations in the data and model

Panel A: Data

Panel B: Simulated model



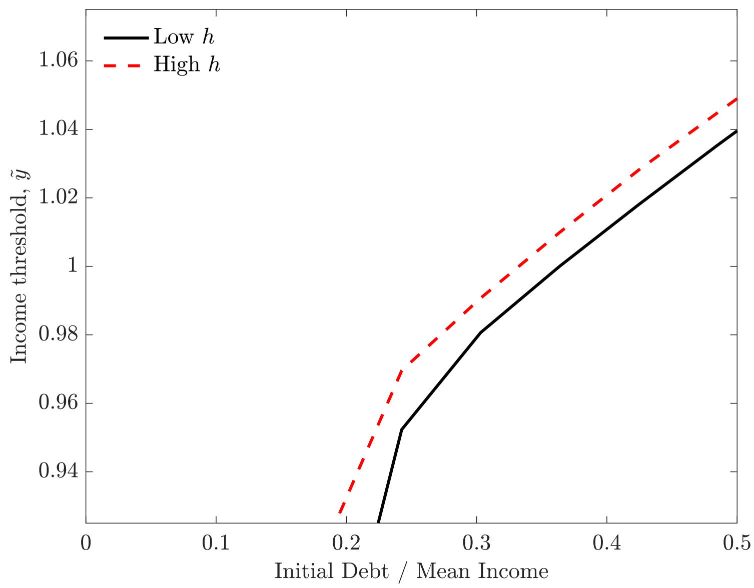
Notes: The figure shows the percentage distribution of hidden debt revelations from our database and the simulated model. In the data, revelations are defined as in equation (2).

6.2 Default incentives, monitoring and borrowing opportunities

Default incentives. Figure 9 uses an "income threshold" to illustrate the default incentives in our model. We define the income threshold $\tilde{y}$ as the value of income at which the government is indifferent between repaying and defaulting, for given values of the other state variables.[37] Figure 9 plots this income threshold over the initial debt stock and for two values of initial hidden debt. For $y < \tilde{y}$ the government defaults (and repays otherwise). As expected, the higher the initial debt is, the higher the income threshold, which implies that there is a larger portion of the income space for which the country prefers to default. Likewise, higher hidden debt increases default incentives: $\tilde{y}$ increases with h.

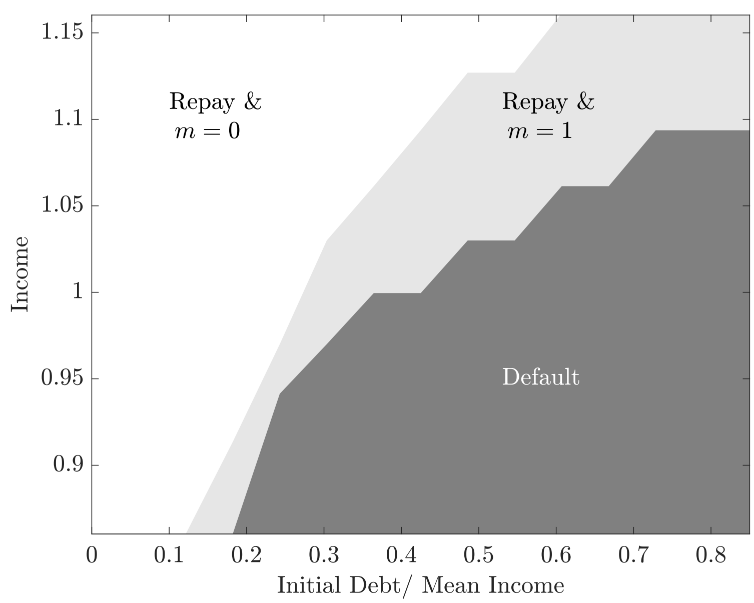
[37] Formally, $\tilde{y}$ is the income level that satisfies $V_0(b, h, \tilde{y}\varepsilon, \tau) = V_1(b, h\tilde{y})$. We numerically verify that this threshold is unique.

Figure 9: Income thresholds, $\tilde{y}$



Notes: Different colors represent different values of hidden debt h in period t. This figure assumes that $\tau = 7$ (the mean in the simulations) and ε below its mean.

Figure 10: Repayment, monitoring and default regions.



Notes: The figure shows equilibrium monitoring and default choices as a function of income and initial debt. The figure assumes that $\tau = 7$ (the mean in the simulations), h at its mean and ε below the mean.

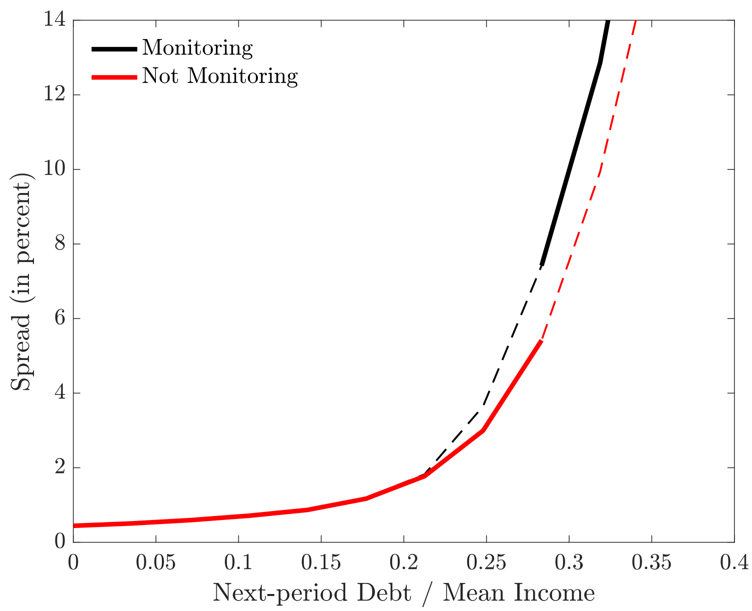
Monitoring and default in equilibrium. Figure 10 illustrates how the equilibrium monitoring and default decisions depend on the initial level of market debt and income.[38] The default region (denoted in dark gray) has the properties discussed above (and given

[38]Recall that lenders' monitoring policy cannot, by construction, depend on the hidden debt process.

our assumption that a default reveals previously hidden debt, there is no monitoring under default). The repayment region has both combinations of the state variables with and without monitoring. Equilibrium monitoring tends to occur when the initial debt and income are close to the default boundary: all other things being equal, higher initial debt and lower income increase the chances of observing monitoring in equilibrium.

Borrowing opportunities. Figure 11 shows the spread-debt menus from which the government can choose, conditional on the monitoring policy of lenders. As is usual in this class of models, higher borrowing comes at the cost of higher spreads. When the chosen borrowing is sufficiently high, the spread increase acts, in effect, as an endogenous borrowing limit.

Figure 11: Spread-debt menus



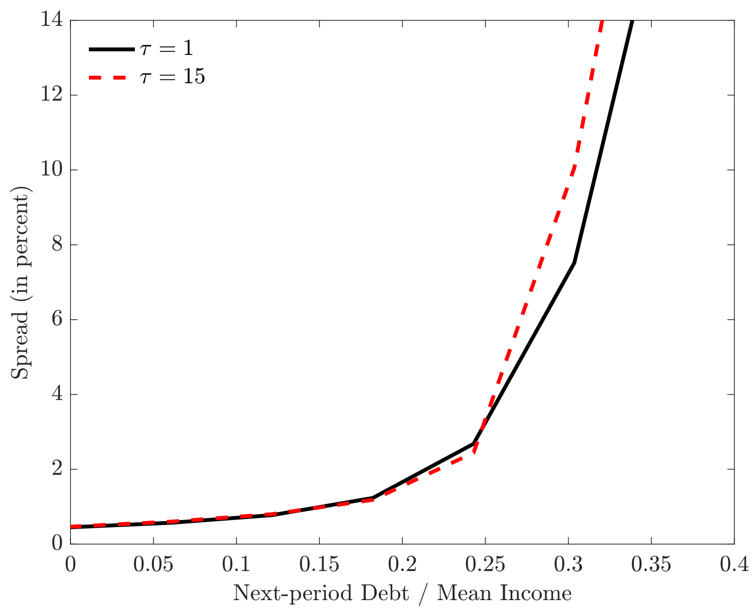
Notes: The curves show combinations of next-period debt and spreads from which the country can choose in the current period, for both monitoring and no-monitoring cases. The thick portion of the curves indicates the levels of next-period debt, which, if selected by the government, prompt either monitoring or no monitoring. The plot assumes that y is at its mean.

The spreads in Figure 11 are shown for the case in which the government has market access in period t. Therefore, a debt revelation can occur in this situation only through monitoring. The thick part of the spread curves shows how higher borrowing can trigger monitoring and, hence, revelations. For the particular combination considered in Figure 11, if the country borrows beyond 28% of mean income, it triggers monitoring and pays higher spreads (approximately 150 bps higher).

6.3 Revelations and spreads

In our model, revelations occur for two reasons: monitoring and default. Monitoring-induced revelations are associated with higher spreads (as suggested by Figure 11): on average, the equilibrium spread on monitoring periods is higher than the mean in the simulations (4.6% vs 3.0%).[39] Upon default, the government cannot borrow; however, since bonds in default are still valuable (due to a positive recovery rate), we can compute the implied spread – this is also higher than the average spread in the simulations.[40]

Figure 12: The effect of τ on spread menus



Notes: The curves show combinations of next-period debt and spreads from which the country can choose in the current period when the country is facing a non-monitoring episode, for two values of τ. The plot assumes that y is at its mean.

Hidden debt revelations impact spreads over an extended period. Focusing on monitoring-induced revelations, we see that revelations in t are related to spreads in $t+1$ in two ways. First, a revelation reduces the uncertainty about the hidden debt stock, which, all other things being equal, lowers the spreads offered to the country in the period after the revelation: Figure 12 shows the spread-debt menu curves that the country faces in period t when a revelation took place in period $t-1$ (and, therefore, the time since the last revelation is $\tau = 1$) and when the last revelation was sufficiently back in time ($\tau = 15$).[41] Having had a recent revelation, lenders understand that both the expected value and the variance of (new) hidden debt are low, which leads them to offer better prices for government bonds. Second, a revelation increases the stock of market debt that lenders know the country has, which, coupled with the more favorable borrowing terms, typically leads to more borrowing by the country and to higher spreads in equilibrium.[42] In our simulations, we see the

[39] These higher spreads are, in turn, due to the higher level of borrowing (which is what triggers the revelation) and compensate for the monitoring fee paid by lenders.

[40] This particular relationship between default-induced revelations and higher spreads is admittedly more mechanical. With an average recovery rate of 55% (a target in our calibration), the typical bond price in default and exclusion periods is substantially lower than that in non-exclusion periods. The implied spread in the default period is 36%, on average.

[41] Note that these two curves are the spread-debt menus for the no-monitoring case, as this is the only bond price that depends on τ.

[42] A movement towards the right on the horizontal axis of Figure 12, along the $\tau = 1$ curve.

combined effect of these forces. All else equal, larger revelations and higher values of τ (higher uncertainty) should lead to larger increases in spreads.

Table 7: Spread response to hidden debt revelations

	Model Output		Database	
	(1)	(2)	(3)	(4)
Revelation size	1.29***	1.25***	0.22***	0.22***
	(0.04)	(0.04)	(0.08)	(0.08)
Years since last revel. (τ)		0.03***		0.01
		(0.00)		(0.07)
Growth	-1.22***	-1.20***	-1.45***	-1.45***
	(0.02)	(0.02)	(0.34)	(0.34)
Debt/GDP	1.76***	1.74***	0.79*	0.79*
	(0.02)	(0.02)	(0.43)	(0.43)
Disclosed borrowing	4.32***	4.38***	-0.25	-0.25
	(0.04)	(0.04)	(0.24)	(0.24)
Constant	4.49***	4.26***	4.73***	4.70***
	(0.02)	(0.03)	(0.12)	(0.26)
Observations	594	594	594	594
Country fixed effects			✓	✓

Notes: This table shows the results of OLS regressions of next-period sovereign spreads (measured in percentage points) on the size of hidden debt revelations, years since the last revelation (τ), and additional control variables. Columns (1) and (2) use the data output from our calibrated benchmark model. We run 500 regressions in samples of 594 randomly drawn observations and report the mean coefficients across runs and their standard errors in parentheses. Columns (3) and (4) use our hidden debt database and spread data from JP Morgan's EMBI+. We include country fixed effects to focus on within-country time variation. Robust standard errors are reported in parentheses.

We validate these spread response predictions in both the simulated data from our model and our new hidden debt database by using a fixed effect regression model.[43] In Table 7, we show that larger revelations are indeed associated with larger increases in spreads after controlling for growth, the initial debt stock and new (disclosed) borrowing. The effects in the benchmark model (column (1)) are much larger (129 bps increase in spread for a revelation of 1 SD) than those in the database (22 bps increase), which is likely explained by the low frequency of our hidden debt database (annual) and by the fact that the availability of data on spreads is limited to countries with typically higher statistical capacity.[44] We then introduce τ into the regression framework to capture the duration of the hidden debt build-up.[45] As expected, in both the benchmark model (column (2)) and real-world data (column (4)), higher uncertainty as measured by higher values of τ is associated with higher

[43] To make the two datasets comparable, we run regressions in 500 randomly drawn samples of identical length as in the real-world data, and we then report the mean coefficients and standard errors.

[44] The spread data is from the EMBI+ compiled by JP Morgan which calculates the average spread for sovereigns based on USD-denominated bond instruments that meet certain minimum liquidity, size, and time-to-maturity criteria.

[45] In our database, we do not measure τ directly but can nonetheless approximate it as the time passed since the country experienced an above-mean revelation (measured in years).

spreads, and the effects are of very similar magnitudes, although only the model coefficient is statistically significant. Regarding the control variables, the growth and debt stock measures have very similar coefficients.

6.4 The costs of hidden debt

In this section, we use our model to study the welfare costs of hidden debt. To do so, we consider two distinct scenarios. First, we compare our model economy with hidden debt and limited information to a hypothetical full-information benchmark in which market investors readily observe the realizations of ε and h at the beginning of each period. [46] In a second comparison, we take the existence of asymmetric information as given and study the welfare implications of moving towards greater market transparency by enabling investors to exercise greater oversight over the sovereign's books. More specifically, we simulate the model with different parameter values for the monitoring fee f and analyze welfare gains (and losses) as monitoring becomes cheaper and more frequent.

Welfare gains of observable h and ε. To assess the welfare implications of hidden debt we measure the welfare gains of moving from our benchmark economy to an otherwise identical economy in which the process for hidden debt is still exogenous but perfectly observable to international lenders. Figure 13 shows these gains as a function of the income level, expressed as the constant proportional change in consumption that would leave a consumer indifferent between living in our benchmark model and moving to the "full information" economy.

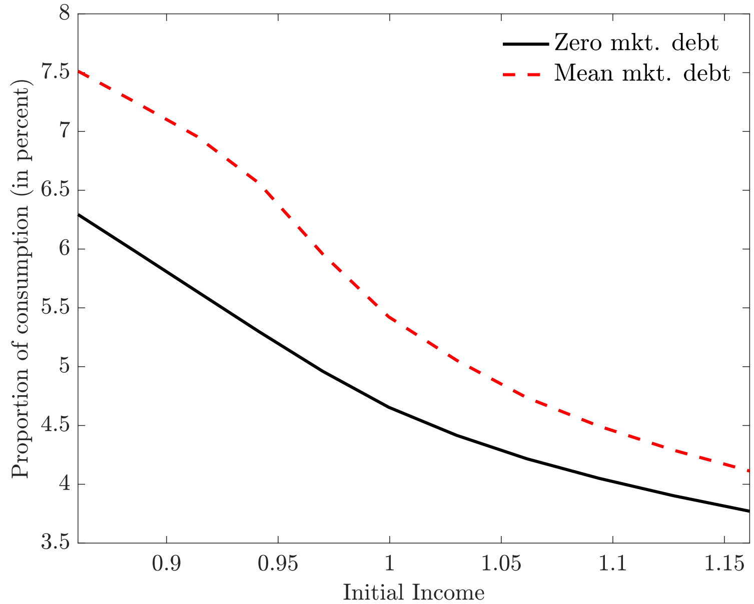
Figure 13 holds h at its mean and shows how welfare gains depend on the initial income level, for two levels of market debt (zero and the mean in the simulations). Welfare gains are uniformly positive and decrease in income. We also see that the country benefits more from moving to the full-information economy when its initial debt is larger. The average welfare gain of moving to the full-information economy (with initial debt equal to the mean level in the simulations) is equal to a 5.5% permanent increase in consumption. These welfare gains are approximately one order of magnitude larger than, for example, those coming from eliminating debt dilution (Hatchondo et al., 2016).

These large welfare gains occur mainly because the full-information economy has a much larger debt capacity than the benchmark economy (averaging 83% of GDP). This higher debt leads to a much higher level of average consumption obtained in the full-information economy than in the benchmark (approximately 45% larger).[47] The larger debt-carrying capacity of the full-information economy illustrates how hidden debt contributes to the "debt intolerance" phenomenon.

[46] See Appendix D.2 for the details on the full-information economy. We compute the equilibrium of this economy using the same parameter values reported in Table 5.

[47] Despite featuring more frequent defaults (24% vs 6%) and more volatile consumption (4.3 vs 1.3), the mean effect of higher consumption dominates and delivers substantial welfare gains.

Figure 13: Welfare gains of making hidden debt observable

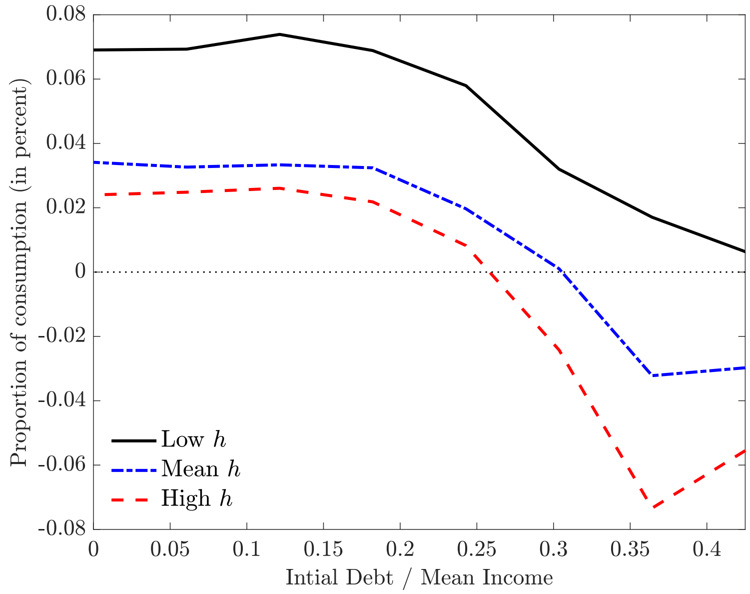


Notes: The figure shows the welfare gains for two possible values of initial market debt (zero and the mean in the simulations, 26% of GDP), keeping initial h at its mean. The figure assumes that ε is at its mean.

Welfare implications of greater oversight. We next show how greater oversight, captured trough lower costs of monitoring, impacts welfare. In Figure 14, we see that moving from an economy with a high monitoring cost (and, hence, little to no monitoring in equilibrium) to another in which monitoring is less expensive (and monitoring-induced revelations are more frequent) can have differing results. At low levels of hidden debt, cheaper monitoring is welfare increasing (irrespective of market debt levels). However, at higher hidden debt levels, monitoring can be welfare detrimental, depending on the initial debt levels. When the level of initial h is kept constant, higher market debt results in lower (and even negative) gains from greater oversight. The same holds true if we keep b constant and increase the initial level of h: higher debt is associated with welfare losses. These results suggest that only countries with strong fundamentals and low hidden debt levels benefit from increased transparency. Countries with high levels of hidden debt, on the other hand, face worse borrowing opportunities after being exposed to greater scrutiny and experience welfare losses. This finding implies that transparency policies are best implemented countercyclically to avoid the negative welfare effects of the exposure of hidden debts during times of crisis.[48]

[48] The average welfare gain of increased oversight is equivalent to a 0.02% permanent increase in consumption. This gain is similar in magnitude to that coming from eliminating the uncertainty in the world interest rate (Johri et al., 2022).

Figure 14: Welfare gains from increased oversight



Notes: The figure shows the mean welfare gains from increased oversight (by lowering the monitoring fee) as a function of initial debt and for different levels of hidden debt. These gains are unconditional averages over the y and ε states.

7 Conclusion

This paper is the first to systematically measure the degree of public debt under-reporting in a large sample of developing and emerging market countries. We use our novel data to motivate and numerically discipline a state-of-the-art quantitative model of sovereign debt and default with hidden debt, endogenous recovery rates, and investor monitoring. Our results from the model indicate a sizeable effect of hidden debt revelations on equilibrium spreads, default incentives, and welfare. We find that eliminating the uncertainty associated with hidden debt and its dynamics delivers substantial welfare gains equivalent to a permanent increase of 5.5% in consumption.

Our results have important implications for both practitioners and academic researchers. Analysts in both asset pricing and country surveillance should take into account that debt statistics tend to increase after their initial publication. For researchers, our findings and data open exciting new avenues for studying information acquisition and expectation formation in sovereign debt markets with asymmetric information.

References

Agarwal, I., D. Jaume, E. Tellez de la Vega, and M. Tobal (2024). Differential crowding out effects of government bonds and loans: Evidence from an emerging market economy. RedNIE Working Paper 314.

Aguiar, M., S. Chatterjee, H. Cole, and Z. Stangebye (2016). Quantitative models of sovereign debt crises. In *Handbook of Macroeconomics*, Volume 2, pp. 1697–1755. Elsevier.

Aguiar, M. and G. Gopinath (2006). Defaultable debt, interest rates and the current account. *Journal of International Economics 69*, 64–83.

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

Akey, P., A. Robertson, and M. Simutin (2023). Noisy factors. Mimeo.

Alesina, A., F. Campante, and G. Tabellini (2008). Why is fiscal policy often procyclical? *Journal of the European Economic Association 6*(5), 1006–1036.

Alfaro, L., S. Kalemli-Ozcan, and V. Volosovych (2008). Why doesn't capital flow from rich to poor countries? An empirical investigation. *The Review of Economics and Statistics 90*(2), 347–368.

Alfaro, L. and F. Kanczuk (2022). Undisclosed debt sustainability. *AEA Papers and Proceedings 112*, 521–525.

Alvarez-Parra, F., L. Brandao-Marques, and M. Toledo (2013). Durable goods, financial frictions, and business cycles in emerging economies. *Journal of Monetary Economics 60*(6), 720–736.

Arellano, C. (2008). Default risk and income fluctuations in emerging economies. *American Economic Review 98*(3), 690–712.

Arellano, C. and A. Ramanarayanan (2012). Default and the maturity structure in sovereign bonds. *Journal of Political Economy 120*(2), 187–232.

Arezki, R., V. A. Ramey, and L. Sheng (2017). News shocks in open economies: Evidence from giant oil discoveries. *The Quarterly Journal of Economics 132*(1), 103–155.

Aruoba, S. B. (2008). Data revisions are not well behaved. *Journal of Money, Credit and Banking 40*(2-3), 319–340.

Asonuma, T., D. Niepelt, and R. Ranciere (2023). Sovereign bond prices, haircuts and maturity. *Journal of International Economics 140*, 103689.

Asonuma, T. and C. Trebesch (2016). Sovereign debt restructurings: Preemptive or post-default. *Journal of the European Economic Association 14*(1), 175–214.

Athreya, K., X. S. Tam, and E. R. Young (2012). A quantitative theory of information and unsecured credit. *American Economic Journal: Macroeconomics 4*(3), 153–183.

Azzimonti, M. and N. Mitra (2023). Sovereign default and tax-smoothing in the shadow of corruption and institutional weakness. NBER Working Paper No. 31943.

Bai, Y., S. T. Kim, and G. Mihalache (2017). The payment schedule of sovereign debt. *Economics Letters 161*, 19–23.

Bai, Y. and J. Zhang (2012). Duration of sovereign debt renegotiation. *Journal of International Economics 86*(2), 252–268.

Beaudry, P. and T. Willems (2022). On the macroeconomic consequences of over-optimism. *American Economic Journal: Macroeconomics 14*(1), 38–59.

Bianchi, J., P. Ottonello, and I. Presno (2023). Fiscal stiumulus under sovereign risk. *Journal of Political Economy 131*(9), 2328–2369.

Bova, E., M. Ruiz-Arranz, F. G. Toscani, and H. E. Ture (2016). The fiscal costs of contingent liabilities: A new dataset. IMF Working Paper No. 2016/014.

Brautigam, D. (2022). China and Zambia: creating a sovereign debt crisis. *International Affairs 98*(4), 1347–1365.

Brunnermeier, M. (2001). *Asset pricing under asymmetric information: Bubbles, crashes, technical analysis, and herding.* Oxford University Press.

Campos, C. F., D. Jaimovich, and U. Panizza (2006). The unexplained part of public debt. *Emerging Markets Review 7*(3), 228–243.

Cattaneo, M., R. Crump, M. Farrell, and Y. Feng (2024). On binscatter. *American Economic Review 114*(5), 1488–1514.

Chatterjee, S., D. Corbae, K. Dempsey, and J.-V. Ríos-Rull (2023). A quantitative theory of the credit score. *Econometrica 91*(5), 1803–1840.

Chatterjee, S. and B. Eyigungor (2012). Maturity, indebtedness and default risk. *American Economic Review 102*(6), 2674–2699.

Christensen, G. and E. Miguel (2018). Transparency, reproducibility, and the credibility of economics research. *Journal of Economic Literature 56*(3), 920–980.

Cole, H., D. Neuhann, and G. Ordonez (2022). Asymmetric information on and sovereign debt: Theory meets mexican data. *Journal of Political Economy 130*(8), 2055–2109.

Cole, H., D. Neuhann, and G. Ordonez (2024). Information spillovers in sovereign debt: Theory meets the eurozone crisis. *The Review of Economic Studies*, rdae017.

Coppola, A. (2024). In safe hands: The financial and real impact of investor composition over the credit cycle. Mimeo.

Cortez, E., A. Orre, B. Fael, B. Nhamirre, C. Banze, I. Mapisse, K. Harnack, and T. Reite (2021). *Costs and consequences of the hidden debt scandal of Mozambique*. Centro de Integridade Pública (CIP), Moçambique.

Cruces, J. J., M. Buscaglia, and J. Alonso (2002). The term structure of country risk and valuation in emerging markets. Universidad de San Andres Working Paper 46.

Cruces, J. J. and C. Trebesch (2013). Sovereign defaults: The price of haircuts. *American Economic Journal: Macroeconomics 5*(3), 85–117.

D'Erasmo, P. (2011). Government reputation and debt repayment. Mimeo.

Dias, D. A. and C. Richmond (2007). Duration of capital market exclusion: An empirical investigation. Mimeo.

Diaz-Alejandro, C. (1983). Good-bye financial repression, hello financial crash. *Journal of Development Economics 19*(1-2), 1–24.

Eaton, J. and M. Gersovitz (1981). Debt with potential repudiation: theoretical and empirical analysis. *The Review of Economic Studies 48*(2), 289–309.

Estefania-Flores, J., D. Furceri, S. Kothari, and J. D. Ostry (2023). Worse than you think: Public debt forecast errors in advanced and developing economies. *Journal of Forecasting 42*(3), 685—714.

Estevão, M. (2021). It's time to get a better handle on debt in developing economies. Available online: /https://www.barrons.com/articles/its-time-to-get-a-better-handle-on-debt-in-developing-economies-51640204237. Barron's.

Fang, X., B. Hardy, and K. Lewis (2023). Who holds sovereign debt and why it matters. NBER Working Paper No. 30087.

Fourakis, S. (2021). Sovereign default and government reputation. Mimeo.

Frankel, J. (2011). Over-optimism in forecasts by official budget agencies and its implications. *Oxford Review of Economic Policy 27*(4), 536–562.

Gamboa, J. (2023). Hidden chinese lending. Mimeo.

Gelpern, A., S. Horn, S. Morris, B. Parks, and C. Trebesch (2023). How China lends: A rare look into 100 debt contracts with foreign governments. *Economic Policy 38*(114), 345—416.

Goes, I. (2024). Measurement uncertainty in international statistics. Mimeo.

Gorton, G. and G. Ordonez (2014). Collateral crises. *American Economic Review 104*(2), 343–378.

Gorton, G. and G. Ordonez (2023). *Macroeconomics and Financial Crises: Bound Together by Information Dynamics*. Princeton University Press.

Graf von Luckner, C. and S. Horn (2024). Creditor dispersion in sovereign debt markets. Mimeo.

Graf von Luckner, C., J. Meyer, C. M. Reinhart, and C. Trebesch (2023). Sovereign debt: 200 years of creditor losses. Mimeo.

Greenwood, J., J. Sanchez, and C. Wang (2010). Financing development: The role of information costs. *American Economic Review 100*(4), 1875–1891.

Gu, G. W. and Z. R. Stangebye (2023). Costly information and sovereign risk. *International Economic Review 64*(4), 1397–1429.

Guler, B., Y. K. Önder, and T. Taskin (2022). Asymmetric information and sovereign debt disclosure. Mimeo.

Gutkowski, V. (2022). Sovereign debt restructuring and credit recovery. Mimeo.

Hatchondo, J. C. and L. Martinez (2009). Long-duration bonds and sovereign defaults. *Journal of International Economics 79*(1), 117–125.

Hatchondo, J. C., L. Martinez, and Y. K. Önder (2017). Non-defaultable debt and sovereign risk. *Journal of International Economics 105*, 217–229.

Hatchondo, J. C., L. Martinez, and H. Sapriza (2010). Quantitative properties of sovereign default models: Solution methods matter. *Review of Economic Dynamics 13*(4), 919–933.

Hatchondo, J. C., L. Martinez, and C. Sosa-Padilla (2016). Debt dilution and sovereign default risk. *Journal of Political Economy 124*(5), 1383–1422.

Hatchondo, J. C., L. Martinez, and C. Sosa-Padilla (2021). Sovereign debt standstills. NBER Working Paper No. 28292.

Horn, S., C. M. Reinhart, and C. Trebesch (2020). Coping with disasters: Two centuries of international official lending. NBER Working Paper No. 27343.

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

Hur, S., C. Sosa-Padilla, and Z. Yom (2024). Optimal bailouts in banking and sovereign crises. NBER Working Paper No. 28412.

IMF (2018). Macroeconomic developments and prospects in low-income developing countries. Available online: `/https://www.imf.org/en/Publications/Policy-Papers/Issues/2021/03/30/Macroeconomic-Developments-and-Prospects-In-Low-Income-Countries-2021-50312`. Washington, D.C.: International Monetary Fund.

Johnson, S., W. Larson, C. Papageorgiou, and A. Subramanian (2013). Is newer better? penn world table revisions and their impact on growth estimates. *Journal of Monetary Economics 60*(2), 255–274.

Johri, A., S. Khan, and C. Sosa-Padilla (2022). Interest rate uncertainty and sovereign default risk. *Journal of International Economics 139*, 103681.

Kaminsky, G., C. M. Reinhart, and C. Végh (2004). When it rains, it pours: Procyclical capital flows and macroeconomic policies. *NBER Macroeconomics Annual 19*, 11–53.

Kletzer, K. (1984). Asymmetries of information and ldc borrowing with sovereign risk. *Economic Journal 94*, 287–307.

Kondo, I. O., A. Mkhitaryan, C. Sosa-Padilla, and Z. Swaziek (2024). Borrowing in the shadow of China. Mimeo.

Lucas, R. E. (1990). Why doesn't capital flow from rich to poor countries? *American Economic Review 80*(2), 92–96.

Marshall, M. G. and T. R. Gurr (2020). Polity V project, political regime characteristics and transitions, 1800-2018. Center for Systemic Peace.

Morelli, J. M. and M. Moretti (2023). Information frictions, reputation, and sovereign spreads. *Journal of Political Economy 131*(11), 3066–3102.

Mosley, L. and B. P. Rosendorff (2023). Government choice of debt instruments. *International Studies Quarterly 67*(2), sqad030.

Newey, W. K. and K. D. West (1987). A simple positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica 55*(3), 703–708.

Reinhart, C. M. and V. Reinhart (2008). Capital flow bonanzas: An encompassing view of the past and present. NBER Working Paper No. 14321.

Reinhart, C. M. and K. Rogoff (2011a). *A decade of debt.* Peterson Institute for International Economics.

Reinhart, C. M. and K. S. Rogoff (2009). *This time is different.* Princeton University Press.

Reinhart, C. M. and K. S. Rogoff (2011b). From financial crash to debt crisis. *American Economic Review 101*(5), 1676–1706.

Reinhart, C. M., K. S. Rogoff, and M. Savastano (2003). Debt Intolerance. *Brookings Papers on Economic Activity 34*, 1–74.

Roch, M. F. and F. Roldán (2023). Uncertainty premia, sovereign default risk, and state-contingent debt. *Journal of Politcal Economy Macroeconomics 1*(2), 334–370.

Sanchez, J. M. (2018). The information technology revolution and the unsecured credit market. *Economic Inquiry 56*(2), 914–930.

Smith, G., L. Jessen, and Z. Chinzara (2017). Zambia economic brief: how Zambia can borrow without sorrow. Zambia Economic Brief No. 10. Available online: `/http://documents.worldbank.org/curated/en/782221512459934813/Zambia-economic-brief-how-Zambia-can-borrow-without-sorrow`. Washington, D.C.: World Bank Group.

Sosa-Padilla, C. and F. Sturzenegger (2022). Does it matter how central banks accumulate reserves? Evidence from sovereign spreads. *Journal of International Economics 140*, 103711.

Veldkamp, L. (2023). *Information Choice in Macroeconomics*. Princeton University Press.

World Bank (2017). External debt reporting and financial statements. Bank Policy OPS5.09-POL.166. Available online: /https://ppfdocuments.azureedge.net/8fcc4c7a-0e1c-47e0-84b3-0950b0fc4d9b.pdf. Washington, D.C.: World Bank Group.

World Bank (2021). Debt transparency in developing economies. Available online: /https://documents.worldbank.org/en/publication/documents-reports/documentdetail/743881635526394087/debt-transparency-in-developing-economies. Washington, D.C.: World Bank Group.

World Bank (2022). *World Development Indicators*. Washington, D.C.: World Bank Group.

Appendix

A Constructing the new database of debt data revisions

This appendix chapter gives a detailed description of how we construct our new database of debt data revisions. We describe all underlying sources, the data digitization and cleaning process and present key descriptive characteristics of the final dataset. We also present a variety of additional empirical exercises that we have carried out to minimize measurement error and to validate the interpretation of our hidden debt measure.

A.1 Data sources and digitization

Our new database of debt data revisions draws on the debt statistics published by the World Bank since the 1970s. More specifically, our database centers around the International Debt Statistics (2012–2023) and its predecessor formats, the Global Development Finance Reports (1997–2012) and the World Debt Tables (1973–1996). Table A1 provides a detailed list of all vintages that enter our final database. All these vintages build on the World Bank's Debtor Reporting System (DRS), which was established in 1951. Sovereign debtors that borrow or guarantee loans extended by the World Bank Group need to agree to report detailed data on their long-term public and publicly guaranteed debt through the DRS. The World Bank compiles this loan-level data and publishes it annually through its flagship debt report. Table A1 gives an overview of all 51 vintages that we have compiled.

Digitization: The data from the most recent debt reports is readily available in a machine-readable format on the World Bank's website. Specifically, we download all vintages of the International Debt Statistics (2013–2023) and eight vintages of the Global Development Finance reports (2005–2012) from the World Bank's website.[49] For all reports prior to 2005, we are required to digitize the original reports and extract the data into a machine-readable format. Original reports were either downloaded from the World Bank website in PDF form or were scanned from the original hard copies that we obtain from different libraries. The third column of Table A1 provides an overview on which vintages were downloaded and which were scanned.[50] The digitization of the PDF reports and hard copies itself relies heavily on the use of Optical Character Recognition (OCR) Software and manual coding. Section A.2 discusses various steps that we undertake to ensure the accuracy of our data.

[49]See /https://www.worldbank.org/en/programs/debt-statistics/idr/products

[50]PDFs of vintages back until 1991–1992 can be found here: /https://www.worldbank.org/en/programs/debt-statistics/publications. PDFs of earlier vintages (1973–1991) can be found via the World Bank's Documents & Reports page here: /https://documents.worldbank.org/en/publication/documents-reports.

Table A1: Overview of WDT, GDF, IDS and IDR vintages

Title	Short form	Availability	Version used
World Debt Tables	WDT1973	PDF only	
World Debt Tables: External Public Debt of LDCs	WDT1974	Hard copy	
World Debt Tables Volume II: External Public Debt of LDCs	WDT1975	PDF only	
World Debt Tables. External Public Debt of LDCs	WDT1976	Hard copy	
World Debt Tables. External Public Debt of Developing Countries	WDT1977	Hard copy	
World Debt Tables. External Public Debt of Developing Countries	WDT1978	Hard copy	
World Debt Tables Volume II: External Public Debt of 96 Developing Countries	WDT1979	PDF only	
World Debt Tables Volume II: External Public Debt of 99 Developing Countries	WDT1980	Hard copy	
World Debt Tables: External Public Debt of Developing Countries and Territories	WDT1981	PDF only	
World Debt Tables: External Debt of Developing Countries – 1982-83 Edition	WDT1982-83	PDF only	
World Debt Tables: External Debt of Developing Countries – 1983-84 Edition	WDT1983-84	Hard copy	
World Debt Tables: External Debt of Developing Countries – 1984-85 Edition	WDT1984-85	PDF only	
World Debt Tables: External Debt of Developing Countries – 1985-86 Edition	WDT1985-86	Hard copy	
World Debt Tables: External Debt of Developing Countries – 1986-87 Edition	WDT1986-87	Hard copy	
World Debt Tables: External Debt of Developing Countries – 1987-88 Edition	WDT1987-88	Hard copy	
World Debt Tables: External Debt of Developing Countries – Volume II. Country Tables – 1988-89 Edition	WDT1988-89	PDF only	
World Debt Tables 1989-90 External Debt of Developing Countries – Volume 2. Country Tables	WDT1989-90	PDF only	
World Debt Tables 1990-91 External Debt of Developing Countries – Volume 2. Country Tables	WDT1990-91	Hard copy	

World Debt Tables 1991-92 External Debt of Developing Countries – Volume 2. Country Tables	WDT1991-92	PDF only	
World Debt Tables 1992-93 External Finance for Developing Countries – Volume 2. Country Tables	WDT1992-93	PDF only	
World Debt Tables 1993-94 External Finance for Developing Countries – Volume 2. Country Tables	WDT1993-94	PDF only	
World Debt Tables 1994-95 External Finance for Developing Countries – Volume 2. Country Tables	WDT1994-95	PDF only	
World Debt Tables 1996 External Finance for Developing Countries – Volume 2. Country Tables	WDT1996	PDF only	
Global Development Finance 1997 – Volume 2 Country Tables	GDF1997	PDF only	
Global Development Finance 1998 – Country Tables	GDF1998	PDF only	
Global Development Finance - Country Tables 1999	GDF1999	PDF only	
Global Development Finance - Country Tables 2000	GDF2000	PDF only	
Global Development Finance: Building Coalitions for Effective Development Finance – Country Tables 2001	GDF2001	PDF only	
Global Development Finance: Financing the Poorest Countries – Country Tables 2002	GDF2002	PDF only	
Global Development Finance: Striving for Stability in Development Finance – II: Summary and Country Tables 2003	GDF2003	PDF only	
Global Development Finance: Harnessing Cyclical Gains for Development – II: Summary and Country Tables 2004	GDF2004	PDF only	
Global Development Finance: Mobilizing Finance and Managing Vulnerability – II: Summary and Country Tables 2005	GDF2005	Online	Apr. 2005
Global Development Finance: The Development Potential of Surging Capital Flows – II: Summary and Country Tables 2006	GDF2006	Online	Nov. 2005

Global Development Finance: The Globalization of Corporate Finance in Developing Countries – II: Summary and Country Tables 2007	GDF2007	Online	Dec. 2006
Global Development Finance: The Role of International Banking – II: Summary and Country Tables 2008	GDF2008	Online	Nov. 2007
Global Development Finance: Charting a Global Recovery – II: Summary and Country Tables 2009	GDF2009	Online	Dec. 2008
Global Development Finance External Debt of Developing Countries 2010	GDF2010	Online	Feb. 2010
Global Development Finance External Debt of Developing Countries 2011	GDF2011	Online	Dec. 2010
Global Development Finance External Debt of Developing Countries 2012	GDF2012	Online	Dec. 2011
International Debt Statistics 2013	IDS2013	Online	Dec. 2012
International Debt Statistics 2014	IDS2014	Online	
International Debt Statistics 2015	IDS2015	Online	
International Debt Statistics 2016	IDS2016	Online	
International Debt Statistics 2017	IDS2017	Online	
International Debt Statistics 2017	IDS2017	Online	
International Debt Statistics 2018	IDS2018	Online	
International Debt Statistics 2019	IDS2019	Online	
International Debt Statistics 2020	IDS2020	Online	
International Debt Statistics 2021	IDS2021	Online	
International Debt Statistics 2022	IDS2022	Online	
International Debt Report 2022	IDR2022	Online	
International Debt Report 2023	IDR2023	Online	

Notes: The table shows all vintages that enter our final database. Vintages with availability "online" and "PDF only" are available from the World Bank's websites. Vintages labeled "hard copy" are vintages which we obtain from different libraries and scan ourselves. For vintages 2005–2011 there is more than one version per vintage available, column "Version used" indicates the ones that enter our database. See text for further details.

Merging data from different vintages: After all 51 vintages have been digitized and brought into machine-readable formats, we merge the data into a single dataset. While the underlying debt data definitions and concepts have remained remarkably stable over time (see B.1 for a detailed examination), some of the variable names and codes have been changed across the history of the World Bank's debt statistics. To merge data across vintages, we create a mapping of the modern series codes into the vintage-specific variable names and codes. Table A2 provides details on each of the key variables that we use in our analysis.

Table A2: Mapping series codes and variable names across vintages

Description	1973-1974	1975-1976	1977-1980	1981-1988	1989-1993	1994-2004	Modern seriescode (2005 onwards)
Panel A: Public and publicly guaranteed (DPPG)							
Debt outstanding and disbursed	Debt Outstanding beginning of period: Disbursed only	TOTAL EXTERNAL PUBLIC DEBT: OUTSTANDING (DISBURSED ONLY)	TOTAL ALL LENDERS: OUTSTANDING (DISBURSED ONLY)	Debt Outstanding & Disbursed (DOD)	DEBT OUTSTANDING (LDOD)		DT.DOD.DPPG.CD
Commitments	Transactions during period: Commitments	TOTAL EXTERNAL PUBLIC DEBT: COMMITMENTS	TOTAL ALL LENDERS: COMMITMENTS	Commitments		Memorandum Items: Commitments	DT.COM.DPPG.CD
Disbursements	Transactions during period: Disbursements	TOTAL EXTERNAL PUBLIC DEBT: DISBURSEMENTS	TOTAL ALL LENDERS: DISBURSEMENTS	Disbursements			DT.DIS.DPPG.CD
Principal repayments	Transactions during period: Service Payments: Principal	TOTAL EXTERNAL PUBLIC DEBT: PRINCIPAL PAYMENTS	TOTAL ALL LENDERS: PRINCIPAL REPAYMENTS	Principal Repayments			DT.AMT.DPPG.CD
Panel B: Creditor categories							
Official creditors			TOTAL OFFICIAL LENDERS	Official Creditors			DT.DOD.OFFT.CD
Multilateral	Loans from International Organizations	INTERNATIONAL ORGANIZATIONS		Multilateral			DT.DOD.MLAT.CD
of which: IBRD				IBRD			DT.DOD.MIBR.CD
of which: IDA				IDA			DT.DOD.MIDA.CD
Bilateral	Loans from DAC Governments Loans from East Bloc Governments Loans from Other Governments	DAC GOVERNMENTS EAST BLOC GOVERNMENTS OTHER GOVERNMENTS	GOVERNMENT LENDERS	Bilateral			DT.DOD.BLAT.CD
Private creditors			TOTAL PRIVATE LENDERS	Private Creditors			DT.DOD.PRVT.CD
of which: Bonds					Bonds		DT.DOD.PBND.CD
of which: Commercial banks	Credits from Private Banks	PRIVATE BANKS			Commercial banks		DT.DOD.PCBK.CD
of which: Other private creditors	Credits from Other Private Creditors	OTHER PRIVATE CREDITORS	OTHER PRIVATE LENDERS		Other private		DT.DOD.PROP.CD

Notes: The table shows the mapping of the modern series codes into variable names and codes in vintages 1973–2004. Panel A provides the series code mapping for the most important stock and flow measures, while Panel B provides the mapping for the different creditor categories. Grey shaded areas indicate that the variable is not available in a vintage.

A.2 Data cleaning

To ensure the quality of our digitized data and to minimize measurement error from the application of the OCR software, we use two algorithmic procedures to detect potential coding errors and to check the consistency of our digitized data *across* and *within* vintages.

Across-vintage consistency checks: In this consistency check, we make use of the fact that each debt figure appears in multiple vintages. For each data point, we check whether the reported value is different from the one published in the previous and the subsequent vintage. A potential measurement error is flagged if the difference between the value in the lead and the lag vintage is zero, but the value itself is unequal to the value in the lag vintage. We resolve these cases by revisiting the original sources.

Within-vintage consistency checks: We further identify potential measurement error by tracking deviations of several accounting identities that need to hold *within* each vintage. First, it must hold that the following aggregates can be derived as the sum of their sub-components,

$$DPPG_{i,t}^{v} = OFFT_{i,t}^{v} + PRVT_{i,t}^{v} \tag{24}$$

$$OFFT_{i,t}^{v} = BLAT_{i,t}^{v} + MLAT_{i,t}^{v} \tag{25}$$

$$PRVT_{i,t}^{v} = PBND_{i,t}^{v} + PCBK_{i,t}^{v} + PROP_{i,t}^{v} \tag{26}$$

where the total public and publicly guaranteed debt stock ($DPPG$) of country i in year t from vintage v is equal to the sum of the debt stock owed to official ($OFFT$) and private ($PRVT$) creditors. These in turn have to be equal to the sum of the debt stocks owed to bilateral ($BLAT$) and multilateral creditors ($MLAT$), and equal to the sum of debt stocks owed to bondholders ($PBND$), commercial banks ($PCBK$), and other private creditors ($PROP$), respectively. The decomposition of debt to private creditors shown in Equation (26) is only available from vintage 1990 onwards.

These identities cannot only be derived for debt stocks ($DPPG$), but also for all flow variables, including disbursements (DIS) and principal repayments (AMT). For commitments (COM), only equation (24) and equation (25) can be checked, since commitment data is not available for all sub-components, as we discuss in greater detail below (see Section A.3 and Table A4).

We derive all these identities from each of the newly digitized vintages. Whenever one of the identities does not hold in our digitized dataset, we return to the original PDFs and make sure that all components of the identity were digitized correctly and that inconsistencies were not introduced by our digitization effort. The procedure ensures with very high probability that our digitized data is an exact replication of the underlying World Bank debt reports.

Elimination of estimates and preliminary data points: If a developing or emerging market country does not fulfil its reporting obligations towards the World Bank's Debtor Reporting System (DRS), the World Bank may choose to provide estimates or other non-reported values. Such cases are clearly labeled in the World Bank debt reports. More precisely, every debtor country is assigned one of the following debtor reporting statuses in each of the vintages:[51]

(A) **"actual"/"as reported".** Indicates that the country was fully current in its reporting and that World Bank staff are satisfied that the reported data give an adequate and fair representation of the country's total public debt.

(E) **"estimate".** Indicates that the country was not current in their reporting and that a significant element of staff estimation has been necessary in producing the data tables.

(P) **"preliminary".** Based on reported or collected information but, because of incompleteness or other reasons, includes an element of staff estimation.

To avoid diluting our hidden debt revelation measure, our analysis only considers country-vintage observations that are classified as "actual" or "as reported" and discards all data points which are classified as either "preliminary" or as "estimates".[52] All revisions that we identify are therefore revisions to data points that World Bank staff considered an "adequate and fair representation of the country's total public debt" at the time of the first data release.

Minor data transformations: To ensure consistency of the data across vintages, we further undertake the following minor data transformations:

- We transform all the data into millions of nominal USD and round all entries to full integers without decimal points.
- Data for the Democratic Republic of the Congo and for Zaire are subsumed under ISO code "COD". Data for Yugoslavia, Serbia and Montenegro, and Serbia are subsumed under ISO code "SRB".
- In WDT1973 and WDT1974, debt stocks are reported as beginning-of-period values, wheres in all following vintages they are reported as end-of-period values. Hence we adjust the 1973 and 1974 values to match the reporting format of all following vintages.
- In IDS2013 and IDS2014, zeros are reported for all values in 1970 and 1971, although non-zero entries are available in vintages prior to 2013 and after 2014. We replace zero entries with the values reported in IDS2015. In some cases, vintages from IDS2018 until IDR2023 report zeros where previous vintages reported missing values. We replace these zeros with missing values. Lastly, IDS2017, IDS2021, IDS2022, IDR2022 and IDR2023 report several values as missing despite the fact that in previous vintages

[51] In the first editions of the World Debt Tables, for vintages from 1973 to 1978, no explicit reporting status is provided. The forewords of these vintages, however, emphasize that only the statistics of those countries are released that World Bank staff considers sufficiently complete to give a fair representation of the country's debt. As a result the number of included countries varies from year to year. We take this as evidence that all data points from these vintages can be considered as "actual" reporting and not as preliminary or estimated figures. The empirical results presented in this paper are robust to dropping all observations from vintages 1973 to 1978.

[52] In a few rare instances, the reporting status is contradicted in the "country notes" section in the appendix of the debt report. For example, the IDS 2021 reporting status for Guinea is classified as "actual", but the country notes state that the long-term PPG debt for 2016 is a World Bank staff estimate. In such cases, we overrule the classification and drop the observation.

these were reported as zeros. We replace these missing values with zeros. We undertake both these steps to ensure that "non-revisions" are neither under-represented (in case of previously missing values) nor overrepresented (in case of previously reported zeros) in our database as a result of inconsistent coding of zero values.

- Lastly, we discard countries from our database for which we have less than five vintages available. These countries are the Czech Republic, Russia, Taiwan (classified as "actual" in only one vintage), Slovenia, Timor-Leste (classified as "actual" in only three vintages), the Bahamas, Israel and South Africa (classified as "actual" in only four vintages).

A.3 Data coverage, descriptive statistics and key variables of interest

Table A3 summarizes the coverage of our final database. Our data comes from 51 vintages, spans years 1970 to 2022, covers 146 different countries and includes 49 different variables. While our final database includes information on 49 different variables, our main analytical interest centers on a few key concepts that we introduce here.

Table A3: New database of debt data revisions: scope and coverage

Number of vintages	51
Number of variables	49
Number of countries	146
Time coverage	1970–2022
Number of observations	3,315,950

Notes: This table provides details on the scope and coverage of our new database on debt data revisions. See Appendix Table C6 for a full list of all countries in our sample.

Debt stocks: Our key measure for the debt stock is the series on external, public and publicly guaranteed debt disbursed and outstanding (series code DT.DOD.DPPG.CD). It captures all external, long-term obligations "of public debtors, including the national government, Public Corporations, State Owned Enterprises, Development Banks and Other Mixed Enterprises, political subdivisions (or an agency of either), autonomous public bodies, and external obligations of private debtors that are guaranteed for repayment by a public entity". Long-term external debt is defined as debt that has an original or extended maturity of more than one year and that is owed to nonresidents by residents of an economy and repayable in currency, goods, or services. The series is available in all vintages and for all countries and years.

Debt flows / commitments: Our key measure for borrowing and lending (i.e. for debt flows) are commitments to public and publicly guaranteed borrowers (series code DT.COM.DPPG.CD). Commitments are the total amount of long-term loans which are contracted in a given year. As before, long-term external debt is defined as debt that has an original or extended maturity of more than one year and that is owed to nonresidents by residents of an economy and repayable in currency, goods, or services. This series is available in all vintages and for all countries and years.

Subcomponents by creditor type: For various parts of the analysis and in particular when measuring creditor characteristics of hidden debt, we are interested in breakdowns of outstanding debts and flows by creditor type. The World Bank's debt statistics offer different decompositions to do this. Unfortunately, not all of these break-downs are consistently available across the past 51 vintages. Total commitments and total debt stocks can be divided into debt to private and debt to official creditors. Data for the group of official creditors can further be decomposed into series for bilateral and multilateral creditors. These series are available in our database for vintages 1977–2023. Since vintage 1989, a decomposition of the data for private creditors is available and includes bondholders, commercial banks and other private creditors.[53] Table A4 summarizes the availability of all these series.

Table A4: Available components by vintage

Panel A: Debt outstanding and disbursed/Disbursements/Repayments		
Creditor category		**Vintage**
Official creditors	Multilateral	1977 - 2023
	Bilateral	1977 - 2023
Private creditors	Bondholders	1989-90 - 2023
	Commercial Banks	1989-90 - 2023
	Other private creditors	1979 - 1980, 1989-90 - 2023
Panel B: Commitments		
Creditor category		**Vintage**
Official creditors	Multilateral	1977 - 1992-93, 2020 - 2023
	Bilateral	1977 - 1992-93, 2020 - 2023
Private creditors	Bondholders	n/a
	Commercial Banks	n/a
	Other private creditors	1979 - 1980

Notes: The table shows the availability of different creditor categories for debt stocks and commitments over all vintages included in our database. Categories "official" and "private" are available for vintages 1977 - 2023, both for stocks and commitments.

[53] In earlier vintages, the private creditor decomposition consisted of categories "financial markets" and "suppliers". However, as these categories were not reported in full, consistency checks as described in A.2 are not possible for these vintages. Hence, we do not take them into account, neither here nor in our analyses.

A.4 Data sources for control variables

Table A5: Data sources for control variables

Variable	Mnemonic (from source)	Description	Source
Nominal GDP	NY.GDP.MKTP.CD	GDP (current US$)	World Bank
		GDP (current US$)	Fouquin and Hugot (2016)
Real GDP	NY.GDP.MKTP.KN	GDP (constant LCU)	World Bank
Real GDP p.c.		GDP at constant national prices divided by population	Feenstra et al. (2015)
Consumption	NE.CON.TOTL.KN	Final consumption expenditure (constant LCU)	World Bank
Income groups		Classifications based on GNI	World Bank
EMBI+ spreads		J.P. Morgan Emerging Markets Bond Spread	J.P. Morgan (2024)
IMF programs		Dummy variable for first year in IMF program	Horn et al. (2020)
Sovereign default		Dummy for years in default	Asonuma and Trebesch (2016)
Institutional strength		Average score on the Polity V dataset	Marshall and Gurr (2020)
Haircuts		Net present value loss suffered by creditors (in percent)	Cruces and Trebesch (2013), Asonuma and Trebesch (2016) and Asonuma et al. (2023)
Duration		Time between the default event and the debt restructuring (in months)	Cruces and Trebesch (2013), Asonuma and Trebesch (2016) and Asonuma et al. (2023)

B Data validation

To validate our hidden debt measure and its interpretation, we engage in a series of empirical tests and validation exercises. We begin this part by systematically comparing reporting guidelines of the World Bank's debt statistics over time and confirm that only minor refinements have occurred across the 51 vintages that we analyze. We also rule out that data revisions are driven by ex post revisions of exchange rates, by contingent liability realizations or reporting lags, and confirm that the systematic upward bias in debt data revisions is also present when only focusing on revisions to the most recent debt data. Finally, we compare our measure of hidden debt revelations to a series of prominent data manipulation cases that were discussed by the IMF board.

B.1 Changes in reporting rules

To what extent are ex post data revisions driven by changes in reporting rules over time? To answer this question, we search for changes in the reporting guidelines of the World Bank's Debtor Reporting Manual. Over the course of the International Debt Statistics' history, the World Bank has published four different Reporting Manuals: In 1962, 1980, 1989 and in 2000. The Debtor Reporting Manual from 2000 is still in effect today and can be downloaded from the World Bank's website. Its three predecessor publications were obtained from the IMF library.

We systematically go through all four reporting manuals and confirm that the manuals define reporting obligations and the perimeter of debt statistics in a highly similar way. Table B1 summarizes our comparison with respect to the definition of external debt, the definition of the public sector and the definition of long-run debt. The only minor change we detect is that the 1980 reporting manual refines the definition of what constitutes an external debt instrument.[54]

[54] Re-running our main analyses over a truncated sample that excludes all vintages prior to 1980 does not lead to any changes in our results.

Figure B1: World Bank Debt Reporting Manuals: 1962 - 2020

Notes: World Bank Debtor Reporting System Reporting Manuals from 1962, 1980, 1989 and 2000.

Table B1: Debtor Reporting System Manuals' Definitions over Time

<table>
<tr><th></th><th>1962</th><th>1980</th><th>1989</th><th>2000</th></tr>
<tr><td>Definition of external debt:</td><td>Debt owed to foreigners and, in the case of publicly-issued loan capital, all bonds issued in foreign markets, including bonds later repatriated. All such debts should be treated as external debt, whether the medium of payment is foreign currency, local currency goods or services.</td><td colspan="3">Debt owed by residents of the reporting country to non-residents thereof. The term non-residents includes, besides non-resident individuals, all foreign public bodies, foreign corporations (except branches thereof in the reporting country), and international organizations; in short, any individual or organization that is not physically located in the reporting country.</td></tr>
<tr><td>Definition of long-term debt:</td><td colspan="4">Long-term debt for purposes of DRS reporting is that with an original contractual or extended maturity of more than one year, measured from the date of signing the loan agreement (commitment date) to the date on which the last payment is due.</td></tr>
<tr><td>Definition of public and publicly guaranteed debt:</td><td colspan="4">Public and publicly guaranteed debt constists of all debt of the public sector together with debt of the private sector with a public-sector guarantee in the borrowing. For purposes of the DRS, the public sector consists of the following types of institutions:
(a) Central governments and their departments;
(b) Political subdivisions such as states, province and municipalities;
(c) Central banks;
(d) Autonomous institutions, such as financial and non-financial corporations,commercial and development banks, railways, utilities, etc., where:
(i) The budget of the institution is subject to the approval of the government of the reporting country; or
(ii) The government owns more than 50% of the voting stock or more than half of the members of the board of directors are government representatives; or
(iii) In case of default, the state would become liable for the debt of the institution.</td></tr>
</table>

Sources: IBRD (1962) and World Bank (1980, 1989, 2000).

B.2 FX data revisions

Debtor countries with large amounts of non-USD debt are exposed to valuation changes in their reported debt stock, even when debt reporting centers entirely on nominal or face values. For such countries, ex post revision to USD exchange rates could lead to ex post revisions in the outstanding debt stock that are inconsistent with our interpretation of ex post upward revisions as cases of hidden debt revelations. To rule out this possibility, we quantify ex post revisions to exchange rate data in the IMF's International Financial Statistics, the data source that underlies exchange rate calculations in the World Bank's IDS. Due to the limited availability of archived IMF IFS data, we only calculate year-on-year revisions to the yearly average and end of period exchange rate data between 2019 and 2021. The average ex post revision of the period average exchange rate ranges between -0.00044 percent and 0.00158 percent, the average ex post revision of the end of period exchange rate ranges between -0.00396 percent and 0.00130 percent in the underlying period. Revisions to exchange rates are therefore far too low to explain the sizeable magnitude of debt stock revisions we document in this paper.

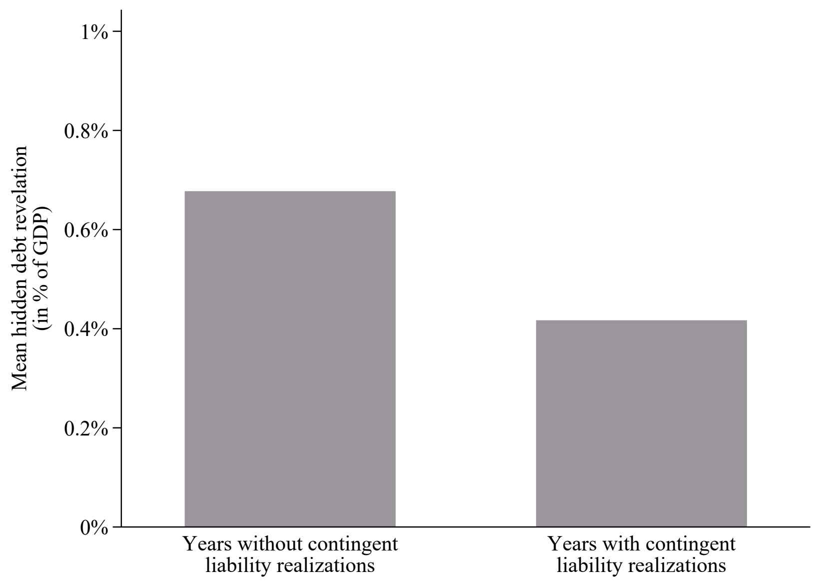
B.3 Treatment and impact of contingent liability realization

An alternative explanation for the documented debt data revisions could come from the realization of contingent liabilities. During downturns, a sovereign might be forced to bail-out private sector entities (e.g. banks or private-public partnerships) and assume their liabilities (see, e.g., Bova et al., 2016). This might mechanically generate the cyclical revision patterns that we observe, without implying any under-reporting of debt. We addressed this competing interpretation of the data in two ways. First, we consulted the World Bank debt data team to understand how debt assumptions are treated in the data. We were informed that debt assumptions do *not* require ex post revision of the debt data, since they do not change the pre-debt assumption debt stocks. Debt assumptions should therefore just lead to a discrete increase in the debt series (within the same vintage).

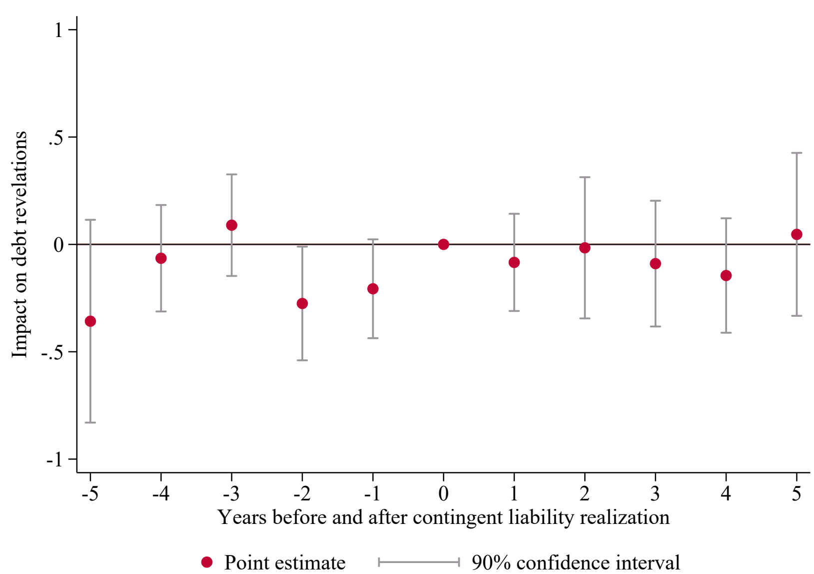
We empirically confirm this information by merging our data on debt data revisions with the dataset of implicit and explicit contingent liability realizations compiled by Bova et al. (2016). Their data captures 111 instances of contingent liability realizations in low and middle-income countries between 1990 and 2014 and allow us to test whether contingent liability realizations are associated with increased debt data upward revisions. We begin our analysis by testing whether years with contingent liability realizations have higher mean debt revelations than years without contingent liability realizations. Panel A of Figure B2 shows that this is not the case. Years in which contingent liability realizations occurred, on average, had lower mean revelations and the difference between the means is not statistically significant. These results are confirmed in an event study regression (Panel B of Figure B2). Years following the realization of contingent liabilities are not associated with significantly higher hidden debt revelations.

Figure B2: Contingent liability realizations and hidden debt revelations

Panel A: Mean comparison



Panel B: Hidden debt revelations before and after contingent liability realizations

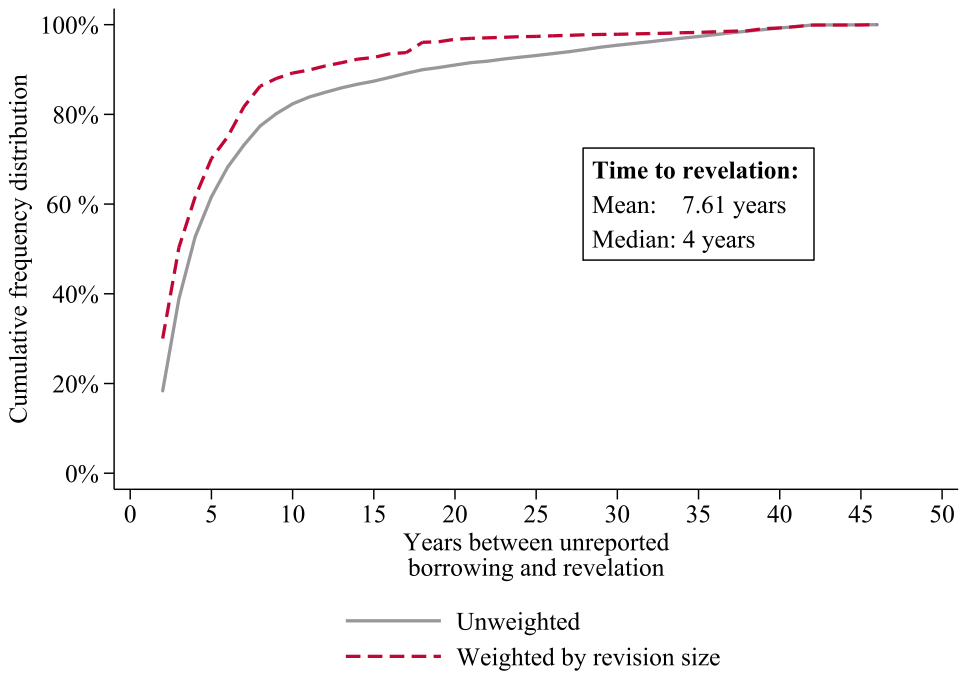


Notes: Panel A compares the mean hidden debt revelation in percent of GDP for years with and without contingent liability realizations between 1990 and 2014. Panel B shows point estimates and 90 percent confidence intervals obtained from regressing standardized hidden debt revelations on a set of year and country fixed effects and lags and leads for contingent liability realization events. Data on contingent liability realizations is from Bova et al. (2016), hidden debt revelations are defined as in equation (2).

B.4 Accounting for the possibility of reporting lags

This subsection tests whether the under-reporting bias could simply be driven by reporting lags. For this purpose, Figure B3 plots the cumulative frequency distribution of the number of years between an unreported borrowing and its revelation.

Figure B3: CFD of the time between unreported borrowing and revelation



Notes: This figure plots the cumulative frequency distribution of the time between an unreported borrowing and its revelation. The red line takes into account the revision size by weighting the years since accumulation by the revision in percent of GDP, while the grey line does not.

The median revelation takes place four years after the unreported borrowing. On average, it takes 7.61 years for hidden borrowing to be revealed. The difference between median and mean is driven by around 10 percent of unreported loans that only get revealed more than 15 years after their commitment date. Around 20 percent of unreported loans get revealed at the first possible instance, that is two years after the (unreported) borrowing. This short time span could be consistent with a pure reporting lag, for example if state-owned enterprises of a country follow fiscal years that differ from the World Bank reporting calendar.

Table B2 shows that our main finding of systematic under-reporting bias is robust to dropping unreported loans that get revealed in the first two vintages. This confirms that the systematic bias that we document is not merely the result of reporting lags.

Table B2: Summary statistics of hidden debt revisions, excluding up to the first two vintages after initial reporting

	N	Mean	Median	Std. Dev.	p-value
Panel A: Debt stocks					
In percent of GDP	5702	1.06	0.09	5.76	0.000
excl. first year	5550	0.88	0.05	5.32	0.000
excl. first two years	5515	0.76	0.02	5.52	0.000
In mn. USD amounts	5702	159.22	5.00	1,909.90	0.000
excl. first year	5550	121.82	3.00	1,635.39	0.001
excl. first two years	5515	97.61	1.00	1,434.19	0.001
Panel B: Commitments					
In percent of GDP	5695	0.70	0.08	4.17	0.000
excl. first year	5542	0.48	0.01	5.45	0.000
excl. first two years	5508	0.39	0.00	2.93	0.000
In mn. USD amounts	5695	148.60	6.00	1,169.82	0.000
excl. first year	5542	91.54	1.00	965.71	0.000
excl. first two years	5508	64.81	0.00	838.86	0.000

Notes: The table reports summary statistics and p-values for data revisions to debt stocks and debt commitments as defined in equation (1), both in percent of GDP and in millions of nominal USD. While rows one, four, seven, and ten repeat the results of Table 2, the remainder of the table repeats the same exercise after excluding the first and the first two vintages after initial publication of a debt stock. GDP data is taken from World Bank (2022) and not subject to revisions. We use Newey-West heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) when calculating p-values.

B.5 Revisions to the latest debt statistics

This subsection tests whether the systematic upward bias in debt data revisions is also present when we focus only on revisions that change the latest available year in a debt data series. Figure B3 shows that it can take more than 30 years for initially unreported debt to be fully revealed. Arguably, revelations that occur after such a long time period are of little relevance to a country's creditors. We therefore derive summary statistics for only those revelations in each vintage that change the latest available debt data point, e.g. a revelation in 2021 which updates the 2019 debt stock value compared to its initially published value in 2020. Table B3 and Figure B4 show that these revelations exhibit the same systematic upward bias as the full sample.

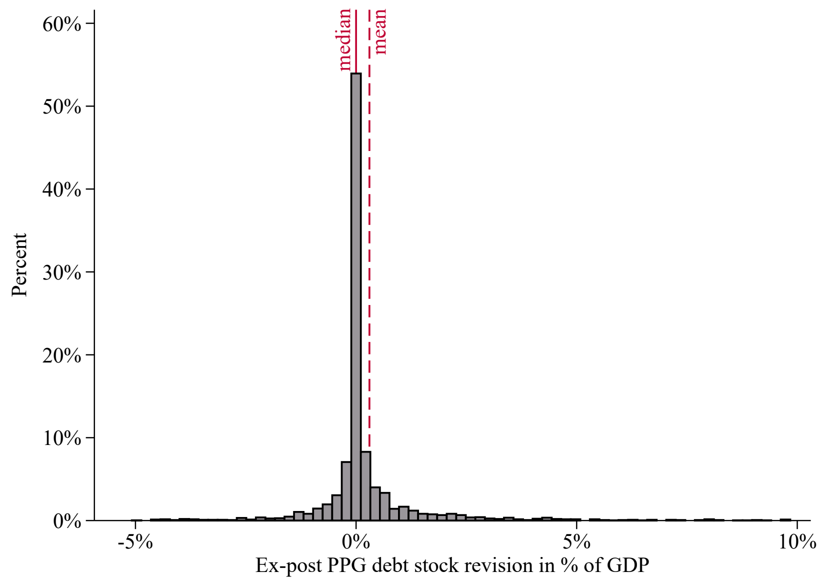
Table B3: Summary statistics of revisions to the latest available data

	N	Mean	Median	Std. Dev.	p-value
In percent of GDP					
Debt stock (DOD)	3,232	0.30	0.00	3.51	0.000
Commitments (COM)	3,213	0.41	0.00	6.88	0.001
In mn. USD amounts					
Debt stock (DOD)	3,232	72.69	0.00	1,561.86	0.005
Commitments (COM)	3,213	104.95	0.00	1,436.02	0.000

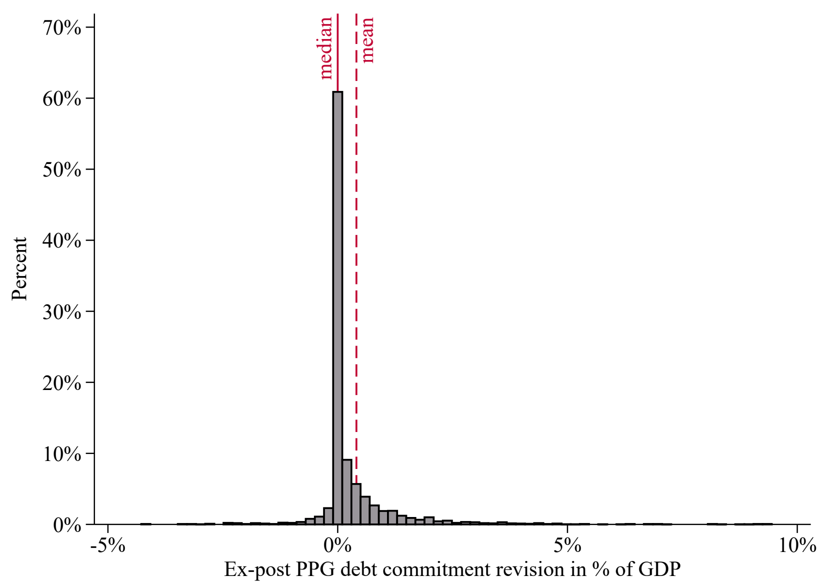
Notes: The table reports summary statistics and p-values for data revisions to debt stocks and debt commitments as defined in equation (1), both in percent of GDP and in millions of nominal USD, only for revisions to the values initially reported in the respective prior year. GDP data is taken from World Bank (2022) and not subject to revisions. We use Newey-West heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) when calculating p-values.

Figure B4: The distribution of recent debt stock and flow revisions

Panel A: Latest revisions to debt stocks in percent of GDP



Panel B: Latest revisions to debt flows in percent of GDP



Notes: The figure shows the percentage distribution of data revisions to debt stocks and debt flows (i.e. commitments) as defined in equation (1), in percent of GDP, only for revisions to the values initially reported in the respective prior year. The solid lines show the median, which is 0% of GDP for debt stocks in Panel A and 0% of GDP for debt flows in Panel B. Dashed lines visualize the mean, which is 0.30% of GDP in Panel A and 0.41% of GDP in Panel B. GDP data is taken from World Bank (2022) and not subject to revisions.

B.6 Comparison with IMF reporting violations

Member countries of the IMF that misreport information to the Fund face sanctions under Article VIII of the IMF's Articles of Agreement, unless misreporting is solely due to a lack of capacity. If the IMF's Executive Board concludes that a member country has misreported information for other reasons than lack of capacity, it can establish a breach of obligation on the part of the member country and decide on the application of sanctions. All Board decisions with respect to a breach of obligations will be publicly announced.

By going through IMF reports and policy documents, we are able to identify 50 instances in which IMF member countries were sanctioned for intentionally misreporting data. 16 of these cases, all but one of which are also listed in a related report by the IMF (2006), are both closely related to the publication of statistics on debt and fiscal policy and affect countries and years that are covered by our new database. Table B4 lists these cases, the dates on which they were discussed by the IMF board, and the size of the revelation we observe in the subsequent vintage. In all but four cases we are able to indeed observe revelations, ranging from USD 4 million to USD 1.3 billion.

Table B4: IMF reporting violations and hidden debt revelations

Country	Date discussed	Revelation *(mln. USD)*	Vintage
Argentina	September 17, 2004	57	GDF 2006
Burkina Faso	February 2, 2005	12	GDF 2006
Chad	June 23, 2003	4	GDF 2005
Djibouti	December 20, 2002	0	GDF 2004
Dominica	April 8, 2004	0	GDF 2006
Dominica	July 3, 2005	12	GDF 2007
Ghana	June 28, 2001	115	GDF 2003
Hungary	February 21, 1990	1,226	WDT 1991–92
Nepal	January 18, 2006	127	GDF 2007
Pakistan	March 4, 2021	800	IDS 2022
Tajikistan	February 7, 1999	0	GDF 2000
Tajikistan	February 13, 2002	23	GDF 2003
Tajikistan	November 12, 2002	78	GDF 2004
Turkey	April 26, 2005	1,270	GDF 2007
Uganda	July 30, 2004	0	GDF 2006
Ukraine	December 13, 1995	49	GDF 1997

Notes: The table lists 16 instances in which IMF member countries were sanctioned for misreporting data, the dates on which these cases were discussed by the IMF board (IMF, 2021; IMF, 2006), and the size of the revelation we observe in the subsequent debt statistics vintage.

C Additional results and figures

C.1 Debt data revisions to total external debt stocks

In addition to public and publicly guaranteed (ppg) external debt, the IDS also publishes series on private non-guaranteed external debt and on total external debt, which is the sum of ppg and private non-guaranteed debt. In contrast to our preferred series of ppg debt, the data on private non-guaranteed debt that the IDS publishes is not based on debtor reported loan-level data but is reported to the World Bank in aggregate by national authorities. It can therefore not be ascertained that this data series exhibits the same desirable properties that facilitate the interpretation of debt data revision for ppg debt and that we discuss in Section 3.2. Still, our collection of historic IDS vintages allows to study revision patterns to private non-guaranteed and total external debt and we discuss these patterns in this appendix section.

Figure C1 plots the distribution of revisions to total external debt (Panel A) and to private non-guaranteed external debt (Panel B). Both revision distributions are highly similar to the distribution for public and publicly guaranteed debt presented in Figure 5 in the main text. The average debt stocks revisions are 2.08 % of GDP and 1.23 % of GDP respectively, while the medians are close to zero, and the distributions exhibit a visible right skew. Table C1 confirms these properties by showing that the means of both distributions are significantly different from zero both in percent of GDP and in USD terms.

Table C1: Revisions to total external and private non-guaranteed debt stocks

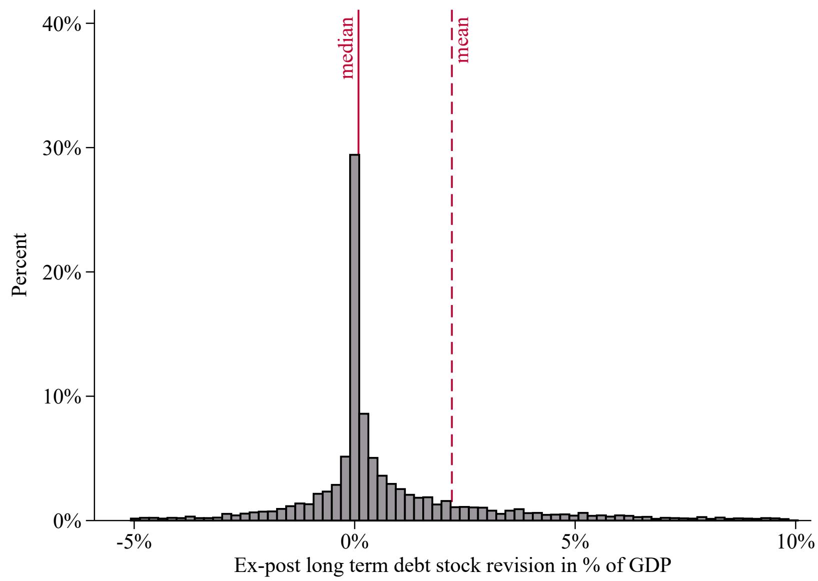
	N	Mean	Median	Std. Dev.	p-value
In percent of GDP					
Total long-term debt (DOD)	5,597	2.20	0.09	12.17	0.000
Private nonguaranteed debt (DOD)	5,605	1.30	0.00	10.94	0.000
In mn. USD amounts					
Total long-term debt (DOD)	5,597	837.01	5.00	6,268.27	0.000
Private nonguaranteed debt (DOD)	5,605	682.57	0.00	5,862.85	0.000

Notes: The table reports summary statistics and p-values for revisions of total external and private non-guaranteed external debt stocks, defined analogously to equation (1), both in percent of GDP and in millions of nominal USD. GDP data is taken from World Bank (2022) and not subject to revisions. We use Newey-West heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) when calculating p-values.

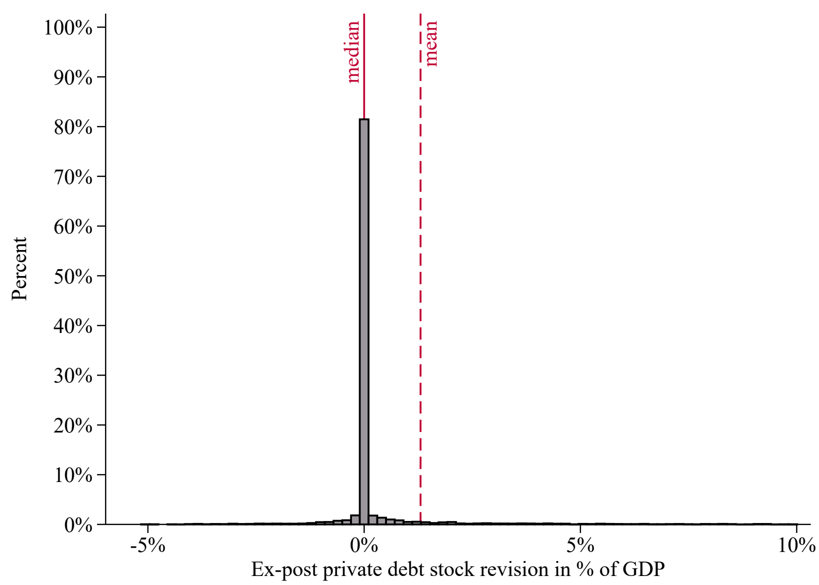
In addition to being interesting and policy relevant findings in their own right, the confirmed upward bias in revisions to private non-guaranteed debt also rules out the possibility that the under-reporting bias in ppg debt is purely driven by changes in the composition of total external debt (i.e. by the ex post reclassification of private non-guaranteed debt into ppg debt).

Figure C1: The distribution of total and private non-guaranteed debt stock revisions

Panel A: Total external debt stocks in percent of GDP



Panel B: Private non-guaranteed debt stocks in percent of GDP



Notes: The figure shows the percentage distribution of data revisions to the total external debt stocks and to the private non-guaranteed debt stocks, defined analogously to equation (1), in percent of GDP. The solid lines show the median, dashed lines show the mean. GDP data is taken from World Bank (2022) and not subject to revisions.

C.2 Hidden debt revelations and political cycles

In section 4.2, we show that hidden debt revelations are more likely to occur during bad times, in particular during episodes of high outside scrutiny. An alternative hypothesis is that governments strategically reveal hidden debts for political gain, for example after coming to power or after elections. This hypothesis is motivated by a large political economy literature that studies institutional and political drivers of government reporting practices (see, e.g., Martinez, 2022). Against this backdrop, this section presents additional regressions results that test whether domestic political factors can explain revelations of hidden debt. We do not find any evidence that governments strategically reveal previously unreported debt for political gains or that hidden debt revelations vary systematically across the political cycle.

More specifically, we consider the following variables as potential political drivers of hidden debt revelations:

- **Elections:** We use data from the Database of Political Institutions to measure the incidence of both legislative and presidential elections (Cruz et al., 2021). In our sample of IDS reporting countries, we identify 687 parliamentary and 408 presidential elections. As in the literature on political business cycles, one might conjecture that hidden debt revelations are less likely before an election but more likely after an election (Nordhaus, 1975).
- **Changes in political leaderships:** We use data from the Archigos dataset of political leaders to measure the incidence of changes in the political leadership of a country (Goemans et al., 2009). Specifically, we use a dummy variable to indicate all years in which a new leader enters office and a dummy variable to indicate all years in which a leader entered office in an irregular manner, e.g., through a coup or through direct imposition by another state. Incoming leaders might have particularly high incentives to reveal unreported debts at the beginning of their tenure. In our dataset of IDS reporting countries, we identify 433 regular changes and 61 irregular changes in political leadership.

We begin our analysis by including these measures in the fixed effects regression presented in section 4.2. Table C2 shows that none of the included political economy variables enters the regression with a statistically significant coefficient. A possible explanation for these null results might be that political events impact hidden debt revelations with a significant time lag or lead, i.e., a change in political leadership could affect debt reporting practices only after a number of years. To test for dynamic effects, we run panel event study regressions as in Schmidheiny and Siegloch (2023) or Clarke and Tapia Schythe (2020). More specifically, we estimate the following model:

$$HDR_{it} = \alpha + \sum_{j=\underline{j}}^{\hat{j}} \beta_j x_{it}^j + \sigma_i + \theta_t + \epsilon_{it}$$

Table C2: Political drivers of hidden debt revelations

	Dep. variable: Hidden debt revelations, 1975-2020				
	(1)	(2)	(3)	(4)	(5)
Executive election	0.03				0.04
	(0.06)				(0.06)
Legislative election		0.01			0.00
		(0.05)			(0.05)
Regular change in leadership			-0.01		-0.03
			(0.04)		(0.05)
Irregular change in leadership				-0.05	-0.05
				(0.10)	(0.12)
Real GDP growth (WDI)					-0.04**
					(0.02)
IMF program					0.11**
					(0.05)
External sov. default					0.10*
					(0.06)
Observations	3,511	3,510	3,924	3,924	3,411
R-squared	0.054	0.057	0.044	0.044	0.063
Country FE	✓	✓	✓	✓	✓
Vintage FE	✓	✓	✓	✓	✓

Notes: This table shows regression results from a fixed effects panel regression of hidden debt revelations on various political economy variables (see text for details and sources). The dependent variable is the sum of all previously unreported loan commitments of a country as revealed by a new vintage (as defined in equation (2)). To account for outliers and to ease interpretation, the dependent variable is standardized. All regressions include country and vintage fixed effects and robust standard errors clustered at the country level. In column (5) we additionally control for the creditor composition of external borrowing.

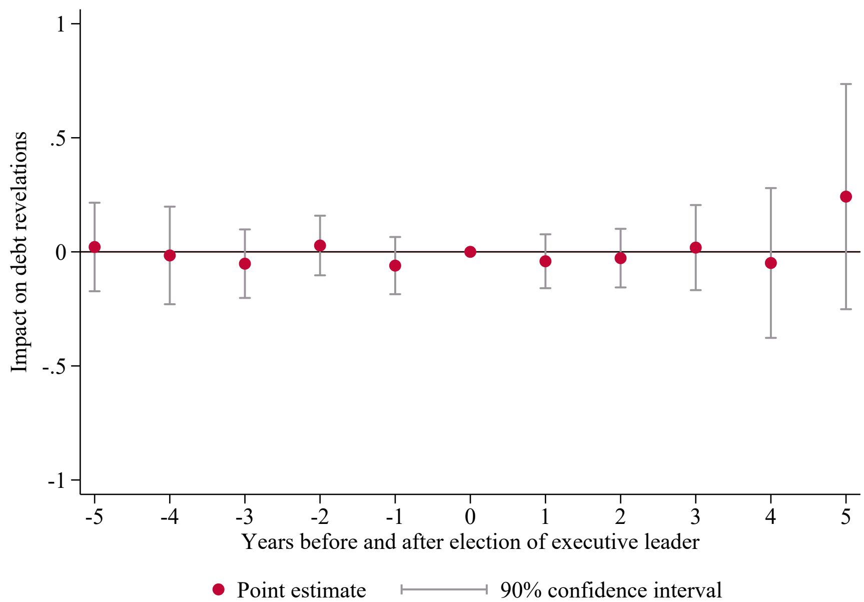
where HDR_{it} are revelations of previously hidden debt as defined in section 3.2 above, σ_i and θ_t are country and vintage fixed effects and ϵ_{it} is an unobserved error term. The leads and lags of x_{it} capture the years before and after a political event of interest and are defined as follows:

$$x_{it}^{j} = \begin{cases} \mathbb{1}[t \leq Events_s + j] & \text{if } j = \underline{j} \\ \mathbb{1}[t = Events_s + j] & \text{if } \underline{j} < j < \hat{j} \\ \mathbb{1}[t \geq Events_s + j] & \text{if } j = \hat{j} \end{cases}$$

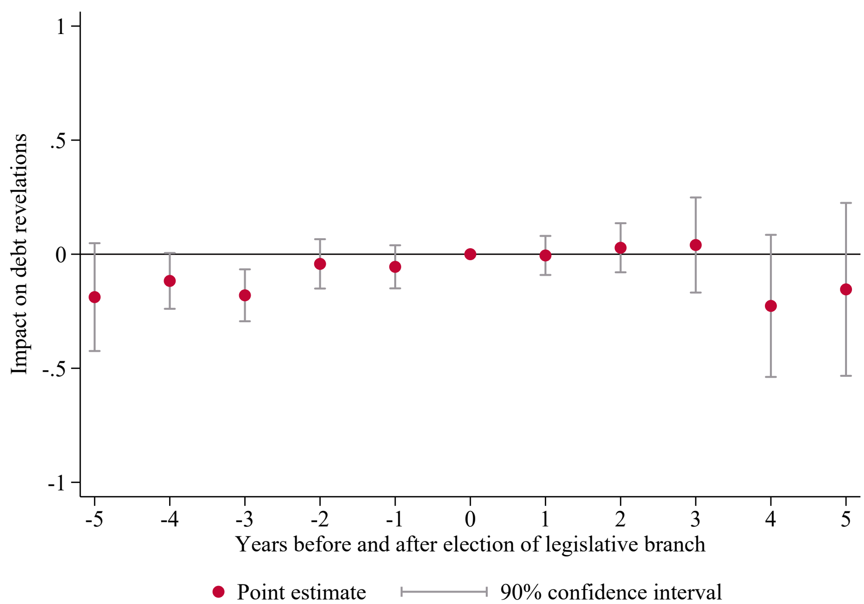
Figures C2 and C3 show the results of the panel event study regressions and confirm the results from the static regression model. Hidden debt revelations show no statistically significant co-movement with the political cycle.

Figure C2: Hidden debt revelations and the political cycle: event study panel regressions

Panel A: Election of executive leader



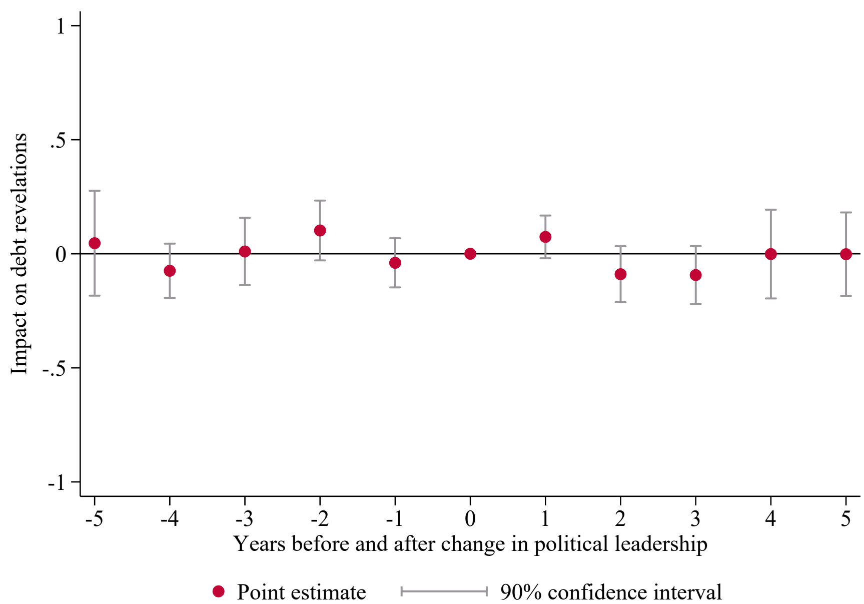
Panel B: Election of legislative branch



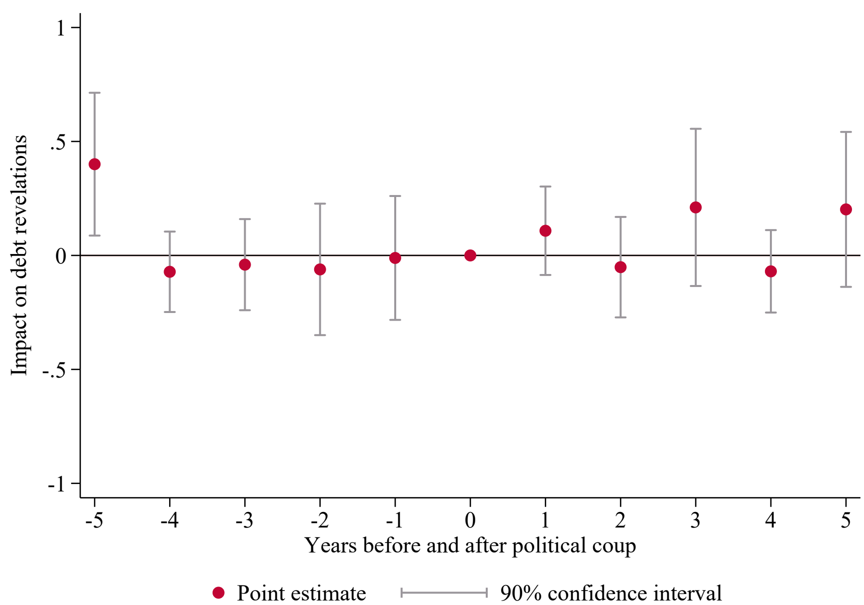
Notes: This figure shows point estimates and 90 percent confidence intervals obtained from regressing standardized hidden debt revelations as defined in equation (2) on a set of lags and leads for elections of the executive (Panel A) and legislative branch of government (Panel B).

Figure C3: Hidden debt revelations and changes in political leadership: event study panel regressions

Panel A: Change in political leadership



Panel B: Irregular change in political leadership



Notes: This figure shows point estimates and 90 percent confidence intervals obtained from regressing standardized hidden debt revelations as defined in equation (2) on a set of lags and leads for regular (Panel A) and unregular changes in political leadership (Panel B).

C.3 Additional descriptive statistics

Table C3: Debtor and creditor characteristics: debt commitment revelations (% of GDP)

	N	Mean	Median	Std. Dev.	p-value
Panel A: Debtor characteristics					
Regions					
Europe	238	0.45	0.14	1.12	0.000
Asia	854	0.59	0.00	18.45	0.081
Middle-East and North Africa	428	0.90	0.15	4.09	0.000
Sub-Saharan Africa	1,152	0.84	0.11	7.84	0.000
Latin America	951	0.70	0.08	3.21	0.000
Income groups					
Low income	557	0.73	0.11	3.04	0.000
Lower middle income	1,325	0.74	0.09	16.27	0.008
Upper middle income	1,229	0.65	0.04	3.45	0.000
High income	59	0.41	0.15	0.89	0.001
Decades					
1970s	458	0.59	0.11	2.67	0.000
1980s	558	0.99	0.24	8.79	0.003
1990s	743	0.92	0.09	3.23	0.000
2000s	885	0.53	0.01	4.83	0.000
2010s	1,028	0.54	0.06	17.20	0.074
Bond market access					
Non-market access countries	2,010	0.82	0.06	5.91	0.000
Market access countries	1,668	0.57	0.09	13.61	0.003
Panel B: Creditor characteristics					
Official creditors	3,482	0.45	0.03	9.64	0.000
Multilateral	962	0.10	0.00	1.62	0.045
World Bank	2,077	0.01	0.00	0.30	0.063
Bilateral	964	0.36	0.01	1.81	0.000
Private creditors	3,456	0.25	0.00	3.75	0.000

Notes: The table reports summary statistics and p-values for debt commitment revelations as defined in equation (2) in percent of GDP, broken down by debtor regions, income groups, decades of reporting and bond market access in Panel A, and creditor groups in Panel B. For commitments, only the official and private creditor breakdown is available for all vintages, which is reflected in the number of observations presented. See Section A.3 and Table A4 for details. We use Newey-West heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) when calculating p-values. Table C4 repeats the exercise for debt stock revisions.

Table C4: Debtor and creditor characteristics: debt stock revisions in % of GDP

	N	Mean	Median	Std. Dev.	p-value
Panel A: Debtor characteristics					
Regions					
Europe	315	-0.23	0.01	2.53	0.232
Asia	1,246	0.65	0.00	4.59	0.001
Middle-East and North Africa	689	0.01	0.04	4.15	0.962
Sub-Saharan Africa	1,874	1.63	0.10	7.73	0.000
Latin America	1,358	1.69	0.48	4.76	0.000
Income groups					
Low income	1,471	1.43	0.01	8.80	0.000
Lower middle income	1,519	0.59	0.11	3.24	0.000
Upper middle income	957	0.55	0.03	2.48	0.000
High income	17	0.41	0.00	1.27	0.203
Decades					
1970s	892	1.51	0.59	4.56	0.000
1980s	1,030	1.88	0.15	8.57	0.000
1990s	1,216	1.40	0.13	7.73	0.000
2000s	1,279	0.24	0.01	3.10	0.061
2010s	1,172	0.56	0.05	2.41	0.000
Bond market access					
Non-market access countries	3,174	1.15	0.03	6.91	0.000
Market access countries	2,351	1.01	0.17	3.91	0.000
Panel B: Creditor characteristics					
Official creditors	5,702	0.58	0.03	5.04	0.000
Multilateral	5,697	0.20	0.00	1.77	0.000
World Bank	5,730	-0.01	0.00	0.49	0.373
Bilateral	5,699	0.38	0.00	4.73	0.000
Private creditors	5,690	0.38	0.00	5.13	0.000
Bonds	5,525	0.09	0.00	1.27	0.002
Banks and other private	5,782	0.29	0.00	3.21	0.000

Notes: The table reports summary statistics and p-values for data revisions of debt stocks as defined in equation (1) in percent of GDP, broken down by debtor regions, income groups, decades of reporting, bond market access and creditor groups. GDP data is taken from World Bank (2022) and not subject to revisions. We use Newey-West heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) when calculating p-values.

Table C5: Creditor characteristics: debt stock revisions in % of initially reported debt

	N	Mean	Median	Std. Dev.	p-value
Total PPG debt	6,157	26.66	0.28	584.38	0.051
Official creditors	6,143	26.79	0.14	585.66	0.051
Multilateral	6,053	3.15	0.00	23.81	0.000
World Bank	5,702	-0.01	0.00	12.39	0.966
Bilateral	6,091	9.81	0.00	84.30	0.000
Private creditors	5,378	59.71	0.00	989.33	0.010
Bonds	2,432	7.47	0.00	235.18	0.150
Banks and other private	5,176	77.02	0.00	1,673.78	0.016

Notes: The table reports summary statistics and p-values for debt stock revisions as defined in equation (1) in percent of initially reported debt, broken down by creditors. GDP data is taken from World Bank (2022) and not subject to revisions. We use Newey-West heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) when calculating p-values.

Table C6: Summary statistics of debt stock revisions in % of GDP by country

	N	Mean	Median	Std. Err.	p-value
Afghanistan	24	0.11	0.04	0.56	0.503
Albania	32	-0.95	-0.01	3.79	0.311
Algeria	51	0.94	0.91	1.78	0.017
Angola	35	2.64	0.38	7.24	0.151
Argentina	51	0.03	0.21	1.01	0.869
Armenia	29	-0.30	0.03	1.00	0.124
Azerbaijan	28	0.68	0.38	0.95	0.004
Bangladesh	50	-0.42	-0.22	1.22	0.122
Barbados	25	0.36	0.21	1.36	0.383
Belarus	29	0.45	0.16	0.94	0.083
Belize	51	0.87	0.00	3.33	0.106
Benin	51	-0.45	0.02	6.02	0.760
Bhutan	41	1.85	0.00	3.58	0.027
Bolivia	51	2.57	1.40	5.60	0.009
Bosnia and Herzegovina	22	-0.91	-0.01	2.10	0.240
Botswana	51	0.89	0.26	2.82	0.119
Brazil	51	0.35	0.03	0.86	0.094
Bulgaria	40	0.04	0.06	2.54	0.942
Burkina Faso	51	-0.21	0.10	1.18	0.483
Burundi	51	-0.51	0.03	1.72	0.196
Cambodia	29	0.12	0.04	0.45	0.083
Cameroon	51	1.10	0.00	3.32	0.137
Cape Verde	41	-0.09	-0.22	1.71	0.786
Central African Republic	51	-0.89	0.11	2.83	0.160
Chad	14	0.90	0.01	1.91	0.195
Chile	42	0.34	0.04	0.84	0.106
Colombia	51	4.46	0.59	9.66	0.050
Comoros	51	0.69	0.52	0.72	0.000
Congo	51	0.78	0.42	1.20	0.000
Costa Rica	41	0.18	0.00	1.50	0.512
Cote d'Ivoire	18	-0.01	0.00	0.01	0.106
Croatia	16	-0.01	0.00	0.10	0.484
Cyprus	51	1.61	0.71	2.95	0.007
Democratic Republic of Congo	51	3.89	1.32	5.06	0.005
Djibouti	17	0.19	0.00	0.54	0.132
Dominica	35	0.98	0.00	5.17	0.280
Dominican Republic	40	3.86	3.49	4.04	0.000
Ecuador	51	1.05	0.22	1.53	0.006
Egypt	51	3.92	0.76	5.08	0.004
El Salvador	51	0.32	0.18	2.87	0.565

	N	Mean	Median	Std. Dev.	p-value
Equatorial Guinea	51	-0.06	0.00	3.60	0.940
Eritrea	51	-2.37	0.00	4.98	0.052
Estonia	17	0.07	0.00	0.91	0.738
Ethiopia	9	0.02	0.00	0.06	0.356
Fiji	11	-0.07	0.00	0.18	0.250
Gabon	40	15.59	0.19	22.11	0.019
Gambia	51	1.32	1.18	2.22	0.009
Georgia	51	0.92	0.54	1.46	0.000
Ghana	51	1.04	0.48	2.98	0.049
Greece	51	11.15	1.45	18.96	0.022
Grenada	15	-7.61	-1.13	13.35	0.116
Guatemala	19	0.27	0.17	0.38	0.025
Guinea	29	0.81	0.38	2.63	0.048
Guinea-Bissau	34	-1.22	-1.21	3.94	0.248
Guyana	44	1.04	1.84	3.22	0.181
Haiti	51	2.99	2.02	3.02	0.000
Honduras	51	7.27	2.41	17.04	0.075
Hong Kong	51	0.20	0.12	1.85	0.665
Hungary	13	-0.28	0.07	2.14	0.618
India	16	0.32	0.19	0.77	0.074
Indonesia	51	2.44	1.25	3.29	0.006
Iran	51	0.71	0.26	1.42	0.015
Jamaica	51	-0.35	-0.14	1.59	0.346
Jordan	49	-1.82	0.00	5.10	0.146
Kazakhstan	13	0.28	0.01	1.00	0.413
Kenya	51	2.57	2.21	3.13	0.001
Kosovo	45	2.25	0.42	2.87	0.007
Kyrgyz Republic	51	0.42	-0.24	5.10	0.727
Laos	28	-2.54	-4.63	12.18	0.347
Latvia	51	0.23	0.19	1.42	0.341
Lebanon	24	2.05	1.57	3.35	0.023
Lesotho	21	-0.37	0.00	0.88	0.195
Liberia	22	0.34	0.00	1.30	0.492
Lithuania	40	0.20	0.00	1.06	0.345
Macedonia	51	3.78	0.21	10.68	0.144
Madagascar	17	-0.43	0.00	0.70	0.109
Malawi	30	1.01	-0.20	4.95	0.392
Malaysia	51	-0.28	-0.12	3.92	0.744
Maldives	51	3.00	2.95	2.97	0.000
Mali	41	-0.18	0.00	1.66	0.541
Malta	51	0.55	0.21	1.11	0.024
Mauritania	21	-0.17	0.00	2.46	0.806

	N	Mean	Median	Std. Dev.	p-value
Mauritius	29	1.13	0.04	2.38	0.045
Mexico	26	0.08	0.06	0.40	0.180
Moldova	17	0.64	0.05	1.32	0.106
Mongolia	32	-0.31	0.00	0.66	0.136
Montenegro	51	0.10	0.00	2.95	0.821
Morocco	51	0.54	0.49	1.81	0.207
Mozambique	51	7.27	3.05	10.46	0.006
Myanmar	28	-0.81	0.07	5.65	0.543
Nepal	51	-0.93	-0.56	2.59	0.073
Nicaragua	34	-0.39	0.00	2.99	0.649
Niger	45	0.00	0.03	0.73	0.989
Nigeria	51	0.50	0.00	1.79	0.203
Oman	51	-0.41	0.01	1.60	0.263
Pakistan	51	3.86	2.32	8.49	0.039
Panama	51	-0.07	0.00	0.43	0.428
Papua New Guinea	51	0.10	0.00	1.74	0.757
Paraguay	51	0.01	0.24	1.20	0.973
Peru	36	-0.01	0.00	1.14	0.982
Philippines	51	0.51	0.32	0.93	0.019
Poland	51	0.60	0.42	1.12	0.024
Romania	51	-0.15	0.00	1.23	0.488
Rwanda	19	-0.21	-0.13	0.44	0.143
Saint Kitts and Nevis	51	0.20	0.12	2.26	0.696
Saint Lucia	37	7.37	1.71	15.14	0.025
Saint Vincent and the Grenadines	51	-0.64	-0.07	2.53	0.106
Samoa	51	1.16	0.38	2.07	0.012
Sao Tome and Principe	51	14.31	7.15	20.30	0.007
Senegal	51	1.86	0.33	2.74	0.010
Serbia	44	0.62	0.00	1.85	0.189
Seychelles	26	-0.54	-0.17	1.43	0.180
Sierra Leone	43	0.81	0.00	2.58	0.208
Singapore	34	-0.02	0.00	0.79	0.912
Slovak Republic	51	2.19	2.12	2.41	0.000
Solomon Islands	51	0.02	0.00	0.63	0.895
Somalia	17	0.43	0.13	0.61	0.062
South Korea	29	0.06	0.07	0.52	0.540
Sri Lanka	33	1.39	0.48	1.84	0.012
Sudan	14	1.94	1.17	2.11	0.031
Swaziland	29	-6.47	-2.72	8.68	0.008
Syria	20	-2.11	-0.62	4.44	0.214
Tajikistan	41	1.18	0.00	3.49	0.120
Tanzania	36	-0.82	0.00	2.32	0.140

	N	Mean	Median	Std. Dev.	p-value
Thailand	39	2.69	0.00	7.90	0.074
Togo	51	1.09	0.71	2.17	0.009
Tonga	51	1.07	0.00	4.70	0.326
Trinidad and Tobago	51	-0.07	-0.01	0.80	0.565
Tunisia	29	0.75	-0.09	3.87	0.330
Turkey	27	0.31	0.00	1.39	0.225
Turkmenistan	50	1.04	0.46	3.35	0.166
Uganda	36	0.11	0.00	1.57	0.797
Ukraine	51	-0.06	0.04	1.37	0.803
Uruguay	51	0.43	0.26	0.72	0.004
Uzbekistan	33	0.34	0.17	4.84	0.746
Vanuatu	29	0.21	0.10	1.10	0.451
Venezuela	29	0.91	0.07	2.26	0.165
Vietnam	42	0.67	0.29	2.43	0.110
Yemen	36	1.39	0.21	3.29	0.106
Zambia	41	-0.10	0.00	0.60	0.515
Zimbabwe	39	-1.20	0.00	2.15	0.021

Notes: The table reports summary statistics and p-values for data revisions to debt stocks as defined in equation (1) in percent of GDP for each country in our sample. N pertains to the number of available years in our dataset. GDP data is taken from World Bank (2022) and not subject to revisions. We use Newey-West heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) when calculating p-values.

Figure C4: Debt stock revisions

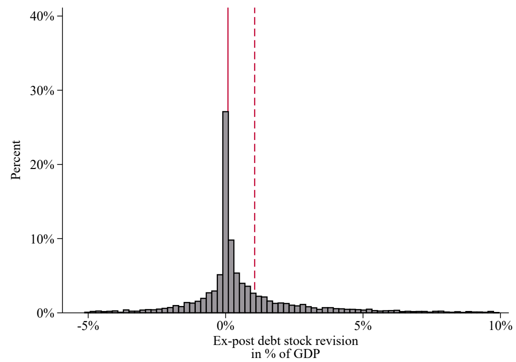


Figure C5: Debt commitment revisions

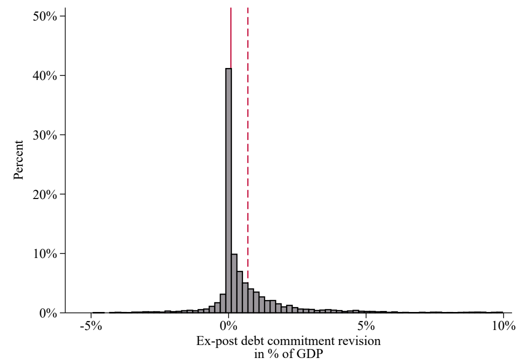


Figure C6: Disbursement revisions

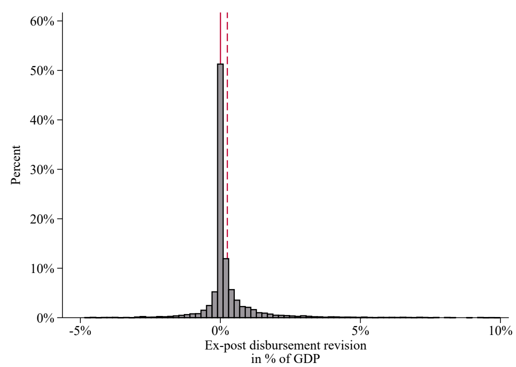


Figure C7: Principal repayments revisions

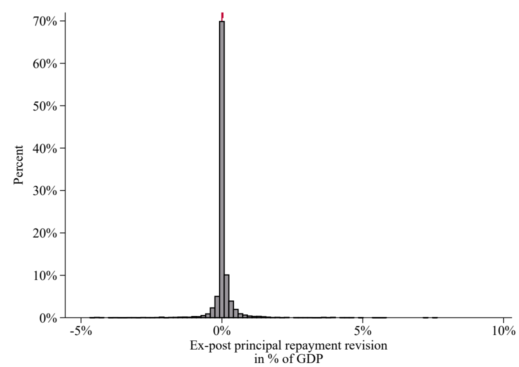


Figure C8: Debt stock revisions vis-a-vis private creditors

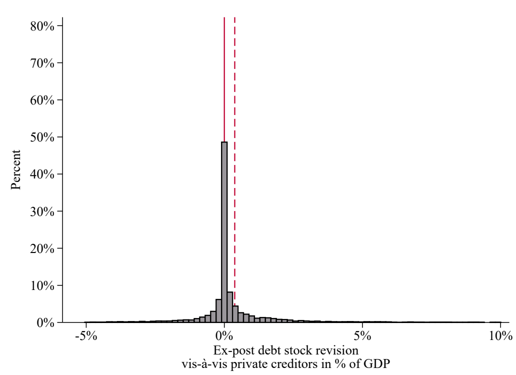


Figure C9: Debt stock revisions vis-a-vis bondholders

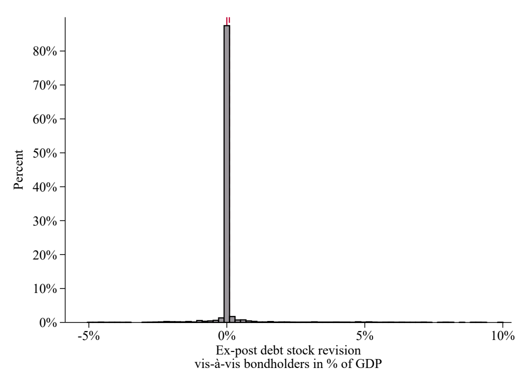


Figure C10: Debt stock revisions vis-a-vis bilateral creditors

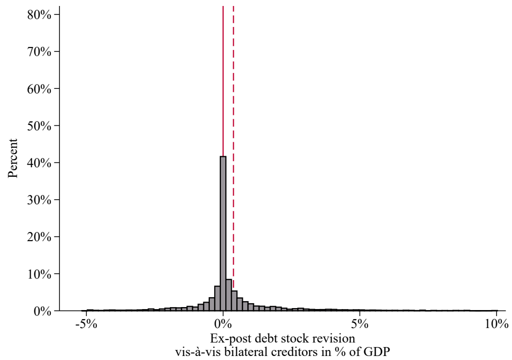


Figure C11: Debt stock revisions vis-a-vis multilateral creditors

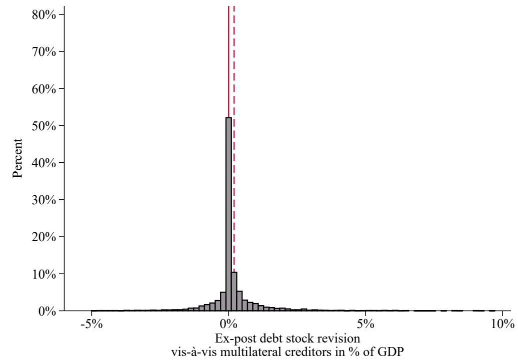


Figure C12: Debt stock revisions vis-a-vis the World Bank

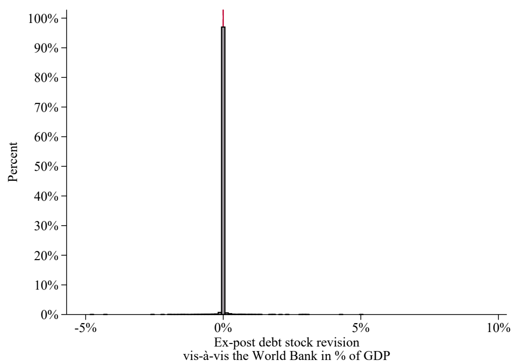


Figure C13: Debt commitment revisions vis-a-vis official creditors

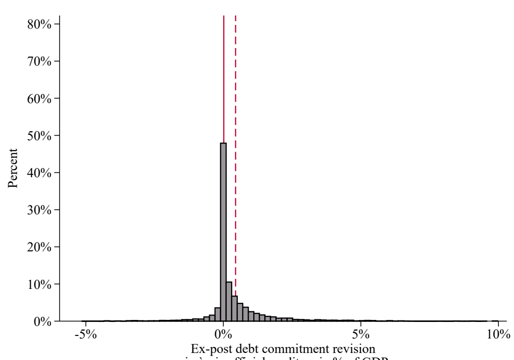


Figure C14: Debt commitment revisions vis-a-vis private creditors

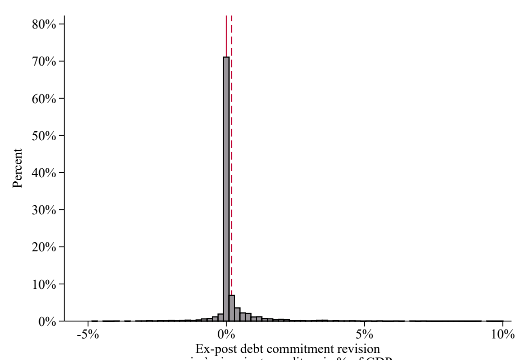


Figure C15: Debt commitment revisions vis-a-vis multilateral creditors

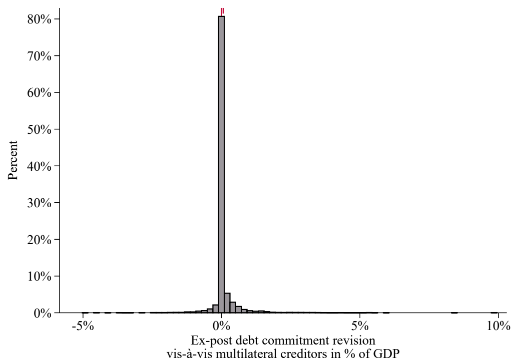
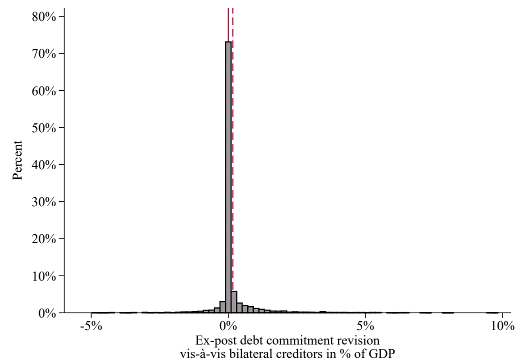


Figure C16: Debt commitment revisions vis-a-vis bilateral creditors



Notes: The histograms in Figures C4 - C16 exclude observations above +10% and below -5% of GDP. The solid red line visualises the respective subsample median, the dashed red line the respective subsample mean.

D Model Appendix

D.1 Details about the lender's expectations

Here we explain how lenders form their expectation over h', conditional on no-revelations for τ periods.

1. In the period of a hidden debt revelation, they observe h and ε both of which get added to the stock of debt. The variable τ gets reset to zero.
2. Standing on that period, they know: $h' = 0$ and $\tau' = 1$, but they need to take expectations over ε'. We have already assumed that $\varepsilon \sim N(\mu_\varepsilon, \sigma_\varepsilon^2)$
3. In the next period (assuming no revelation), they know that $\tau = 1$ and that $h = 0$, but they still need to form expectations over h' and ε'. They also know $h' = (1-\delta)h + \varepsilon$, but they did not observe ε. So $h' \sim N(\mu, \sigma^2)$.
4. In the next period, $\tau = 2$. They understand that $h' = (1-\delta)h + \varepsilon$ but this time both terms are random variables. The first one is a normal multiplied by $(1-\delta)$ and the second is a normal. That sum is distributed $N((1-\delta)\mu + \mu, (1-\delta)\sigma^2 + \sigma^2)$
5. In the following period, $\tau = 3$. The lender understands

   $$h' = (1-\delta)h_3 + \varepsilon_3$$

   where h_3 is the h' in the previous period (when τ was 2). So, now $(1-\delta)h_3$ is itself a random variable that is distributed $N\left(\mu((1-\delta)+(1-\delta)^2), \sigma^2((1-\delta)+(1-\delta)^2)\right)$, and ε_3 is still distributed $N(\mu, \sigma^2)$. So, h' (the sum of the two) is:

   $$h' \sim N\left(\mu((1-\delta)+(1-\delta)^2) + \mu, \sigma^2((1-\delta)+(1-\delta)^2) + \sigma^2\right)$$

   which can be rewritten as:

   $$h' \sim N\left(\mu(1+(1-\delta)+(1-\delta)^2), \sigma^2(1+(1-\delta)+(1-\delta)^2)\right)$$

6. Finally, for a generic period with $\tau \geq 1$ we have

   $$h' \sim N\left(\mu \sum_{j=1}^{\tau}(1-\delta)^{j-1}, \, \sigma^2 \sum_{j=1}^{\tau}(1-\delta)^{j-1}\right),$$

   and using the formula for the geometric sum we obtain

   $$h' \sim N\left(\mu \frac{1-(1-\delta)^\tau}{\delta}, \, \sigma^2 \frac{1-(1-\delta)^\tau}{\delta}\right),$$

   which is the expression used in section 6.1.

D.2 Details about the full-information economy

We model the full-information economy as one in which the lenders perfectly observe h, know how it evolves, and also see the realization of ε. Therefore, there is no concept of monitoring anymore. Given this assumption, τ is no longer a state variable. Therefore, since h is not hidden anymore, all agents in the model treat h and b in the same way. The only remaining difference between them is that b is chosen by the government but h is still governed by the random variable ε. Below we outline the equations of the model that are changed to capture this full-information economy.

Recovery rate. Recalled we used b_D to denote the non-negative amount of debt with which the country reenters after a default episode. This level is now given by

$$b_D(b, h, y) = \min\{\alpha(y), b + h\} \ , \tag{27}$$

where $\alpha(y)$ is still a non-decreasing function of the income level realized upon reentry. As before, these new bonds b_D get divided among holders of the previously issued debt (both market b and hidden h). This implies the following recovery rate (for all types of debt):

$$\omega^b(b, h, y) = \frac{b_D(b, h, y)}{b + h} \ .$$

Foreign lenders. We keep the assumption that foreign lenders arrive in overlapping generations, each with wealth W. They have access to a risk-free asset that yields a net return of r. The lender's problem is specified below.

$$V^{\ell}(b'; y, h') = \max_{B'} \ E_{y',\varepsilon'|y}\left[u_{\ell}\left(C'_{\ell}\right)\right] \tag{28}$$

subject to

$$\begin{aligned} C'_{\ell}\left(B', h', y', \varepsilon'\right) =& (W - q(b', h', y)B')(1 + r) + B'\mathcal{R}' \\ \text{with } \ \mathcal{R}'(b', h', y', \varepsilon') \equiv& \ \ d'(b', h', y', \varepsilon')\, q_D(b', h', y') + \\ & (1 - d'(b', h', y', \varepsilon')) \times \Big[\kappa + (1 - \delta)\, q(b'', h', y')\Big] \ , \end{aligned}$$

where q_D denotes the price of a bond in default, $b'' = \mathcal{B}(b', h', y', \varepsilon')$, with $\mathcal{B}$ denoting the optimal borrowing policy that lenders expect the government to follow, and the lender understands the law of motion for hidden debt: $h' = h(1 - \delta) + \varepsilon$.

The solution to this problem features a demand schedule for sovereign bonds given by[55]

$$q(b', y, h) = \frac{E_{y',\varepsilon'|y}\left\{u'_{\ell}\left(C'_{\ell}\left(B', h', y', \varepsilon'\right)\right) \times \mathcal{R}'(b', h', y', \varepsilon')\right\}}{E_{y',\varepsilon'|y}\left[u'_{\ell}\left(C'_{\ell}\left(B', h', y', \varepsilon'\right)\right)(1 + r)\right]} \ . \tag{29}$$

[55] The lenders observe ε. However, the fact that ε is *iid*, implies that its period-t realization does not affect the bond price and hence it is not an argument in $q(b', y, h)$.

A foreign lender that arrives in a state in which the government is in default faces a similar problem, but with a different set of returns. Namely,

$$V_D^\ell(b,h,s) = \max_{B'} \; E^\ell\left[u_\ell(C_\ell')\right] \tag{30}$$

subject to

$$C_\ell'(B',h,y',\varepsilon') = (W - q_D(b,h,y)B')(1+r) + B'\mathcal{R}_{\mathcal{D}}'$$
$$\mathcal{R}_{\mathcal{D}}'(b,h,y',\varepsilon') = (1-\theta)\, q_D(b,h,y') + \theta\, \omega(b,h,y')\Big[d(b_D,0,y',\varepsilon')q_D(b_D,0,y') +$$
$$(1-d(b_D,0,y',\varepsilon'))\Big[\kappa + (1-\delta)q(b'',0,y')\Big]\Big]$$

The solution to this problem implies the following demand schedule for defaulted bonds:

$$q_D(b,h,y) = \frac{E^\ell\left\{u_\ell'(C_\ell')\,\mathcal{R}_{\mathcal{D}}'(B,h,y',\varepsilon')\right\}}{E^\ell\left[u_\ell'(C_\ell')(1+r)\right]}\,. \tag{31}$$

Government's problem. A government that starts the period in good standing has the option to default on its debt. Therefore,

$$V(b,h,y,\varepsilon) = \max_{d\in\{0,1\}} \Big\{d\,V_1(b,h,y) + (1-d)\,V_0(b,h,y,\varepsilon)\Big\}$$

As in the benchmark model, a government default triggers (i) the "revelation" of all the "hidden" debt (that is to say, h is added to b and $h'=0$) and (ii) temporary market exclusion and income losses. The value under default is therefore given by:

$$V_1(b,h,y) \;=\; u\left(y-\phi(y)\right) + \beta E_{y',\varepsilon'|y}\Big[(1-\theta)\,V_1(b,h,y') + \theta\,V(b_D,0,y',\varepsilon')\Big] \tag{32}$$

where $b_D(b,h,y')$ is given by (27). The function $\phi(y)$ captures the income cost of defaults.

Finally, the government's value under repayment is as follows.

$$V_0(b,y,h,\varepsilon) = \max_{b'} \left\{u(c) + \beta E_{y',\varepsilon'|y}\,V(b',y',h',\varepsilon')\right\} \tag{33}$$

subject to

$$\begin{aligned}
c &= y - \kappa(b+h) + q(b',h',y)\iota + q_h\varepsilon \\
\iota &= b' - (1-\delta)b \\
h' &= (1-\delta)h + \varepsilon \\
\iota &> 0 \quad \text{only if} \quad q(b',h,y) > \underline{q}\,.
\end{aligned}$$

Calibration. The results in section 6.4 are obtained by solving the full-information economy using the same calibration as in the benchmark economy (Table 5).

References for Online Appendix

Asonuma, T., D. Niepelt, and R. Ranciere (2023). Sovereign bond prices, haircuts and maturity. *Journal of International Economics 140*, 103689.

Asonuma, T. and C. Trebesch (2016). Sovereign debt restructurings: Preemptive or post-default. *Journal of the European Economic Association 14*(1), 175–214.

Bova, E., M. Ruiz-Arranz, F. G. Toscani, and H. E. Ture (2016). The fiscal costs of contingent liabilities: A new dataset. IMF Working Paper No. 2016/014.

Clarke, D. and K. Tapia Schythe (2020). Implementing the panel event study. IZA Discussion Paper No. 13524.

Cruces, J. J. and C. Trebesch (2013). Sovereign defaults: The price of haircuts. *American Economic Journal: Macroeconomics 5*(3), 85–117.

Cruz, C., P. Keefer, and C. Scartascini (2021). DPI2020 database of political institutions: Changes and variable definitions. Available online: /https://publications.iadb.org/en/database-political-institutions-2020-dpi2020. IDB Department of Research.

Feenstra, R. C., R. Inklaar, and M. P. Timmer (2015). The next generation of the Penn World Table. *American Economic Review 105*(10), 3150–82.

Fouquin, M. and J. Hugot (2016). Two centuries of bilateral trade and gravity data: 1827-2014. CEPII Working Paper No. 2016-14.

Goemans, H., K. S. Gleditsch, and G. Chiozza (2009). Introducing archigos: A data set of political leaders. *Journal of Peace Research 46*(2), 269–283.

Horn, S., C. M. Reinhart, and C. Trebesch (2020). Coping with disasters: Two centuries of international official lending. NBER Working Paper No. 27343.

IMF (2006). Making the misreporting policies less onerous in de minimis cases. Available online: /https://www.imf.org/-/media/Websites/IMF/imported-full-text-pdf/external/np/pp/eng/2006/_070506.ashx. Washington, D.C.: International Monetary Fund.

IMF (2021). IMF Executive Board Reviews Pakistan's Remedial Actions, Data Revision Linked to Noncomplying Purchase. Press Release 21/82. Washington, D.C.: International Monetary Fund.

Marshall, M. G. and T. R. Gurr (2020). Polity V project, political regime characteristics and transitions, 1800-2018. Center for Systemic Peace.

Martinez, L. R. (2022). How much should we trust the dictator's GDP growth estimates? *Journal of Political Economy 130*(10), 2731–2769.

Newey, W. K. and K. D. West (1987). A simple positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica 55*(3), 703–708.

Nordhaus, W. D. (1975). The political business cycle. *The Review of Economic Studies 42*(2), 169–190.

Schmidheiny, K. and S. Siegloch (2023). On event studies and distributed-lags in two-way fixed effects models: Identification, equivalence, and generalization. *Journal of Applied Econometrics 38*(5), 695–713.

World Bank (2022). *World Development Indicators*. Washington, D.C.: World Bank Group.