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 the World Bank's debt statistics. In a sample of 146 countries and 53 years of debt data, we establish three new stylized facts about hidden debt: (i) hidden debt is large and common; (ii) hidden debt builds up in boom years, and tends to be revealed in bad times, often during IMF programs and sovereign defaults; (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 the model to study the effects of hidden debt on sovereign default risk, asset pricing, and welfare. Our model simulations show that hidden debt has non-trivial costs: it increases default incentives and borrowing costs and is, therefore, welfare detrimental.

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JEL classification: *F34, H63, G01*

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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 fraught with major limitations and incomplete reporting (World Bank, 2021; Gelpern, 2018). 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 (Estevao, 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 this importance, there is little work that systematically measures the magnitude, characteristics, and effects of hidden debt.

We fill this gap by quantifying hidden debt through 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 data set 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 under-reporting of public debts is a pervasive phenomenon. 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 only added to debt statistics in hindsight, more than twelve percent of total sovereign borrowing by all countries in our sample. This 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, but 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 most prone to under-reporting.

Second, we document the cyclical properties of the accumulation and revelation of hidden debt. We show that hidden debt tends to build up when growth is strong and tends to be revealed in economic downturns. For example, the COVID-19 recession was followed by the largest hidden debt revelation in 50 years.[1] Hidden debt is also often revealed during IMF programs and sovereign default episodes (resulting in further bad news). Our findings

[1] /https://blogs.worldbank.org/developmenttalk/systematic-underreporting-public-debt-statistics-50-years-evidence-and-recent

suggest that outside monitoring and international scrutiny in times of distress play a key role in driving greater debt transparency. In contrast, we do not find evidence that governments strategically reveal their hidden debt for political gain.

Third, we use our new data to shed light on the role of hidden debts during sovereign default episodes and the debt resolution process. A 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, suggesting 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 (Eaton and Gersovitz, 1981, Arellano, 2008, Aguiar and Gopinath, 2006) with hidden debt, incomplete information and a simple 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 or not. In line with our empirical evidence, the model features an endogenous recovery rate for market debt that gets diluted by undisclosed hidden debts of the sovereign. This gives bond investors an incentive to monitor the sovereign, therefore triggering revelations of hidden debt, in particular 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 show that hidden debt has non-trivial effects on equilibrium outcomes: It increases default incentives and depresses sovereign bond prices. To compensate investors for the uncertainty about true debt levels, sovereign borrowers with hidden debt need to pay larger spreads for given levels of market debt. 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 large average welfare gains of 5.5% of permanent income. Our model also allows 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 levels benefit from increased transparency. In contrast, countries with high levels of hidden debt are likely to find it costly to be exposed to greater scrutiny. This finding suggests that transparency policies are best implemented during good times to avoid the negative welfare effects of exposing hidden debts during crisis times.

[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.

Our findings and data can shed new light on several well-documented empirical patterns in sovereign debt markets. A 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, 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 reported levels of debt. Similarly, the threat of large upward revisions introduces an additional source of uncertainty, for which foreign bond investors need to be compensated, and can therefore help to understand the high risk premia that most developing country borrowers pay on their external sovereign bonds (Meyer et al., 2022). Our results may also help explain the large and positive forecast errors that often plague public debt projections (Flores et al., 2021) and the finding that only a small share of debt accumulation in developing countries can be traced back to fiscal deficits (Campos et al., 2006). More generally, the high uncertainty over the true value of developing country sovereign debt may contribute to the high levels of consumption volatility in developing countries documented for example by Arellano (2008) or Aguiar and Gopinath (2007).

Our paper also contributes to a growing theoretical literature that analyzes sovereign debt markets with asymmetric information and opaque borrowing (Alfaro and Kanczuk, 2022; Guler et al., 2022a,b; Kondo et al., 2024; Gamboa, 2023) and to the literature that studies the implications of costly information acquisition and investors' attention for the pricing of hidden debt (Gu and Stangebye, 2023; D'Erasmo, 2011; Fourakis, 2021; Morelli and Moretti, 2023). We add to this literature by bringing rich new data and combining it with a state-of-the-art model of debt and default.

Finally, our results relate to a large empirical literature on the reliability of government statistics and systematic reporting biases. Using a similar methodology on a broad range of US macroeconomic indicators, Aruoba (2008) shows that data revisions often exhibit systematic biases and large variances. Our finding of systematic under-reporting of public debt has a further interesting analogy in the well-documented tendency of economic growth data to be over-reported (Chen et al., 2019; Martinez, 2022). While our paper employs a similar approach and similar statistical concepts, we note one key difference between debt data revisions and the revisions of other macroeconomic indicators: The (nominal) debt stock and flow measures that we analyze rely, in principle, solely on basic accounting guidelines and are derived exclusively from a country's loan and bond portfolio. As such, only new information about the underlying loans and bonds should cause revisions to the total figures. This stands in contrast with real GDP growth or other macroeconomic variables, which need to be estimated and can be revised in response to methodological refinements or updated assumptions across a wide range of inputs.

The rest of the paper is structured as follows: Section 2 introduces our new database of debt data revisions and our measure of hidden debt revelations. We motivate our approach by presenting a case study and explain in detail how our measure of hidden debt should be interpreted. Section 3 presents the main statistical properties of debt data revisions and documents new stylized facts about the size, characteristics, and timing of hidden debt and its revelation. Section 4 presents our quantitative model of sovereign debt and default with hidden debt and an endogenous monitoring decision. Section 5 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 6 concludes.

2 Data, measurement and interpretation

In this section we introduce our new dataset of debt data revisions and explain how we use it to quantify hidden debt and hidden debt revelations. To illustrate the main mechanisms and ideas, subsection 2.1 draws on the recent case study of Mozambique's hidden debt scandal. Throughout this section, we focus on the main principles of data construction and measurement and refer interested readers to Appendix A for further details.

2.1 Mozambique's hidden debt scandal

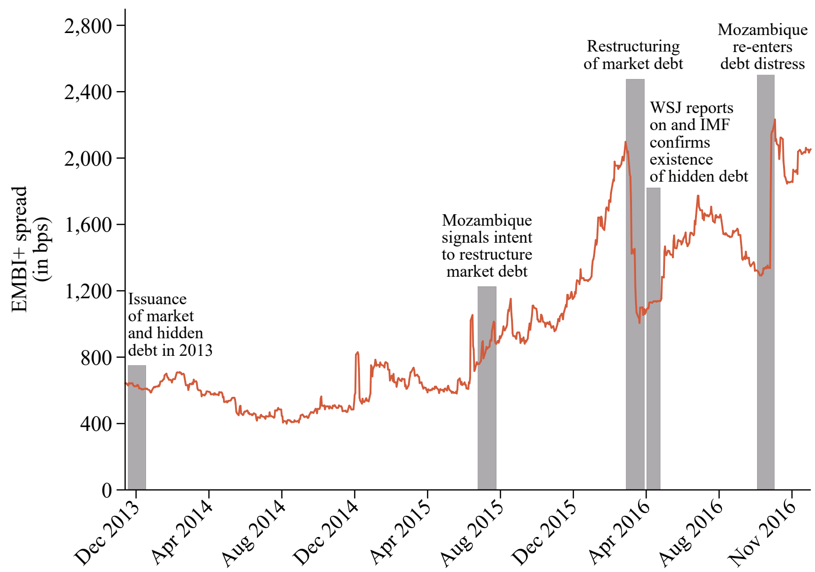
In 2016, Mozambique made international headlines when an international audit discovered USD 2 billion in unreported sovereign debt liabilities. During the early 2010s, Mozambique was considered a development success story. The discovery of large natural gas deposits off the northern coastline of Mozambique 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 close to USD 2 billion from international banks Credit Suisse and VTB without disclosing these additional liabilities to bond investors and the public.

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

The rumors about hidden debt led to a surge in Mozambique's bond spreads (see Figure 1), with bond investors expressing concern 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. They confirmed the existence of close to USD 2 billion in hidden liabilities.(Cortez et al., 2021). It ultimately took 4 years to settle the renegotiation with bondholders and the country has not been able to access the international bond market ever since.

Figure 1: Market reactions to 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 (2022).
Notes: The figure plots the EMBI+ spread for Mozambique from December 2013 until December 2016, covering the market reactions to various announcements and press reports regarding its market and hidden debt. EMBI+ spread in basis points.

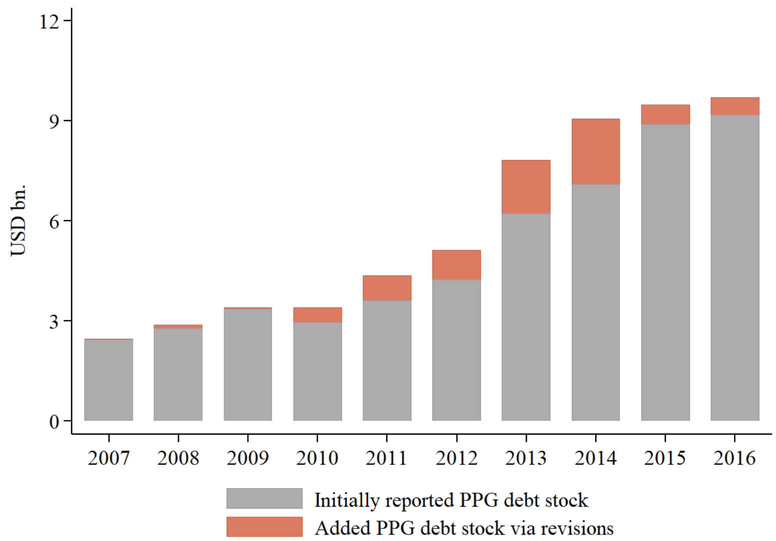
Mozambique's hidden debts and their revelation can be quantified by comparing its debt reports across different vintages of the World Bank's International Debt Statistics. When initially reported, the 2014 debt figure for Mozambique was USD 7.1 billion (see Figure 2). Subsequent vintages strongly upward revised this figure as the previously undisclosed loans became public knowledge. The latest debt figure (published in IDS 2022) for year 2014 is USD 9.1 billion, an increase of USD 2 billion (which amounts to 28 percent of the initially reported value and 11 percent of GDP).

2.2 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 ("vintages") of the World Bank's International Debt Statistics 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 debt data and frequently

Figure 2: Mozambique's hidden debt scandal, 2007 – 2016



Sources: World Bank (various years) and authors' calculations
Notes: The figure shows the initially and most recently reported public and publicly guaranteed debt stocks for Mozambique between 2007 and 2016 in billion USD. Grey bars show initially reported debt stocks. Orange bars show additional debt stocks added though revisions in subsequent reporting.

cited by researchers, investors, rating agencies and market commentators. Reporting to the debt statistics is mandatory for all countries with outstanding liabilities to the World Bank, ensuring high coverage across countries and time. Debtor countries that violate their reporting obligations risk losing eligibility for financial support from the World Bank.[3]

Second, the IDS exhibits a number of desirable features that facilitate the interpretation of debt data revisions as a measure of hidden debt (revelations):

- The International Debt Statistics and its predecessor publications are based on direct debtor reporting. While the World Bank compiles the annual statistical report and carries out consistency checks, all underlying data on debt instruments are reported by the national debt management offices. Omissions and revisions of debt data can therefore be traced back to reporting decisions of sovereign debtor countries.[4] 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

[3] World Bank Policy on External Debt Reporting and Financial Statement

[4] As explained in greater detail in appendix section A.2, the World Bank might provide estimates on debt data when a reporting country does not fulfil its reporting obligations, but in our analysis, we exclude all data points where the data is only preliminary or estimated.

ex-post data revisions do not reflect valuation changes but changes in the underlying debt reporting.[5]

- 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 DRS reporting manual over time and confirms that only minimal refinements have occurred over the past four decades.[6] This ensures that ex-post data revisions do not reflect the evolution of reporting guidelines, but can be traced back to changes in the compliance with a stable rules set over time.

Sources and digitization: Our new database combines more than 50 different editions ("vintages") of the World Bank's International Debt Report (2022–2023), and its predecessor publications the International Debt Statistics (2013–2022), the Global Development Finance reports (1997-2012) and the World Debt Tables (1973-1996). While the name of the publication has changed over the past decades, all reports build on the same underlying data series from the World Bank's Debtor Reporting System (DRS).

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 the data from PDFs or hard-copy reports. Specifically, we download all vintages of the International Debt Report (2022–2023) and the International Debt Statistics (2013–2022) as well as eight vintages of the Global Development Finance reports (2005–2012) from the International Debt Statistics website.[7] For all editions prior to 2005, we obtain PDFs or hard copies from different libraries and to turn reports into machine-readable formats we rely on a combination of Optical Character Recognition (OCR) software and manual coding. Finally, we verify and reconcile the consistency of the data series and merge data from all vintages into a single data set (see Appendix A for details).

Scope of database: Our new database covers debt statistics for an unbalanced sample of 146 developing and emerging market countries and for 53 years of data from 1970 to 2022. The database combines all information from a total of 51 different vintages so that each statistic can be compared across dozens of different debt reports.

[5] See appendix section B.3 below for a discussion of ex-post foreign exchange rate revisions. They are minuscule in size.

[6] Appendix section B also shows that all our results are robust to excluding data revisions from vintages with slightly different reporting guidelines.

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

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

No. of vintages	51
No. of variables	49
No. of countries	146
Time span	1970–2022 (53 years)
No. of individual data points	3,315,950

Notes: The table shows basic metrics from our new database on debt data revisions.

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

- **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, 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) are 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.

2.3 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 the previously unreported debt. More formally, we rely on the following two measures that we construct for both the debt stock and the 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 the flow value, reported in vintages V and v_0, with V the most recent vintage and v_0 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.

Hidden debt revelations, that is the amount of hidden debt uncovered in a given vintage, are defined by the difference in debt values in vintage v and vintage $v-1$ summed across all past years for which both vintages report the debt values.

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

with $Debt_{i,t}$ defined as above, with t_0 the first year available in both vintages v and $v-1$, and T the most recent year available in the same two vintages.[8]

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: 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. Revisions should therefore be exclusively caused by changes in information about the underlying loans and bonds portfolio.[9] 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 in hindsight. As reporting guidelines are stable over time, any previously unreported loan should have been reported in the previous vintage and therefore constitutes a violation of World Bank reporting guidelines. Our measure of hidden debt can therefore be regarded as initially under-reported debt in violation of prevailing reporting standards that is revealed ex-post through a statistical revision.

Validation and robustness: In Appendix Section B, we conduct several robustness and validation exercises to rule out 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.3), contingent liability realizations (Section B.4), or by mere reporting lags (Section B.5), among others.

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 reporting requirements but would imply less

[8] Note that equation (2) has a clearer interpretation for the flow measure rather than the stock measure of debt. This is because an ex-post addition of a single loan leads to revisions across the full loan life-cycle over multiple years and therefore involves double-counting.

[9] This stands in contrast with real GDP growth or other macro variables, which need to be estimated and can be revised in response to methodological refinements or updated assumptions across a wide range of inputs.

secrecy. Similarly, revelations within the IDS may have followed revelations through other sources with a lag (see the Mozambique case study in section 2.1 where the hidden loans were added to the IDS after being revealed by an international audit). This warrants caution in treating our debt data revisions as pure 'news shocks' (Arezki et al., 2017).

It finally deserves emphasis that 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 only captures 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 is never incorporated into debt statistics.

3 Quantifying hidden debt

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: 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 1.06 percent of GDP. Under-reporting of debt has occurred persistently across all decades, debtor regions and income groups, in particular in countries with weak institutions. On the creditor side, under-reporting is most severe for bilateral and non-bond commercial lending.
- **Stylized Fact 2: 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 each of these three propositions in turn.

3.1 Hidden debt is large and common

In this section we quantify the magnitude of hidden debt using the methodology outlined above. Figure 3 shows the distribution of hidden debt, as measured by data revisions to the external public and publicly guaranteed debt stock and to new debt flows across all vintages, years and countries in our database. Revisions are scaled by debtor country GDP, which is taken from the latest World Bank (2022) WDI and not subject to revisions.

Two results stand out. First, Figure 3 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.[10] Around 70 percent of all debt stock statistics and 50 percent of all debt flow statistics published through the World Bank International Debt Statistics get revised at least once after their initial publication. This is also reflected by the large standard deviation of 5.76 percent of GDP for stock 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, i.e. akin to noise or accidental misreporting, we would expect the mean of the distribution to not be significantly different from zero (Aruoba, 2008). Figure 3 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 approximately 1 percent of GDP. Likewise, yearly undisclosed new borrowing has a mean of 0.7 percent of GDP. Table 2 combines mean and median debt revisions with the standard deviation and shows that the mean revision in percent of GDP is positive and statistically different from zero at the 1% significance level.[11] This result is clearly incompatible with the notion of a purely noisy revision process and indicates systematic under-reporting of initial debt stocks and flows.[12]

In Appendix Table C5 we show that our result is not driven by a specific subgroup but holds across all decades and most debtor regions and income groups. The under-reporting bias is strongest in low- and middle-income countries as well as in Latin America and Sub-Saharan Africa. In contrast, we do not observe statistically significant revision patterns in Europe and among high income countries. This could be caused by a smaller sample size but might also reflect higher institutional quality. We also document that upward bias is evident and statistically significant across all large lender categories (multilateral, bilateral and private creditors).

Our data also allows to understand the determinants of under-reporting across countries. To test for the role of debtor country institutions, Panel A of Figure 4 depicts the distribution of debt data revisions across country groups with different institutional strength, as measured by their average score on the Polity V dataset. Figure 4 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. It is noteworthy, however, that even the countries with the strongest institutions

[10]For the flow measures, ex-post upward revisions are four times as likely as downward revisions.The same metric is not as insightful for stock revisions, since a single flow revision (e.g. a missing borrowing) may lead to persistent debt stock revisions until loans are repaid.

[11]We use Newey-West heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) to account for the autocorrelated structure of revisions (also see Aruoba, 2008).

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

Table 2: Summary statistics of debt data revisions

	N	Mean	Median	Std. Dev.	p-value
In percent of GDP					
Debt stock (DOD)	5702	1.06	0.09	5.76	0.000
Commitments (COM)	5695	0.70	0.08	4.17	0.000
In mn. USD amounts					
Debt stock (DOD)	5702	159.22	5.00	1,909.90	0.000
Commitments (COM)	5695	148.60	6.00	1,169.82	0.000

Sources: Authors' calculations
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) WDI and not subject to revisions. P-values are obtained from t-tests testing the null hypothesis of revisions having a zero mean against the alternative of a positive mean. We use Newey-West heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) to account for the autocorrelated structure of revisions when calculating p-values.

in our sample systematically under-report their debt, with a significant mean revision of 0.4 percent of GDP. This suggests that besides capacity constraints, the persistence of hidden debt also reflects debtor country incentives to under-report their true level of indebtedness. We confirm these descriptive results on institutional strength in a cross-country regression setup presented in Table C3 in the Appendix, where we additionally control for the debtor countries' share of borrowing from multilateral institutions and bondholders, as well as their time spent in default and IMF programs.

We next disaggregate debt data revisions by creditor group. However, relative debt amounts differ greatly across lender groups and, thus, scaling revisions by GDP makes it difficult to assess the relative susceptibility to under-reporting across creditors.[13]. In Panel B of Figure 4 we therefore scale debt data revisions by the initially reported value to account for differences in the relative magnitude of lending across creditors.[14] Panel B of Figure 4 reveals that the upward bias in revisions is largest in debt to bilateral and non-bond private creditors. For debt owed to the World Bank (IBRD and IDA) and for debt owed to private bondholders, however, the figure shows only very small revisions. This is not surprising, given that the data on (publicly traded) bonds is generally widely available and the World Bank can readily monitor its own lending activities and ensure 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 often shielded from public scrutiny through non-disclosure clauses (Gelpern et al., 2021; Mosley and Rosendorff, 2023).

[13] The results from such an exercise can be found in Appendix Table C4

[14] As further discussed in the data appendix, private creditor decompositions are not available for earlier vintages. The results presented in Table C4 and Figure 4 are therefore based on a smaller data sample. See appendix A for details. In appendix section C.2, we show full distributions for each creditor type.

3.2 Hidden debt builds up in boom years, and is revealed during busts

Our next subsection turns to the cyclical properties of hidden debt and analyses, when hidden debt is revealed. We start by documenting that hidden debt tends to build up during boom years and tends to be revealed during bust years. Figure 5 presents this key result in the form of binned scatter plots, following the approach of 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 data points of boom years are subject to higher upward revisions, implying that more unreported borrowing takes place 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.

Table 3 sheds further light on the mechanisms that underlie hidden debt revelations in bad times. Specifically, we show in a fixed effects panel regression 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 only explain a small share of the overall variation in our noisy revision data, they are associated with economically sizeable effects. An IMF program and a sovereign default episode are both associated with an increase in hidden debt revelations of 12 percent of the standard deviation of hidden debt revelations. This corresponds to around USD 200 mn in newly revealed loans during the first year of the average IMF program or while a country is in a sovereign default episode.

These findings confirm existing anecdotal evidence on the discovery of hidden debt during financial crises and point to outside monitoring as the key driver of greater debt transparency.[15] Both IMF programs and external sovereign defaults are times of intense external scrutiny on a country's debt statistics. In exchange for a lending program, the IMF requires detailed access to a country's debt statistics in order to assess debt sustainability and to 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 2.1 and the next subsection).

[15] 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.3.1, we therefore 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.

Table 3: Drivers of hidden debt revelations

	Dep. variable: Hidden debt revelations, 1975-2022			
	(1)	(2)	(3)	(4)
Real GDP growth (WDI)	-0.04**			-0.04**
	(0.02)			(0.02)
External sov. default		0.15***		0.12**
		(0.05)		(0.06)
IMF program			0.13***	0.12**
			(0.04)	(0.05)
Observations	3796	3924	3924	3796
R-squared	0.047	0.046	0.046	0.051
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 2.3 and equation (2) for details). To account for outliers and to ease 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 above average private borrowing. Robust standard errors shown in parenthesis.

3.3 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 creditors are often particularly concerned about the existence of hidden debt that may dilute the recovery value of their claims. In several recent debt distress episodes, e.g. in Zambia, Chad or Mozambique, uncertainty over the true level of indebtedness has been a key stumbling block for distress resolution. In these cases, the lack of debt transparency delayed the restructuring process and amplified coordination issues among creditors (Estevao, 2021; World Bank, 2021).

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 spell (defined by the time between the initial missed payment and the final resolution through a debt restructuring). This data allows to test whether high hidden debts at the onset of the default episode is associated with (i) larger haircuts and (ii) longer default spells.

Table 4: Hidden debt and default spells

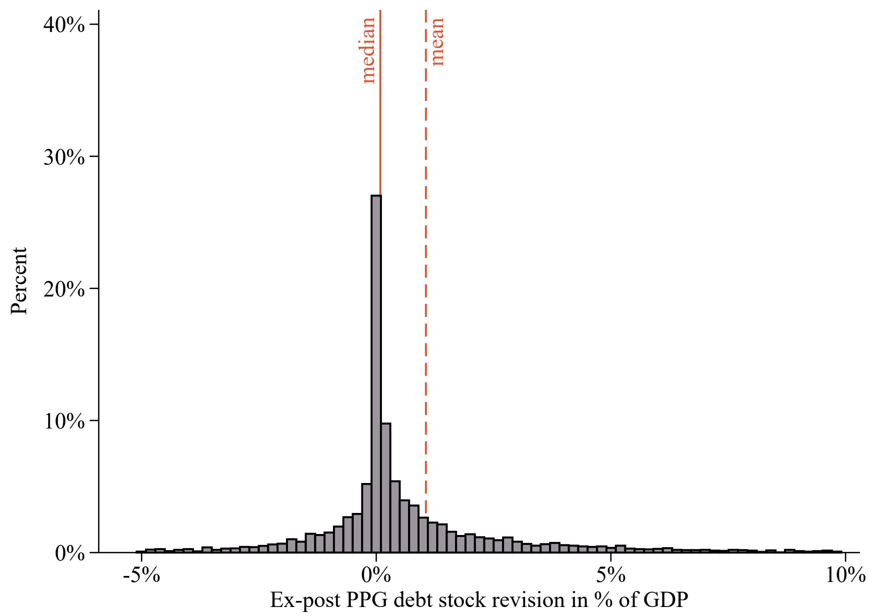
	Haircut		Duration of spell	
	(1)	(2)	(3)	(4)
Hidden debt	0.24**	0.25***	0.62***	0.69***
	(0.11)	(0.10)	(0.21)	(0.19)
Real GDP growth		-0.44		-0.55
		(0.36)		(0.70)
Debt to GDP ratio		0.27***		0.26***
		(0.05)		(0.09)
Real GDP p.c.		-1.08**		-0.60
		(0.48)		(0.93)
Institutional quality		-0.49*		-1.00*
		(0.28)		(0.55)
Constant	35.21***	24.06***	39.89***	23.72**
	(2.26)	(4.96)	(4.26)	(9.67)
Observations	153	140	153	140
R-squared	0.031	0.308	0.057	0.183

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 in percent ("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 final 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 in percent of reported debt and is constructed as defined by equation (1) in Section 2.3. Standard errors are reported in parenthesis. See Appendix Section A.4 and text for details and sources on the included control variables.

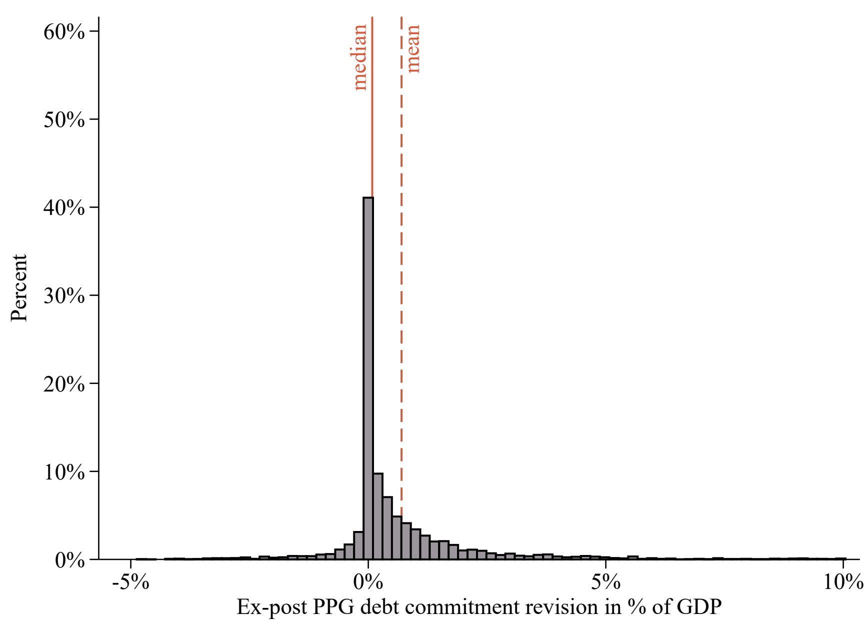
Table 4 shows the results from this exercise. Columns (1) and (2) show that higher unreported debts are indeed associated with higher creditor losses in statistically and economically meaningful ways. A one percentage point increase in the amount of unreported debt (in percent of reported debt) is associated with an increase in the haircut of 0.24 percentage points. The correlation remains virtually unchanged when we control for other common predictors of creditor losses, such as real GDP growth, the debt to GDP ratio, real p.c. GDP and institutional strength of the crisis country (all measured at the onset of the default episode, column 2). Columns (3) and (4) repeat the exercise but focus on the duration of the default spell. 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 around 0.7 months. Again, this result holds when controlling for other potential determinants of the length of the default spell.

Figure 3: The distribution of debt stock and flow revisions

Panel A: Revisions to debt stocks in percent of GDP



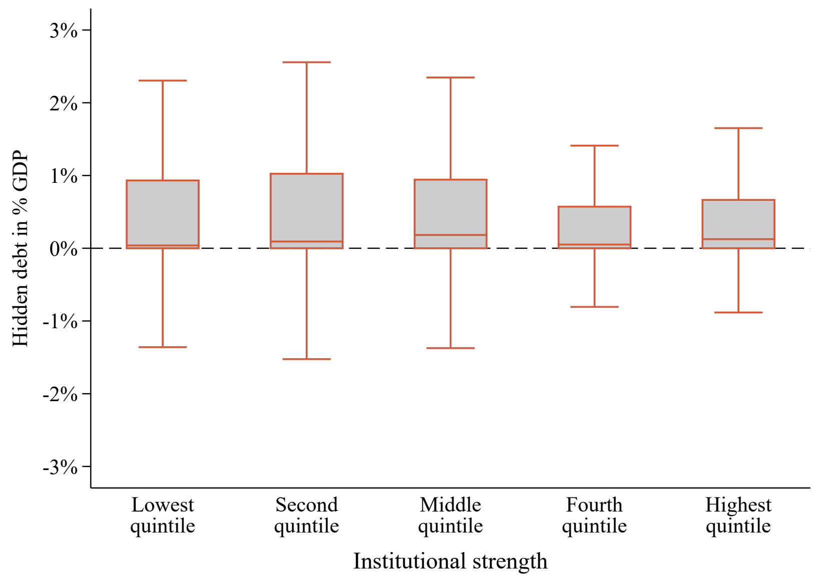
Panel B: Revisions to debt flows in percent of GDP



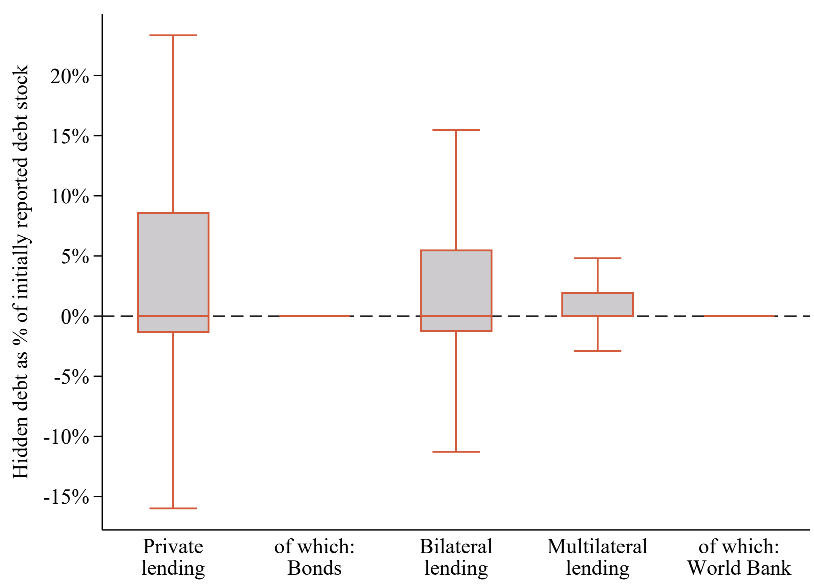
Sources: Authors' calculations.
Notes: The figure shows the percentage distribution of data revisions to debt stocks and debt flows (i.e. commitments) as defined in equation (1),, in percent of GDP. The solid lines show the median, which is 0.09% of GDP for debt stocks in Panel A and 0.08% of GDP for debt flows in Panel B. Dashed lines visualize the mean, which is 1.06% of GDP in Panel A and 0.70% of GDP in Panel B. GDP data is taken from World Bank (2022) WDI and not subject to revisions.

Figure 4: Where is hidden debt the largest?

Panel A: In borrower countries with weaker institutions



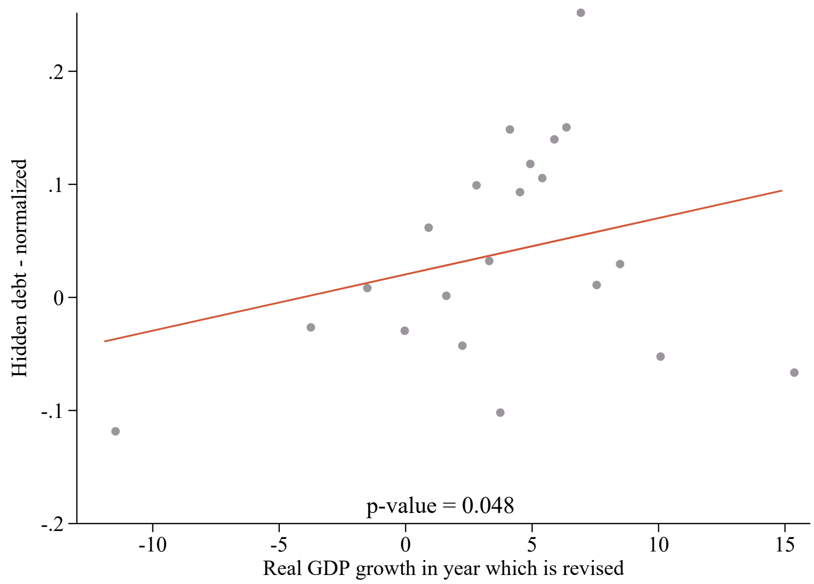
Panel B: In loans from bilateral and private creditors



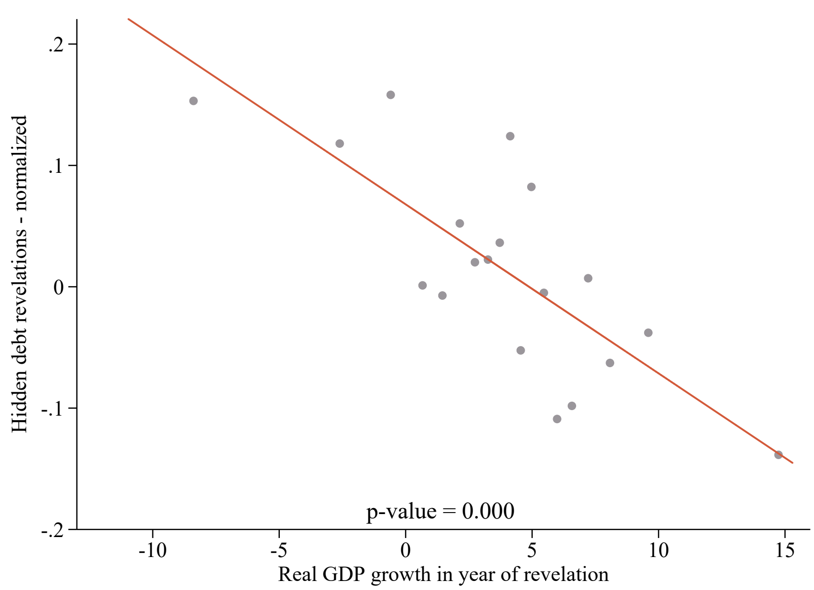
Sources: Authors' calculations.
Notes: This boxplot denotes the distribution of observations of hidden debt as defined in equation (1) split across five debtor groups in Panel A and split across five creditor groups in Panel B. The box's bottom denotes the 25$^{\text{th}}$ percentile, a line in between shows median and the box's top is the 75$^{\text{th}}$ percentile. The whiskers show upper and lower adjacent values. Outliers are not shown. GDP data is taken from World Bank (2022) WDI and not subject to revisions. Panel A splits observations by the institutional strength of the borrower country as measured by its average score on the Polity V dataset Polity (2020) between 1970-2020. Panel B splits observations by creditor group.

Figure 5: The cyclical nature of hidden debt events

Panel A: Which years are being revised?



Panel B: When do revisions happen?



Sources: Authors' calculations
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. The solid line represents a linear fit based on the underlying data and bins are constructed following the approach of Cattaneo et al. (2024). P-values were obtained from a bivariate panel regression in which we control for private borrowing needs.

4 Model

In order to study the effects of hidden debt, we develop a new model building on the workhorse model of sovereign debt and default (Eaton and Gersovitz, 1981, Arellano, 2008, Aguiar and Gopinath, 2006) with long-term debt and positive recovery rates (as in Hatchondo et al., 2016 and Hatchondo et al., 2021). The main modifications are the inclusion of an (exogenous) hidden debt accumulation process and allowing for international lenders to monitor the country's accounts and in this way triggering endogenous revelations of hidden debt. We use our novel dataset to inform the statistical properties of the process underlying the (exogenous) hidden debt accumulation.

4.1 Environment

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

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

where $\mathbb{E}$ denotes the expectation operator, 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.[16]

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, which decreases at a constant rate δ.[17] In particular, a bond issued in period t promises to pay $(1-\delta)^{j-1}$ 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. As long as there has not been a revelation in the

[16]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.

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

previous period (more details on the revelation below), the country starts period t with a level of hidden debt, h, which (for simplicity) has the same coupon structure of the market debt. In addition, absent a default in period t, the country draws a "hidden-debt issuance" realization ε from a probability distribution $G(\varepsilon\,|\cdot)$, which may depend on, among other variables, the realization of y and the previous realizations of ε. We assume this probability distribution is common knowledge and we use our novel dataset to parameterize it. The hidden debt issuance shock ε: (i) delivers new flows in period t, (ii) gets added to the stock of debt, and (iii) the country starts servicing it from period $t+1$ onward.

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, the lenders have an option to "monitor" the country's statistics: they have to pay a monitoring fee f and in this way, they 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 consideration the additional uncertainty of not knowing the true indebtedness of the country. Throughout the paper, we are maintaining the assumption that this monitoring is the only way (apart from a default) in which lenders can know the true level of hidden debt.[18]

Defaults and recovery rates. When the government defaults, it does so on all current and future debt obligations. This is consistent with the observed behavior of defaulting governments and it is a standard assumption in the literature.[19] 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 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 gets back into markets with a non-negative amount of debt. We can call that amount, b_D. We assume the following regarding b_D:

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

[18] 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.) the lenders are still unable to perfectly infer the level of hidden debt.

[19] Sovereign debt contracts often contain an acceleration clause and a cross-default clause. The first clause allows creditors to call the debt they hold in case the government defaults on a payment. The cross-default clause states that a default in any government obligation constitutes a default in the contract containing that clause. These clauses imply that after a default event, future debt obligations become current.

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 get split among holders of the previously issued market and hidden debt as follows. Holders of legacy hidden debt (which was revealed at the default event) get $b_D^h = \chi\tilde{h}$, with $\chi \in [0, 1]$.[20] Holders of the previously issued market debt get $b_D - b_D^h$. This implies the following recovery rate for market debt:

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

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

0. $\{b, h\}$ are known to the government. Lenders know b and how many periods have passed since the last hidden debt revelation, τ.
1. y and ε are realized. All agents observe y, only the government observes ε.
2. Government default decision: $d \in \{0, 1\}$
   - If default ($d = 1$): then no coupons are paid, all hidden debt gets revealed, the country does not any get flows from ε and it suffers from income losses and exclusion while the default status persists.
   - If repay ($d = 0$): the government evaluates different levels of b', for each the lender decides whether to monitor $m \in \{0, 1\}$
     – If there is monitoring ($m = 1$), all discovered debt gets added to b and the hidden debt going forward is zero ($h' = 0$).
     – If there is no monitoring ($m = 0$), $h' = h\,(1 - \delta) + \varepsilon$.
3. Consumption and coupon payments (if relevant) take place.

For a country that ended $t - 1$ in financial exclusion, the first thing that happens 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 gets 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). Then, the country finds itself at step 2 above, and the timing continues as specified there.

4.2 Foreign Lenders

We follow the modeling of lenders presented in Gu and Stangebye (2023) but, to use the full extent of our novel dataset on hidden debt revelations and retain tractability, we simplify

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

the information acquisition problem. We assume 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 problem for a foreign lender when the sovereign starts the period in good standing and has not defaulted is to decide whether to monitor the country's debt: $m = 1$ denotes monitoring, and $m = 0$ denotes not monitoring. Monitoring is costly: the 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 unknown to lenders or gets fully revealed and then the lenders have to choose how many bonds to buy.[21] In the exposition of the lenders' problem will use b' to denote the borrowing choice of the government and B' the lenders' investment in government bonds.[22]

The lenders' problem can be written as

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

Their value under monitoring is, in turn, given by

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

subject to

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

$$\text{and} \quad \mathcal{R}'(b', h', y', \varepsilon', \tau') \equiv \; d'\, q_D(b', h', y') + \tag{9}$$

$$(1-d') \times \Big[\kappa + (1-\delta) \Big(m^{*}(b'', y', \tau') q_{\text{M}}(b'', y') +$$

$$(1 - m^{*}(b'', y', \tau')) q_{\text{NM}}(b'', y', \tau') \Big) \Big]$$

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 the current lenders expect the future generation of lenders will follow, and E^{ℓ} denotes the expectations operator of the lenders in the case of monitoring.[23]

[21] Note that in this framework, differently from Gu and Stangebye (2023), the government does have an informational advantage over the lenders (it knows h and ε), but we assume that it has no credible way of communicating the true level of hidden debt. Moreover, we assume there is no communication between the different overlapping generations of lenders, so even if something about h or ε were to be learned, it cannot be communicated to future lenders.

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

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

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 the one above, except for two things: (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 expectations operator of the 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:

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

subject to

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

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

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

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

where C_{ℓ}' is given by (12) and $\tau'=\tau+1$.

Finally, 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. Debt is not serviced in default, but 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:

$$V_{D}^{\ell}(b,h,y)=\max_{B'}\ E^{\ell}\left[u_{\ell}(C_{\ell}')\right] \tag{14}$$

subject to

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

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

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 (4) and (5). Therefore, the price of a bond in default is given by

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

4.3 Government's Problem

Given the timing of events, the default decision is the first decision in the model. At this time, the monitoring decision has not yet been made, but the government has enough information (i.e., it knows the full state vector) to perfectly anticipate it.

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

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

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

If the government decides to repay, then the problem is more involved, as this depends on the monitoring decision of the 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. In the case of monitoring ($m^* = 1$), then hidden debt is revealed and it gets 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:

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

subject to

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

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

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

$$V_0^{NM}(b,y,h,\varepsilon;\tau) = \max_{b'} \left\{ u(c) + \beta E_{y',\varepsilon'|y} \, V(b',y',h',\varepsilon',\tau+1) \right\} \tag{22}$$

subject to

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

4.4 Equilibrium Definition

Definition 1 (Markov perfect equilibrium)**.** 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 a bond price schedules $\{q_{\mathrm{M}}(b',y), q_{\mathrm{NM}}(b',y,\tau), q_D(b,h,y)\}$ such that: **(i)** given the bond price schedules and the monitoring rules, the government policy and value functions solve the dynamic programming problem defined by equations (18)–(22), **(ii)** given bond price schedules and government policies, the monitoring rule solve the problem in (6), **(iii)** given government and lender policies, the price functions satisfy equations (10), (13), and (17), and **(iv)** the market for government debt clears.

5 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 Section 2. 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 one (otherwise identical model) where monitoring by creditors is cheaper and another one with full information on debt accumulation.

5.1 Calibration

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

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

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

The endowment process for the borrowing country follows:

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

with $|\rho|<1$, 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 $\phi\left(y\right)=\max\left\{y\left[\lambda_0+\lambda_1[y-\mathbb{E}(y)]\right],0\right\}$. 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. It is important to note that while lenders know the distribution of ε, they only get to observe ε and h upon a revelation. Knowing this distribution, how many periods went by since the last revelation (τ), and the law of motion for hidden debt conditional on no-revelation (i.e. $h'=(1-\delta)h+\varepsilon$), the lenders understand that h' is distributed as:[24]

[24] The distribution of h', conditional on τ, is a simple consequence of properties of the Normal distribution. See Appendix D for more details.

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

Parameter values. Table 5 presents the benchmark values given 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, the risk-free interest rate, and the discount factor β take standard values.

The parameters that govern the endowment process are estimated from our dataset. These values, $\rho = 0.6$ and $\sigma_\nu = 4\%$, are close to those typically found in studies of emerging and low-income countries.[25] 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.[26] The coupon is normalized to $\kappa = (r+\delta)e^{-r}$, which ensures that a default-free bond (with the same coupon structure as our sovereign bonds) trades at a price of e^{-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	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	$(r+\delta)e^{-r}$	Risk-free bond price = e^{-r}
Price floor	$\underline{q}$	$0.7\, e^{-r}$	Never binding
Lender's risk aversion	γ_ℓ	2	Aguiar et al. (2016)
Lender's wealth	W	2.5	Aguiar et al. (2016)
Hidden debt price	q_h	e^{-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%

The second part of Table 5 details our parametrization of the lender's side of the model as well as of the hidden debt properties. We follow Aguiar et al. (2016) in setting the risk aversion coefficient of the lenders to the same value as the one for the borrower ($\gamma_\ell = \gamma = 2$). The

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

[26] We use the Macaulay definition of duration that, with the coupon structure in this paper, is given by $D = (1+r)/(\delta + r)$, where r denotes the risk-free rate. Using a sample of 27 emerging economies, Cruces et al. (2002) find an average duration of 4.77 years, with a standard deviation of 1.52 years. Bai et al. (2017) report an average debt duration of 6.7 years in a panel of 11 emerging economies.

lender's wealth W is set to 2.5 (i.e., 250% of the mean income in the borrowing country), 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.

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 the recovery rate parameter ($\overline{\alpha}$) to target four moments from the data: (i) an average debt-to-GDP ratio of 26 percent, a (ii) a mean spread of 3.0 percent, (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 while the mean recovery rate is taken from Graf von Luckner, Meyer, Reinhart, and Trebesch (2024). We solve the model using value function iteration and interpolation (Hatchondo et al., 2010).

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.

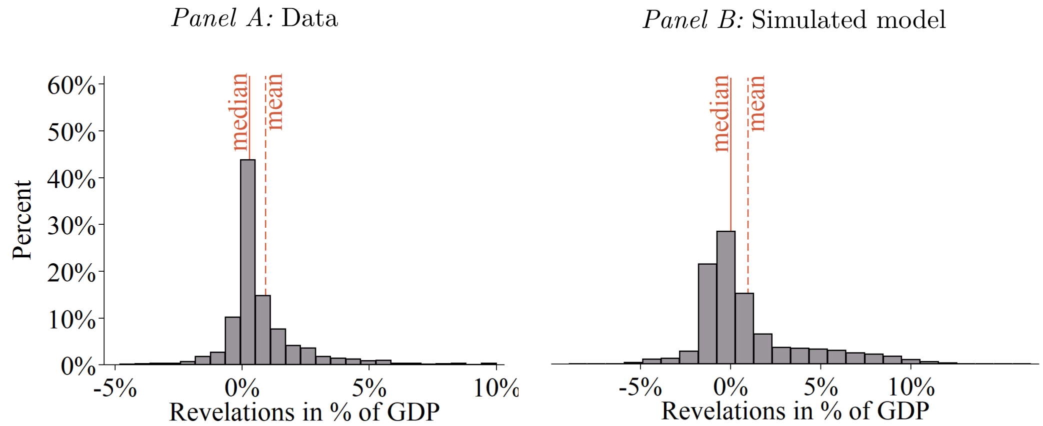
Table 6: Model fit

	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
$\rho\,(r_s, y)$	-0.1	-0.4
$\sigma\,(r_s)$	2.8	1.8
b) Hidden debt revelation patterns		
Mean Revelation$/y$	0.94	0.87
$\rho(\text{Revelation}/y, b/y)$	0.10	0.03
$\rho(\text{Revelation}/y, y)$	-0.07	-0.19
$\rho(\text{Hidden debt}, \text{HC})$	0.24	0.13

Note: 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. Moments for the simulations 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 that amount for at least 1% of GDP, and then report the frequency of those (7.1%).

Table 6 shows that our model approximates well the moments used as targets and is broadly consistent with non-targeted moments in the data. In both model and data, consumption

Figure 6: Hidden debt revelations in data and model



Notes: The figure shows the percentage distribution of hidden debt revelations from our database and the model. Panel A presents revelations from the data, as defined in equation (2), while Panel B presents revelations in the simulated model output. The solid and dashed lines respectively represent median and mean.

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 have highly similar (mean) size, are negatively correlated with income and are 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, just as observed in the data (see Section 3.3).

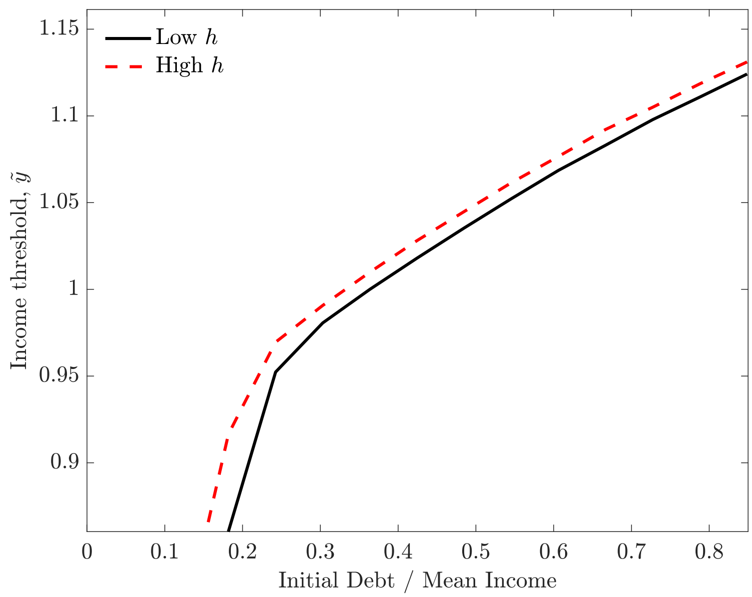
This ability of our model to replicate the revelations observed in the data also becomes evident when looking at the full distribution of revelations in the data and the model output, presented in Figure 6. Both distributions exhibit a right skew, positive means and near-zero medians.

5.2 Default Incentives, Monitoring and Borrowing Opportunities

Default incentives. Figure 7 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.[27] Figure 7 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, the higher the income threshold, implying that there is a larger set of the income space in which the country prefers to default. Likewise, higher hidden debt increases default incentives (i.e. $\tilde{y}$ increases with h).

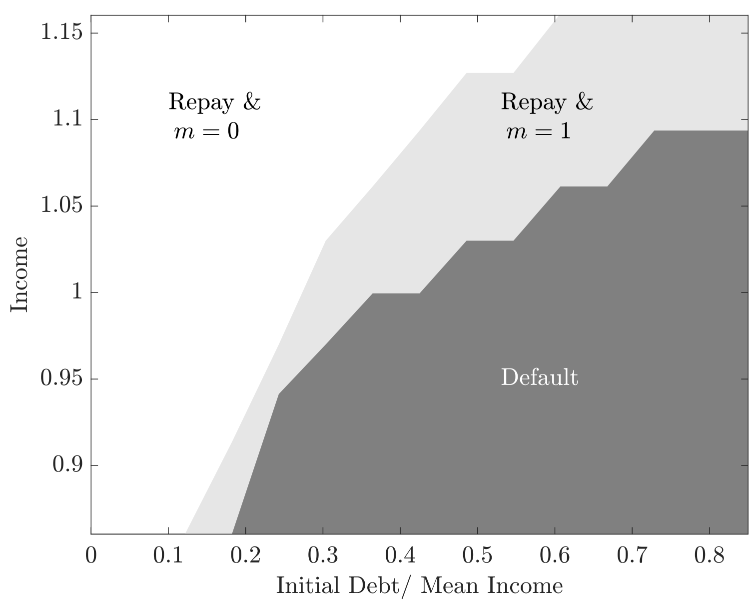
[27] Formally, $\tilde{y}$ is the income level that satisfies $V_0(b, h, \tilde{y}\varepsilon, \tau) = V_1(b, h\tilde{y})$. We verify numerically that this threshold is unique.

Figure 7: Income thresholds, $\tilde{y}$



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

Figure 8: Repayment, Monitoring and Default regions.



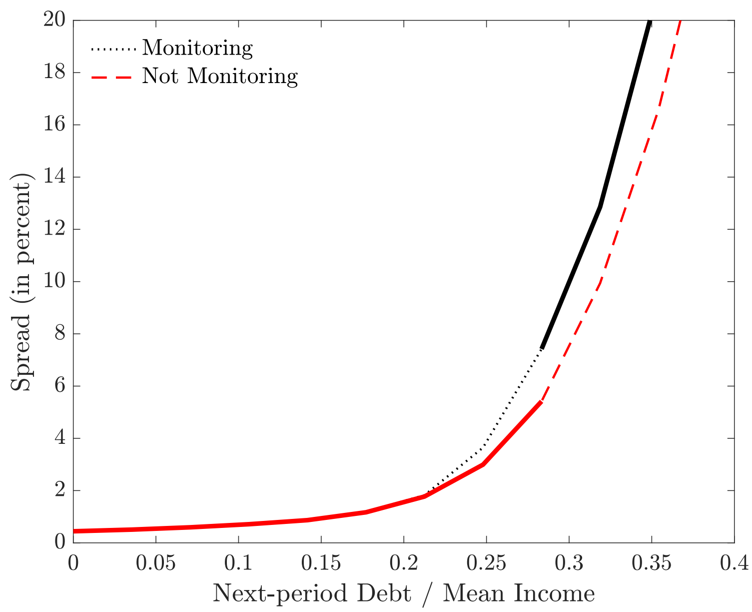
Monitoring and default in equilibrium. Figure 8 illustrates how the equilibrium monitoring and default decision depend on the initial level market debt and income.[28] The default region (denoted in dark gray) has the properties discussed above (and consistent with our model assumptions that there is no monitoring under default). The repayment region has both combinations of the state variables with and without monitoring. Equilibrium moni-

[28]Recall that the lenders' monitoring policy cannot (by construction) depend on the hidden debt process.

toring tends to occur when the initial debt and income are close to the default boundary: other things equal, higher initial debt and lower income increase the chances of observing monitoring in equilibrium.

Borrowing opportunities. Figure 9 shows the debt-spread menus that the government can choose from, conditional on the monitoring policy of the 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 9: Spread-debt menus



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

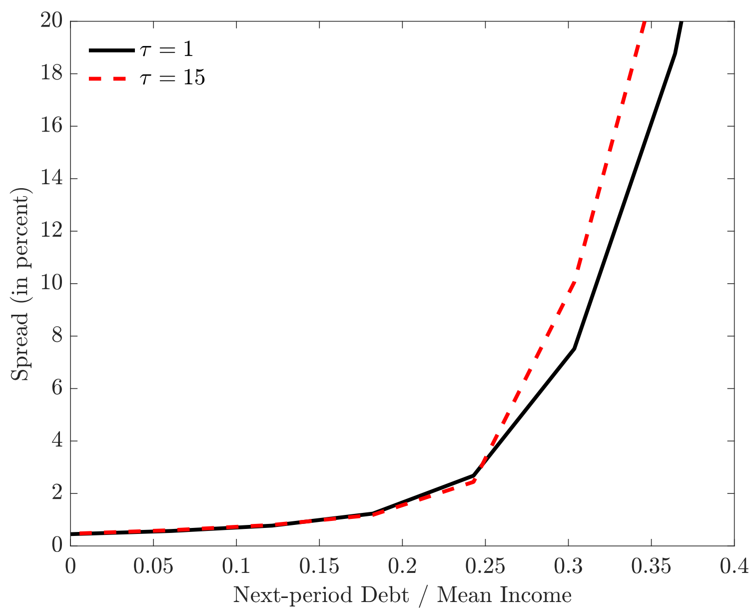
The spreads depicted in Figure 9 are for the case in which the government has market access in period t. Therefore, a debt revelation can occur in this situation only through monitoring. The bolder part of the spread curves shows how higher borrowing can trigger monitoring and hence revelations. For the particular combination considered in Figure 9, if the country borrows beyond 28% of mean income it triggers monitoring and pays higher spreads (roughly 150 bps higher).[29]

[29]These higher spreads compensate for the higher default risk and for the monitoring fee that the lenders paid.

5.3 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 9): on average, the equilibrium spread on monitoring periods is higher than the mean in the simulations (4.6% vs 3.0%).[30] Upon default, the government cannot borrow, but 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.[31]

Figure 10: The effect of τ on spread menus



Notes: The curves show combinations of next-period debt and spreads that the country can choose from in the current period when the country is facing a non-monitoring episode, for two values of τ. The plot assumes 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, and this, other things equal, lowers spreads offered to the country in the period after the revelation: Figure 10 shows the spread-debt menu curves that the country faces when a revelation took place in the period immediately before (and therefore the time since the last revelation is $\tau = 1$) and when the last revelation was sufficiently back in time ($\tau = 15$).[32] Having had a recent revelation, the lenders understand that both the expected value and the variance of (new)

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

[31] 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 in non-exclusion periods. The implied spread in the default period is 36%, on average.

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

hidden debt are low and this leads them to offer better prices for the government bonds. Second, a revelation increases the stock of market debt that lenders know the country has and this, coupled with the more favorable borrowing terms, typically leads to more borrowing by the country and to higher spreads in equilibrium.[33] In our simulations, we see the combined effect of these forces.

We contrast how spreads respond to hidden debt revelation in the calibrated benchmark economy vs in our hidden debt database depending on the size and timing using a fixed effect regression model. In Table 7, we show that larger revelations are 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 (137 bps increase in spread for a revelation of 1 SD) than in the database (22 bps increase), which is likely partly explained by the low frequency of our hidden debt database (annual) and that data availability on spreads is limited to countries with typically higher statistical capacity.[34] We then introduce τ into the regression framework to capture the duration of hidden debt build-up. In the benchmark model (column 2), the higher the value of τ, the higher the spreads which reflects increased uncertainty in the volume of hidden debt. 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), but do not find it having a significant effect on spreads. With regard to the control variables, the growth and debt stock have similar coefficients.

[33] A movement towards the right on the horizontal axis of Figure 10, along the $\tau = 1$ curve.

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

Table 7: Spread response to hidden debt revelations

	Next period spreads			
	Benchmark		Database	
	(1)	(2)	(3)	(4)
Revelation size (std)	1.37***	1.33***	0.22***	0.21***
	(0.05)	(0.05)	(0.08)	(0.08)
Years since last revel. (τ)		0.03***		0.01
		(0.00)		(0.07)
Growth (std)	-1.21***	-1.19***	-1.45***	-1.45***
	(0.02)	(0.02)	(0.34)	(0.34)
Debt/GDP (std)	1.82***	1.80***	0.73*	0.74*
	(0.02)	(0.02)	(0.42)	(0.42)
Disclosed borrowing (std)	4.36***	4.43***	-0.26	-0.26
	(0.05)	(0.05)	(0.24)	(0.24)
Constant	4.49***	4.19***	4.71***	4.68***
	(0.02)	(0.04)	(0.11)	(0.26)
Observations	201430	201430	595	595
R-squared	0.09	0.09	0.49	0.49
Fixed Effects	✓	✓	✓	✓
Clustered SE	✓	✓	✓	✓

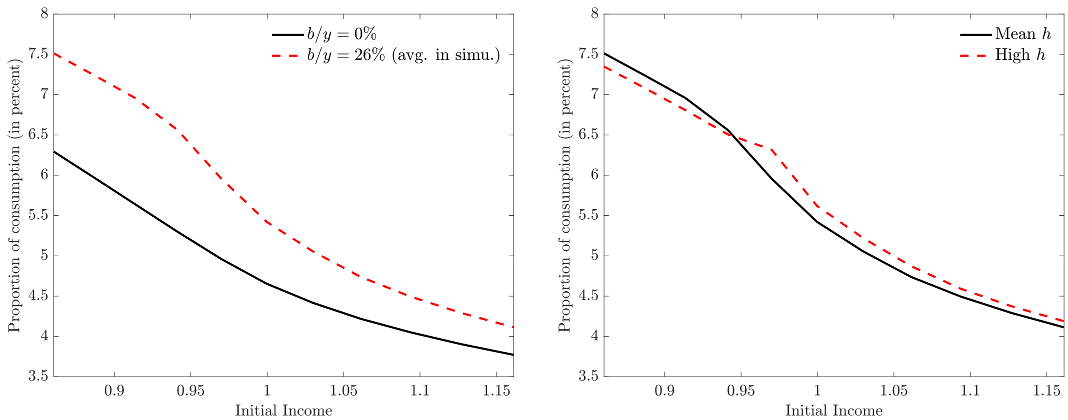
Notes: This table shows the results of OLS regressions of next period sovereign spreads (measured in percentage points) on the size of hidden debt revelation, tau and additional control variables. Columns (1) and (2) uses data from the calibrated benchmark model. Columns (3) and (4) uses our hidden debt database directly. Revelation, growth, debt stock, new borrowing are standardized to a mean of 0 and standard deviation of 1. The revelation measure is equivalent to that used in Table 3. Debt to GDP ratio is calculated pre-revelation (same period). New disclosed borrowing is the market issuance to GDP ratio for benchmark model and the debt disbursement to GDP ratio (pre-revelation) from the database. Robust standard errors are reported in parenthesis.

5.4 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. In a second comparison, we take the existence of hidden debt 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. In order 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 11 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 or moving to the "full information" economy.

Figure 11: Welfare gains of making hidden debt observable



Notes: The left panel shows the welfare gains for two possible values of initial market debt (zero and the mean in the simulations), keeping the level of initial h at its mean. The right panel keeps market debt at its mean in the simulations and shows the welfare gains for two values of initial h. Both panels assume the initial ε is equal to the mean.

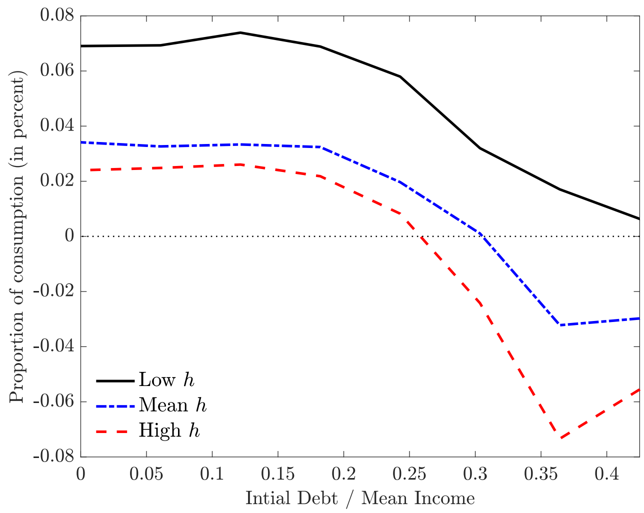
The left panel of this figure holds h at its mean and shows how the welfare gains depend on the initial income level, for two levels of market debt (zero and the mean in the simulations). The welfare gains are uniformly positive and decreasing in income: the benefits of higher transparency are larger in (relatively) bad times. We also see that the country benefits more from moving to the full information economy when its initial debt is larger. The right panel keeps the market debt at its mean and shows the welfare gains for two levels of h (mean and high). The two lines on this panel are fairly close to each other, but for the mean income level the gains are larger if the initial h is higher. The average welfare gain of moving to the full-information economy (with initial debt equal to the mean level observed in the simulations) is equal to a 5.5% permanent increase in consumption.[35]

Welfare implications of greater oversight. Next we show how greater oversight - as captured by our model economy trough lowered costs of monitoring - impacts welfare. In Figure 12, 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 more frequent) can have differing results. At low levels of hidden debt, cheaper monitoring is welfare increasing (irrespective of market debt levels). But at higher hidden debt levels, monitoring can be welfare detrimental, depending on the initial debt levels. Keeping the level of initial h constant, higher market debt results in lower (and even negative) gains from greater oversight. The same holds if we keep b constant and

[35]These welfare gains are mostly coming from the much larger level of average consumption attained in the full-information economy (approximately 45% larger). Despite featuring more frequent defaults (25% vs 6%) and more volatile consumption (3.3 vs 1.3), the mean effect of higher consumption dominates and delivers substantial welfare gains. These welfare gains are roughly one order of magnitude larger than those from eliminating debt dilution (Hatchondo et al., 2016).

increase the initial level of h: higher debt is associated with welfare losses. These results suggest that the benefits coming from reforms aimed at having better oversight of public debt statistics may be curtailed if the reforms are implemented when countries are "too indebted". [36]

Figure 12: Welfare gains from increased oversight.



6 Conclusion

This is the first paper to systematically measure the degree of public debt under-reporting in a large sample of developing and emerging market countries. We use our novel estimates to shed new light on the implications of debt under-reporting on sovereign default decisions, asset prices, and welfare using a state-of-the-art quantitative model of sovereign debt and default. 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 factor in that debt statistics tend to increase after their initial publication. For researchers, our findings and data open exciting new avenues to study information acquisition and expectation formation in sovereign debt markets with asymmetric information.

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

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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. A final subsection presents 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 Report (2022–2023) and its three predecessor formats, the International Debt Statistics (2013–2022), the Global Development Finance Reports (1997–2012) and the World Debt Tables (1973–1996). Table A1 provides a detailed list of 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.

Dealing with multiple versions per year: For each of the 2005 until 2012 vintages of the Global Development Finance reports several versions of the data are available on the World Bank's website. In these cases, we use the first version available for that year, following our convention to capture each data point the first time it is released. Column 4 of Table A1 reports explicitly which version we use in these cases.

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" can be found in machine-readable format here: `/https://www.worldbank.org/en/programs/debt-statistics/idr/products`. "PDF only" vintages back until 1991-92 are only available as PDF and linked here: `/https://www.worldbank.org/en/programs/debt-statistics/publications`. Earlier "PDF only" vintages from 1973 - 1991 can be found via the World Bank's Documents & Reports page here: `/https://documents.worldbank.org/en/publication/documents-reports`. 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.

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 Report (2022–2023), the International Debt Statistics (2013–2022) and eight vintages of the Global Development Finance reports (2005–2012) from the World Bank's website.[37] For all reports prior to 2005, we are required to digitize the original reports and extract the data into a machine-readable format.[38] Original reports were either downloaded from the World Bank website in PDF form or were scanned from the original hard copies, we obtain from different libraries. Table A1 provides an overview on which vintages were downloaded and which were scanned.[39] 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 steps we undertake to ensure data quality.

A.2 Data cleaning

To ensure the quality of our digitized data and to minimize measurement error, we employ a series of data cleaning procedures. First, we ensure all entries generated by the OCR software are of the correct data type and data labels in the form of row names are uniform within each digitized vintage. To merge data across vintages, we apply the modern series codes to the corresponding variables in older PDFs. Table A2 provides a mapping of the modern series codes to each vintage's variable names and creditor categories. To reduce OCR induced measurement error, we check the difference between the cross-vintage lag and lead value of a series. A measurement error is flagged, if the difference is zero, but the value in question is unequal to the lag. In that case we replace the value in question by the lag.

Within-vintage consistency checks: Our final database has 3,315,950 data points (see section A.3 for details). The large size of the dataset makes it infeasible to manually check for OCR induced measurement error. To ensure the accuracy of our digitized database, we therefore make use 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,

$$DPPG_{i,t}^{v} = OFFT_{i,t}^{v} + PRVT_{i,t}^{v} \tag{23}$$

$$OFFT_{i,t}^{v} = BLAT_{i,t}^{v} + MLAT_{i,t}^{v} \tag{24}$$

$$PRVT_{i,t}^{v} = PBND_{i,t}^{v} + PCBK_{i,t}^{v} + PROP_{i,t}^{v} \tag{25}$$

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

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

[38] The World Bank is currently in the process of adding the 1989–2005 vintages to the WDI archive on DataBank, however, as of writing, available series from earlier vintages there are rather sparse.

[39] PDFs of vintages back until 1991-92 can be found here: /https://www.worldbank.org/en/programs/debt-statistics/publications. PDFs of earlier vintages (1973–1991-91) can be found via the World Bank's Documents & Reports page here: /https://documents.worldbank.org/en/publication/documents-reports.

Table A2: Seriescode to variable name mapping for all vintages

Seriescode	Description	1979	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991
Panel A: Public and publicly guaranteed (DPPG)														
DT.DOD.DPPG.CD	Debt outstanding and disbursed	TOTAL ALL LENDERS: OUTSTANDING (DISBURSED ONLY)		Debt Outstanding & Disbursed (DOD)								DEBT OUTSTANDING (LDOD)		
DT.COM.DPPG.CD	Commitments	TOTAL ALL LENDERS: COMMITMENTS		Commitments								COMMITMENTS		
DT.DIS.DPPG.CD	Disbursements	TOTAL ALL LENDERS: DISBURSEMENTS		Disbursements								DISBURSEMENTS		
DT.AMT.DPPG.CD	Principal repayments	TOTAL ALL LENDERS: PRINCIPAL REPAYMENTS		Principal Repayments								PRINCIPAL REPAYMENTS		
Panel B: Creditor categories														
DT.DOD.OFFT.CD	Official creditors	TOTAL OFFICIAL LENDERS		Official Creditors										
DT.DOD.MLAT.CD	Multilateral	INTERNATIONAL ORGANIZATIONS		Multilateral										
DT.DOD.MIBR.CD	of which: IBRD			IBRD										
DT.DOD.MIDA.CD	of which: IDA			IDA										
DT.DOD.BLAT.CD	Bilateral	GOVERNMENT		Bilateral										
DT.DOD.PRVT.CD	Private creditors	TOTAL PRIVATE		Private Creditors										
DT.DOD.PBND.CD	of which: Bonds											Bonds		
DT.DOD.PCBK.CD	of which: Commercial banks											Commercial banks		
DT.DOD.PROP.CD	of which: Other private creditors	OTHER PRIVATE LENDERS										Other private		

Seriescode	Description	1992	1993	1994	1996	1997	1998	1999	2000	2001	2002	2003	2004
Panel A: Public and publicly guaranteed (DPPG)													
DT.DOD.DPPG.CD	Debt outstanding and disbursed	DEBT OUTSTANDING (LDOD)											
DT.COM.DPPG.CD	Commitments	COMMITMENTS		Memorandum Items: Commitments									
DT.DIS.DPPG.CD	Disbursements	DISBURSEMENTS											
DT.AMT.DPPG.CD	Principal repayments	PRINCIPAL REPAYMENTS											
Panel B: Creditor categories													
DT.DOD.OFFT.CD	Official creditors	Official Creditors											
DT.DOD.MLAT.CD	Multilateral	Multilateral											
DT.DOD.MIBR.CD	of which: IBRD	IBRD											
DT.DOD.MIDA.CD	of which: IDA	IDA											
DT.DOD.BLAT.CD	Bilateral	Bilateral											
DT.DOD.PRVT.CD	Private creditors	Private Creditors											
DT.DOD.PBND.CD	of which: Bonds	Bonds											
DT.DOD.PCBK.CD	of which: Commercial banks	Commercial banks											
DT.DOD.PROP.CD	of which: Other private creditors	Other private											

Sources: World Bank (various years)
Notes: The table shows the mapping of modern seriescodes and variable names to which we assign them for vintages 1979–2004. Panel A provides the seriescode mapping for the most important stock and flow measures, while Panel B provides the mapping for the different creditor categories.

owed to bondholders ($PBND$), commercial banks ($PCBK$), and other private creditors ($PROP$), respectively. Equation (25) is only applicable from vintage 1989 onwards.

This not only has to hold for debt stocks ($DPPG$), but also for the flow variables disbursements (DIS) and principal repayments (AMT). For commitments (COM), only equation (23) and equation (24) can be checked, since not all sub-components are published for commitments. Component availability is discussed in more detail in appendix section A.3. Table A4 provides an overview.

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, exist in the original World

Bank data source and measurement errors were not induced 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, the World Bank might choose to replace the reported numbers with estimates or otherwise preliminary values. All such cases are clearly labeled in the World Bank data. More precisely, every debtor country is assigned one of the following debtor reporting statuses in each of the vintages:[40]

(A) **"actual"/"as reported".** Indicates that the country was fully current in its reporting under the DRS 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".[41] 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 across vintages, 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

[40] 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.

[41] There are some cases where 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.

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 these were reported as zeros. We replace these missing values with zeros. We undertake both these steps to ensure that "non-revisions" are neither underrepresented (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.[42]

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: Hidden debt database: scope and coverage

No. of vintages	51
No. of variables	49
No. of countries	146
Time span	1970–2022 (53 years)
No. of individual data points	3,315,950

Notes: The table shows basic metrics from our constructed database on hidden debt.

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 for which contracts were signed in the year specified." As before, long-term external debt is defined

[42] 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).

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 and hidden borrowing, 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 breakdowns 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.[43] 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 - 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

Sources: World Bank (various years)
Notes: The table shows availability of the 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.

[43] 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
Real GDP	NY.GDP.MKTP.KN	GDP (constant LCU)	World Bank
Trade balance	NE.RSB.GNFS.ZS	External balance on goods and services (% of GDP)	World Bank
Consumption	NE.CON.TOTL.KN	Final consumption expenditure (constant LCU)	World Bank
Statistical capacity	IQ.SCI.OVRL	Index (0-100) assessing the capacity of a country's statistical system	World Bank
Income categories		Classifications based on GNI	World Bank
EMBI+ spreads		J.P. Morgan Emerging Markets Bond Spread	J.P. Morgan (2022)
IMF programs		Dummy variable for years in IMF program	Horn et al. (2020)
Sovereign default		Dummy for year of default	Asonuma and Trebesch (2016)

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 to the World Bank's debt statistics over time and confirm that only minor refinements have occurred across the four decades of vintages that we analyze. We further use the law of motion for the debt stock to decompose revisions of the debt stock into revisions to each of its parts. We also rule out that our measure and results are driven by ex-post revisions of exchange rates, by contingent liability realizations or reporting lags. 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.[44]

[44] Re-running our main results 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

	1962	1980	1989	2000
Definition of **external** debt:	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.	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.		
Definition of **long-term** debt:	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.			
Definition of **public and publicly guaranteed** debt:	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.			

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

B.2 What drives debt stock revisions?

In this exercise, we use the law of motion for the debt stock to investigate what drives the debt stock revisions that we document. Year-on-year changes in the debt stock within a vintage can be due to net debt flows, net changes in interest arrears, interest capitalized, debt reduction and forgiveness, and cross-currency valuation changes. Formally, this can be represented as

$$\Delta DOD_{i,t} = NFL_{i,t} + \Delta IXA_{i,t} + IXR_{i,t} + DFR_{i,t} + \Delta XCV_{i,t} \tag{26}$$

where $\Delta DOD_{i,t} = DOD_{i,t} - DOD_{i,t-1}$ is the change in the debt stock, $\Delta IXA_{i,t} = IXA_{i,t} - IXA_{i,t-1}$ is the change in interest arrears, $IXR_{i,t}$ is interest capitalized, $DFR_{i,t}$ is debt forgiveness and reduction, and $\Delta XCV_{i,t} = XCV_{i,t} - XCV_{i,t-1}$ is the cross-currency valuation change, for year t and country i. Net debt flows $NFL_{i,t}$ can further be written as

$$NFL_{i,t} = DIS_{i,t} - AMT_{i,t} \tag{27}$$

that is, the difference of disbursements ($DIS_{i,t}$), and principal repayments ($AMT_{i,t}$).

While this accounting identity should hold in principle, residual differences often emerge in practice, indicating inconsistencies in the reported data (see World Bank, 2022, p. 174). Still, for the data to be internally consistent, each revision of the debt stock must have a counterpart in a revision of its components. We make use of this law of motion to analyze to what extent revisions in each of the subcomponents contribute to revisions in the total debt stock.[45] To calculate the contributing shares, we first identify the debt stock revisions which are due to reporting inconsistencies, which we obtain via

$$\epsilon^v_{i,t} = R\Delta DOD^v_{i,t} - RNFL^v_{i,t} - R\Delta IXA^v_{i,t} - RIXR^v_{i,t} - RDFR^v_{i,t} \ \forall\, R\Delta DOD^v_{i,t} > 0 \tag{28}$$

where ϵ are the calculated "reporting inconsistency revisions" in vintage v for country i and year t, and prefix R on the right hand side indicates the revision to one of the variables introduced in equation (26). In cases where it holds that

$$RNFL^v_{i,t} + R\Delta IXA^v_{i,t} + RIXR^v_{i,t} + RDFR^v_{i,t} > R\Delta DOD^v_{i,t} \tag{29}$$

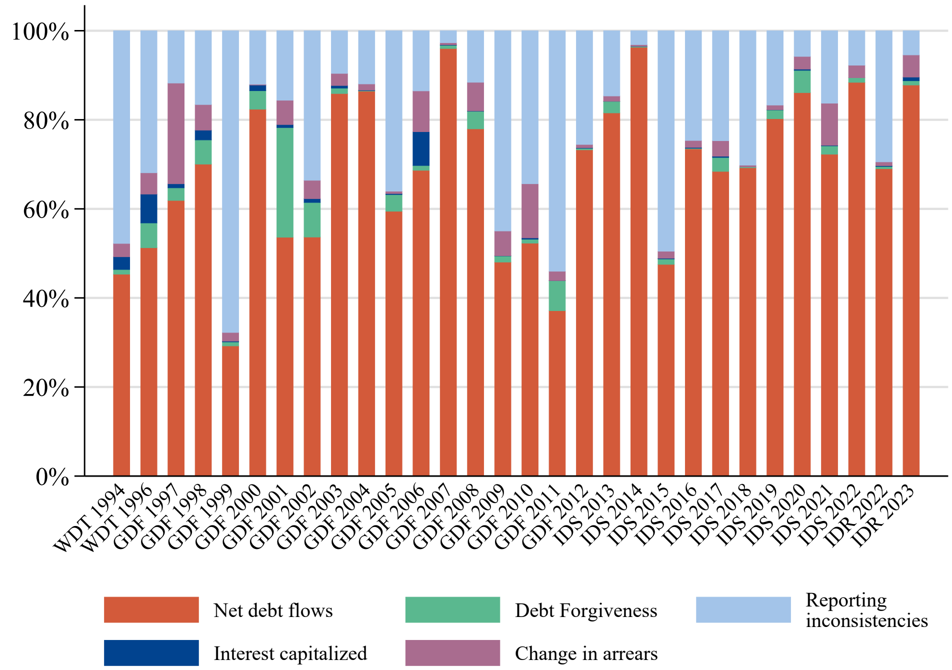
we set $\epsilon^v_{i,t} = 0$.[46] The shares are then calculated as

$$share^v_x = \frac{\sum_{i=1}^{I}\sum_{t=1970}^{T}|x^v_{i,t}|}{\sum_{i=1}^{I}\sum_{t=1970}^{T}\left(|RNFL^v_{i,t}| + |R\Delta IXA^v_{i,t}| + |RIXR^v_{i,t}| + |RDFR^v_{i,t}| + |\epsilon^v_{i,t}|\right)}$$

[45] We do not calculate the contribution of revisions to cross-currency valuation changes to revisions to the change in the debt stock due to its limited and inconsistent availability in our database. Hence, such revisions to $\Delta XCV_{I,t}$ would end up in the calculated reporting inconsistency revisions of our analysis.

[46] For this exercise, we ignore cases where one or more components are revised but there is no simultaneous revision of the debt stock.

Figure B2: Explaining factors for revisions to the change in debt stocks



Sources: Authors' calculations
Notes: The figure shows to what extent revisions to the year-on-year change in debt stocks can be explained by revisions to net debt flows, debt forgiveness, interest capitalized and change in interest arrears. In cases where revisions to the debt stock are not explained by these, revisions are due to the consolidation of reporting inconsistencies. The exercise was carried out for vintages 1994 to 2023, where all necessary data series are readily available.

where $x_{i,t}^v$ is either $RNFL_{i,t}^v$, $R\Delta IXA_{i,t}^v$, $RIXR_{i,t}^v$, $RDFR_{i,t}^v$, or $\epsilon_{i,t}^v$. Figure B2 visualizes the results of this exercise.

It demonstrates that the majority of debt stock revisions is indeed accompanied by revisions to the underlying debt flows. This confirms that most upward revisions in the debt stock are indeed caused by the ex-post addition of previously unreported borrowing or net debt flows. At the same time, Figure B2 also shows that a notable part of debt stock revisions cannot be explained by any sub-component of the above accounting identity. This result confirms similar findings by Campos et al. (2006) and indicates substantial inconsistencies in debtor reporting.

B.3 FX data revisions

Debtor countries with large amounts of non-USD debt are exposed to important valuation changes in their 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 possibly large 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 revisions to exchange rate data in the IMF's International Financial Statistics, the series 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.4 Contingent liability realization, debt assumption and data revisions

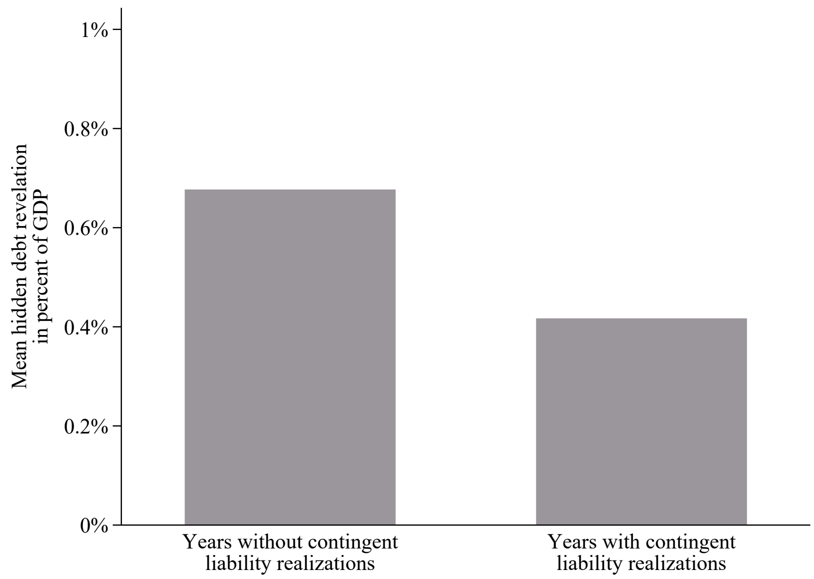
Another concern might be that upward revisions result from the realization of contingent liabilities. During downturns, a sovereign might be forced to bail-out private sector entities (e.g. banks or private-public partnerships) and assume their liabilities (see e.g. Bova et al., 2016). This might mechanically generate the cyclical revision patterns that we observe, without implying any under-reporting of debt. We address 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 data set 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 B3 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 B3).

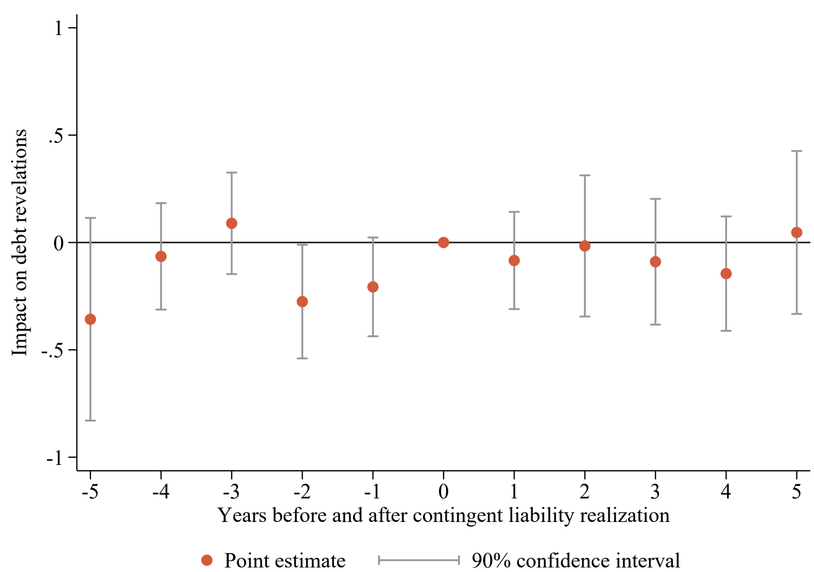
Years after contingent liability realizations are not associated with significantly higher hidden debt revelations

Figure B3: Contingent liability realizations and hidden debt revelations

Panel A: Mean comparison



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

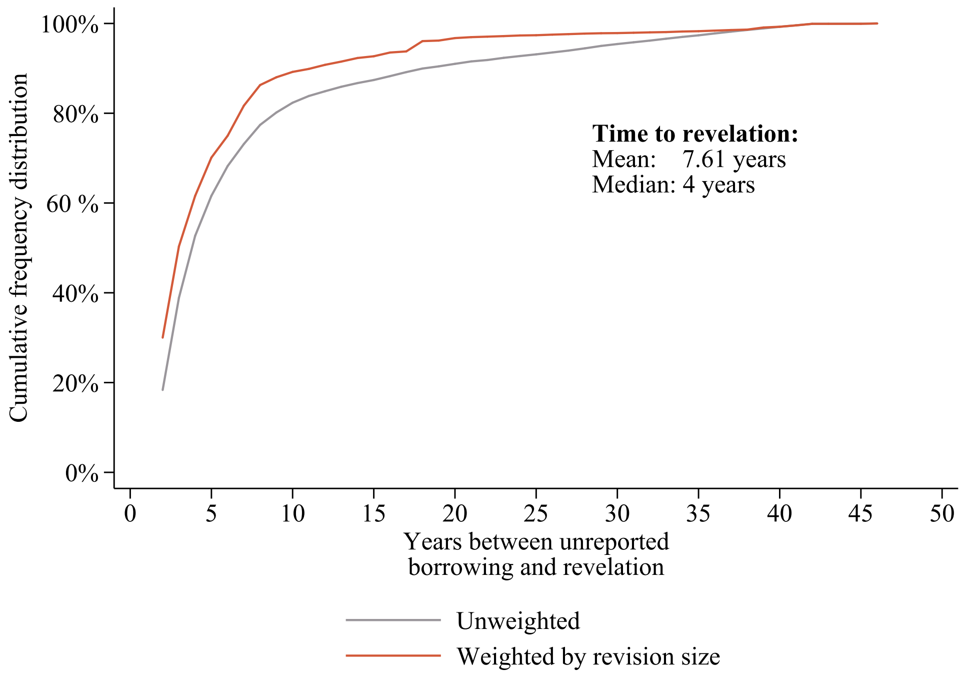


Notes: Panel A compares the mean hidden debt revelation in percent of GDP for years with and without contingent liability realizations between 1990 and 2014. Panel B shows point estimates and 90 percent confidence intervals obtained from regressing standardized hidden debt revelations on a set of year 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 defined as in equation (2).

B.5 Accounting for the possibility of reporting lags

This subsection tests whether the underreporting bias could simply be driven by reporting lags. For this purpose, Figure B4 plots the cumulative frequency distribution of the number of years between an unreported borrowing and its revelation.

Figure B4: CFD of the time between unreported borrowing and revelation



Sources: Authors' calculations.
Notes: This figure plots the cumulative frequency distribution of the time between an unreported borrowing and its revelation. The orange 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 year after their commitment date. Around 20 percent of unreported loans gets revealed at the first instance, two years after initial reporting, a duration of non-reporting that might be consistent with pure reporting lags.

Table B2 shows that our main finding of systematic underreporting bias is even robust to dropping unreported loans that get revealed in the first two vintages. This confirms that the systematic bias 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 % of GDP	5702	1.06	0.09	5.77	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 mln USD	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 % 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	0.40	0.00	2.93	0.000
In mln USD	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

Sources: Authors' calculations

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) WDI and not subject to revisions. We use Newey-West heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) to account for the autocorrelated structure of revisions when calculating p-values.

B.6 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 B4 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 already available debt data, 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 B5 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

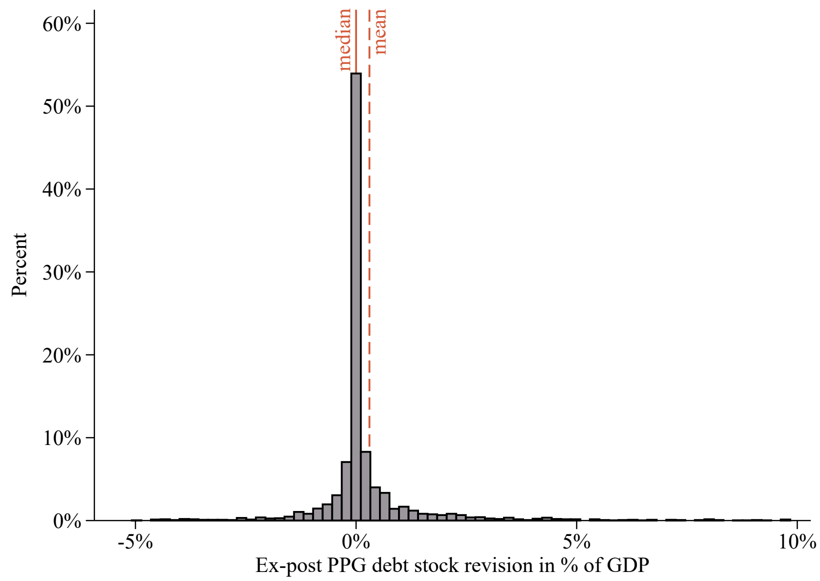
	N	Mean	Median	Std. Dev.	p-value
In percent of GDP					
Debt stock (DOD)	3232	0.30	0.00	3.51	0.000
Commitments (COM)	3213	0.41	0.00	6.88	0.001
In mn. USD amounts					
Debt stock (DOD)	3232	72.69	0.00	1,561.86	0.005
Commitments (COM)	3213	104.95	0.00	1,436.02	0.000

Sources: Authors' calculations

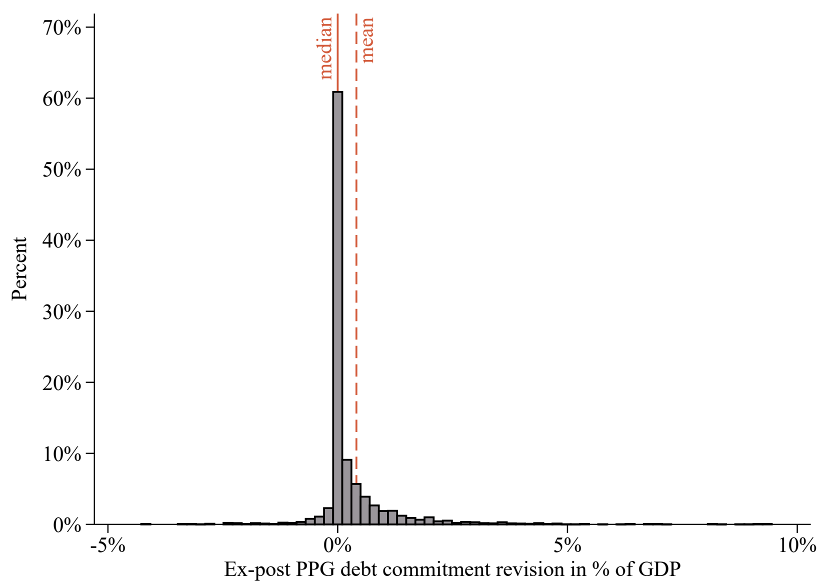
Notes: The table reports summary statistics and p-values for data revisions to debt stocks and debt commitments as defined in equation (1), both in percent of GDP and in millions of nominal USD, only for revisions to the values initially reported in the respective prior year. GDP data is taken from World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

Figure B5: 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



Sources: Authors' calculations.
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) WDI and not subject to revisions.

B.7 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. 15 of these cases, all 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 are covered by our 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
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

Sources: IMF (2006) and authors' calculations.
Notes: The table lists 15 instances in which IMF member countries were sanctioned for misreporting data, the dates on which these cases were discussed by the IMF board, and the size of the revelation we observe in the subsequent debt statistics vintage. The observed pattern is indicative of the heightened scrutiny countries find themselves in after misreporting.

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 2.3. 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 3 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: Summary statistics of revisions to total long-term and private nonguaranteed debt stocks

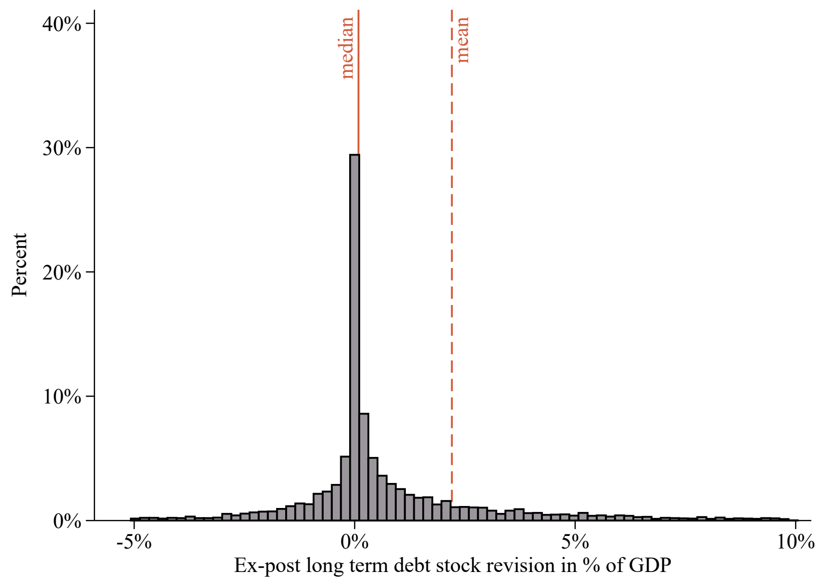
	N	Mean	Median	Std. Dev.	p-value
In percent of GDP					
Total long-term debt (DOD)	5597	2.20	0.09	12.17	0.000
Private nonguaranteed debt (DOD)	5605	1.30	0.00	10.94	0.000
In mn. USD amounts					
Total long-term debt (DOD)	5597	837.01	5.00	6,268.27	0.000
Private nonguaranteed debt (DOD)	5605	682.57	0.00	5,862.85	0.000

Sources: Authors' calculations
Notes: The table reports summary statistics and p-values for revisions of total long-term 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) WDI and not subject to revisions. We use Newey-West heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) to account for the autocorrelated structure of revisions when calculating p-values.

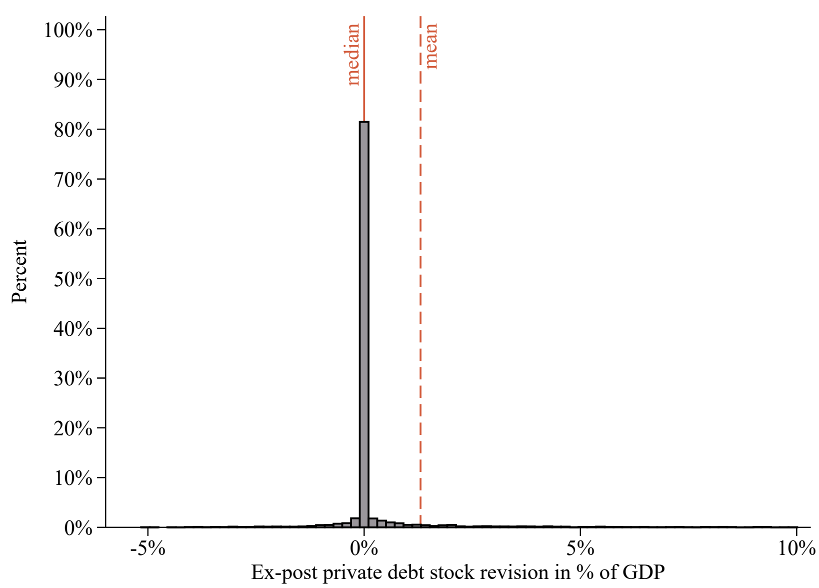
In addition to being interesting and policy relevant findings in their own right, the confirmed upward bias in revisions to private non-guaranteed debt also rules out the possibility that the underreporting bias in ppg debt is purely driven by changes in the composition of total external debt (i.e. by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

Figure C1: The distribution of total and private nonguaranteed debt stock revisions

Panel A: Revisions to total long-term external debt stocks in percent of GDP



Panel B: Revisions to private nonguaranteed debt stocks in percent of GDP



Sources: Authors' calculations.
Notes: The figure shows the percentage distribution of data revisions to the total long-term external debt stocks and to the private nonguaranteed debt stocks, defined analogously to equation (1), in percent of GDP. The solid lines show the median, which is 0.09% of GDP for total debt stocks in Panel A and 0% of GDP for private debt stocks in Panel B. Dashed lines visualize the mean, which is 2.20% of GDP in Panel A and 1.30% of GDP in Panel B. GDP data is taken from World Bank (2022) WDI and not subject to revisions.

C.2 Additional figures

Figure C2: Histogram of DPPG DOD revisions

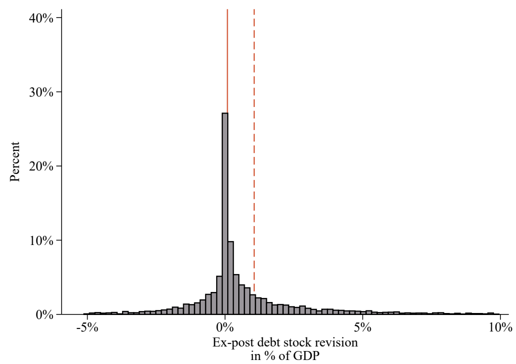


Figure C3: Histogram of DPPG COM revisions

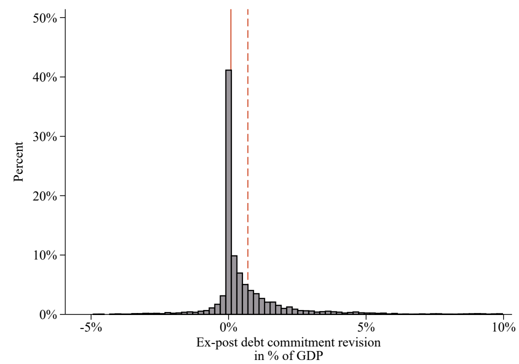


Figure C4: Histogram of DPPG DIS revisions

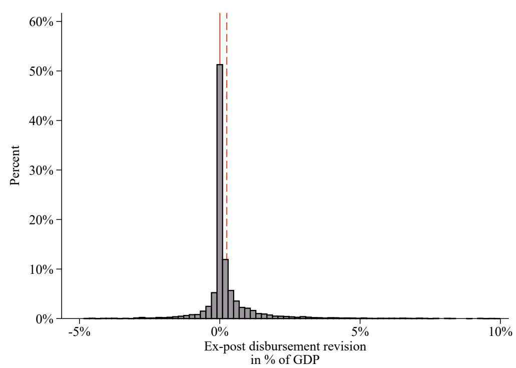


Figure C5: Histogram of DPPG AMT revisions

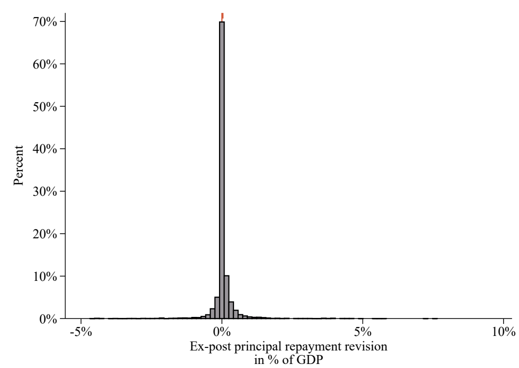


Figure C6: Histogram of PRVT DOD revisions

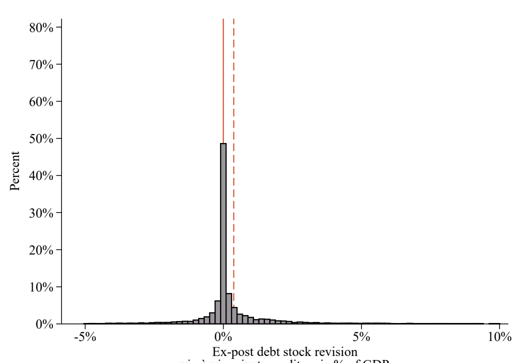


Figure C7: Histogram of PBND DOD revisions

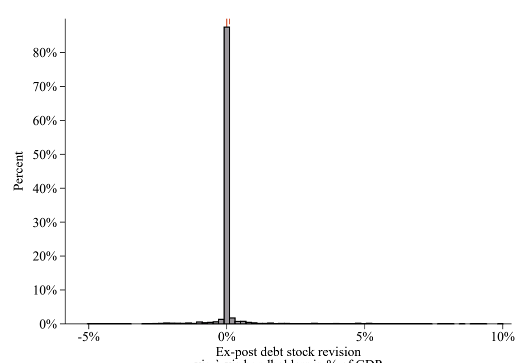


Figure C8: Histogram of BLAT DOD revisions

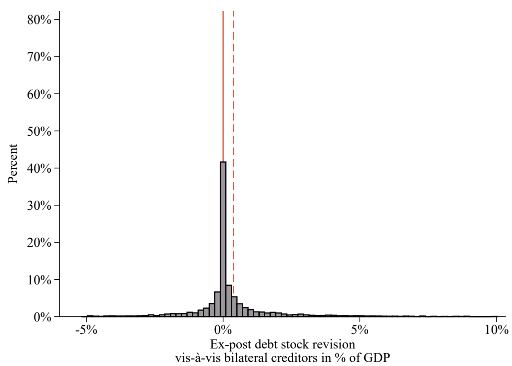


Figure C9: Histogram of MLAT DOD revisions

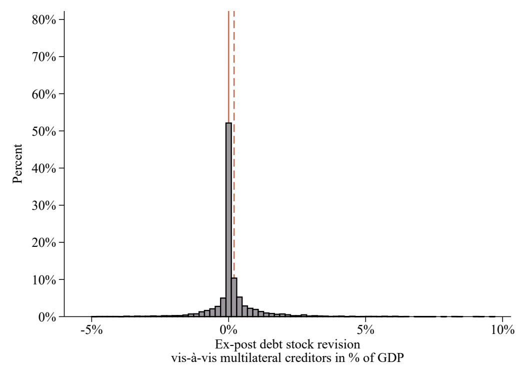


Figure C10: Histogram of World Bank DOD revisions

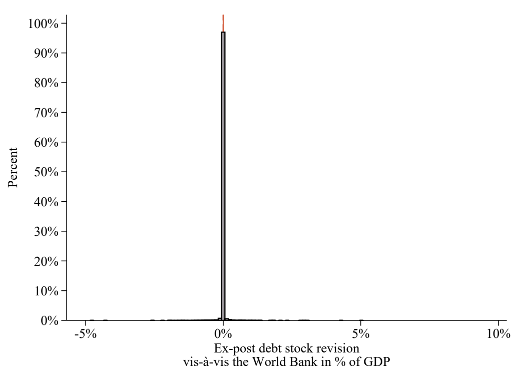


Figure C11: Histogram of OFFT COM revisions

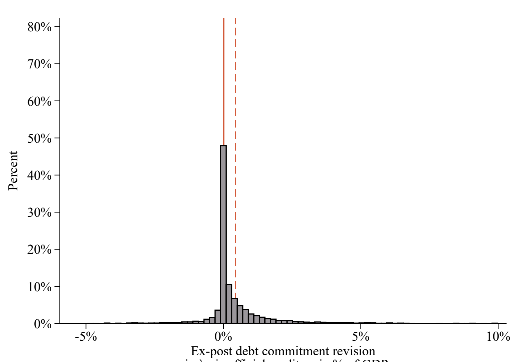


Figure C12: Histogram of PRVT COM revisions

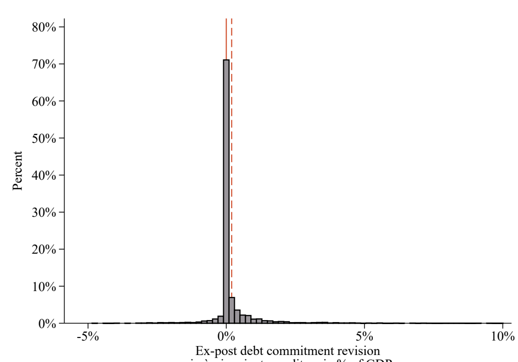


Figure C13: Histogram of MLAT COM revisions

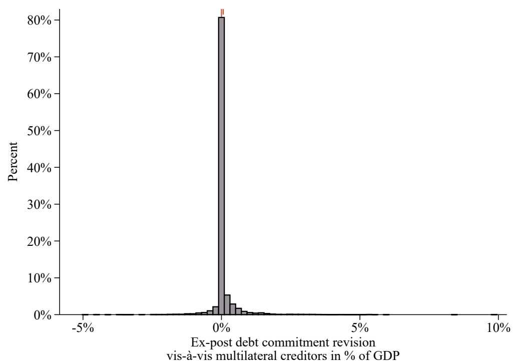
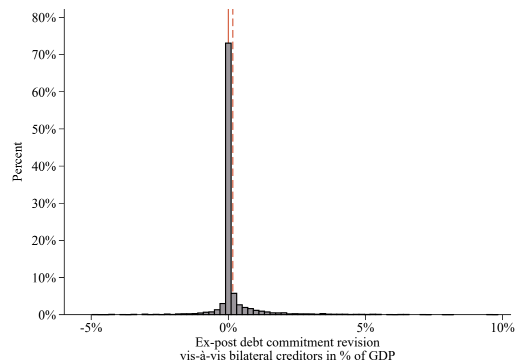


Figure C14: Histogram of BLAT COM revisions



Sources: Authors' calculations

Notes: The histograms in Figures C2 - C14 exclude observations above +10% and below -5% of GDP. Solid orange line visualises the respective subsample median, dashed orange line the respective subsample mean.

C.3 Additional regression results

C.3.1 Hidden debt revelations and political cycles

In section 3.2, we show that hidden debt revelations are more likely to occur during bad times, often in the context of IMF programs or sovereign defaults. 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 (Martinez, 2022; De Castro et al., 2013). 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 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 further 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 3.2. 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 Siegloch and Schmidheiny (2023) or Clarke and Tapia Schythe (2020). More specifically, we estimate the following model:

Table C2: Political drivers of hidden debt revelations

	Dep. variable: Hidden debt revelations, 1970-2020				
	(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	3511	3510	3924	3924	3411
R-squared	0.054	0.057	0.044	0.044	0.063
Country FE	✓	✓	✓	✓	✓
Vintage FE	✓	✓	✓	✓	✓

Sources: Authors' calculations
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 (see section 2.3 and (2) for details). 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.

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

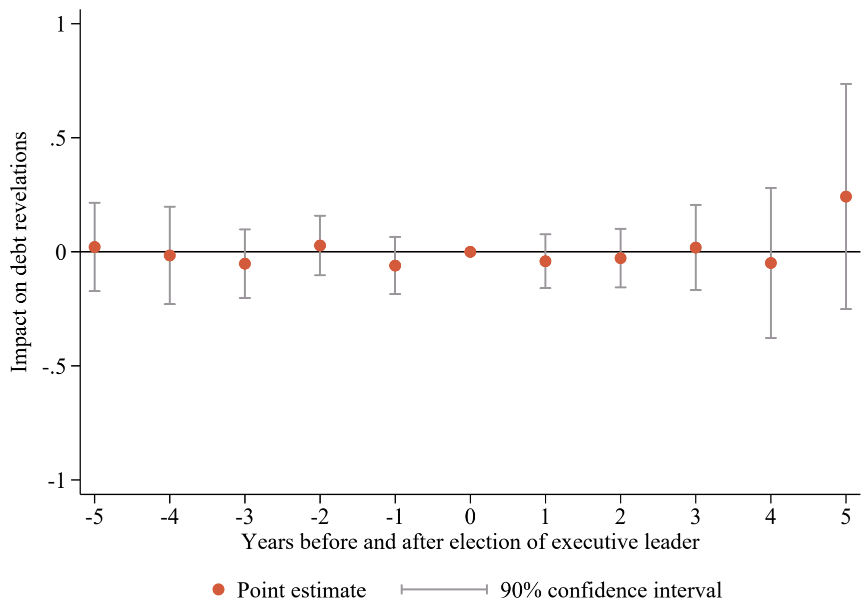
where HDR_{it} are revelations of previously hidden debt as defined in section 2.3 above, σ_i and θ_t are country and vintage fixed effects and ϵ_{it} is an unobserved error term. The leads and lags of x_{it} capture the years before and after a political event of interest and are defined as follows:

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

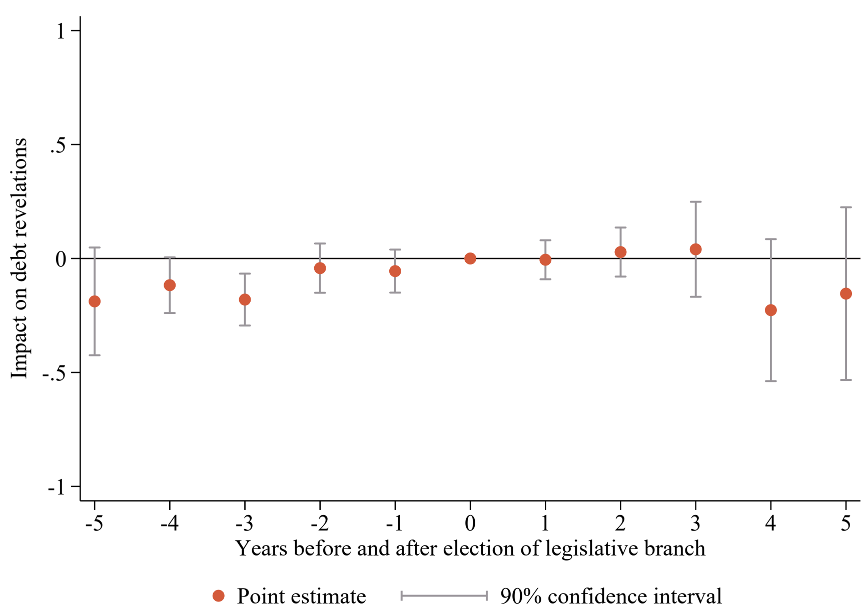
Figures C15 and C16 show the results of the panel event study regressions and confirm the results from the static regression model. Hidden debt revelations show no statistically significant co-movement with the political cycle.

Figure C15: Hidden debt revelations and the political cycle: event study panel regressions

Panel A: Election of executive leader



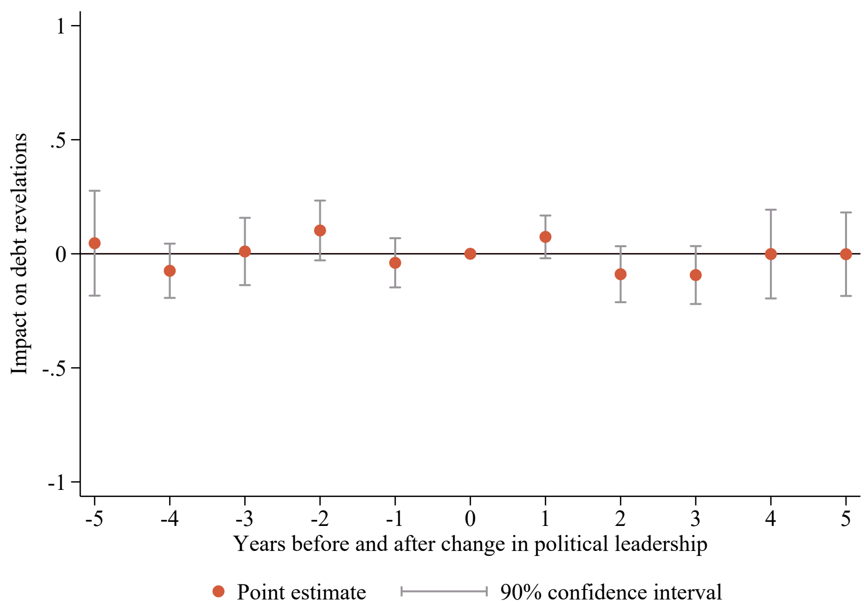
Panel B: Election of legislative branch



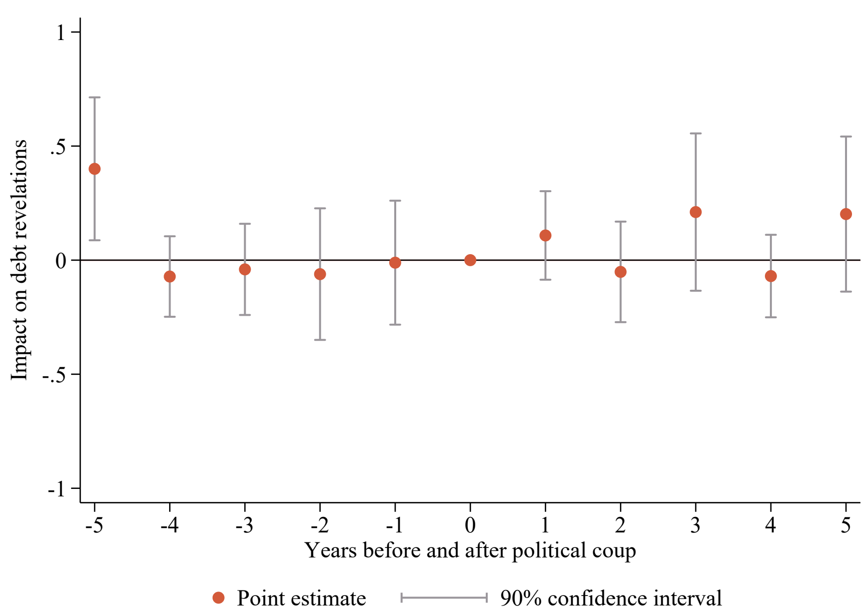
Notes: This figure shows point estimates and 90 percent confidence intervals obtained from regressing standardized hidden debt revelations as defined in equation (2) on a set of lags and leads for elections of the executive (Panel A) and legislative branch of government (Panel B).

Figure C16: 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.4 Additional tables

Table C3: Determinants of hidden debt

	(1)	(2)	(3)	(4)
Panel A: Dep. variable: Mean hidden debt (in % of GDP)				
Institutional strength	-0.02	-0.02	-0.02	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)
Borrowing from bondholders		-0.01		-0.01
(in % of total borrowing)		(0.01)		(0.01)
Borrowing from multilaterals		0.00		0.00
(in % of total borrowing)		(0.00)		(0.00)
Years in IMF program			0.00	-0.00
(as % of all years)			(0.00)	(0.00)
Years in sovereign default			-0.00	-0.00
(as % of all years)			(0.01)	(0.01)
Observations	129	123	129	123
R-squared	0.023	0.029	0.026	0.033
Panel B: Dep. variable: Std. dev. of hidden debt (in % of GDP)				
Institutional strength	-0.19***	-0.19***	-0.18***	-0.18***
	(0.06)	(0.07)	(0.06)	(0.07)
Borrowing from bondholders		0.01		0.01
(in % of total borrowing)		(0.03)		(0.03)
Borrowing from multilaterals		0.02*		0.03
(in % of total borrowing)		(0.01)		(0.02)
Years in IMF program			-0.01	-0.02
(as % of all years)			(0.01)	(0.02)
Years in sovereign default			0.02	0.02
(as % of all years)			(0.03)	(0.03)
Observations	129	123	129	123
R-squared	0.086	0.084	0.095	0.098

Notes: This table shows regression results from cross-country regressions of average hidden debt (Panel A) and the standard deviation of hidden debt (Panel B), both in percent of GDP, on institutional strength, borrowing from bondholders, borrowing from multilateral institutions, years in IMF programs and years in external sovereign default. All independent variables are country-level averages for 1970-2022. Institutional strength is measured by a country's average score on the Polity V dataset (Polity, 2020), years in IMF programs from Horn et al. (2020) and years in external sovereign default from Asonuma and Trebesch (2016) enter the regressions as shares of time spent in each during the whole sample period. Borrowing from bondholders and multilaterals is calculated as commitments vis-à-vis the respective creditor in percent of total public and publicly guaranteed commitments, using the latest reported statistics. This is done as commitments vis-à-vis bondholders are only published in the very recent vintages of the World Bank's International Debt Reports. Robust standard errors in parentheses.

Table C4: Debtor and creditor characteristics: debt commitment revelations (% of GDP)

	N	Mean	Median	Std. Err.	p-value
Panel A: Debtor characteristics					
Regions					
Europe	238	0.45	0.14	0.08	0.000
Asia	854	0.59	0.00	0.34	0.081
Middle-East and North Africa	428	0.90	0.15	0.20	0.000
Sub-Saharan Africa	1152	0.84	0.11	0.22	0.000
Latin America	951	0.70	0.08	0.10	0.000
Income groups					
Low income	557	0.73	0.11	0.14	0.000
Lower middle income	1325	0.74	0.09	0.28	0.008
Upper middle income	1229	0.65	0.04	0.10	0.000
High income	59	0.41	0.15	0.12	0.001
Decades					
1970s	458	0.59	0.11	0.11	0.000
1980s	558	0.99	0.24	0.34	0.003
1990s	743	0.92	0.09	0.13	0.000
2000s	885	0.53	0.01	0.15	0.000
2010s	1028	0.54	0.06	0.30	0.074
Panel B: Creditor characteristics					
Official creditors	3482	0.45	0.03	0.11	0.000
Multilateral	962	0.10	0.00	0.05	0.045
World Bank	2011	0.01	0.00	0.01	0.063
Bilateral	964	0.36	0.01	0.06	0.000
Private creditors	3456	0.25	0.00	0.06	0.000

Sources: Authors' calculations
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 and decades of reporting 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) to account for the autocorrelated structure of revelations when calculating p-values. Table C5 repeats the exercise for debt stock revisions.

Table C5: Debtor and creditor characteristics: debt stock revisions in % of GDP

	N	Mean	Median	Std. Err.	p-value
Panel A: Debtor characteristics					
Regions					
Europe	315	-0.23	0.01	0.19	0.232
Asia	1246	0.65	0.00	0.20	0.001
Middle-East and North Africa	689	0.01	0.04	0.26	0.962
Sub-Saharan Africa	1874	1.63	0.10	0.32	0.000
Latin America	1358	1.69	0.48	0.22	0.000
Income groups					
Low income	1471	1.43	0.01	0.39	0.000
Lower middle income	1519	0.59	0.11	0.13	0.000
Upper middle income	957	0.55	0.03	0.11	0.000
High income	17	0.41	0.00	0.31	0.203
Decades					
1970s	892	1.51	0.59	0.25	0.000
1980s	1030	1.88	0.15	0.44	0.000
1990s	1216	1.40	0.13	0.36	0.000
2000s	1279	0.24	0.01	0.13	0.061
2010s	1172	0.56	0.05	0.11	0.000
Panel B: Creditor characteristics					
Official creditors	5702	0.58	0.03	0.11	0.000
Multilateral	5697	0.20	0.00	0.04	0.000
World Bank	5708	-0.01	0.00	0.01	0.353
Bilateral	5699	0.38	0.00	0.11	0.000
Private creditors	5690	0.38	0.00	0.10	0.000
Bonds	5525	0.09	0.00	0.03	0.002
Banks and other private	5652	0.27	0.00	0.07	0.000

Sources: Authors' calculations
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 and decades of reporting and creditor groups. GDP data is taken from World Bank (2022) WDI and not subject to revisions. We use Newey-West heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) to account for the autocorrelated structure of revisions when calculating p-values.

Table C6: Creditor characteristics: debt stocks in % of initially reported debt

	N	Mean	Median	Std. Err.	p-value
Total PPG debt	6157	26.66	0.28	13.68	0.051
Official creditors	6143	26.79	0.14	13.72	0.051
Multilateral	6053	3.15	0.00	0.45	0.000
World Bank	5609	-0.01	0.00	0.18	0.964
Bilateral	6091	9.81	0.00	1.56	0.000
Private creditors	5378	59.71	0.00	23.05	0.010
Bonds	2432	7.47	0.00	5.19	0.150
Banks and other private	5065	75.85	0.00	32.48	0.020

Sources: Authors' calculations
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) WDI and not subject to revisions. We use Newey-West heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) to account for the autocorrelated structure of revisions when calculating p-values.

Table C7: Summary statistics of debt stock revisions in % of GDP by country

	N	Mean	Median	Std. Err.	p-value
Afghanistan	24	0.11	0.04	0.17	0.503
Albania	32	-0.95	-0.01	0.92	0.311
Algeria	51	0.94	0.91	0.38	0.017
Angola	35	2.64	0.38	1.80	0.151
Argentina	51	0.03	0.21	0.20	0.869
Armenia	29	-0.30	0.03	0.19	0.124
Azerbaijan	28	0.68	0.38	0.22	0.004
Bangladesh	50	-0.42	-0.22	0.27	0.122
Barbados	25	0.36	0.21	0.40	0.383
Belarus	29	0.45	0.16	0.25	0.083
Belize	51	0.87	0.00	0.53	0.106
Benin	51	-0.45	0.02	1.47	0.760
Bhutan	41	1.85	0.00	0.80	0.027
Bolivia	51	2.57	1.40	0.95	0.009
Bosnia and Herzegovina	22	-0.91	-0.01	0.75	0.240
Botswana	51	0.89	0.26	0.56	0.119
Brazil	51	0.35	0.03	0.20	0.094
Bulgaria	40	0.04	0.06	0.51	0.942
Burkina Faso	51	-0.21	0.10	0.29	0.483
Burundi	51	-0.51	0.03	0.39	0.196
Cambodia	29	0.12	0.04	0.07	0.083
Cameroon	51	1.10	0.00	0.73	0.137
Cape Verde	41	-0.09	-0.22	0.35	0.786
Central African Republic	51	-0.89	0.11	0.63	0.160
Chad	14	0.90	0.01	0.66	0.195
Chile	42	0.34	0.04	0.20	0.106
Colombia	51	4.46	0.59	2.22	0.050
Comoros	51	0.69	0.52	0.15	0.000
Congo	51	0.78	0.42	0.20	0.000
Costa Rica	41	0.18	0.00	0.27	0.512
Cote d'Ivoire	18	-0.01	0.00	0.00	0.106
Croatia	16	-0.01	0.00	0.02	0.484
Cyprus	51	1.61	0.71	0.57	0.007
Democratic Republic of Congo	51	3.89	1.32	1.33	0.005
Djibouti	17	0.19	0.00	0.12	0.132
Dominica	35	0.98	0.00	0.90	0.280
Dominican Republic	40	3.86	3.49	0.90	0.000
Ecuador	51	1.05	0.22	0.36	0.006
Egypt	51	3.92	0.76	1.29	0.004
El Salvador	51	0.32	0.18	0.56	0.565

	N	Mean	Median	Std. Err.	p-value
Equatorial Guinea	51	-0.06	0.00	0.75	0.940
Eritrea	51	-2.37	0.00	1.19	0.052
Estonia	17	0.07	0.00	0.19	0.738
Ethiopia	9	0.02	0.00	0.02	0.356
Fiji	11	-0.07	0.00	0.06	0.250
Gabon	40	15.59	0.19	6.38	0.019
Gambia	51	1.32	1.18	0.48	0.009
Georgia	51	0.92	0.54	0.25	0.000
Ghana	51	1.04	0.48	0.52	0.049
Greece	51	11.15	1.45	4.72	0.022
Grenada	15	-7.61	-1.13	4.55	0.116
Guatemala	19	0.27	0.17	0.11	0.025
Guinea	29	0.81	0.38	0.39	0.048
Guinea-Bissau	34	-1.22	-1.21	1.04	0.248
Guyana	44	1.04	1.84	0.76	0.181
Haiti	51	2.99	2.02	0.78	0.000
Honduras	51	7.27	2.41	4.00	0.075
Hong Kong	51	0.20	0.12	0.47	0.665
Hungary	13	-0.28	0.07	0.54	0.618
India	16	0.32	0.19	0.17	0.074
Indonesia	51	2.44	1.25	0.84	0.006
Iran	51	0.71	0.26	0.28	0.015
Jamaica	51	-0.35	-0.14	0.36	0.346
Jordan	49	-1.82	0.00	1.23	0.146
Kazakhstan	13	0.28	0.01	0.34	0.413
Kenya	51	2.57	2.21	0.69	0.001
Kosovo	45	2.25	0.42	0.79	0.007
Kyrgyz Republic	51	0.42	-0.24	1.21	0.727
Laos	28	-2.54	-4.63	2.65	0.347
Latvia	51	0.23	0.19	0.24	0.341
Lebanon	24	2.05	1.57	0.84	0.023
Lesotho	21	-0.37	0.00	0.27	0.195
Liberia	22	0.34	0.00	0.48	0.492
Lithuania	40	0.20	0.00	0.21	0.345
Macedonia	51	3.78	0.21	2.55	0.144
Madagascar	17	-0.43	0.00	0.25	0.109
Malawi	30	1.01	-0.20	1.16	0.392
Malaysia	51	-0.28	-0.12	0.87	0.744
Maldives	51	3.00	2.95	0.75	0.000
Mali	41	-0.18	0.00	0.29	0.541
Malta	51	0.55	0.21	0.24	0.024
Mauritania	21	-0.17	0.00	0.67	0.806

	N	Mean	Median	Std. Err.	p-value
Mauritius	29	1.13	0.04	0.54	0.045
Mexico	26	0.08	0.06	0.06	0.180
Moldova	17	0.64	0.05	0.37	0.106
Mongolia	32	-0.31	0.00	0.20	0.136
Montenegro	51	0.10	0.00	0.44	0.821
Morocco	51	0.54	0.49	0.43	0.207
Mozambique	51	7.27	3.05	2.53	0.006
Myanmar	28	-0.81	0.07	1.31	0.543
Nepal	51	-0.93	-0.56	0.51	0.073
Nicaragua	34	-0.39	0.00	0.85	0.649
Niger	45	0.00	0.03	0.16	0.989
Nigeria	51	0.50	0.00	0.39	0.203
Oman	51	-0.41	0.01	0.37	0.263
Pakistan	51	3.86	2.32	1.82	0.039
Panama	51	-0.07	0.00	0.09	0.428
Papua New Guinea	51	0.10	0.00	0.33	0.757
Paraguay	51	0.01	0.24	0.17	0.973
Peru	36	-0.01	0.00	0.23	0.982
Philippines	51	0.51	0.32	0.21	0.019
Poland	51	0.60	0.42	0.26	0.024
Romania	51	-0.15	0.00	0.22	0.488
Rwanda	19	-0.21	-0.13	0.14	0.143
Saint Kitts and Nevis	51	0.20	0.12	0.50	0.696
Saint Lucia	37	7.37	1.71	3.15	0.025
Saint Vincent and the Grenadines	51	-0.64	-0.07	0.39	0.106
Samoa	51	1.16	0.38	0.44	0.012
Sao Tome and Principe	51	14.31	7.15	5.09	0.007
Senegal	51	1.86	0.33	0.70	0.010
Serbia	44	0.62	0.00	0.47	0.189
Seychelles	26	-0.54	-0.17	0.39	0.180
Sierra Leone	43	0.81	0.00	0.63	0.208
Singapore	34	-0.02	0.00	0.19	0.912
Slovak Republic	51	2.19	2.12	0.57	0.000
Solomon Islands	51	0.02	0.00	0.12	0.895
Somalia	17	0.43	0.13	0.21	0.062
South Korea	29	0.06	0.07	0.10	0.540
Sri Lanka	33	1.39	0.48	0.52	0.012
Sudan	14	1.94	1.17	0.80	0.031
Swaziland	29	-6.47	-2.72	2.26	0.008
Syria	20	-2.11	-0.62	1.64	0.214
Tajikistan	41	1.18	0.00	0.74	0.120
Tanzania	36	-0.82	0.00	0.54	0.140

	N	Mean	Median	Std. Err.	p-value
Thailand	39	2.69	0.00	1.47	0.074
Togo	51	1.09	0.71	0.40	0.009
Tonga	51	1.07	0.00	1.08	0.326
Trinidad and Tobago	51	-0.07	-0.01	0.12	0.565
Tunisia	29	0.75	-0.09	0.76	0.330
Turkey	27	0.31	0.00	0.25	0.225
Turkmenistan	50	1.04	0.46	0.74	0.166
Uganda	36	0.11	0.00	0.42	0.797
Ukraine	51	-0.06	0.04	0.26	0.803
Uruguay	51	0.43	0.26	0.14	0.004
Uzbekistan	33	0.34	0.17	1.03	0.746
Vanuatu	29	0.21	0.10	0.28	0.451
Venezuela	29	0.91	0.07	0.64	0.165
Vietnam	42	0.67	0.29	0.41	0.110
Yemen	36	1.39	0.21	0.84	0.106
Zambia	41	-0.10	0.00	0.14	0.515
Zimbabwe	39	-1.20	0.00	0.50	0.021

Source: Authors' calculations.

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) WDI and not subject to revisions. We use Newey-West heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) to account for the autocorrelated structure of revisions when calculating p-values.

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 5.1.