

*This online annex details the data sources, methodology and complementary results referenced in the main text. Further details are available in the accompanying replication package.*

## Online Annex 3.1 Construction of Debt-to-GDP Surge, Reduction and Stable Episodes

### Methodology

The method to decompose the time series of debt to GDP into a sequence of episodes proceeds in two steps. The first step involves identifying turning points in the time series of debt to GDP for each country. This is done using the business cycle dating methodology of Harding and Pagan (2002), imposing a minimum of 2 years between successive peaks and troughs, and a minimum length of 4 years for a complete cycle.<sup>1</sup> The result is a decomposition of the entire time series into non-overlapping periods of surges and reductions. Next, a subset of such periods is now defined as stable (with a minimum length of 3 years) if either one of two conditions holds: 1) the cumulative change in the debt to GDP ratio is between 2 and 10 percentage points, or 2) if it is less than 10 percentage points of the country-specific standard deviation.

### Data Sources

The data for debt to GDP used for the computation of the episodes includes several sources. The objective of the exercise is to have the longest possible consistent time series of debt to GDP ratio for each country in the sample. While general government is the preferred measure, due to data availability, central government debt is used for most countries.<sup>2</sup>

The Global Debt Database (Mbaye, Moreno-Badia, Chae, 2018) is the primary source. It is complemented with the Historical Public Finance Dataset compiled (HPFD) by Mauro and others (2013), Historical Public Debt Database (HPDD) compiled by Abbas and others (2010), and the World Economic Outlook database, depending on whichever source provides best coverage across time. Definitions are not mixed within countries when combining databases, i.e. for each country, the final debt to GDP series in the database corresponds to either central government for all years or general government for all years. Finally, gaps not exceeding three years sometimes exists within a database, and these are filled with linear interpolations.

### Stylized Facts

The method identifies 927 episodes from 1970 to 2021 (425 surges, 328 reductions and 174 stable episodes). The sample is unbalanced, including 52 countries in 1970 (4 AEs, 20 EMs, 28 LICs) and progressively increasing in the 1970s and 1980s to reach a maximum of 129 countries

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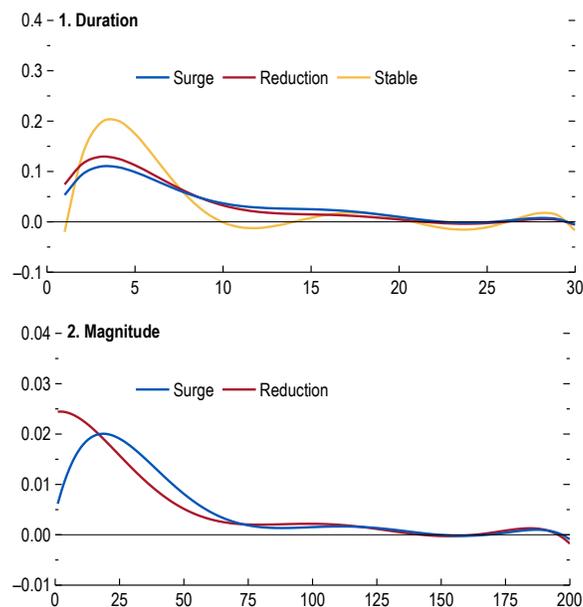
<sup>1</sup> Results are robust to alternate parameterizations that yield a higher share of stable periods.

<sup>2</sup> In cases where both general and central government data are available, the correlation between them is typically high (>0.75 on average), and the main results reported in the chapter are robust to a sample consisting of only general government debt.

by 1995 (28 AEs, 62 EMs, 39 LICs). The median surge lasts 6 years while the length of median reduction episode is 5 years (Annex Figure 3.1.1, panel 1). However, there are large number of surges and reductions which last much longer: a quarter (10%) of surges last for 11 (15) years or more. The corresponding number for debt reductions are somewhat lower and their duration is more limited: a quarter of reductions ends after at least 8 years and 10% last for 12 years or more. Stable periods tend to last much less: the median is only 4 years, even though a restriction for minimum length of three years is imposed, and three quarter of these episodes last no more than 6 years.

The cumulative change in debt over the episodes also shows large variation across episodes. The median debt accumulation during surges is around 30 percentage points (pp) of GDP, with 10 percent of the surges having an increase as small as 9 pp of GDP and another 10 percent registering surges of at least 85 pp of GDP.<sup>3</sup> The variation of debt during reductions is generally smaller in magnitude, consistent with the global upward trend in public debt: the median reduction is about 21 pp of GDP and in about a quarter of the episodes the reduction in debt-to-GDP ratios is lower than 10 pp (Annex Figure 3.1.1, panel 2).<sup>4</sup>

Online Annex Figure 3.1.1. Density of Episodes (Percent)



Sources: IMF, Global Debt Database; IMF, Historical Public Debt Database; and IMF staff calculations. Note: Figure shows smoothed densities using trendlines. Sample is unbalanced spanning from 1970 to 2021.

### Online Annex 3.2 Debt-to-GDP Ratio Decomposition

The change in debt-to-GDP ratio can be decomposed into the contributions from interest expense, inflation, real growth, primary balance, and the rest,

$$d_t - d_{t-1} = \frac{i_t}{1 + \gamma_t} d_{t-1} - \frac{\pi_t}{1 + \gamma_t} d_{t-1} - \frac{g_t}{1 + g_t} d_{t-1} - pb_t + o_t,$$

where  $d_t$  is general government gross debt over GDP,  $i_t$  is the effective interest rate defined as the interest expense over the previous period's debt stock,  $\gamma_t$  is the nominal growth rate,  $\pi_t$  is the inflation rate based on GDP deflator,  $g_t$  is the real GDP growth rate,  $pb_t$  is the primary

<sup>3</sup> Large and protracted surges in debt characterize countries at different income levels. Among LICs, in the Republic of Congo debt increased from 33% of GDP in 1973 to 191% in 1985; similar large changes have been recorded in Burundi between 1976 and 1999 (+130 pps) and Sierra Leone between 1971 and 1994 (+146 pp), among others. In emerging markets, Argentina's public debt-to-GDP ratio increased from 27% in 1993 to 147% in 2002, while Bulgaria's debt ratio moved from 4% in 1981 to 233% in 1993. In advanced economies, Japan's surge started in 1992 and increased debt-to-GDP by over 190 pps, while Greece's surge started in 2002 and raised debt from 102% to 225% of GDP in 2020.

<sup>4</sup> As for surges, there are examples of large and protracted declines in debt-to-GDP. Some of these episodes follow earlier large surges (e.g., Argentina in starting in 2003 when debt declined by 108 pp of GDP in 9 years; Bulgaria in 1994, when a massive decline of 168 pp was achieved in 5 years; and Sierra Leone which reduced debt by 126 pp between 1995 and 2008). Many of these large debt reductions happened in LICs as a result of debt relief initiatives (e.g., Bolivia, Cote d'Ivoire, DRC, Republic of Congo, Tanzania, Zambia). One exception among AEs is Israel, where debt increased by over 200 pp of GDP between 1973 and 1984, reaching 277% of GDP, and then declined back to 77% of GDP by 2000.

balance over GDP, and  $o_t$  is the residual. The decomposition can be conducted for each country and year.

The residual may consist of any other factors that affect the debt ratio. For example, financial transactions in which a government issue debt and uses the proceeds to buy assets enter the residual. Changes in the price due to market revaluation and exchange rate fluctuations also enter the residual. Face value reductions are another factor that can enter the residual. When a face value reduction is involved, the residual can be further decomposed into the contribution from the face value reduction in percent of GDP and the residual.

$$o_t = -fvr_t + o_t^{fvr},$$

where  $fvr_t$  is reduction in the face value of debt in percentage of GDP. One caveat is that face value reductions may be recorded in primary balance as revenue, depending on whether a country's statistics in the World Economic Outlook database is recorded according to IMF (2014).

*Details of debt decomposition reported in the text*

The results of the debt decomposition reported in Text Figure 3.2 are based on data from the World Economic Outlook database, together with the reduction episodes constructed in Annex 3.1. The number of country-year observations during reduction episodes in Figure 3.2 are 320 for 28 AEs from 1979 to 2021, 810 for 83 EMs from 1991 to 2021, and 501 for 55 LICs from 1985 to 2021. The economies with the three largest positive and negative residuals, including Equatorial Guinea, Sudan, and Venezuela are considered outliers and are not part of the calculations. We also drop an outlier whose effective interest rate is higher than 100 percent. Each bar in Text Figure 3.2 is an unweighted average of the decomposition of changes in debt ratios at the country-year level, over the income-group and reduction episodes. Since both the World Economic Outlook database and reduction episodes are unbalanced, the average is over unbalanced observations with various countries and years.

### Online Annex 3.3 Details and Supplementary Results on Structural Vector Autoregressions (SVAR)

#### Data

The structural vector autoregressions are estimated country by country on an annual sample of 21 AEs (1981-2019) and 37 EMs (1994-2019).<sup>5</sup>

Six variables are included in the VAR results reported in the main text: (1) the growth rate of real GDP (percent), (2) the growth rate of real government revenues (percent), (3) the change in primary balance to GDP ratio (percentage points), (4) the change in the public debt to GDP ratio (percentage points), (5) the change in effective interest rate (percentage points) and (6) the change in inflation (percentage points). Figure 3.3.4 and 3.3.5 in this annex is based on a 7 variable VAR which uses revenues to GDP and expenditures to GDP separately and drops the

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<sup>5</sup> The AE sample includes: AUS, AUT, BEL, CAN, CHE, DEU, DNK, ESP, FIN, FRA, GBR, GRC, IRL, ISL, ITA, JPN, NLD, NOR, PRT, SWE, and USA. The EM sample includes ARG, ATG, BHR, BHS, BOL, BRA, CHL, CHN, COL, CRI, DOM, ECU, GAB, GTM, HUN, IDN, IND, JAM, JOR, LKA, MAR, MEX, MYS, OMN, PAN, PER, PHL, POL, PRY, QAT, ROU, SUR, SYC, THA, TTO, TUR and URY. The starting year in the EM samples differs by 1-3 years based on data availability.

primary balance to GDP ratio variable. These indicators refer to general government coverage and were obtained from the World Economic Outlook database for 2002-2019, and from the Historical Public Finance Dataset (HPFD) compiled by Mauro and others (2013) for 1981-2011. Since small differences exist across the two databases for overlapping years, a smooth linear interpolation was applied to link WEO series with HPFD over a 10-year period from 2002 to 2011 for all countries except ESP, SWE and NOR for which WEO data was available throughout the sample going back to 1981.

### Estimation

The identification is based on sign restrictions summarized in Table 3.1 in the main text. All sign restrictions are imposed on impact, with the exception of the sign restrictions on GDP and debt to GDP in the case of the primary balance consolidation shocks, which are imposed one period ahead.

The reduced form VAR is estimated with two lags using Bayesian techniques with Minnesota priors, where hyperparameters are chosen to maximize marginal data density (see for instance Canova (2007)). The estimation is conducted using the Empirical macro toolbox of Canova and Ferroni (2021). Impulse responses are computed using inverse variance weights, as in Di Pace and others (2020). The contribution of shocks reported in Table 3.2 in the main text is computed by summing the absolute value of the contribution of all shocks in the historical decomposition of debt to GDP for years in which debt to GDP declined, and taking medians across countries and over time, separately for AE and EM samples.

- The remainder of this annex contains complementary results that are referenced in the main text
  - Annex Figure 3.3.1 shows the response of debt to GDP to a primary balance consolidation shock from a VAR without splitting the shock into successful and unsuccessful components (i.e., using the identification based on Table 3.1 in the main text, but with only a single primary balance consolidation shock where no sign restriction is imposed on debt to GDP).
  - Annex Figure 3.3.2 displays the impulse response to successful and unsuccessful primary balance consolidation shocks for EMs, similar to Figure 3.4 in the main text for AEs.
  - Annex Figure 3.3.3 shows the implied impulse response in terms of levels of GDP, primary balance to GDP and debt to GDP, based on the first difference estimates shown in Figure 3.4 and Annex Figure 3.3.2.
  - Annex Figure 3.3.4 and Annex Figure 3.3.5 show the results from the VAR replacing primary balance to GDP with its two components—revenue to GDP and expenditure to GDP, and figure 3.3.6 shows a comparison of the contribution of revenues and expenditures to the impact response of primary balance in figures 3.3.4 and 3.3.5.
  - Finally, outside of the VAR setup, Annex Figure 3.3.7 shows the unconditional probability of observing periods of primary balance to GDP improvements and debt

ratio declines. The bars reveal that consolidations are as likely to be accompanied by debt ratio increases as they are by declines.

### Fiscal Consolidations and Debt Ratios: A Simplified Arithmetic Approach

This section aims to provide a framing device for understanding the impact of fiscal consolidations on Debt to GDP ratios. To keep the expressions manageable, it makes several simplifying assumptions, including fixing the maturity of the entire stock of debt to one year and assuming that inflation and nominal rates do not change. The results are therefore best suited to learn qualitative features rather than a precise quantification.

The first expression below comes from the standard debt dynamics equation above and the second one from the definition of the fiscal multiplier ( $m_y < 0$ ). Here  $D_t$  denotes the nominal stock of debt,  $PB_t$  denotes nominal primary balance,  $Y_t$  is nominal GDP and  $r_t$  the effective real interest rate.

$$\Delta \ln D_t = r_t - \frac{PB_t}{D_{t-1}}, \quad \Delta \ln Y_t = -m_y \frac{\Delta PB_t}{Y_{t-1}}$$

Combining the above two expressions yields

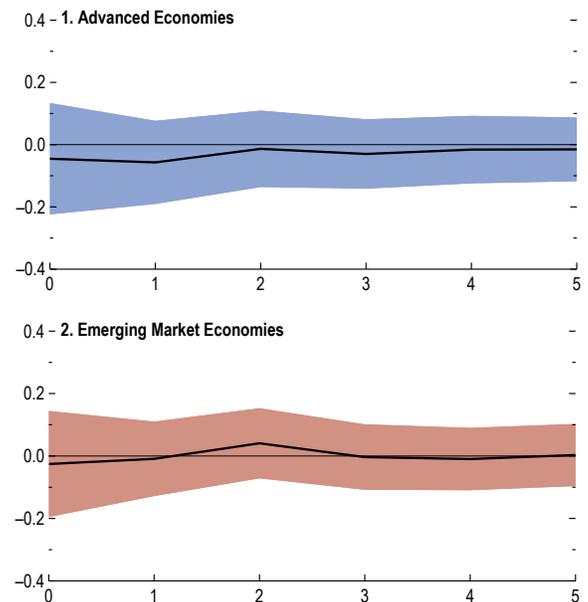
$$\Delta \ln (D_t/Y_t) = r_t - \frac{PB_{t-1}}{D_{t-1}} + \frac{\Delta PB_t}{Y_{t-1}} (m_y - \frac{Y_{t-1}}{D_{t-1}})$$

Assuming a constant rate of inflation and effective interest rate, the above expression highlights that a consolidation ( $\frac{\Delta PB_t}{Y_{t-1}}$ ) reduces the debt ratio when the following inequality holds

$$m_y \frac{D_{t-1}}{Y_{t-1}} < 1$$

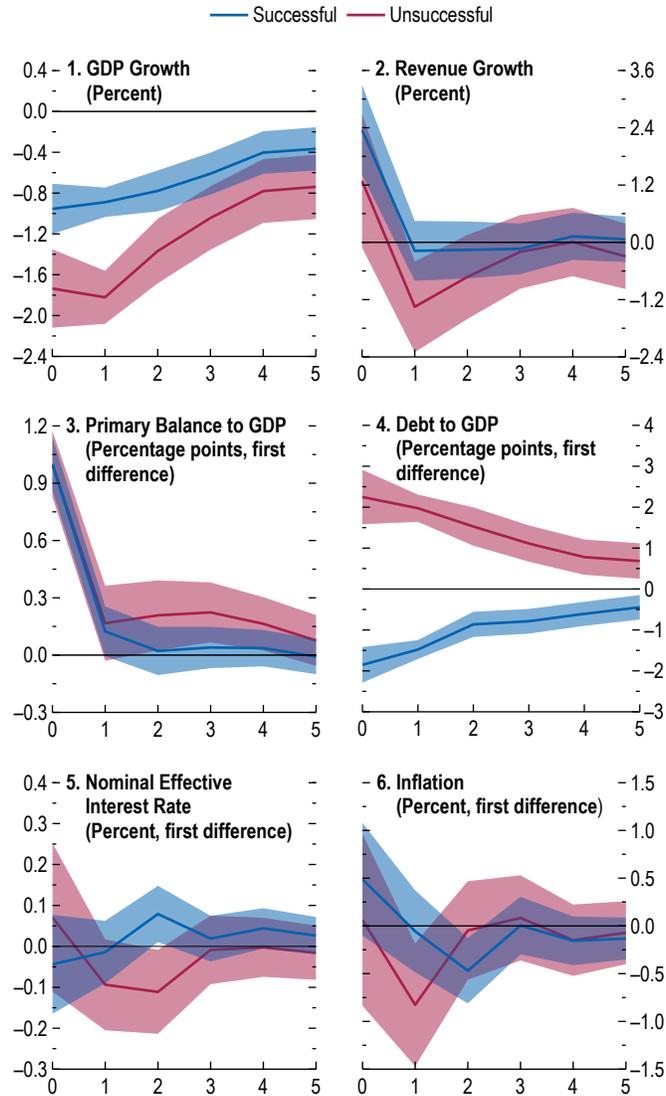
Two takeaways follow from this condition in relation to the results presented in the main text. First, in line with Figure 3.4, the size of the multiplier is a key determinant of whether consolidations reduce debt ratios. Second, all else equal, higher debt ratios tend to mitigate the impact of consolidations in reducing debt ratios. At the same time, Figure 3.5 in the main text reveals that consolidations are more likely to be successful when crowding out effects are high, with one indicator of the high crowding out effect being the level of Debt to GDP itself. This finding can nevertheless be reconciled with the above expression by appealing to strong evidence in the literature showing that the multiplier is not constant but declines with the level of debt to GDP ratio (see for instance Ilzetki and others (2013) and Kirchner and others (2012)).

Online Annex Figure 3.3.1. Impulse Response of Debt to GDP to a Primary Balance Shock (Percentage points, first difference)

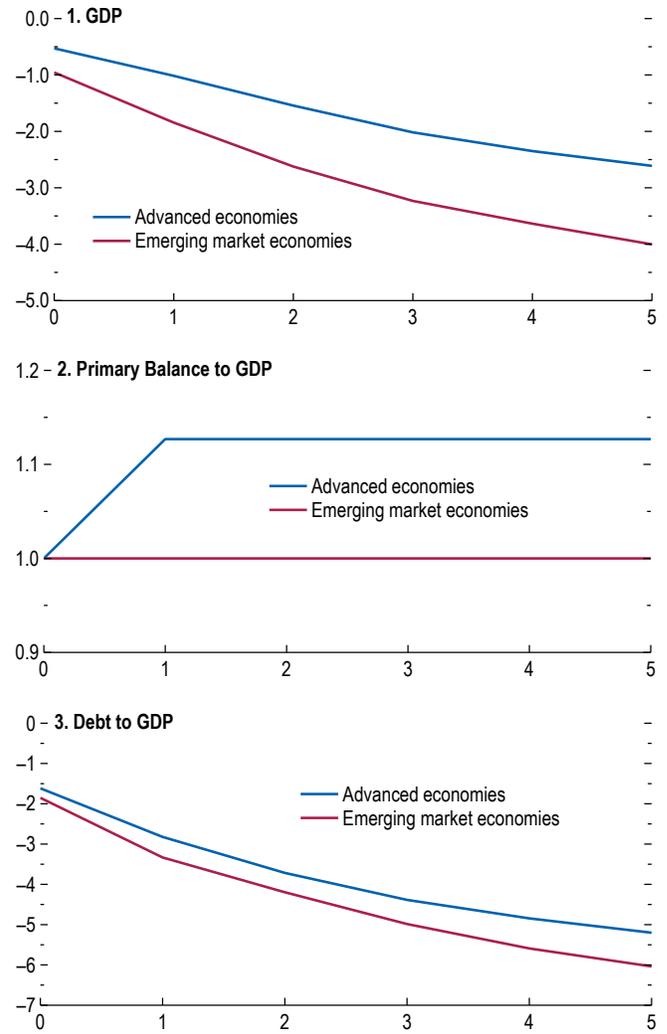


Sources: Canova and Ferroni (2022); IMF, Global Debt Database; IMF, Historical Public Debt Database; and IMF staff calculations.  
 Note: Primary balance shock is scaled to 1 percentage point of GDP on impact on average. Displayed impulse responses are inverse variance weighted means across countries from a Bayesian vector autoregression estimated country by country at annual frequency. X-axis denotes horizon in years. Shaded areas represent the 16th–84th percentile range of the posterior distribution. Sample consists of 21 advanced economies from 1981 to 2019 and 37 emerging economies from 1991 to 2019.

Online Annex Figure 3.3.2. Impulse Responses to 1 Percentage Point of GDP Primary Balance Shock, Emerging Market Economies



Online Annex Figure 3.3.3. Impulse Response Levels to an Average Successful Consolidation Shock (Percentage points)

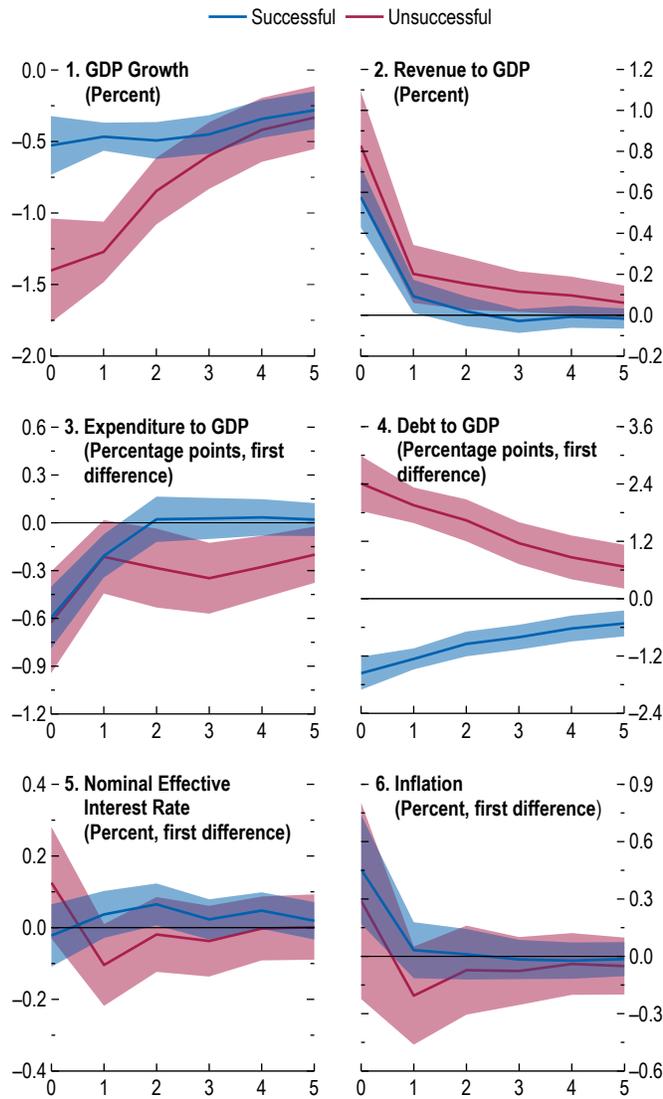


Sources: Canova and Ferroni (2022); IMF, Global Debt Database; IMF, Historical Public Debt Database; and IMF staff calculations.  
 Note: Primary balance shock is scaled to 1 percentage point of GDP on impact on average. Displayed impulse responses are inverse variance weighted means across countries from a Bayesian vector autoregression estimated country by country with two lags at annual frequency. X-axis denotes horizon in years. Shaded areas represent the 16th–84th percentile range of the posterior distribution. Sample consists of 37 emerging market economies from 1991 to 2019.

Sources: Canova and Ferroni (2022); IMF, Global Debt Database; IMF, Historical Public Debt Database; and IMF staff calculations.  
 Note: Figure shows median values implied by the vector autoregression estimates at annual frequency. X-axis denotes horizon in years. Sample consists of 21 advanced economies from 1981 to 2019 and 37 emerging market economies from 1991 to 2019.

## CHAPTER 3 COMING DOWN TO EARTH: HOW TO TACKLE SOARING PUBLIC DEBT

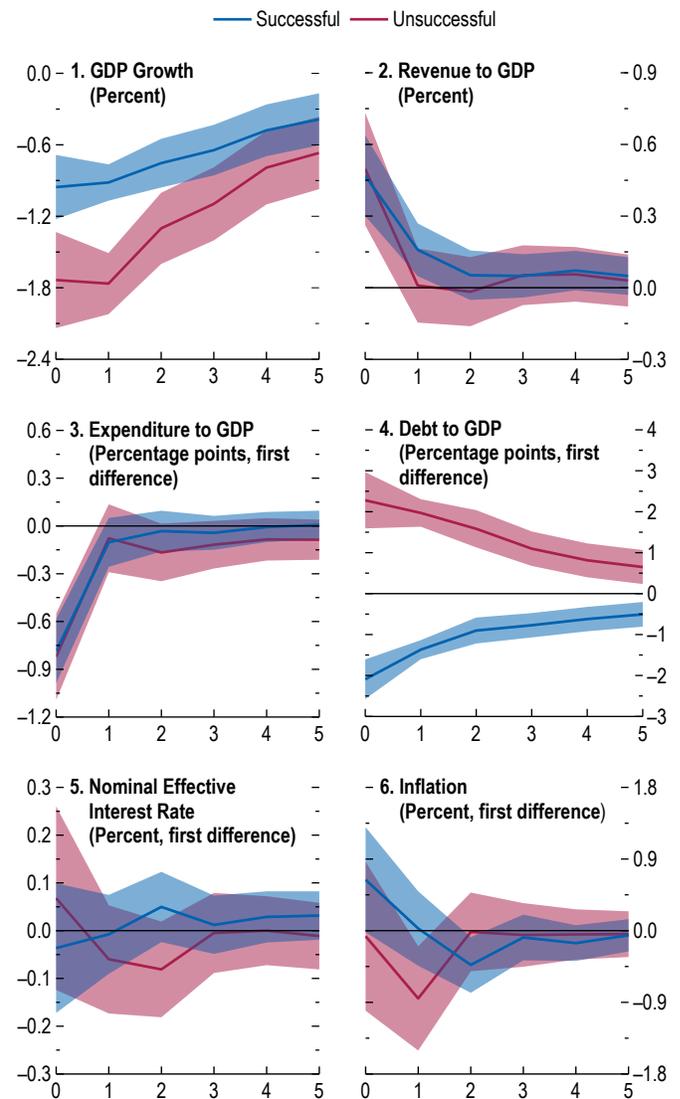
**Online Annex Figure 3.3.4. Impulse Responses to 1 Percentage Point of GDP Primary Balance Shock, Advanced Economies**



Sources: Canova and Ferroni (2022); IMF, Global Debt Database; IMF, Historical Public Debt Database; and IMF staff calculations.

Note: Primary balance shock is scaled to 1 percentage point of GDP on impact on average. Displayed impulse responses are inverse variance weighted means across countries from a Bayesian vector autoregression estimated country by country with two lags at annual frequency. X-axis denotes horizon in years. Shaded areas represent the 16th–84th percentile range of the posterior distribution. Sample consists of 21 advanced economies from 1981 to 2019.

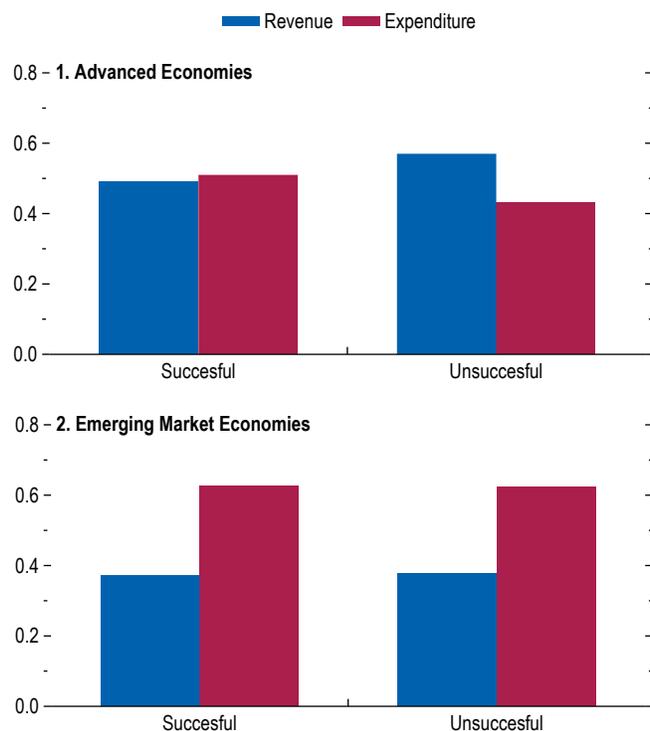
**Online Annex Figure 3.3.5. Impulse Responses to 1 Percentage Point of GDP Primary Balance Shock, Emerging Market Economies**



Sources: Canova and Ferroni (2022); IMF, Global Debt Database; IMF, Historical Public Debt Database; and IMF staff calculations.

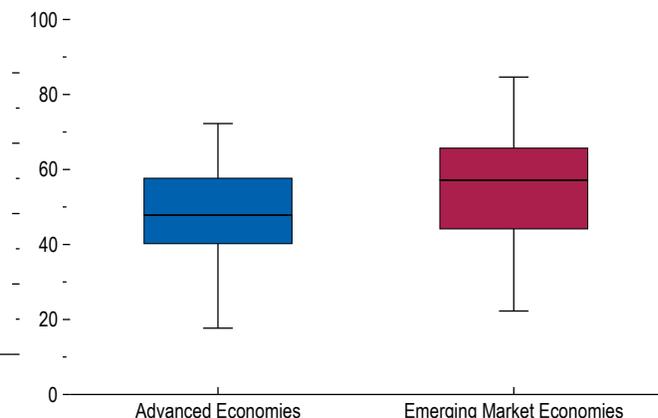
Note: Primary balance shock is scaled to 1 percentage point of GDP on impact on average. Displayed impulse responses are inverse variance weighted means across countries from a Bayesian vector autoregression estimated country by country with two lags at annual frequency. X-axis denotes horizon in years. Shaded areas represent the 16th–84th percentile range of the posterior distribution. Sample consists of 37 emerging market economies from 1991 to 2019.

**Online Annex Figure 3.3.6. Contribution to Primary Balance Shock on Impact**  
(Percent change)



Sources: Canova and Ferroni (2022); IMF, Global Debt Database; IMF, Historical Public Debt Database; and IMF staff calculations.  
Note: Figure shows estimates displayed in Online Annex Figure 3.3.4 and 3.3.5.

**Online Annex Figure 3.3.7. Unconditional Probability of Observing Consolidations with Reduction in Debt to GDP**  
(Percent)



Sources: IMF, Global Debt Database; IMF, Historical Public Debt Database; and IMF staff calculations.  
Note: Figure shows distribution of the probability of observing consolidations with reduction in debt to GDP, where the horizontal lines stand for the medians, the box represents the 25th and 75th percentiles, and the whiskers represent the extremes, excluding outliers. Consolidations are defined as period of positive change in the primary-balance-to-GDP ratio at annual frequency. Sample consists of 22 advanced economies from 1980 to 2020 and 37 emerging market economies from 1991 to 2020.

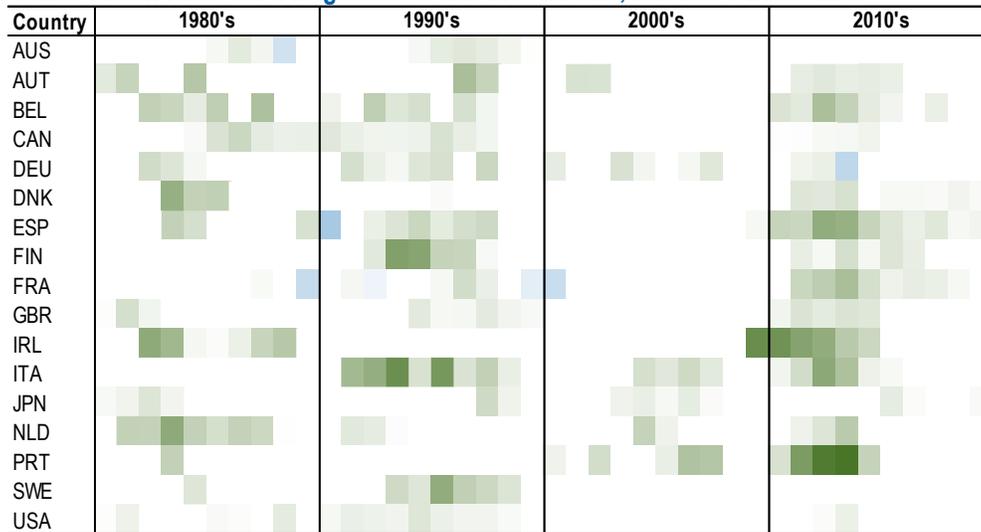
### Online Annex 3.4 Description of Narrative Fiscal Consolidation Shocks

This annex presents the updated dataset of fiscal consolidation episodes used in this chapter (Annex Table 3.4.1 and Annex Table 3.4.2). The dataset builds on existing multi-country narrative databases, including additional economies, and identifying additional fiscal policy changes up to 2019. For advanced economies, the starting point is the data set of Devries and others (2011) for 17 Organisation for Economic Co-operation and Development (OECD) economies for 1978–2009. For the years 2010–14, the dataset uses the cases of fiscal consolidation identified by Alesina and others (2018) who extended the narrative dataset of Devries and other for 16 of the OECD economies—not including The Netherlands. For The Netherlands the dataset includes newly identified cases of fiscal consolidation during the years 2010–2019. The dataset also includes newly identified cases of fiscal consolidation for the 16 other OECD economies for 2015–2019. Overall, the dataset now covers the years 1978–2019 for the 17 advanced economies. For emerging market and developing economies, the starting point is the data set of Carriere-Swallow, David, and Leigh (2021), which includes 14 countries in Latin

America and the Caribbean for 1989–2016. The dataset extends and updates the sample for all 14 emerging market and developing economies through 2019.<sup>6</sup>

As in the previous aforementioned studies, the focus of the new datasets is on cases of documented tax or government spending policy actions motivated primarily by the desire to reduce the budget deficit and ensure longer-term fiscal sustainability. As explained in Devries and others (2011), the existing literature usually identifies fiscal policy consolidation using a statistical concept such as the increase in the cyclically-adjusted primary budget balance (CAPB). However, as a number of studies explain, using the CAPB to estimate the macroeconomic effects of fiscal consolidation is problematic. First, cyclical adjustment methods suffer from measurement errors that are likely to be correlated with economic developments. Second, even if the change in the CAPB accurately reflects discretionary changes in fiscal policy, those can be motivated by a desire to respond to cyclical fluctuations, raising reverse causality concerns. To avoid these problems associated with the conventional approach, the fiscal consolidation episodes included in this dataset are identified using a narrative approach, by examining policymakers’ intentions and actions as described in contemporaneous policy documents, and identifying measures motivated primarily by deficit reduction. As a result, the fiscal consolidation episodes included in this database are unlikely to be systematically correlated with other developments affecting output in the short term, and are thus valid for estimating the macroeconomic effects of fiscal consolidation. The new narrative episodes added in this database are described – a link with a document with the description of all new episodes will be here - (previously identified episodes are described in the papers mentioned above). Sources include IMF Article IV Staff Reports and other program documents, European Commission Assessment of Stability Programmes, OECD Economic Surveys, and country budget documents.

**Online Annex Table 3.4.1. Magnitude of Narrative Shocks, Advanced Economies**

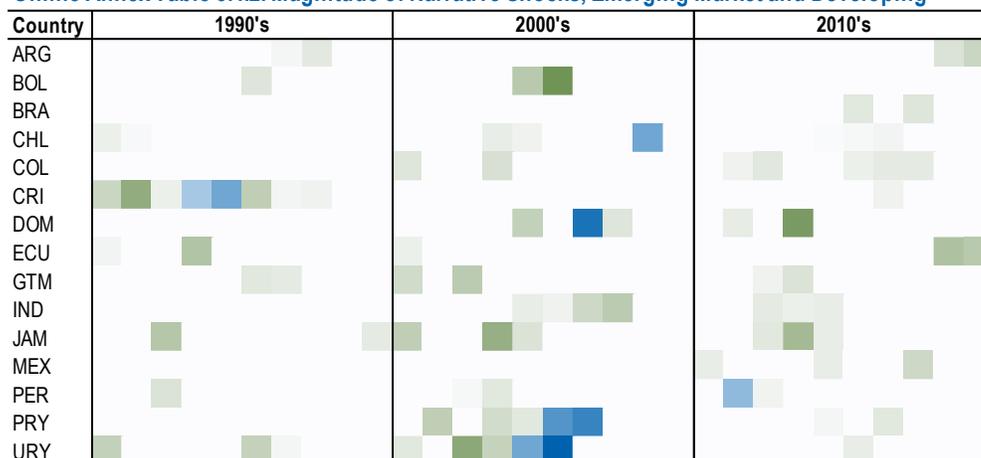


Source: IMF staff calculations.

Note: Green indicates positive consolidation shocks, ranging from 0 to 5.23 percent of GDP. Blue indicates negative consolidation shocks, ranging from -0.90 to 0 percent of GDP. Country list uses International Organization for Standardization (ISO) country codes.

<sup>6</sup> The countries included in the data set are Argentina, Australia, Austria, Belgium, Bolivia, Brazil, Canada, Chile, Colombia, Costa Rica, Denmark, the Dominican Republic, Ecuador, Finland, France, Germany, Guatemala, Ireland, Italy, Jamaica, Japan, Mexico, The Netherlands, Paraguay, Peru, Portugal, Spain, Sweden, the United Kingdom, the United States, and Uruguay.

Online Annex Table 3.4.2. Magnitude of Narrative Shocks, Emerging Market and Developing



Source: IMF staff calculations.

Note: Green indicates positive consolidation shocks, ranging from 0 to 5.23 percent of GDP. Blue indicates negative consolidation shocks, ranging from -0.90 to 0 percent of GDP. Country list uses International Organization for Standardization (ISO) country codes.

### Online Annex 3.5 Details on Local Projections and AIPW Estimation

#### Data

Country-level economic indicators (GDP, general government debt, inflation, exchange rates) are obtained from the WEO database. Fiscal consolidations in this section are measured using the narrative shocks data described above. Jamaica is removed from the dataset because of repeated restructuring events since the mid-1970s and their impact on the debt ratio, which drives many of the estimated results when that country is included in the data. The final dataset contains 17 AEs between 1978 and 2019, and 13 EMs between 1989 and 2019.

Data on restructuring events is compiled using several different sources: Asonuma, Niepelt and Ranciere (2022), Asonuma and Trebesch (2016) and Asonuma and Wright (2022), Cheng, Diaz-Cassou, and Erce (2018), Cruces and Trebesch (2013), Horn Reinhart and Trebesch (2022), IMF (2021). The data include types of restructuring (private or official), timing (post-default or preemptive), and whether they were implemented with face value reductions on debt, or through reprofiling (change in maturities or coupon rates). Because very few AEs engaged in debt restructuring, the analysis focuses on EMs and LICs only. The final dataset contains 706 restructuring events, spanning 111 EMs and LICs between 1987 and 2021. Roughly 80 percent of restructuring events last for a single year (or less); but some events can be much longer (e.g., Argentina between 2001 and 2013), pushing the average duration to about 1.4 years.

The outcome variable analyzed is changes in the debt ratio. To avoid outliers in either case, those variables are first winsorized at the 1 percent level. In addition, to ensure that the data is consistent across regressions estimated at different treatment horizons, the sample only includes periods for which at least 5 leads of the outcome variable are available (see below).

### Estimating the Impact of Fiscal Consolidations with Local Projections and AIPW

Text Figure 3.3 shows the effect of fiscal consolidation estimated using the Augmented Inverse Probability Weighted (AIPW) estimator of Jorda and Taylor (2016). There are two steps in calculating the average treatment effects (ATE):

- 1) Estimate the probability that a country consolidates every year. This is done by estimating a probit model where the outcome variable is the treatment dummy indicating whether narrative consolidation is positive, and the predictors include 2 lags of GDP growth, 2 lags of the treatment dummy, global output gap (controls for global economic conditions), nominal exchange and inflation rates (control for changes in the real value of debt), and the initial level of the debt ratio (since countries do not typically consolidate when their debt ratio is low). We also include a dummy that indicates whether the country is undergoing a debt restructuring event as a control.
- 2) Estimate the outcome model from a local projection that includes lags of the outcome, lags of the treatment, and interactions between the treatment and other controls:

$$\Delta^h y_{c,t} = \alpha_c^h + \alpha_t^h + \beta^h T_{c,t} + \sum_{j=1}^2 [\gamma_j^h \Delta^0 y_{c,t-j} + \psi_j^h T_{c,t-j} + \phi_j^h X_{c,t} + T_{c,t} (\Gamma_j^h \Delta^0 y_{c,t-j} + \Psi_j^h T_{c,t-j} + \Phi_j^h X_{c,t})] + \epsilon_{c,t}^h$$

where  $h$  is the horizon of the impact (ranging from 0 to 5 years),<sup>7</sup>  $\Delta^h y_{c,t} = y_{c,t+h} - y_{c,t-1}$  indicates changes in the debt ratio over different horizons (note that  $\Delta^0$  is simply a one-year change),  $T_{c,t}$  is a treatment dummy indicating that country  $c$  starts a narrative consolidation at year  $t$ .  $X_{c,t}$  represents additional covariates, including the global output gap, and several country-year level variables including inflation, the nominal exchange rate, and a dummy that indicates whether the country is undergoing debt restructuring. The regression specification also interacts all control variables with the treatment to account for heterogeneous impacts based on macroeconomic conditions, and includes country and year fixed effects,  $\alpha_c^h$  and  $\alpha_t^h$ .<sup>8</sup>

The ATE is then calculated as

$$ATE^h = \frac{1}{n} \sum_{c,t} \left\{ \left[ \frac{T_{c,t} \Delta^h y_{c,t}}{\hat{p}_{c,t}} - \frac{(1 - T_{c,t}) \Delta^h y_{c,t}}{1 - \hat{p}_{c,t}} \right] - \frac{T_{c,t} - \hat{p}_{c,t}}{\hat{p}_{c,t}(1 - \hat{p}_{c,t})} \left[ (1 - \hat{p}_{c,t}) m_{c,t}^h(1) + \hat{p}_{c,t} m_{c,t}^h(0) \right] \right\},$$

<sup>7</sup> As mentioned above, to ensure the consistency of the sample across different horizons  $h$ , the estimation sample only includes country-year pairs for which  $y_{c,t+h}$  is observed for all  $h \in \{0,1,2,3,4,5\}$ .

<sup>8</sup> Note that fixed effects are included only in the outcome model. The treatment model (propensity score) adopts a simpler specification to avoid estimating a large number of incidental parameters in a probit model.

where  $m_{c,t}^h(T_{c,t})$  is the predicted value for  $\Delta^h y_{c,t}$  given the treatment value (0 or 1) and  $\hat{p}_{c,t}$  is the estimated probability in the first step. To avoid outliers, we only use observations for which  $\hat{p}_{c,t} \in (10^{-4}, 1 - 10^{-4})$ .

Intuitively, this estimator can be interpreted as the average difference in outcomes between treated and untreated economies, reweighted by the inverse probability of treatment, plus a bias adjustment term. The AIPW consistently estimates the average treatment effect under the assumption of selection-on-observables, *i.e.*, the treatment and potential outcomes are independent conditional on the covariates. The estimator is ‘doubly robust’, meaning that if either the treatment or the outcome models are correctly specified, then the estimated ATE is consistent.

### **Estimating the Impact of Debt Restructuring**

The estimation of the ATE for restructuring episodes uses the same AIPW estimator above, with the exception that the treatment dummy now indicates when a country starts a restructuring event. The effects of different types of restructuring events (joint with fiscal consolidation; HIPC & MDRI; with face value reduction) are calculated by running the same estimator on a subset of events that only include the desired outcome. For example, the ATE of restructurings that happen with fiscal consolidation (defined as a positive cyclically adjusted primary balance) only includes those events, dropping restructurings without fiscal consolidation from the sample.

Because authorities often do not know whether there will be a face-value reduction (FVR) in any given restructuring event, calculating the ATE of the events where an FVR is realized could lead to bias. As a result, for each event, the probability of a face value reduction is estimated based on information available before negotiations start. This is once again estimated using a probit model, where the explanatory variables include a country’s level of debt/GDP, GDP growth, the global output gap (controlling for overall economic conditions), inflation and nominal exchange rates, whether the restructuring event involves official creditors, whether the country qualifies for either the HIPC or MDRI programs, and whether the country is undergoing sequential restructuring events. An event is said to be likely to involve a face value reduction if the estimated probability exceeds the median of its distribution.

## Additional Results

### *First Stage Estimation*

To account for selection into treatment, the AIPW estimator first estimates the probability that a country is treated (consolidates or restructures) based on observable macroeconomic variables. Here we present the result of this estimation for the baseline consolidation and restructuring cases. Table 3.5.1 shows the results of the probit estimation, highlighting the fact that both fiscal consolidation and restructuring are more likely to happen when GDP growth is lower, global conditions are less favorable, and in sequence – the coefficient on lagged treatments (i.e., consolidation or restructuring) is highly positive and significant.

The table also shows that the model can predict the probability of treatment fairly well, with the area under the receiver operating curve (AUROC) between 0.7 and 0.87.

Lastly, table 3.5.1 presents the p-value of the Imai and Ratkovic (2014) test. In this test, the null hypothesis is that the treatment model is correctly specified. In all cases, we do not reject this hypothesis at the 5 percent level. Finally,

**Online Annex Table 3.5.1. Probit Estimation**

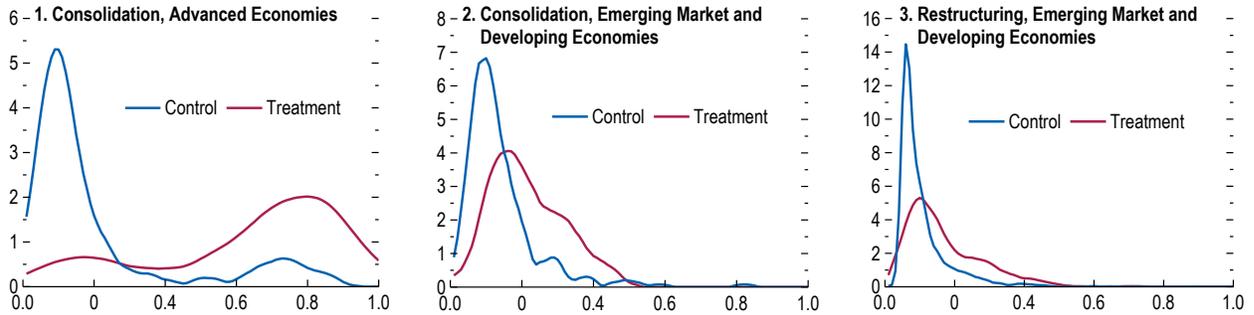
	Consolidation		Restructuring
	AEs	EMDEs	EMDEs
	(1)	(2)	(3)
$\Delta \text{GDP}_{t-1}$	-0.097*** (0.033)	-0.057 (0.038)	-0.121* (0.006)
$\Delta \text{GDP}_{t-2}$	-0.119*** (0.034)	-0.066* (0.037)	-0.001 (0.006)
Treatment <sub>t-1</sub>	1.737*** (0.167)	0.613** (0.237)	0.552*** (0.090)
Treatment <sub>t-1</sub>	-0.064 (0.169)	0.030 (0.259)	0.353*** (0.094)
Global Output Gap <sub>t-1</sub>	-0.043 (0.034)	0.012 (0.051)	-0.583*** (0.156)
$\Delta \text{NER}_{t-1}$	0.005 (0.006)	0.007 (0.005)	0.0001 (0.001)
Inflation <sub>t-1</sub>	0.029 (0.027)	-0.016 (0.018)	0.0002 (0.002)
Debt/GDP <sub>t-1</sub>	0.002 (0.002)	-0.003 (0.005)	0.003*** (0.001)
Restructuring		-0.171 (0.364)	
Number Observations	560	271	2677
Pseudo $R^2$	0.354	0.090	0.076
AUROC	0.8706	0.7597	0.7141
Balancing test (p-value)	0.9955	0.4248	0.0709

Source: IMF staff calculations.

Note: AEs = advanced economies; AUROC = area under the receiver operating curve; EMDEs = emerging market and developing economies; NER = nominal exchange rate. Balancing test refers to the Imai and Ratkovic (2014) test for balance. \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$ .

Figure 3.5.1 plots the distribution of the estimated probability of treatment in each case. Despite the high AUROC, there is significant overlap between the distributions of propensity scores.

**Online Annex Figure 3.5.1. Estimated Probabilities of Consolidation and Restructuring**  
(Density)

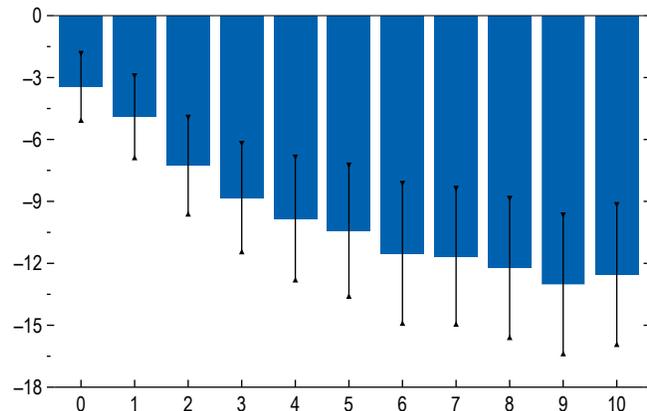


Source: IMF staff calculations.  
Note: X-axis denotes probability of treatment.

### Impact of Restructuring over Long Horizons

Annex Figure 3.5.2 shows the impact of restructuring events over long horizons – up to 10 years after the start of the event. The ATE in this case is slightly different from what is shown in Figure 3.9 due to sample differences (not all events have 10 leads in the data), but overall comparable. Note also that the effects are very stable in the long run as well, fluctuating between -8 and -10 percentage points decrease in the debt ratio. This suggests that most of the impact of debt restructuring happens in the first 5 years, and that those effects are long lasting, on average.

**Online Annex Figure 3.5.2. Impact of Restructuring on Debt to GDP: Long Horizon**  
(Percentage point change)



Sources: Asonuma, Niepelt, and Ranciere (2023); Asonuma and Trebesch (2016); Asonuma and Wright (2022); Cheng, Diaz-Cassou, and Erce (2018); Cruces and Trebesch (2013); Horn, Reinhart, and Trebesch (2022); IMF (2021); and IMF staff calculations.

Note: Figure shows the average treatment effect of restructuring on debt to GDP and on GDP growth using augmented inverse probability weighted estimation. Vertical lines indicate the 90 percent confidence interval. X-axis shows the number of years since the restructuring event starts. Sample consists of 111 emerging market and developing economies from 1987 to 2021.

## Online Annex 3.6 Definition of Debt Restructuring and Coverage of Restructuring Datasets

### Definition of Debt Restructuring

A sovereign debt restructuring is defined as a *debt distressed exchange*, i.e., an exchange of outstanding sovereign debt instruments, such as syndicated (bank) loans or bonds, of a sovereign debtor *under debt distress* for new debt instruments and/or cash through a formal renegotiation process. It typically involves a net present value (NPV) loss for creditors (Asonuma and Papaioannou forthcoming; Das and all 2012).<sup>9</sup> Sovereign debt indicates debt issued/contracted or guaranteed by the central or general government of a sovereign country. “Under debt distress” refers to a circumstance where a sovereign government loses market access and/or faces difficulty in servicing principal and interest payments. Debt distressed exchanges should be differentiated from regular liability management operations (LMOs), i.e., debt swap including debt buybacks. LMOs are voluntary market exchanges and often implemented under normal times and are not generally implemented as a part of crisis resolution (Das and all. 2012).

In principle, the definition of debt restructuring applies to both domestic and external debt—a debt obligation governed by domestic and external law—and to debt held by both private and official (multilateral and bilateral) creditors. Specifically on a domestic debt restructuring, the definition is broader to include cases of changes to contractual payment terms to the detriment of the creditors through legislative/executive acts (IMF 2021).

A sovereign default is highly correlated with a debt restructuring, but they may not always happen at the same time. This is because a sovereign debtor could approach the creditors and engage in restructuring preemptively (discussed below). A sovereign default is generally defined as the failure of a sovereign government to make a principal and/or interest payment by the time specified in debt contracts (i.e., beyond a grace period).<sup>10</sup>

On timing of restructuring, Asonuma and Trebesch (2016) distinguish two types of restructuring strategies: (i) preemptive restructurings, defined as those which are implemented with no missed payments (i.e., no legal default) or with some missed payments but only over a short period after the start of renegotiation process with creditors (i.e., no unilateral default); (ii) post-default restructuring, defined as those where payments are missed unilaterally and without the agreement on debt settlement with creditors (i.e., an unilateral default ahead of negotiations).

While there is no universally agreed taxonomy on debt restructuring types, the chapter follows Das and others (2012), Asonuma and Papaioannou (forthcoming) and considers two types: (i) face value reduction—also called as principal (nominal) debt reduction—defined as a cut in the

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<sup>9</sup> Credit rating agencies usually define restructurings as distressed debt exchanges at terms less favorable than the original bond or loan.

<sup>10</sup> Credit rating agencies, e.g., Moody’s (2008) define a sovereign default either (i) a missed or delayed payments of principal and/or interest or (ii) a distressed debt exchange. Defaults can be full (complete), when a suspension of all debt payments to creditors occurs or partial, when only a fraction of the sovereign country’s debt is not being serviced.

nominal amount of the old (existing) instruments; and (ii) debt rescheduling—also called a reprofiling—, defined as maturity extension of the old instruments, sometimes with a coupon rate (interest rate) reduction which results in a change in cash flow streams of the old debt.

Alternative classifications for debt restructuring types include the one employed by the Paris Club creditors, which focus on (i) restructurings that reduce the present value (PV) of debt, whether through face value reduction or other modalities including maturity extensions and/or coupon rate reductions; and (ii) restructurings that do not reduce the PV of debt. Note that a classification based on PV of debt is not employed in the chapter due to lack of data on present values of debt for a broad sample.

By completing a debt distress exchange, creditors often suffer losses (i.e., creditor losses). There are broadly two approaches to quantify the losses; (i) face value measure, which compares the face value of a “new” debt and an “old” debt and corresponds to the size of debt reduction in nominal (face value) terms (Alesina and Weder 2002); (ii) present value measure based on cash flows which compares the net present values of two cash flows streams, a “new” debt and an “old” debt, in a ratio with respect to the face value of debt. Both new and old cash flow streams are discounted at the yield of the new debt at exchange (Sturzenegger and Zettelmeyer 2008). Face value reduction results in creditor losses when we apply both face value and present value measures. On the contrary, cash flow relief without face value reductions results in creditor losses only when we apply present value measure, but not when we apply face value measure.

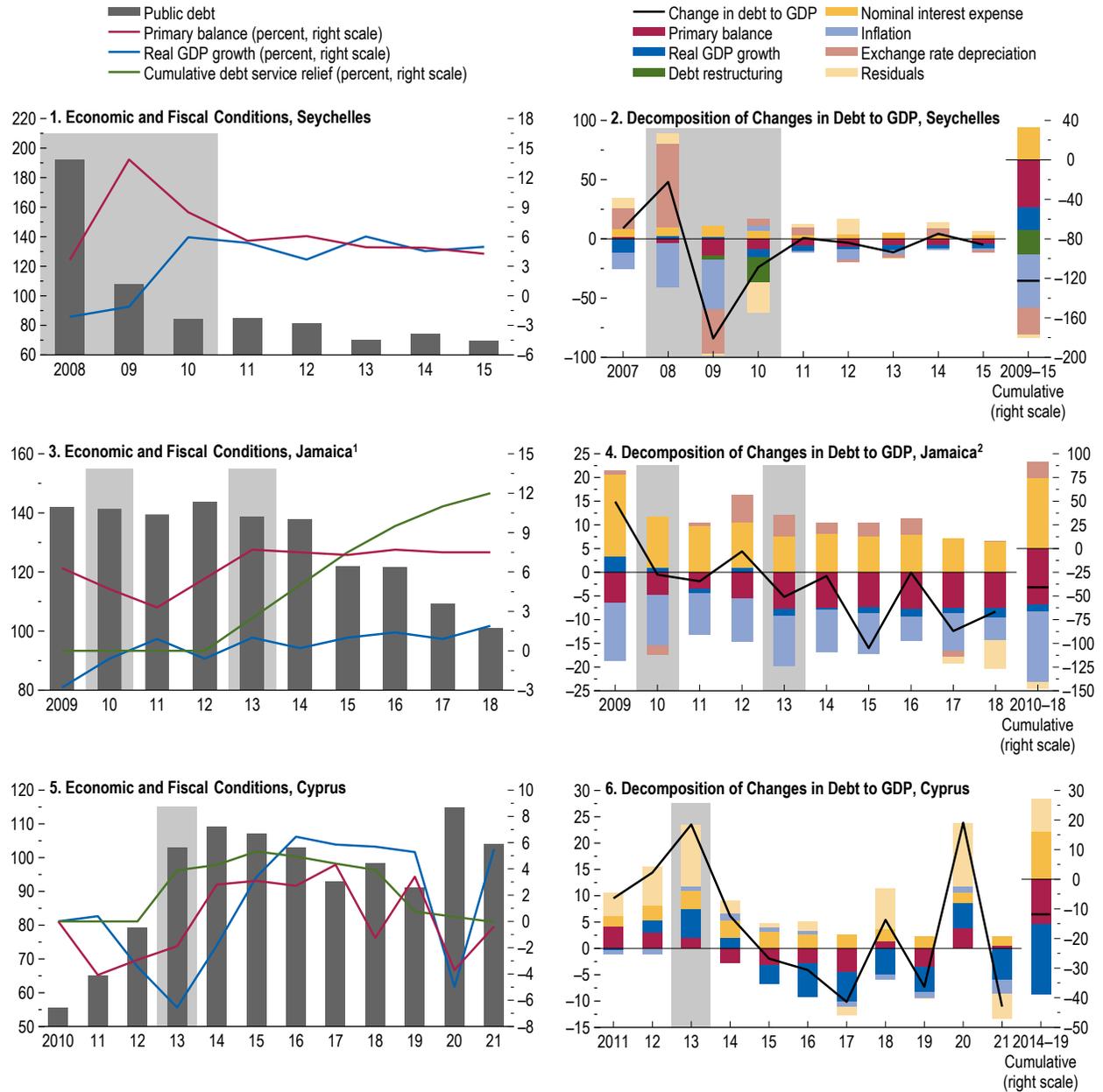
### Coverage and Sources of Restructuring Dataset

Our comprehensive debt restructuring dataset covers (i) private external debt restructurings; (ii) official (bilateral) external debt restructurings—by both the Paris Club creditors and China—; (iii) domestic debt restructurings in 1950–2021.

Our main sources of data on restructurings are as follows: (i) Asonuma and Trebesch (2016) for private external debt restructurings; (ii) Horn and all (2022) and Paris Club database for official (bilateral) external debt restructurings; (iii) IMF (2021) for domestic debt restructurings. We complement our main sources with additional data sources which provide granular information (e.g., face value reduction, cash flow relief) such as Asonuma, Niepelt and Ranciere (2023), Asonuma and Wright (2022), Cheng and all (2018) and Cruces and Trebesch (2013).

### Online Annex 3.7 Case Studies

Online Annex Figure 3.7.1. Case Studies on Restructurings with Durable Debt Reductions  
(Percent of GDP, unless noted otherwise)



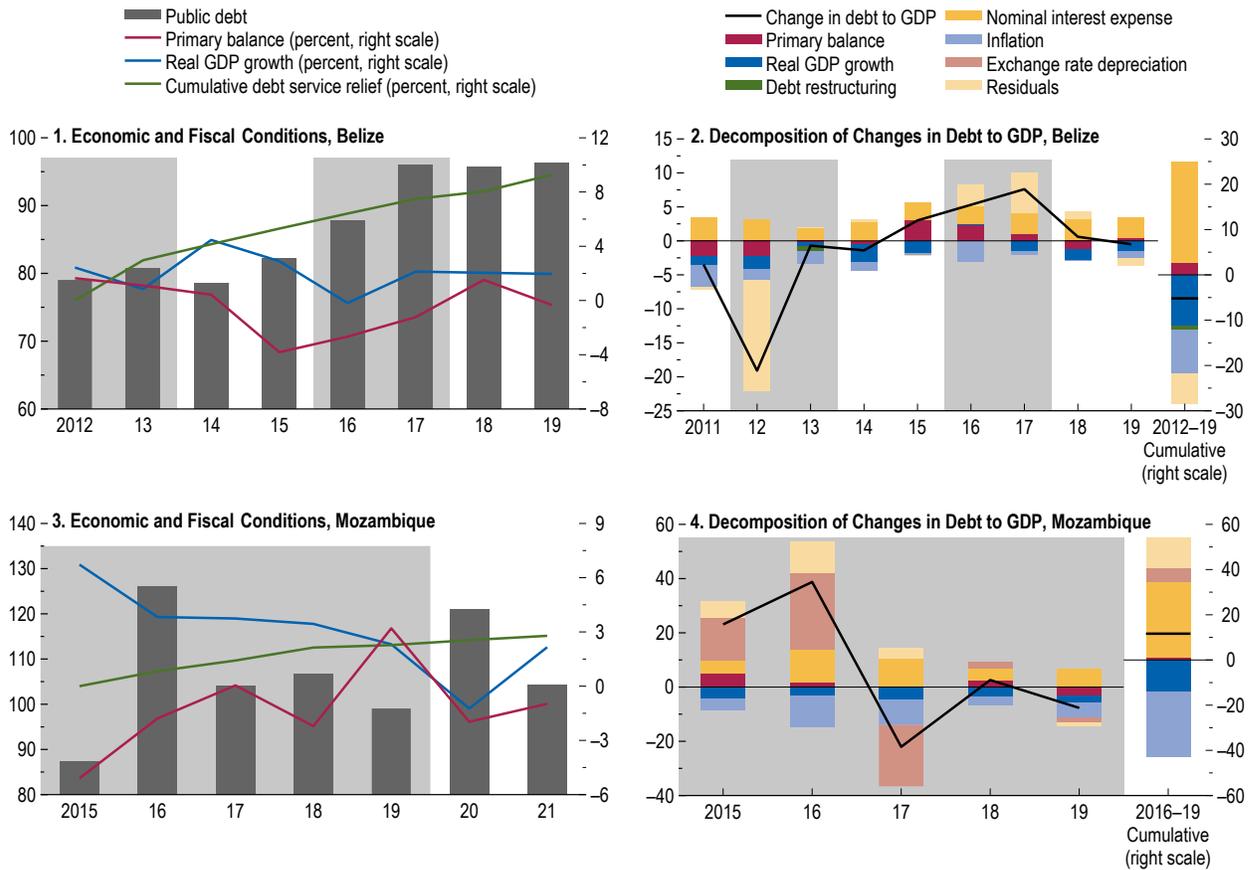
Source: IMF staff calculations.

Note: Grey shaded areas denote the duration of restructuring events. "Residuals" includes other debt-creating flows.

<sup>1</sup>Cumulative debt service relief corresponds to that provided at only domestic debt restructuring in 2013. Domestic debt restructuring in 2010 is not available.

<sup>2</sup>There was a non-Paris Club bilateral (Venezuela) debt restructuring in 2015.

Online Annex Figure 3.7.2. Case Studies on Restructurings with Elevated Debt  
(Percent of GDP, unless noted otherwise)



Source: IMF staff calculations.

Note: Grey shaded areas denote the duration of restructuring events. "Residuals" includes other debt-creating flows. For Mozambique, there are two sequential debt restructurings from 2015 to 2016 and from 2016 to 2019.

## Online Annex 3.8 Further Details on Box 3.2

### Data Construction and Sources

- Long term nominal rate:
  - We take the long-term interest rate (“lrate”) from Jorda and others (2017), covering eighteen advanced economies. These rates are government bond yields, mostly of ten year maturity, and for some countries different maturities for years earlier in the sample (see their documentation for details). Then we add long-term government bond yields from the IMF WEO database and IFS. These series represent yields to maturity of government bonds or other bonds that would indicate longer term rates. The maturity of these securities varies across countries and is described in the IFS World and Country Notes. These sources cover 96% of the data. We then supplement with 10 year government bond yields from Bloomberg and Haver.
- Inflation rate:

- WEO: CPI inflation and GDP deflator.
- Inflation expectations are calculated as MA(5) of inflation. Inflation is here constructed as CPI inflation, and missing values are filled with deflator if available
- Real effective interest rate on debt is calculated using deflator, with missing values filled with CPI inflation if available
- Effective interest rate on debt, nominal
  - Historical Public Finance Database, Government Finance Statistics, WEO
  - For years before 2011, the primary source of data is the Historical Public Finance Database (HPFD). For years after 2011, when HPFD is not available, data comes from the IMF Global Debt Database (GDD) and the World Economic Outlook (WEO) database.
  - Few additional country-year observations come from Mauro and others (2013).

### Specification for Local Projection

Local projections in Box 3.2 are in the spirit of Jorda (2005). We estimate

$$r_{i,t+h}^{eff} = \alpha_i + \alpha_t + \beta_h x_{i,t} + \sum_{l=1}^L \gamma_l r_{i,t-l}^{eff} + \sum_{l=1}^L \delta_l x_{i,t-l} + \epsilon_{i,t+h}, \text{ for } 0 \leq h \leq H$$

where  $r_{i,t+h}^{eff}$  is the effective interest rate of country  $i$  at time  $t+h$ ,  $x_{i,t}$  denotes explanatory variable of interest of country  $i$  at time  $t$ ,  $\alpha_i$  are country fixed effects,  $\alpha_t$  year fixed effects, and  $\epsilon_{i,t+h}$  is an error term. Lagged dependent and independent variables are included in the specification, with a lag length of  $L = 3$ .<sup>11</sup> The explanatory variables used are spot interest rates and the inflation rate, where separate regressions for each variable are run. The coefficients of interest are  $\beta_h$ , which give the response of the effective interest rate in period  $t+h$  to a transitory change in the spot rate in year  $t$  or the inflation rate in year  $t$ , respectively. It should be noted that our approach can be prone to endogeneity and simultaneity problems. This is why we interpret our estimates as mere associations, but not causal relationships.

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<sup>11</sup> Results are qualitatively insensitive to different lag length.

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