Online Annex 1.1. Poverty Projections using Growth Forecasts[1]

Chapter 1 reports on the estimated impact of the COVID-19 pandemic on global poverty. This annex presents details on the data and methodology used to obtain such estimates and further results.

1.1.1. Global Poverty Assuming Unchanged Inequality

Poverty statistics are usually derived from nationally representative surveys of households' consumption and/or income. These surveys are not conducted regularly, and their results are often reported with long delays. To overcome this deficiency, poverty statistics are projected using current and prospective micro and macroeconomic indicators that are deemed to be highly correlated with the evolution of poverty. Specifically, historical and projected per capita GDP growth based on national accounts data are used to update the household surveys. This approach has been used by the World Bank (Lakner and others 2020; Mahler and others 2021) and others (for example, Valensisi 2020). The emphasis on GDP growth is based on a long-standing empirical regularity that growth is negatively associated with the change in poverty. This approach only partially reflects policies and distributional factors that also influence poverty through their impacts on actual and projected GDP growth.

The pandemic's impact on global poverty can be assessed in real time by examining the difference between the latest projections and pre-pandemic projections. Growth data and its latest projections are taken from the April 2022 *World Economic Outlook* (WEO; IMF 2022), and pre-pandemic projections are taken from the January 2020 WEO database. PovcalNet (World Bank 2021) provides information from the available household surveys, and the projections of population (SP.POP.TOTL) are taken from the Health Nutrition and Population Statistics (World Bank, 2022).

Under the assumption of no change in inequality within countries from pre-pandemic levels, every household is assumed to have a uniform change in its income (or consumption) as implied by the growth rate of a country's real GDP per capita.[2] This assumption leads to a shift in the household distribution without modifying its shape (Online Annex Figure 1.1.1, panel 1). The shift is equivalent to moving the poverty threshold while keeping the distribution unchanged from the latest observation (Online Annex Figure 1.1.1, panel 2).[3] In practice, computation is easier for shifting poverty thresholds than shifting distributions.

In this scenario, the global population under extreme poverty—measured as the number of people living on less than $1.90 PPP per day—is estimated to have increased by about 70 million in 2021 relative to pre-pandemic projections, down from an estimated 85 million in 2020 (Online Annex Table 1.1.1). The estimated increase in global poverty stems primarily from emerging markets (about 60 million in 2020 and 41 million in 2021), although the poverty rate is much higher in low-income developing countries.

[1] Prepared by Hamid Davoodi (FAD), Brooks Evans (FAD), Futoshi Narita (RES), and Cedric Okou (RES). This online annex is part of a research project on macroeconomic policy in low-income countries supported by the United Kingdom's Foreign, Commonwealth and Development Office (FCDO). The views expressed here do not necessarily represent the views of the FCDO.

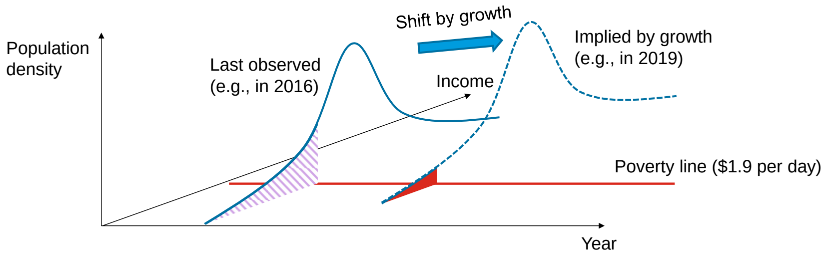
[2] An unchanged inequality may not be realistic. However, it serves as a proxy for poverty movements when the effects of redistribution policies largely offset inequality pressures.

[3] This poverty extrapolation exercise covers 167 economies. Although the shifts illustrated in panels 1 and 2 of the Online Annex Figure 1.1.1 are equivalent in terms of the poverty rate, the shift in panel 2 is more tractable thanks to the Stata command povcalnet (Castañeda Aguilar and others, 2019) which provides the population share of those living under any growth-adjusted poverty threshold based on the latest available household survey data in the PovcalNet (World Bank, 2021). The authors of this annex are grateful for the use of the Stata commands povcalnet provided by Castañeda Aguilar and others (2019) and wbopendata (Azevedo, 2011), both of which substantially increase accessibility to the data needed in this analysis.

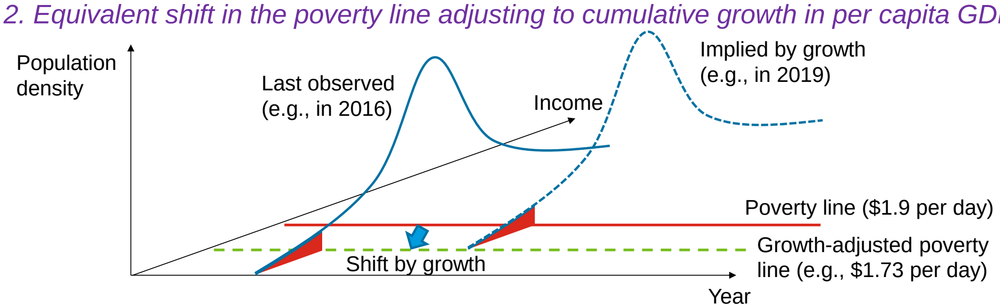
Although estimates in the literature vary, they all show a large increase in global poverty relative to pre-pandemic trends. Differences in the estimates originate mainly from two factors: the assumption on the elasticity of household income growth with respect to GDP growth, and GDP growth projections.[4] For example, despite using similar methodology, the global poverty estimates in the Chapter differ from those produced by the World Bank—Mahler and others (2021) estimate 97 million more poor people in 2021 relative to pre-pandemic trends. The difference is mainly driven by different growth projections. The Chapter assumes uniform elasticity of 0.85 for all economies instead of country-specific elasticities based on a decision tree algorithm (Mahler and others, 2021; Lakner and others, 2020). In general, the elasticity matters more for computing poverty levels than changes in poverty, and therefore plays a relatively minor role for assessing the impact of the COVID-19 pandemic on global poverty. For instance, the estimated pandemic impact of 69 million for 2021 becomes 62 (or remains close to 69) million if the elasticity is assumed to be 0.66 (or 1.00), respectively. As such, different growth projections largely explain the discrepancy in the estimated pandemic impact on poverty.

Online Annex Figure 1.1.1. Aggregate Growth and Poverty Projection

1. Shift in the distribution by cumulative growth in per capita GDP



2. Equivalent shift in the poverty line adjusting to cumulative growth in per capita GDP



Source. IMF staff illustrations.

Note. Panel 1 illustrates a thought experiment where the household income distribution kept its shape from the year when the distribution was last observed (e.g., 2016) to the year of interest (e.g., 2019) while everyone's income grew at the same rate in proportion to aggregate growth per capita. The poverty shares for 2016 (purple striped area) and for 2019 (red solid area) are the areas below a poverty line (red solid line, e.g., $1.90 per day) with respect to the observed 2016 distribution (solid bell curve) and the extrapolated 2019 distribution (dashed bell curve), respectively. Panel 2 illustrates an equivalent calculation of the red area by shifting the poverty line after adjusting for income growth (green dashed line, e.g., $1.73 per day assuming a 10 percent increase in the average household income growth from 2016 to 2019) while still using the observed 2016 distribution.

1.1.2. Global Poverty Assuming Changes in Inequality

The estimates in the previous section assume that inequality has not changed. However, the impact of the COVID-19 pandemic on poverty may also depend on distributional factors. This section presents poverty

[4] There are minor differences that arise from use of real GDP or real consumption, depending on whether the latest household survey uses either of them for poverty estimates as well as from imputing poverty estimates for countries not covered by PovcalNet (Mahler and others, 2021; Lakner et al, 2020).

estimates based on the approach of Davoodi and others (2022) that also allows for changes in inequality. The results suggest that changes in inequality have sizable implications on poverty estimates: a 1-percent increase in the Gini coefficient has an equivalent impact on the poverty estimate as a 1-percentage point decline in per capita real GDP growth (Online Annex Table 1.1.2). This finding is broadly consistent with Lakner and others (2020).

Online Annex Table 1.1.1. Estimates of the Global Extreme Poverty by Income Group

(Millions, percent of total population in parentheses)

Post-pandemic data and projections	2019	2020	2021
Global (167 economies) level	**618 (8.3)**	**689 (9.1)**	**658 (8.6)**
Advanced economies (32)	6 (0.6)	6 (0.6)	6 (0.6)
Emerging market economies (79)	161 (3.2)	207 (4.1)	173 (3.4)
Low-income developing countries (56)	451 (30.6)	476 (31.6)	480 (31.2)
Global (167 economies) change relative to pre-pandemic	**…**	**85 (1.1)**	**69 (0.9)**
Advanced economies (32)	…	0 (0.0)	0 (0.0)
Emerging market economies (79)	…	60 (1.2)	41 (0.8)
Low-income developing countries (56)	…	24 (1.6)	28 (1.8)

Source: IMF staff estimates

Online Annex Table 1.1.2. Estimates of the Global Population in Extreme Poverty

(Millions, percent of total population in parentheses)

Post-pandemic data and projections	2020	2021
Level		
Reducing inequality by 2 percent of the Gini coefficients	657 (8.7)	626 (8.2)
Reducing inequality by 1 percent of the Gini coefficients	673 (8.9)	642 (8.4)
Baseline	**689 (9.1)**	**658 (8.6)**
Widening inequality by 1 percent of the Gini coefficients	706 (9.3)	675 (8.8)
Widening inequality by 2 percent of the Gini coefficients	724 (9.6)	691 (9.1)
Higher per capita growth by 1 percentage points	677 (9.0)	646 (8.5)
Lower per capita growth by 1 percentage points	702 (9.3)	671 (8.8)
World Bank's latest projection (Mahler and others 2021)[1]	732 (9.4)	711 (9.1)
Change		
Reducing inequality by 2 percent of the Gini coefficients	53 (0.7)	37 (0.5)
Reducing inequality by 1 percent of the Gini coefficients	69 (0.9)	53 (0.7)
Baseline	**85 (1.1)**	**69 (0.9)**
Widening inequality by 1 percent of the Gini coefficients	102 (1.4)	86 (1.1)
Widening inequality by 2 percent of the Gini coefficients	120 (1.6)	102 (1.3)
Higher per capita growth by 1 percentage points	72 (1.0)	57 (0.7)
Lower per capita growth by 1 percentage points	98 (1.3)	82 (1.1)
World Bank's latest projection (Mahler and others 2021)[1]	97 (1.2)	97 (1.3)

Source: IMF staff estimates

Online Annex 1.2. Analysis of Poverty, Social Safety Nets, and Informality [1]

Chapter 1 reports on the simulated efficacy of social safety nets in poverty alleviation across countries that reflect the design of social safety nets. This annex presents data and methodological details supporting these findings while controlling for other factors that reflect changes in the simulated poverty changes that go beyond the design of social safety nets. A case study (*Brazil*) on the impact of cash transfers on poverty headcount—especially female poverty—is presented at the end of the annex.

1.2.1. Data and Econometric Methodology

Cross-country regressions are used to estimate the correlation between social protection and informality and poverty while controlling for per capita income and inequality. The regressions allow for three dimensions of social protection and labor programs (SPLs): adequacy, coverage, and benefits of a program relative to its costs (benefit-cost ratio). The effectiveness of a SPL depends on all three dimensions (World Bank 2018).

Data on SPLs in 98 emerging markets and low-income developing countries during 2000–19 were collected from the World Bank's *Atlas of Social Protection Indicators of Resilience and Equity* (ASPIRE). This database records all social protection benefits and labor programs captured as policy instruments in household surveys. The regressions use the latest available SPL for each country as a proxy for their pre-pandemic social protection and labor program structure. Definition of each variable and other data sources used in the regressions are provided in the Online Annex Table 1.2.1.

Online Annex Table 1.2.1. Data Sources and Definitions

Variable	Definition	Source
Poverty reduction	Simulated percentage point change in poverty due to Social Protection and Labor (SPL) programs at $1.90 international PPP poverty line. Poverty reduction is defined as pre-transfer poverty headcount rate minus post-transfer poverty headcount rate (both are in percent)	World Bank ASPIRE database
Adequacy	Amount of SPL transfers received by the poorest quintile divided by total pre-transfer income or consumption of beneficiaries in the poorest quintile (in percent).	World Bank ASPIRE database
Coverage	Number of individuals in the poorest quintile who live in a household where at least one member receives the SPL transfer divided by total number of individuals in the poorest quintile (in percent)	World Bank ASPIRE database
Benefit-cost ratio	Reduction in poverty gap obtained for each $1 spent on SPL programs. Benefit-cost ratio (in percent) is estimated as (poverty gap before transfer minus poverty gap after transfer) divided by total transfer amount.	World Bank ASPIRE database
Informality	Informal labor as a percent of total employment.	International Labor Organization (ILOSTAT)
Real per capita PPP GDP	Per capita GDP for 2019 (in thousands of $2011 Purchasing Power Parity).	World Bank World Development Indicators
Income inequality	Income inequality is measured by the Gini coefficient of income or consumption. It ranges from 0 (no inequality) and 1 (maximum inequality).	IMF FAD Income Inequality Dataset (Gini); and Word Bank's PovcalNet

Note: IMF staff compilation

1.2.2. Econometric Results

The results suggest that higher adequacy, coverage, and benefit-cost ratios for SPLs are jointly statistically significantly and are associated with larger simulated poverty reductions (Online Annex Table 1.2.2, column 4). For instance, increases of one standard deviation in adequacy, coverage, and benefit-cost ratio are associated with declines of 0.6, 1.2, and 3.3 percentage points in poverty, respectively. Results also show that higher level of per capita income and lower income inequality tend to be associated with larger simulated

[1] Prepared by Diala Al Masri (Oxford University), Hamid Davoodi (FAD), Brooks Evans (FAD), Futoshi Narita (RES), and Cedric Okou (RES). This online annex is part of a research project on macroeconomic policy in low-income countries supported by the *United Kingdom*'s Foreign, Commonwealth and Development Office (FCDO). The views expressed here do not necessarily represent the views of the FCDO.

poverty reductions. While these results suggest the importance of social safety nets and other factors, they do not necessarily prove causality, which would require more in-depth analysis, but the results are consistent with the existing evidence in the literature.[2]

The presence of large informal sectors that are not part of the formal system of social protection, taxation, and regulation, can complicate the efficacy of SPLs in reducing poverty (Chong and Gradstein. 2007). Pervasive informality could constrain the government's ability to provide policy support during the COVID-19 pandemic (Kose, Ohnsorge, and Yu, 2022). This has proven to be the case during past pandemic episodes (Cuesta and Hannan, 2021). The econometrics results show that the interactions between informality and adequacy, coverage, and benefit-cost ratio are statistically significant, and their signs suggest that higher informality reduces the impact of SPLs in simulated poverty alleviation (Online Annex Table 1.2.2, columns 5, 6, and 7).

Online Annex Table 1.2.2. Regressions: Poverty, Social Safety Nets, and Informality

	Dependent variable: Poverty Reduction						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Adequacy	0.0170			0.0202**	0.238***		
Coverage		0.0665***		0.0362*		0.315***	
Benefit-cost ratio			0.314***	0.280***			0.730***
Adequacy × informality [1]					-0.274***		
Coverage × informality [1]						-0.355***	
Benefit-cost ratio × informality [1]							-0.823***
Real per capita PPP GDP [2]	0.668***	0.489***	0.547***	0.458***	0.183***	0.166**	0.194**
Income inequality	-0.266***	-0.250***	-0.0729	-0.101	-0.0865*	-0.0957**	0.00655
Constant	8.802**	7.467*	-2.313	-2.877	3.859*	4.918**	-0.730
Observations (number of countries)	98	98	98	98	73	73	73
R-squared	0.59	0.60	0.69	0.73	0.74	0.78	0.78

Based on robust standard errors: *** p<0.01, ** p<0.05, * p<0.1

[1] Multiplied by 100

[2] Multiplied by 1000.

Source: IMF staff estimates

1.2.3. Case Study

The pandemic had severe impacts on labor market outcomes in *Brazil* with both employment and labor force participation falling in mid to late 2020. Employment losses were concentrated in contact-intensive sectors such as construction, household services, and hospitality. Furthermore, these losses were disproportionately felt among women, youth, and informal workers (Al Masri, Flamini, and Toscani, 2021).

[2] See Ravallion (1997) on the importance of inequality in poverty reduction. There is a voluminous literature on how SPLs—consisting of social safety nets/social assistance (e.g., cash transfers, food stamps), contributory social insurance (e.g., unemployment benefits, pay-as-you go retirement systems) and labor programs (e.g., job retention schemes)—help support incomes and consumption, enhance human capital formation, and reduce poverty (World Bank 2018).

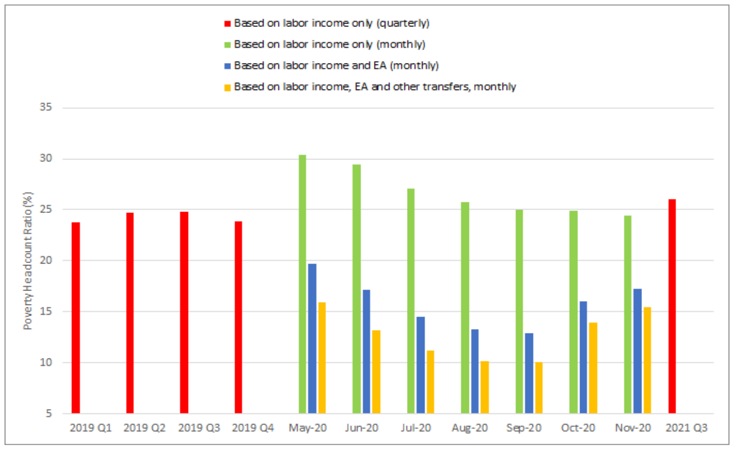
During 2020–21, *Brazil* relied on its pre-pandemic social safety net while also introducing programs that involved horizontal and vertical expansions of its social protection system.[3] Specifically, in April 2020 *Brazil* launched the Emergency Aid (henceforth EA) program—a means-tested cash-transfers initiative offering basic income to informal workers (employed and unemployed) and vulnerable households, with coverage of up to 60 percent of the total workforce and fiscal costs of up to 4.3 percent of GDP. The program is

expected to have delayed a dramatic rise in poverty and inequality during the pandemic. Moreover, it is estimated to have had a GDP multiplier of 0.5–1.5 in 2020 (Cunha, Pereira, Perrelli, and Toscani 2022).

The Online Annex Figure 1.2.1 shows the evolution of different measures of poverty under different transfers. All measures include labor income. These estimates suggest that, based on labor income alone and without any transfers, poverty rate rose during May-August 2020 compared with pre-pandemic period. Comparing the pre- and post-transfer poverty during May-November 2020 shows that the EA alone significantly reduced the poverty rate (on average by about 14 percentage points) and other transfers on average reduced poverty by about an additional 3 percentage points. The decline in poverty was the largest in August-September 2020 when the coverage and benefit levels were at their highest. Moreover, female poverty headcount ratio was also reduced on average by 14 percentage points during May-November 2020 when compared to what would have happened without it. Female poverty headcount ratio was about 10 percentage points less than the pre-COVID-19 average across all months.

Online Annex Figure 1.2.1. Poverty Headcount Ratio

(In percent)



Source: PNAD COVID; PNAD Continua, and IMF staff calculations.

Notes: Estimates are based on international upper middle income poverty lines ($5.5 in 2011 PPP), also used by Brazilian Institute of Geography and Statistics (IBGE). All poverty measures include earned labor income. Pre-COVID-19 poverty headcount ratio is based on reported labor income in PNAD Continua. Quarterly transfers for years prior to 2020 are not available in PNAD Continua. Other social transfers considered in the calculation of poverty headcount ratio from May through November 2020 include, in addition to the EA, Bolsa Familia, income from donations, alimony, income from retirement, unemployment insurance and others (like rent).

[3] Only 16 percent of countries worldwide attempted both types of expansions during the pandemic (Gentilini and others 2022).

Online Annex 1.3. Inflation and Fiscal Nexus: Empirical Findings[1]

Chapter 1 reports on fiscal implications of inflation, namely: (i) the effect of inflation surprises on fiscal outcomes; (ii) the correlation between policy rate changes and sovereign borrowing costs; and (iii) the impact of higher inflation uncertainty on sovereign borrowing costs. This annex presents further details on the data, methodology, and results.

1.3.1 The Effect of Inflation Surprises on Fiscal Outcomes

Data and econometric methodology

The effect of inflation surprises on fiscal outcomes is estimated using data from the IMF *World Economic Outlook* (WEO) vintages from 1992 to 2020. Surprises are defined as the realized value in year t given the information available as of the WEO published in October of the year $t+1$, minus the forecast in year t available in the WEO published in October of the year t. For example, the inflation surprise in 2019 is equal to the 2019 realization estimated as of October 2020 WEO minus the 2019 inflation forecast reported in the October 2019 WEO. This timing assumption filters out discretionary fiscal policy changes that were expected as of October of the concurrent year, thus alleviating endogeneity concerns.

The regression specification is as follows:

$$\hat{g}_{i,t} = \hat{\pi}_{i,t} + \hat{y}_{i,t} + \delta_i + \delta_t + \epsilon_{i,t}, \tag{1.3.1}$$

where hats indicate surprises, e.g.:

$$\hat{x}_{i,t} = E_{October(t+1)}(x_{i,t}) - E_{October(t)}(x_{i,t}),$$

and g is the nominal annual growth rate of a given fiscal outcome, π the inflation rate, y is the real growth rate of private demand, δ refers to country and year fixed effects, and ϵ is a potentially autocorrelated independent error term. The fiscal outcomes g are the nominal growth rates of general government revenues and expenses, as well as the change in the overall balances (in percent of GDP). Inflation is based on either the headline consumer price index (CPI) growth (period average) or the GDP deflator. Real private demand growth is defined as real GDP growth net of real growth in public consumption and in public investment (the latter only for countries where it is available in the WEO database). Netting out the contribution of the public sector avoids a mechanical correlation with growth in spending.

The sample excludes oil exporters, financial centers, periods of historical revisions to the entire time series (e.g., SNA updates), and observations with regressors outside their 5th-95th percentiles. The latter implies that the regression estimates show the impact of moderate inflation surprises. The estimated elasticities tend to be higher for larger inflation surprises. The results for the group of oil exporters are statistically insignificant.

The regression is also run for 1-year-ahead surprises in fiscal plans as the dependent variable, defined as $\tilde{x}_{i,t} = E_{October(t+1)}(x_{i,t+1}) - E_{October(t)}(x_{i,t+1})$. This alternative specification tests whether forecasters expect the impacts of surprise inflation to persist beyond the concurrent year.

Econometric results

The regression results for the three fiscal outcomes and the two measures of inflation considered in this annex are presented in the tables below. The values reported in Figure 1.11 of the Chapter correspond to the inflation estimates in these tables, averaging headline CPI and GDP deflator estimates. Specifically, in the

[1] Prepared by Jean-Marc Fournier, Daniel Garcia-Macia, Carlos Gonçalves, Anh Nguyen, and Roberto Perrelli (all FAD).

sample of advanced economies, an inflation surprise of 1 percent is associated with an increase of 0.4 percent in revenues (Online Annex Table 1.3.1, second column). Meanwhile, in the sample of emerging markets, an inflation shock of similar magnitude corresponds to an increase of 0.8 percent in nominal revenues (Online Annex Table 1.3.2, second column). The estimated response of revenues to inflation surprises is larger in the sample of emerging markets because countries in this group tend to present larger inflation surprises, and larger surprises lead to a more-than-proportionally larger revenue response.

Online Annex Table 1.3.1. Advanced Economies: Effect of Inflation Surprises on Same-Year Fiscal Outcomes

	Expense	Revenue	Ov. Bal./GDP	Expense	Revenue	Ov. Bal./GDP
Inflation	-0.465	0.247	0.334**	0.343***	0.352***	0.038
	-0.297	-0.315	-0.130	-0.116	-0.121	-0.051
Private demand	-0.189**	0.137	0.195***	-0.165**	0.149*	0.193***
	-0.084	-0.089	-0.037	-0.084	-0.088	-0.037
N	660	694	694	660	694	694
Inflation measure	HCPI	HCPI	HCPI	GDP Deflator	GDP Deflator	GDP Deflator
Fixed effects			Country & Year			

Source: IMF staff estimates
Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, and * p<0.1. N is the number of country-year observations.

Online Annex Table 1.3.2. Emerging Markets: Effect of Inflation Surprises on Same-Year Fiscal Outcomes

	Expense	Revenue	Ov. Bal./GDP	Expense	Revenue	Ov. Bal./GDP
Inflation	0.287	0.825**	0.019	0.281	0.743***	0.120***
	-0.366	-0.36	-0.091	-0.178	-0.172	-0.044
Private demand	0.168	0.382**	0.095**	0.161	0.356**	0.091**
	-0.152	-0.149	-0.038	-0.151	-0.147	-0.037
N	497	514	515	497	514	515
Inflation measure	HCPI	HCPI	HCPI	GDP Deflator	GDP Deflator	GDP Deflator
Fixed effects			Country & Year			

Source: IMF staff estimates
Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, and * p<0.1. N is the number of country-year observations

1.3.2. Policy Rates and Sovereign Borrowing Costs

Data and econometric methodology

Central banks are shifting towards monetary policy tightening in many countries. This sub-section provides estimates on the correlation between monetary policy tightening and sovereign borrowing costs in a sample of advanced economies and emerging markets. Two complementary econometric approaches are used: (i) estimating the correlation between short-term policy rates and the effective sovereign interest rate using fixed effects regressions in panel of 85 countries during 1990–2019 and (ii) estimating the same correlation using country by country regressions and collecting the distribution of coefficients pertaining to the policy rates obtained from the country-specific regressions. For *Euro Area* countries, *Japan*, the *United Kingdom,* and the *United States*, shadow interest rates are used whenever they are available, though the coefficients change only slightly when instead of the shadow rates, short-term interest rates are set to zero. For some of these countries, the estimated shadow rate serves as an alternative to the observed nominal policy interest rate that accounts for the effects of unconventional monetary policy at the effective lower bound (Adrian, Gaspar, and Vitek 2022).[2]

The inclusion of time-fixed effects attempts to capture global common factors that are likely more relevant for emerging markets, such as global interest rates and global risk sentiment indicators. Meanwhile, country-fixed effects help to control for institutional factors, including credibility of central bank and debt tolerance.

The baseline models are:

Panel-based specification:

$$i\_eff_{it} = c + \beta . i\_mpol_{it} + \gamma_i + \delta_t + \varepsilon_{it} \quad (1.3.2)$$

Country-by-country specification:

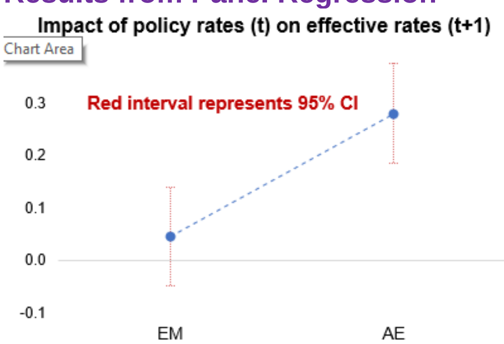
$$i\_eff_{it} = c + \beta . i\_mpol_{it} + \varphi . US10_t + d_{2008-2019} + \varepsilon_{it} \quad (1.3.3)$$

Where i_mpol_{it} is the monetary policy rate, i_eff_{it} is the effective nominal interest rate on sovereign debt, $US10_t$ is the average yield on *United States* 10-year Treasury bonds, $d_{2008-2019}$ is an indicator of the zero lower bound period, γ_i and δ_t are country- and time-fixed effects, respectively, and the subscripts *i* and *t* refer to countries and years. To capture potential heterogeneity across income groups, the econometric analysis is conducted separately for a group of 31 advanced economies and for another group of 54 emerging markets during 1990–2019, using data from World Economic Outlook database.

Econometric results

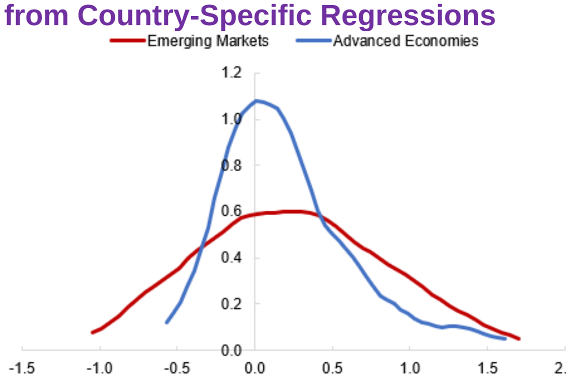
Results from country-specific regressions suggest that the correlation between short-term policy rates and effective sovereign interest rates is smaller (but it also has a more heterogenous distribution) in the sample of emerging markets than in the sample of advanced economies. This likely reflects more pronounced differences in debt composition, debt maturity, intervening external variables such as global risk aversion indicators, credibility of central bank, and debt tolerance levels, amongst other factors.

Online Annex Figure 1.3.1. Baseline Results from Panel Regression



Sources: IMF World Economic Outlook database and IMF staff calculations.
Note: AEs= Advanced Economies, EMs= Emerging Markets.

Online Annex Figure 1.3.2. Baseline Results from Country-Specific Regressions

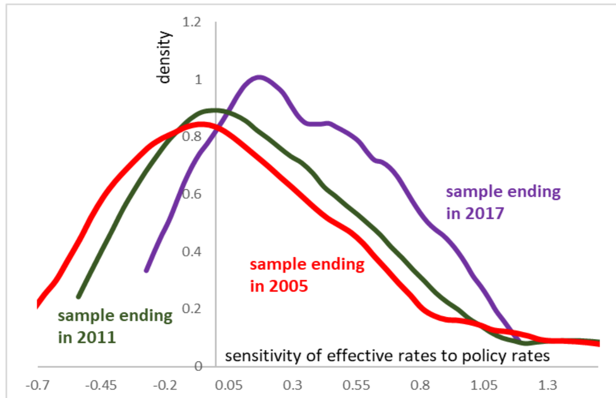


Sources: IMF World Economic Outlook database and IMF staff calculations
Note: Figure shows the distribution of the correlation between short-term policy rates and real effective interest rates based on country-by-country ordinary least square estimation for the 1990–2019 period and kernel approximations. The country-specific estimation also controls for the *United States* long-term interest rates and a dummy variable for the post-2009 period.

[2] Shadow rates for the *United States* were sourced from the Atlanta Federal Reserve Bank, based on Wu and Xia (2016), and for *Japan*, *Euro Area* countries, and the *United Kingdom* from a measure compiled by Morgan Stanley).

Baseline results obtained after estimating panel-based regressions—equation (1.3.2)—indicate that the correlation is statistically significant for the sample of advanced economies but not for the sample of emerging markets considered in this study (Online Annex Figure 1.3.1). Similar findings are obtained when considering the correlation between the short-term policy rate and the real effective interest rate using country-specific regressions (Online Annex Figure 1.3.2). Robustness checks using longer time series—specifically, three different windows of 30 years each—on a panel of advanced economies reveals evidence of a moderate increase in the correlation between sovereign borrowing costs and changes in monetary policy rates over time in this group of countries (Online Annex Figure 1.3.3).

Online Annex Figure 1.3.3. Time-Varying Sensitivity Estimates



Sources: IMF World Economic Outlook database and IMF staff calculations

Note: Advanced economies' data over three different windows of 30 years each were collected from Mauro and Zhou (2021).

Other robustness tests (adding lagged dependent variables, dropping zero-lower bound indicators, and dropping the *United States*' long-term interest rates) were conducted and supported the baseline results. When the lagged dependent variable is added, the long-term sensitivity (which considers the fact that any shock propagates through time via the autocorrelation of the variable of interest) is very close to the ones estimated using equations (1.3.2) and (1.3.3).

1.3.3. Inflation Uncertainty and Sovereign Borrowing Costs

Risks of new and severe virus variants, supply chains disruptions, and food and energy price volatility have raised uncertainty on the inflation path (IMF, 2022). Such uncertainty is gradually being observed in increasingly disperse distributions of inflation forecasts. Higher inflation volatility is relevant for the government's costs of borrowing because investors tend to demand higher premium for holding long-term sovereign debt in such environment to compensate for higher uncertainty about future real returns (Rudebusch and Swanson, 2012).

The impact of inflation uncertainty on sovereign borrowing costs is estimated with a panel of 16 advanced economies over the period 1975–2017, covering both high and low inflation episodes. First, a measure of inflation uncertainty is constructed for each country using a stochastic volatility framework.: higher volatility implies more uncertain forecasts (Bloom, 2014; Jurado, Ludvigson, and Ng 2015; Lastauskas and Nguyen 2021). Second, the impulse response of long-term sovereign interest rates to an increase in inflation uncertainty is obtained by applying the local-projection methods (Jordà, 2005) in a dynamic panel regression framework.

Data and econometric methodology

In the first stage, inflation volatility for each country is estimated based on the following stochastic volatility specification:

$$\pi_{it} = c_i + \sum_{h=1}^{q} \beta_{ih}\, \pi_{it-h} + \sigma_{it}^{\frac{1}{2}} \varepsilon_{it} \qquad (1.3.4)$$

$$\log(\sigma_{it}) = v_i + \sum_{h=1}^{p} \theta_{ih} \log(\sigma_{it-h}) + e_{it} \qquad (1.3.5)$$

$$\varepsilon_{it} \sim N(0,1) \text{ and } e_{it} \sim N(0, g_i)$$

where π_{it} is the annualized monthly inflation of country *i* at time *t* and σ_{it} is the time-varying variance capturing the volatility of inflation. The first moment (ε_{it}) and second moment shocks (e_{it}) are assumed to be orthogonal (see also Jacquier and others, 2002).

In the second stage, the impulse-response functions of long-term sovereign interest rates to an increase in inflation volatility are analyzed using the following specification:

$$y_{it+h} = \alpha_{i,h} + \gamma_{t,h} + \beta_h y_{it-1} + \theta_h \sigma_{it} + A_h Z_{it-1} + \sum_{k=0}^{1} B_{k,h} D_{it-k} + \varepsilon_{it+h} \qquad (1.3.6)$$

where y_{it} is the long-term sovereign interest rate, σ_{it} is the annual average of the inflation volatility measure estimated in the first stage, D_{it} is an indicator of systemic financial crisis episodes, Z_{it} includes proxies for the volatilities of real GDP growth rates and bilateral nominal exchange rates (vis-à-vis the *United States*' dollar).

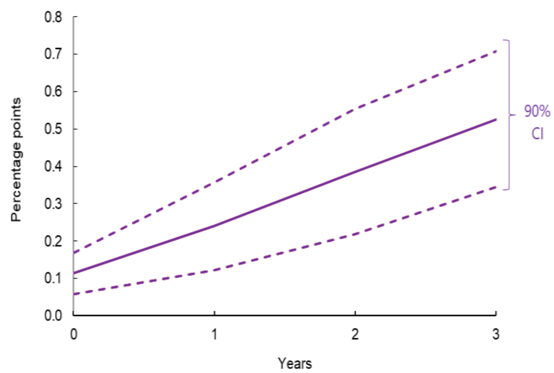
The level and volatility shocks to inflation are assumed to be orthogonal in equations (1.3.4) and (1.3.5), such that the endogeneity issue is limited when compared with alternative econometric approaches to this problem, such as generalized autoregressive conditional heteroskedasticity (GARCH) models and actual variances of monthly inflation over the year. The assumption of contemporaneous impact is equivalent to ranking the uncertainty indicator first in a vector-autoregressive (VAR) framework (as in Baker et al., 2016).

Monthly inflation data is obtained from Ha, Kose, and Ohnsorge (2021). Long-term sovereign interest rates, real GDP growth rates, indicators of systemic financial crisis episodes, and bilateral nominal exchange rates (vis-à-vis the USD) are collected from Jordà, Schularick, and Taylor (2017).

Model extensions

In addition to the specification described above, an extended model that attempts to control for states of nature characterized by high and low debt levels is considered. The goal is to capture heterogeneous impacts of inflation volatility on long-term bond yields across debt regimes:

Online Annex Figure 1.3.4. Response of Sovereign Long-term Interest Rate to Inflation Volatility Shocks



Sources: Jordà, Schularick, and Taylor (2017), Mauro and Zhou (2021), Ha, Kose, and Ohnsorge (2021).

Note: The broken lines represent the 90-percent confidence intervals using cluster standard errors. Regressions are based on local-projection method for a dynamic panel. Country and year fixed effects are included.

$$y_{it+h} = \alpha_{i,h} + \gamma_{t,h}\gamma_{t,h}I_{it-1}\left(\beta_h^1 y_{it-1} + \theta_h^1 x_{it} A_h^1 Z_{it-1} + \sum_{k=0}^{1} B_{k,h}^1 D_{it-k}\right) + (1 - I_{it-1})\left(\beta_h^2 y_{it-1} + \theta_h^2 x_{it} + A_h^2 Z_{it-1} + \sum_{k=0}^{1} B_{k,h}^2 D_{it-k}\right) + \varepsilon_{it+h}$$

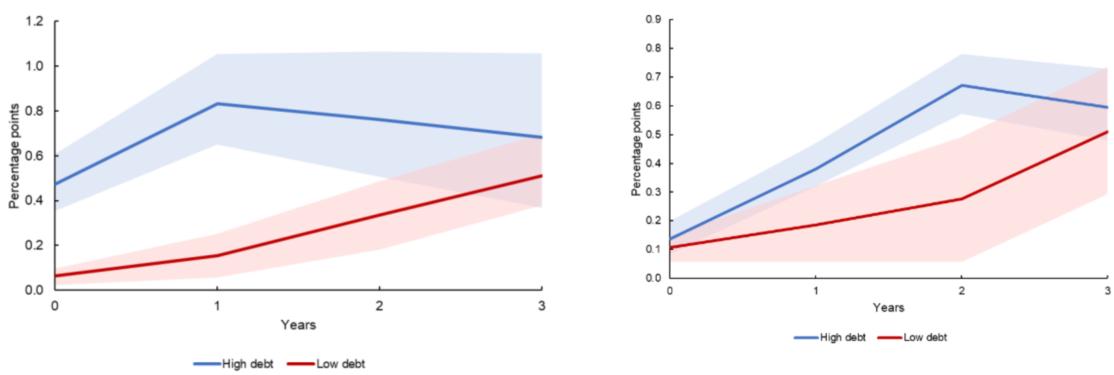
Where I_{it}^r is an indicator of the debt regime, with $I_{it-1} = 1 \; if \; d_{it-1} > \bar{d}_{it-1}$, i.e., debt-to-GDP at time $t - 1$ (d_{it-1}) is above its trend $(\bar{d}_{it-1})$. The trend of debt is estimated by using two different approaches: the Hodrick-Prescott and the Hamilton filtering methods (see Drehmann and Yetman, 2021 for a discussion).[3] Data on debt-to-GDP ratios were collected from Mauro and Zhou (2021).

Econometric results

Results from the baseline linear model suggest that a one-standard-deviation rise in inflation volatility is associated with a gradual increase in the long-term sovereign interest rate, from 0.1 percentage points on impact to 0.5 percentage points after 3 years (Online Annex Figure 1.3.4). The results are robust when considering an alternative specification where the first effect happens with a one-year lag. Regarding the debt-dependent responses, while the choice of filtering trend-cycle method matters quantitatively, both cases indicate a stronger response under high debt regime, reflecting an interaction between inflation uncertainty and debt vulnerability (Online Annex Figure 1.3.5).

Online Annex Figure 1.3.5: Debt-dependent Response of Long-term Interest Rate to Inflation Volatility Shocks

1. Using HP-filtered Trend
2. Using Hamilton-filtered Trend



Sources: Jordà, Schularick, and Taylor (2017), Mauro and Zhou (2021) , Ha, Kose, and Ohnsorge (2021).
Note: The shaded areas represent the 90% confidence intervals using cluster standard errors. Nonlinear regressions are based on local-projection method for a dynamic panel. Country and year fixed effects are included. High (resp. low) debt regime is when the country public debt-to-GDP ratio is above (resp. below) its trend. For HP-filtered exercise, the last two years are excluded to avoid the endpoint problem.

[3] The end-point issue relating to the Hodrick-Prescott filter is less problematic in the present exercise. Indeed, the results are almost identical with and without the last two years from the estimation.

References

Adrian, Tobias, Vitor Gaspar, and Francis Vitek. 2022. "A Medium-Scale DSGE Model for the Integrated Policy Framework." IMF Working Paper 2022/015, International Monetary Fund, Washington, DC.

Al Masri, Diala, Valentina Flamini, and Frederick Toscani. 2021. "The Short-Term Impact of COVID-19 on Labor Markets, Poverty and Inequality in Brazil." IMF Working Paper 21/66, International Monetary Fund, Washington, DC.

Azevedo, Joao Pedro. 2011. "WBOPENDATA: Stata Module to Access World Bank Databases." Statistical Software Components S457234, Boston College Department of Economics.

Bloom, Nicholas. 2014. "Fluctuations in Uncertainty." Journal of Economic Perspectives 28 (2): 153–76.

Castañeda Aguilar, R. Andrés, Christop Lakner, Eespen B. Prydz, Jorge Soler Lopez, R. Wu, and Q. Zhao. 2019. "Estimating Global Poverty in Stata: The PovcalNet Command." Global Poverty Monitoring Technical Note 9, World Bank, Washington, DC.

Chong, Alberto, and Mark Gradstein. 2007. "Inequality and Informality." Journal of Public Economics 91 (1–2): 159–79.

Cuesta, Juan P., and Swarnali Ahmed Hannan. 2021. "Recoveries After Pandemics: The Role of Policies and Structural Features." IMF Working Paper 21/181, International Monetary Fund, Washington, DC.

Cunha, Daniel, Joana Pereira, Roberto Perrelli, and Frederick Toscani. 2022. "Estimating the Employment and GDP Multiplier of Emergency Cash Transfers in Brazil." IMF Working Paper 2022/055, International Monetary Fund, Washington, DC.

Davoodi, Hamid, Brooks Evans, Futoshi Narita, and Cedric Okou. 2022. "Poverty Projections." IMF Working Paper, International Monetary Fund, Washington, DC.

Drehmann, Mathias, and James Yetman. 2021. "Which Credit Gap Is Better at Predicting Financial Crises? A Comparison of Univariate Filters." International Journal of Central Banking 70: 225–55.

Gentilini, Ugo, Mohamed Almenfi, Ian Orton, and Pamela Dale. 2022. "Social Protection and Jobs Responses to COVID-19: A Real-Time Review of Country Measures" (Version 16). World Bank, Washington, DC.

Ha, Jongrim, M. Ayhan Kose, and Franziska Ohnsorge. 2021. "Inflation during the Pandemic: What Happened? What Is Next?" CEPR Discussion Paper 16328, Centre for Economic Policy Research, London, UK.

Hanan, Swarnali A., Juan Pablo Cuesta Aguirre, and David Bartolini. 2021. "Social Spending in Mexico: Needs, Priorities and Reforms." Working Paper 2021/244, International Monetary Fund, Washington, DC.

Jacquier, Eric, Nicholas G. Polson, and Peter E. Rossi. 2002. "Bayesian Analysis of Stochastic Volatility Models." Journal of Business & Economic Statistics 20 (1): 69–87.

Jordà, Òscar, Moritz Schularick, and Alan M. Taylor. 2017. "Macrofinancial History and the New Business Cycle Facts." NBER Macroeconomics Annual 31 (1): 213–63.

Jurado, Kyle, Sydney C. Ludvigson, and Serena Ng. 2015. "Measuring Uncertainty." American Economic Review 105 (3): 1177–1216.

Kose, M. Ayhan, Franziska Ohnsorge, and Shu Yu. 2022. "The Informal Sector: Compounding the Damage of COVID-19." VoxEU, Center for Economic and Policy Research, Washington, DC.

Lakner, Christoph, Daniel G. Mahler, Mario Negre, Espen B. Prydz. 2020. "How Much Does Reducing Inequality Matter for Global Poverty?" Global Poverty Monitoring Technical Note 13, Washington, DC, World Bank.

Lastauskas, Povilas, and Anh Dinh Minh Nguyen. 2021. “Global Impacts of US Monetary Policy Uncertainty shocks.” Working Paper Series 2513, European Central Bank.

Mahler, Daniel Gerszon, Nishant Yonzan, Christopher Lakner, R. Andres Castaneda Aguilar, and Haoyu Wu. 2021. “Updated Estimates of the Impact of COVID-19 on Global Poverty: Turning the Corner on the Pandemic in 2021?” World Bank Blog, World Bank, Washington, DC.

Mauro, Paulo, and Jing Zhou. 2021. “r–g< 0: Can We Sleep More Soundly?” IMF Economic Review 69 (1): 197–229.

Ravallion, Martin. 1997. “Can High-Inequality Developing Countries Escape Absolute Poverty?” Economics Letters 56: 51–57.

Rudebusch, Glenn D., and Eric T. Swanson. 2012. “The Bond Premium in a DSGE Model with Long-Run Real and Nominal Risks.” American Economic Journal: Macroeconomics 4 (1): 105–43.

Sánchez-Páramo, Carolina, Ruth Hill, Daniel Gerszon Mahler, Ambar Narayan, Nishant Yonyan. 2021. “COVID-19 Leaves a Legacy of Rising Poverty and Widening Inequality.” World Bank Blog, World Bank, Washington, DC.

Valensisi, Giovanni. 2020. “COVID-19 and Global Poverty: Are LDCs Being Left Behind?” European Journal of Development Research 32: 1535–57.

World Bank. 2018. The State of Social Safety Nets. Washington, DC: World Bank.

World Bank. 2021. PovcalNet: An Online Analysis Tool for Global Poverty Monitoring. Washington, DC.

World Bank. 2022. Health Nutrition and Population Statistics. Washington, DC.