Annex 2.1. Data Sources, Sample Coverage, and Variable Definitions

Data sources used in the chapter are listed in Annex Table 2.1.1. The list of economies used for each exercise is provided in Annex Table 2.1.2.

Stylized facts on household balance sheets in Figure 2.2 in the chapter are built using aggregate data on household debt, financial and housing assets from the World Inequality Database. Household debt information is supplemented by data from the IMF's Global Debt Database. The correlation between income and wealth inequality in Figure 2.3 is measured using the shares of income and wealth that accrue to the bottom 50 percent of households along each dimension respectively. Data are taken from the World Inequality Database.

The distributions of household income and debt in Figure 2.4 for China, South Africa, Hungary, France, Italy, Germany, and the United Kingdom are derived from household wealth surveys for each country. The latest two available waves for each survey are used to train the nowcasting algorithm described in Annex 2.2 below. Macroeconomic and financial statistics on sectoral and regional gross value added, employment, wages, unemployment, house prices and sales, and bank lending are used to update the density estimates through 2020. Data sources and definitions vary slightly by country depending on data availability. For the United States, the analysis uses the 2019 and 2020 waves of the Consumer Expenditure Survey to directly estimate changes in debt ratios by income levels. Households are grouped by fixed income bands across years instead of income deciles. See Annex Table 2.1.1 below for details.

Stylized facts on current firms' balance sheet developments presented in Figures 2.5, 2.7, 2.8 are based on Standard & Poor's Capital IQ database, covering the period from 2006Q1 to 2021Q2. The database provides balance sheet and income statement information at the firm-level and at the quarterly frequency. The data was cleaned to remove firms which had negative values for assets or debt in any year, and observations with the incorrect sign for revenue, capital expenditure, cash, tangible assets, and interest expenditure were set to missing.[1] Additionally, ratios have been winsorized at 1% (leverage, return on assets (ROA), and interests coverage ratio (ICR)).

Firms are assigned into 20 sectors by Standard & Poor's Capital IQ. Sectors are further classified into "worst-hit industries", "middle", and "least-hit industries" based on the asset-weighted median operating revenue growth rate in 2020 (Figure 2.5). The top 5 worst-hit industries are consumer services; energy; automobiles and components; transportation; and consumer durables and apparel. The top 5 least-hit industries are semiconductors; software and services; pharmaceuticals and biotechnology; health care equipment and services; and household and personal products. The remaining 10 middle industries are capital goods; materials; professional services; utilities; media and entertainment; telecommunication services; food, beverage and

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[1] See Kim, Mano, and Mrkaic (2020) and Arbatli-Saxegaard, Firat, Furceri, and Verrier (forthcoming) for details.

tobacco; food and staples retailing; technology hardware and equipment; and retailing. In Figure 2.8, panel 3 sectors from Standard & Poor's Capital IQ are mapped to OECD STAN sectors using concordance tables between SIC and ISIC Rev. 4 industry classifications.

Relevant variables are computed as follows:

- Leverage: total liabilities over total assets.
- Interest coverage ratio (ICR): earnings before interest and taxes (EBIT) over interests paid.
- Return on assets (ROA): net income over total assets.
- Vulnerable firm dummy: firm-level dummy that equals one if, at time *t*, firm's leverage is in the top tercile of the sector leverage distribution, in the bottom tercile of ROA and it has an ICR<1; zero otherwise. The distribution is calculating pooling all firms across time within sector in order to account for sectoral structural differences, such as high fixed costs, that may require heterogeneous structure of indebtedness or low ICR.

Firms' investment analysis of the effect of firms' excess leverage on investment is constructed with Bureau van Dijk Orbis firm-level data from 1998 to 2018, at an annual frequency. The analysis covers all sector of the economy except for financial and insurance activities, public administration and defense, agriculture, forestry and fishing. Data have been cleaned as in Díez and others (2021), following closely Kalemli-Özcan and others (2015). Capital variables are deflated using investment (gross fixed capital formation) deflators at the country level from the World Bank's World Development Indicators database. For monetary non-capital variables, sector-specific deflators (producer price, or value added, or gross output by sector) from various sources (OECD, Eurostat, CEIC database, and government websites) are used. All variables are expressed in constant 2015 U.S. dollars. Additionally, ratios have been winsorized at 1% (leverage, liquidity ratio, return on assets (ROA), and interests coverage ratio (ICR)).

Relevant variables for the analysis are derived as follows:

- Liquidity ratio: current assets net of current liabilities over total assets.
- Excess debt-to-assets: three-year change in liabilities-to-assets, lagged to mitigate endogeneity concerns and standardized over the entire sample to ease interpretation.
- Investment ratio: log-difference of tangible fixed assets.
- Size: logarithm of total assets.
- Revenue growth: percentage change in turnover.

Additionally, the vulnerable firm dummy, ROA, ICR and leverage are defined as in the stylized facts.

Excess credit and subsequent output, consumption, and investment dynamics. Data on the private credit for households and non-financial corporations as percent of GDP is taken from the Bank for International Settlements. The response variables (GDP, consumption, and investment) are from the IMF's World Economic Outlook database. The proxy measurement of fiscal space is derived using principal components drawing on the database compiled by the World Bank (see Kose and others 2017). The wealth inequality sample split is based on the dissaving of the bottom 50 percent of households as computed in Allen, Kolerus, and Xu (2022). Temporal coverage is the most extensive unbalanced sample available starting in 1965, with the vast majority of economies entering the sample in the 1990s. Sample availability was determined by the intersection of available data. The IMF's WEO has the most extensive coverage, but fiscal space and wealth inequality coverage is somewhat more limited. See Annex Tables 2.1.1 and 2.1.2 for a detailed list of variables and country coverage.

Policy transmission. At the country level, data from the IMF's WEO, International Financial Statistics (IFS), Global Debt Database (GDD), and Integrated Macroprudential Policy (iMaPP) database are used. In addition, fiscal policy shocks are from IMF External Sector Report 2021 Chapter 2 and monetary policy shocks are constructed from Consensus Economics data following the approach of Furceri, Loungani, and Zdzienicka (2016). For a subset of countries, household consumption by income quintiles is from Allen, Kolerus, and Xu (2022) and corporate investment by leverage quintiles is constructed from the Bureau van Dijk Orbis dataset (with the data processed in a similar way as in the *Firms' investment analysis* section above).

Annex Table 2.1.1. Data Sources

Indicators	Source
Stylized Facts on Household Balance Sheets	
Household Debt (Percent of GDP)	International Monetary Fund, Global Debt Database
Household Financial Assets; Household Housing Assets; Wealth and Income Shares	Word Inequality Database; Eurostat; Bureau of Economic Analysis
Household Income and Debt Distributions	Household wealth survey data: China Family Panel Studies (China); Consumer Expenditure Survey (United States); Household Finance and Consumption Surveys (France and Hungary); Wealth and Assets Survey (United Kingdom); Survey of Household Income and Wealth (Italy); National Income Dynamics Study (South Africa); Luxembourg Wealth Study (LWS) Database (Germany). Macroeconomic and financial statistics: CEIC Data Company Limited; Haver Analytics; OECD; Eurostat; Hungarian Central Statistical Office; Italian National Institute of Statistics; Bank of Italy; Statistics South Africa; Office for National Statistics, UK Finance.
Stylized Facts on Current Firms' Balance Sheet Developments and Firms' Investment Analysis	
Total Liabilities; Total Assets; Current Liabilities; Current Assets; Tangible Fixed Assets; EBIT; Interest Paid; Net Income; Turnover (National Currency Converted to Constant 2015 U.S. Dollars)	Bureau van Dijk Orbis
Total Liabilities; Total Assets; EBIT; Net Interest Expense; Net Income (Current Prices, National Currency Converted to U.S. Dollars)	Standard & Poor's Global Market Intelligence, Capital IQ (IMF Aggregated Data is Not Standard & Poor's Information)
Gross Fixed Capital Formation (Current and Constant Prices, National Currency) to Derive Investment Deflators	World Bank, World Development Indicators
Sector-Specific Deflators (Producer Price, or Value Added, or Gross Output by Sector)	Diez and others (2021); OECD; Eurostat; CEIC Data Company Limited; Government Websites
Indicator of Crisis Preparedness	International Monetary Fund, Strategy, Policy, and Review and Legal Departments
Excess Credit and Subsequent Output, Consumption, and Investment Dynamics	
Total Credit to Households, and Total Credit to Nonfinancial Corporations (Percent of GDP)	Bank for International Settlements, Credit to the Non-Financial Sector database
Gross Domestic Product, Private Consumption Expenditure, and Gross Fixed Capital Formation (Constant Prices, National Currency)	International Monetary Fund, World Economic Outlook database
Dissaving by the Bottom 50 Percent	Allen, Kolerus, and Xu (2022); World Inequality Database
General Government Gross Debt (Percent of GDP); Primary Balance (Percent of GDP); Fiscal Balance (Percent of GDP); Cyclically-Adjusted Balance (Percent of Potential GDP); General Government Gross Debt (Percent of Average Tax Revenues); Fiscal Balance (Percent of Average Tax Revenues)	Kose and Others (2017); World Bank, A Cross-Country Database of Fiscal Space
Policy Transmission	
Gross Domestic Product (Constant Prices, National Currency)	International Monetary Fund, World Economic Outlook database
Private Debt (Loans and Debt Securities, Percent of GDP)	International Monetary Fund, Global Debt Database
Household Consumption by Income Quintile	Allen, Kolerus, and Xu (2022); World Inequality Database
Corporate Investment by Leverage Quintile	Bureau van Dijk Orbis
Macroprudential Index	International Monetary Fund, Integrated Macroprudential Policy (iMaPP) database

Source: IMF staff compilation.

Annex Table 2.1.2. Economies Included in the Analysis

Exercise	List of Economies
Stylized Facts on Household Balance Sheets	
Aggregate Household Balance Sheets (Figure 2.2)	Austria; Belgium; Cyprus; Czech Republic; Germany; Denmark; Spain; Estonia; Finland; France; United Kingdom; Italy; Lithania; Luxembourg; Netherlands; Norway; Slovak Republic; Slovenia; Sweden; United States
Correlation Between Wealth and Income Inequality (Figure 2.3)	Afghanistan; Albania; Algeria; Angola; Argentina; Armenia; Australia; Austria; Azerbaijan; Bahamas, The; Bahrain; Bangladesh; Belarus; Belgium; Belize; Benin; Bhutan; Bolivia; Bosnia and Herzegovina; Botswana; Brazil; Brunei Darussalam; Bulgaria; Burkina Faso; Burundi; Cabo Verde; Cambodia; Cameroon; Canada; Central African Republic; Chad; Chile; China; Colombia; Comoros; Congo, Democratic Republic of the; Congo, Republic of; Costa Rica; Croatia; Cyprus; Czech Republic; Côte d'Ivoire; Denmark; Djibouti; Dominican Republic; Ecuador; Egypt; El Salvador; Equatorial Guinea; Eritrea; Estonia; Eswatini; Ethiopia; Finland; France; Gabon; Gambia, The; Georgia; Germany; Ghana; Greece; Guatemala; Guinea; Guinea-Bissau; Guyana; Haiti; Honduras; Hungary; Iceland; India; Indonesia; Iran; Iraq; Ireland; Israel; Italy; Jamaica; Japan; Jordan; Kazakhstan; Kenya; Korea; Kuwait; Kyrgyz Republic; Lao P.D.R.; Latvia; Lebanon; Lesotho; Liberia; Libya; Lithuania; Luxembourg; Madagascar; Malawi; Malaysia; Maldives; Mali; Malta; Mauritania; Mauritius; Mexico; Moldova; Mongolia; Montenegro, Rep. of; Morocco; Mozambique; Myanmar; Namibia; Nepal; Netherlands, The; New Zealand; Nicaragua; Niger; Nigeria; North Macedonia; Norway; Oman; Pakistan; Panama; Papua New Guinea; Paraguay; Peru; Philippines; Poland; Portugal; Qatar; Romania; Russia; Rwanda; Saudi Arabia; Senegal; Serbia; Seychelles; Sierra Leone; Singapore; Slovak Republic; Slovenia; Somalia; South Africa; Spain; Sri Lanka; Sudan; Suriname; Sweden; Switzerland; Syria; São Tomé and Príncipe; Tajikistan; Tanzania; Thailand; Timor-Leste; Togo; Trinidad and Tobago; Tunisia; Turkey; Turkmenistan; Uganda; Ukraine; United Arab Emirates; United Kingdom; United States; Uruguay; Uzbekistan; Venezuela; Vietnam; Yemen; Zambia; Zimbabwe
Household Income and Debt Distributions (Figure 2.4)	China; France; Germany; Hungary; Italy; South Africa; United Kingdom; United States
Stylized Facts on Current Firms' Balance Sheet Developments	
Advanced Economies	Australia; Austria; Belgium; Canada; Cyprus; Czech Republic; Estonia; Finland; France; Germany; Greece; Hong Kong SAR; Iceland; Ireland; Israel; Italy; Japan; Korea; Latvia; Lithuania; Luxembourg; Macao SAR; Malta; Netherlands; New Zealand; Norway; Portugal; Singapore; Spain; Sweden; Switzerland; Taiwan Province of China; United Kingdom; United States
Emerging Market Economies	Argentina; Bahrain; Botswana; Brazil; Bulgaria; Chile; China; Colombia; Croatia; Egypt; Hungary; India; Indonesia; Jamaica; Jordan; Kazakhstan; Kuwait; Malaysia; Mauritius; Mexico; Oman; Pakistan; Peru; Philippines; Poland; Qatar; Romania; Russia; Saudi Arabia; South Africa; Sri Lanka; Thailand; Trinidad and Tobago; Tunisia; Turkey; Ukraine; United Arab Emirates
Firms' Investment Analysis	
Advanced Economies	Finland; France; Germany; Greece; Ireland; Israel; Italy; Japan; Korea; Latvia; Lithuania; Luxembourg; Netherlands, The; New Zealand; Norway; Portugal; Slovak Republic; Spain; Sweden; Switzerland; United States
Emerging Market and Developing Economies	Bulgaria; Chile; China; Colombia; Egypt; Hungary; Indonesia; Kazakhstan; Malaysia; Mexico; the Philippines; Poland; Romania; Russia; Thailand; Turkey; Vietnam
Excess Credit and Subsequent Output, Consumption, and Investment Dynamics	
Advanced Economies	Australia; Austria; Belgium; Canada; Czech Republic; Denmark; Finland; France; Germany; Greece; Hong Kong SAR; Ireland; Israel; Italy; Japan; Korea; Luxembourg; Netherlands, The; New Zealand; Norway; Portugal; Singapore; Spain; Sweden; Switzerland; United Kingdom; United States
Emerging Market Economies	Argentina; Brazil; Chile; China; Colombia; Hungary; India; Indonesia; Malaysia; Mexico; Poland; Russia; Saudi Arabia; South Africa; Thailand; Turkey
Policy Transmission	
Effects of Fiscal Consolidation: Benchmark	Argentina; Australia; Austria; Belgium; Brazil; Canada; Chile; China; Colombia; Costa Rica; Denmark; Dominican Republic; Ecuador; Finland; France; Germany; Guatemala; India; Ireland; Italy; Jamaica; Japan; Mexico; Netherlands, The; Peru; Portugal; Spain; Sweden; United Kingdom; United States; Uruguay
Effects of Monetary Tightening: Benchmark	Argentina; Australia; Brazil; Canada; Chile; Czech Republic; France; Germany; Hong Kong SAR; Hungary; India; Indonesia; Italy; Japan; Korea; Malaysia; Mexico; Netherlands, The; New Zealand; Norway; Philippines; Poland; Singapore; Slovak Republic; Spain; Sweden; Switzerland; Taiwan Province of China; Thailand; Turkey; United Kingdom; United States
Consumption by Income Quintiles (Figure 2.15, panel 1)	Belgium; Denmark; Finland; France; Germany; Ireland; Italy; Netherlands, The; Portugal; Spain; Sweden; United Kingdom; United States
Investment by Leverage Quintiles (Figure 2.15, panel 2)	Australia; Chile; Czech Republic; France; Germany; Hungary; Indonesia; Italy; Japan; Korea; Malaysia; Mexico; Netherlands, The; New Zealand; Norway; Philippines; Poland; Slovak Republic; Spain; Sweden; Switzerland; Thailand; Turkey; United Kingdom; United States

Source: IMF staff compilation.

Annex 2.2. Nowcasting Household Income and Debt Distributions

Conceptual Framework

We wish to nowcast the joint distribution of household income and debt in 2020. To do this, we build and train a nowcasting algorithm to predict this joint distribution for an earlier year when the nowcast can be compared to actual household survey microdata. The training is done by minimizing the squared distance of the actual joint density at some time $s+1$ with our nowcast of the distribution based on the previous survey wave conducted at time s. Specifically, our objective function is given by

$$\min \iint \left[f(y,l|t=s+1)-\hat{f}(y,l|t=s)\right]^2 dldy, \qquad (A.2.2.1)$$

where y and l are log household income and debt and $f(y,l)$ denotes their joint pdf. We also make explicit that this distribution depends on whether households have any debt $q=1[L>0]$, with $L=\exp(l)$, and on macroeconomic and financial data z

$$f(y,l|t)=\iint f(y,l|q,z,t)dF_q(q|z,t)dF_z(z|t=s). \qquad (A.2.2.2)$$

We follow DiNardo, Fortin and Lemieux (1996) and use reweighting and regression adjustment to estimate $\hat{f}(y,l|t=s)$ in terms of the income and debt distributions observed at time s and the growth rates of macroeconomic variables between s and $s+1$

$$\hat{f}(y,l|t=s)=\iint f(y+\Delta y,l+\Delta l|q,z,t=s)\psi_{q|z}(q,z)dF_q(q|z,t=s)\psi_{\dot{z}}(z)dF_z(z|t=s), \qquad (A.2.2.3)$$

where Δy and Δl are the change in y and l between s and $s+1$. Equation $(A.2.2.3)$ also includes the reweighting terms

$$\psi_{q|z}(q,z)=\frac{dF_q(q|z,t=s+1)}{dF_q(q|z,t=s)} \quad \text{and} \quad \psi_z(z)=\frac{dF_z(z|t=s+1)}{dF_z(z|t=s)},$$

which are the ratios of conditional mass and density functions of q and z respectively between time $s+1$ and s.

Since q is a binary variable and using Bayes' rule, $\psi_{q|z}(q,z)$ can be re-expressed as

$$\psi_z(z)=\frac{\Pr(t=s+1|z)}{\Pr(t=s|z)}\frac{\Pr(t=s)}{\Pr(t=s+1)}.$$

The weighting function $\psi_z(z)$ can be estimated non-parametrically using macro variables z in periods s and $s+1$, for example with a constant kernel estimator as in Hall, Li and Racine (2007). In practice, we regress the dummy variable $\tau=1[t=s+1]$ on z using a logit estimator so that $\psi_z(z)=c\exp(z_{k,t}\theta)$, with constant c.

Identification

In order to estimate equation $(A.2.2.3)$, we make the following two identifying assumptions:

Assumption 1. Conditional on their indebtedness status q, changes in household income and debt along the intensive margin can be modeled as a linear function[2] of the growth rates of macroeconomic and financial variables $\Delta z_{k,t}$, which include regional, sectoral and time dummies

$$E\left[\Delta x_{i\in k,t} | q_{i\in k,t} = j, \Delta z_{k,t}\right] = \Delta z_{k,t}\eta_x^j \qquad x = \{y, l\};\ j = \{0,1\}.$$

Assumption 2. Changes in the probability that a household has positive or zero debt can be estimated as a function of the growth rate of observed macroeconomic variables $\Delta z_{k,t}$

$$E\left[\Delta \Pr\left(q_{i\in k} = 1 | \Delta z_{k,t}\right)\right] = \Delta z_{k,t}\gamma^1 \quad \text{and} \quad E\left[\Delta \Pr\left(q_{i\in k} = 0 | \Delta z_{k,t}\right)\right] = \Delta z_{k,t}\gamma^0.$$

Using Assumptions 1 and 2, we can express the forecasted joint distribution $\hat{f}(y, l; t = s)$ as a function of microdata available at time s and macroeconomic and financial data through time $s + 1$ as

$$\hat{f}(y, l | t = s) = \iint \Psi(z, \Delta z) f\left(y + \Delta z\eta_y, l + \Delta z\eta_l \middle| q, z, t = s\right) dF_q(q | z, t = s) dF_z(z | t = s), \tag{A.2.2.4}$$

with $\Psi(z, \Delta z) = \exp(z\theta)\left[q(1 + \Delta z\gamma^1) + (1 - q)(1 + \Delta z\gamma^0)\right]$.

Estimation

We empirically estimate equation $(A.2.2.2)$ using a bivariate Gaussian kernel product function

$$f(y, l | t = s + 1) = \frac{1}{2\pi} \sum_{i\in\{t=s+1\}} \frac{\omega_i}{h^y h^l} \exp\left[-\frac{1}{2}\left(\frac{y - y_i}{h^y}\right)^2 - \frac{1}{2}\left(\frac{l - l_i}{h^l}\right)^2\right],$$

where ω_i denotes individual household survey weights and $\{h^y, h^l\}$ are the bandwidths for log household income and debt.

The forecasted density in equation $(A.2.2.4)$ is estimated using a weighted bivariate Gaussian kernel product function[3]

$$\hat{f}(y, l | t = s) = \frac{1}{2\pi} \sum_{i\in\{t=s\}} \frac{\omega_i}{h^y h^l} \Psi_i \exp\left[-\frac{1}{2}\left(\frac{y - y_i - \Delta z\eta_y}{h^y}\right)^2 - \frac{1}{2}\left(\frac{l - l_i - \Delta z\eta_l}{h^l}\right)^2\right],$$

with the parameter vector $\Gamma = \{\eta, \gamma, \theta\}$ chosen to minimize equation. $(A.2.2.1)$.[4]

Implementation

We assign households to k groups defined by region and industry of work of the first and second earners in each household.[5] We then match households by group to a set of observable macroeconomic variables, including GVA and GDP, employment, unemployment, labor

[2] We use splines to increase flexibility and explanatory power of the macro and financial variables $z_{k,t}$.

[3] DiNardo, Fortin and Lemieux (1996) use a univariate weighted Gaussian kernel function to estimate wage distributions in the US.

[4] The algorithm also constrains the total change in income and debt to match published statistics for 2020.

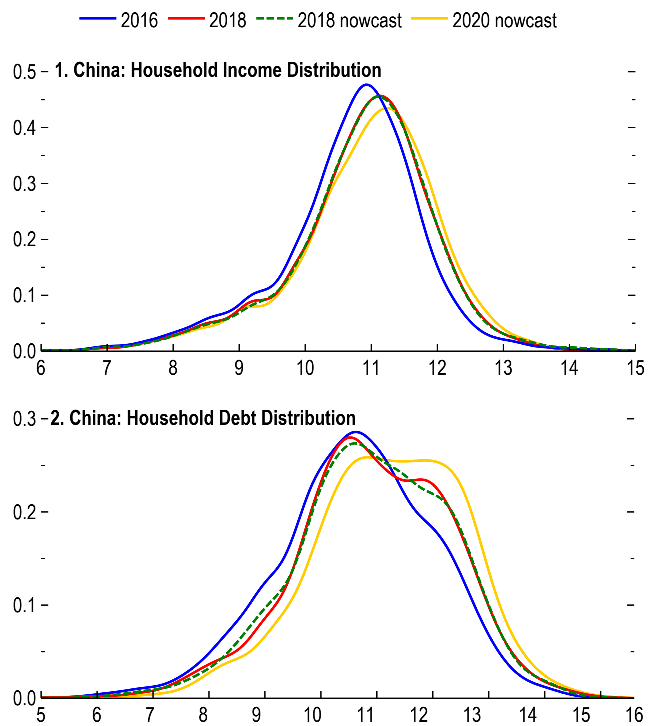
[5] Observations where industry is not observed, for example because respondents do not work, are assigned to a residual group.

compensation, house volume sales and prices and bank loans at the regional and industry levels.[6] We also include region and sector fixed effects.

The procedure then involves training the algorithm on an initial wave of the household survey to predict the joint distribution of household income and debt for the subsequent wave. The same model coefficients are then used to nowcast the distribution in 2020 based on aggregate changes in macro and financial variables through 2020. The performance of the algorithm can be assessed by comparing the 2018 nowcast curves to the actual 2018 kernel densities for income and debt (Figure 2.2.1).

Importantly, our identifying assumptions rely on regional and industry-level economic variation to predict changes in income and debt for individual households. The advantage offered by these data is that they are published with a much shorter lag than household survey data, which allows us to extrapolate the microdata until 2020.

Annex Figure 2.2.1. Nowcasting the Joint Distribution of Income and Debt
(Density; log real yuan on the x-axis)



Sources: CEIC Data Company Limited; and IMF staff calculations.

Finally, since household microdata vintages vary by country, we adjust the estimated changes in debt ratios from the nowcasted estimates to match the aggregate change between 2019 and 2020. This is done by subtracting from the nowcasted changes the aggregate change between the last year of microdata—2016 for Italy, 2017 for France, United Kingdom, Germany, Hungary and South Africa, and 2018 for China—and 2019.

Annex 2.3. Firms' Investment Analysis

Methodology

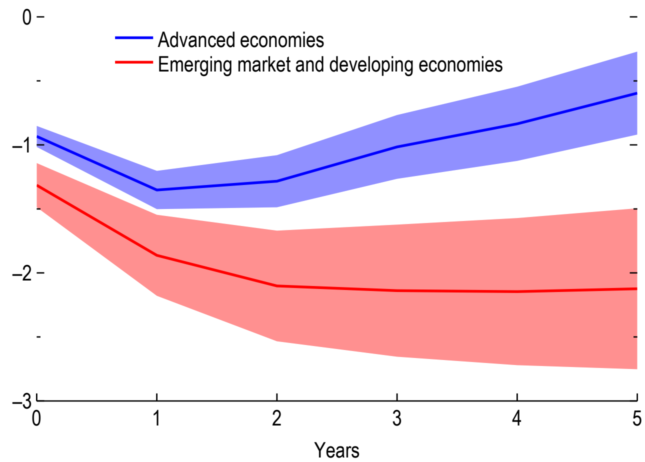
Following Albuquerque (2021), we estimate the following *unconditional equation* at the firm-level in a local projection framework. The sample covers 21 advanced and 17 emerging market and developing economies, over the timeframe 1998–2018:

$$k_{it+h} - k_{it-1} = \boldsymbol{\beta_1^h} \Delta_3 Lev_{i,t-1} + \beta_2^h X_{it-1} + \alpha_i^h + \mu_{cst}^h + \epsilon_{csit}^h \qquad (A.2.3.1)$$

[6] The specific variables vary by country depending on their availability.

The dependent variable is the firms' cumulative investment ratio in tangible fixed assets at different horizons $h=0,..,5$,[7] $\Delta_3 Lev_{i,t-1}$ is the firms' leverage buildup, defined as the three-year change in debt-to-assets $(Lev_{i,t-1} - Lev_{i,t-4})$ and standardized over the entire sample to ease the interpretation, X_{it-1} is a vector of lagged firm level controls (liquidity ratio, leverage, revenue growth, size, ICR and the dependent variable). The specification includes firms fixed effects. Thus, the firms' leverage buildup captures leverage accumulation above firms' average debt-to-assets. Sector-country-year fixed effects allow to pin down the partial equilibrium effect of credit booms by absorbing other time-varying confounding factors and general equilibrium forces at play. Finally, robust standard errors are clustered at firm level.

Annex Figure 2.3.1. Unconditional Effect of Firms' Leverage Buildup on Investment Ratio
(Cumulative percentage points)



Sources: Bureau van Dijk Orbis; and IMF staff calculations.
Note: Shaded areas represent 90 percent confidence intervals. The figure reports firms' investment ratio response to a one-standard-deviation change in leverage buildup.

The key parameter of interest is β_1^h, which captures the unconditional sensitivity of investment ratio to firms' leverage buildup over a five-year horizon. As illustrated in Annex Figure 2.3.1, investment ratio drops relatively more in EMDEs, consistently with the evidence found using country-level data, where investment spending decreases following a one percent of GDP persistent rise in debt-to-GDP. Following a one-standard-deviation change in cumulated leverage, investment ratio decreases by almost 1 percentage points at impact in advanced economies and 1.7 percentage points in emerging economies. While in the former the cumulated loss gradually decreases after the first year, in EMDEs, the cumulated effect on firms' investment ratio leads to permanent effects on the tangible capital stock. As underlined in Albuquerque (2021), the inclusion of pre-determined firms' controls in the specification reduces concerns that the observed behavior of firm's investment ratio is driven by other factors than leverage accumulation.

To estimate the *contribution of vulnerable firms*, the unconditional equation (A.2.3.1) is augmented to include the interaction between excess leverage accumulation with the vulnerable dummy (I_{it}), constructed as described in Online Annex 2.1. To control for heterogeneity between vulnerable and non-vulnerable firms via channels other than leverage buildup, the dummy is included by itself as well as interacted with the other covariates.

$$k_{it+h} - k_{it-1} = \boldsymbol{\beta_1^h} \Delta_3 Lev_{i,t-1} + \boldsymbol{\beta_2^h} \Delta_3 Lev_{i,t-1} * I_{it} + \beta_3^h X_{it-1} + \beta_4^h X_{it-1} * I_{it} + \beta_5^h I_{it} + \alpha_i^h + \mu_{cst}^h + \epsilon_{csit}^h \qquad (A.2.3.2)$$

[7] Although intangible capital is another important aspect to consider, it is out of the scope of this analysis.

Results are reported in Figure 2.12, panel 1 and 2 in the main text, for AEs and EMDEs respectively. For both advanced and emerging market economies, most of the effect is attributable to vulnerable firms and is measured by $\beta_1^h + \beta_2^h$.

As robustness check, we identify vulnerable firms pooling firms across time within sector and country group to additionally account for structural differences between advanced and emerging markets economies. Finally, we use an alternative definition of vulnerable firms similar to Albuquerque (2021). The dummy equals one if, at time *t*, firm's leverage is in the top quartile of the sector leverage distribution, and in the bottom quartile of the sector liquidity ratio distribution; zero otherwise. In both cases, results are consistent with the baseline analysis.

Finally, the role of *insolvency and reorganization proceedings* in preventing a large drop of investment is analyzed using the same specification as in (A.2.3.2) above but replacing the dummy indicator by a country level one based on the cross-country distribution of the newly created IMF crisis preparedness (Araujo and others 2022). The indicator captures the existence and availability of a comprehensive set of legal tools and institutions relevant for restructuring and insolvency proceedings in response to systemic crises, and it is based on five sub-indicators: out-of-court restructuring, hybrid restructuring, reorganization, liquidation, and institutional framework.[8] Figure 2.13, in the main text, compares the cumulated response of investment ratios to firms' leverage buildup for firms located in countries with well-prepared insolvency systems in place versus firms in jurisdictions with shortcomings in crisis preparedness. As illustrated by the cumulative investment ratio response, inadequate insolvency and restructuring proceedings account for most of the long-term decline in the stock of tangible capital.

Annex 2.4. Credit-Output Dynamics

Excess Credit and Subsequent Macroeconomic Dynamics. Little consensus exists among economists on an operational concept of private *excess credit*—leverage buildup that leads to subsequent deleveraging pressures (Dell'Ariccia and others 2016). Here we define excess credit ($excess\ credit_{i,t}$) as the cyclical component of the Hamilton filter (Hamilton 2018) which we use to disentangle secular trends—associated with financial deepening—from cyclical changes.[9] To improve the noise-to-signal ratio and focus on large and persistent credit cycles, we compute a three-year trailing average of the cyclical component that is then used in local projections in the spirit of Jordà (2005) to quantify the impact of excess credit on future output, consumption, and investment. This is comparable to other approaches such as Mian, Sufi, and Verner (2017). Country-level measures of excess credit are used in a panel of 43 countries (27 advanced economies, AEs, and 16 emerging market and developing economies, EMDEs) for with an unbalanced time coverage from 1969 to 2020 with time- and country-fixed effects for each projection horizon.

[8] For further discussion on the construction of the indicator, tailored policy recommendations and the value of the indicator for the full set of countries, also the ones not included in this analysis, refer to Araujo and others (2022).

[9] In an ideal empirical setting, we would be able to identify instruments for excess credit buildups across a broad range of countries and time-periods. Due to data constraints, the chapter instead relies on three-year trailing average of the Hamilton-filtered excess credit.

The two country groupings for which the empirical exercises are conducted are the IMF World Economic Outlook sub-groups "Advanced Economies" (AEs) and "Emerging Market and Developing Economics" (EMDEs) that have data on credit, fiscal space, and wealth inequality available. The list of economies in the sample is provided in Annex Table 2.1.2. The local projection equation is defined as:

$$\Delta y_{i,\,t+h|t-1} = \mu_i^h + \beta^h \cdot excess\ credit_{i,t} + v_t^h + \varepsilon_{i,t+h} \qquad (A.2.4.1)$$

where the left-hand-side variables are the cumulative percent change from $t-1$ to $t+h$ with $h = 1,2,\dots,5$

$$\Delta y_{i,\,t+h|t-1}^{(k)} = 100 \cdot \left(\frac{y_{i,t+h}^{(k)} - y_{i,t-1}^{(k)}}{y_{i,t-1}^{(k)}}\right)$$

and where k is either output, consumption, or investment. The figures 2.9–2.11 in the chapter visualize the β^h and their confidence intervals for the different projection horizons and can be interpreted as the cumulative change in left-hand-side variable to a one-percentage point increase in the credit-to-GDP ratio.

Differential Fiscal Position Credit-Output-Dynamics. Measuring the fiscal position is a science in and of itself. IMF (2018) uses a multi-dimensional framework that incorporates country-specific factors and judgements. Such assessments are not available for a sizeable cross-country panel of historical data. This subsection computes the fiscal position based on six indicators: (1) general government gross debt, (2) primary balance, (3) fiscal balance – (1) – (3) as percent of GDP – (4) cyclically-adjusted balance as a percent of potential GDP, (5) general government gross debt and (6) fiscal balance as percent of average tax revenues. These six indicators (Kose and others 2017) jointly reflect government's pre-existing debt stock, relative to overall output and relative to the government's revenue generating capacity and its fiscal cost of existing debt. While by no means an in-depth, country specific assessment of fiscal position, these six ratios taken together proxy for an economy's ability to undertake discretionary fiscal policies. The fiscal indicator used in the chapter's analysis is a proxy for the fiscal position based on a principal component of those six indicators. The first principal component explains about 60 percent of the variation in the data. Within year the data is sorted into quartile bins and the dynamics credit-output are contrasted between economies with weak and strong fiscal position classified by the principal component proxy. The resultant differential cumulative output responses for the two groups of economies, contrasting the response of the quartile with the strongest fiscal position and the weakest fiscal position after three years are presented in Figure 2.10.

Differential Wealth Inequality Excess Credit-Output-Dynamics. Figure 2.11 displays the household credit output dynamics for two different sets of economies with high and low wealth concentrations respectively. The group of advanced economies is split into two subgroups: First, one where the dissaving of the bottom 50 percent over a trailing three-year moving average had been highest, those are the economies that are, by that flow-based proxy, most unequal in terms of their wealth. Second, those economies where the dissaving of the bottom 50 percent over a trailing three-year average had been lowest. Note that in Allen, Kolerus, and Xu (2022) the bottom 50 percent households always dissave.

Robustness Checks. A couple of exercises to check on the robustness of the results were implemented. For the baseline results we also consider a credit-to-GDP ratio where the GDP figure is lagged by one year to ensure that results are not driven by abrupt movements in the denominator. For the fiscal space exercises, variations that included variables about the maturity structure ("Sovereign debt average maturity, years", mnemonic *avglife* in the World Bank Fiscal Space Database) and currency denomination ("General government debt in foreign currency, percent of total", mnemonic *fxovsh* in the World Bank Fiscal Space Database) as part of the principal component fiscal position classification. Another variant of the robustness checks was to include a long-term interest rate differentials vis-à-vis the United States using the "Long-term bond yield (Percent, Units)" in the IMF WEO database. Due to data limitations these robustness checks reduce the sample coverage, but the overall results are little changed. They are available upon request.

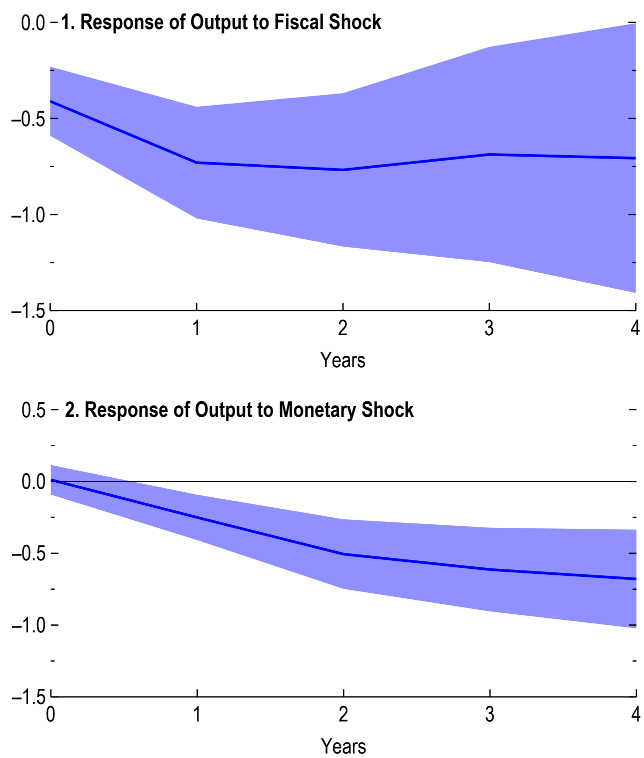
Annex 2.5. Effectiveness of Countercyclical Policies in the Presence of High Private Debt

This section analyses how private-sector debt affects the transmission of fiscal and monetary policies, with a focus on the effects for heterogeneous households and firms, with weaker and stronger balance sheets. Using fiscal policy shocks and monetary policy shocks that have been validated in previous cross-country studies, the effects of fiscal and monetary policy on real GDP are first estimated using local projections:

$$y_{i,t+h} - y_{i,t-1} = \mu_i^h + X_{i,t}\gamma^h + s_{i,t}\beta^h + v_t + \varepsilon_{i,t+h}, \quad s \in \{fiscal,\ monetary\}$$
(A.2.5.1)

where the dependent variable of interest is the change in real GDP over various horizons, *h*; μ_i and v_t are country fixed effects and year dummies, respectively; and $s_{i,t}$ is the annual fiscal or monetary policy shock. The coefficient β^h measures the cumulative response of real GDP in year *t+h* to a policy shock in year *t*. Robust standard errors are clustered by country.

Annex Figure 2.5.1. Effects of Macro Policy Tightening
(Percent change)



Sources: Consensus Economics Inc.; Guajardo, Leigh, and Pescatori (2014); and IMF staff calculations.
Note: Shaded areas represent 90 percent confidence intervals.

Fiscal and monetary transmission: aggregate data benchmark

The fiscal shocks employed are fiscal consolidations from Chapter 2 of the 2021 External Sector Report, who use a narrative approach to identify exogenous changes in government spending or taxes. The sample consists of 31 countries, half AEs and half EMs, from 1978 to 2019. Monetary policy shocks are constructed from forecast errors for the short-term (3-month) interest rate as in Furceri, Loungani, and Zdzienicka (2016). That is, unanticipated changes in the policy rate (proxied by 3-month interest rates) are calculated as the forecast error (FE_{it}^{r}). This is the difference between the actual short-term rate at the end of the year and the rate expected by analysis as of the beginning of October (3-months prior) for the same year. For each country, the interest rate forecast error is then regressed on the forecast errors for real GDP growth and inflation, calculated in the same manner. The residuals then capture the unanticipated movements in the rate that are not driven by news about economic activity.

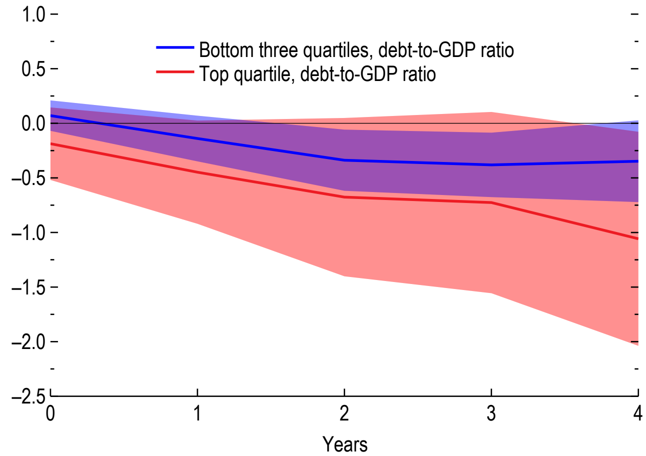
$$FE_{it}^{r} = \alpha_i + \beta_i FE_{it}^{r} + \gamma_i FE_{it}^{r} + \varepsilon_{it} \qquad \text{(A.2.5.2)}$$

Data needed to calculate FE_{it}^{r} is available for 31 countries, 21 AEs and 12 EMs, which thus make up the benchmark sample for the analysis for monetary tightening. For the United States, the resulting monetary policy shocks are very similar to an (annualized version) of the Romer and Romer (2004) monetary shocks.

Annex Figure 2.5.1 shows the *benchmark results*. The effects of fiscal and monetary policy estimated using these shocks are similar to that seen in the literature. A 1 percent of GDP fiscal consolidation leads to 3/4 percent decline in output after 2 years, which is the peak effect (Panel A). In panel 2, a 100 basis points monetary policy tightening leads to a ½ percent decline in output after 2 years, increasing to ¾ percent decline in year 4. Both the size and lagged impact of the monetary tightening are in line with the literature.[10]

Annex Figure 2.5.2. Response of Output to Monetary Shock: High Private-Debt-to-GDP Ratio

(Percent change)



Sources: Consensus Economics Inc.; IMF, Global Debt Database; and IMF staff calculations.

Note: Shaded areas represent 90 percent confidence intervals. The *x*-axis indicates the number of years after the monetary policy shock.

High aggregate private debt. The analysis then investigates whether the policy transmission is affected by the level of aggregate private-sector debt. This is done by including an interaction term equal to 1 when private debt-to-GDP is in the top-quartile of observations for each country. That is

$$y_{i,t+h} - y_{i,t-1} = \mu_i^h + X_{i,t}\gamma^h + s_{i,t}I_{i,t}\beta_A^h + s_{i,t}(1 - I_{i,t})\beta_B^h + v_t + \varepsilon_{i,t+h}$$

(A.2.5.3)

where $I_{i,t}$=1 if private debt to GDP is in the top quartile of observations for each country. This is similar to the approach of Ramey and Zubairy (2018), April 2020 WEO Chapter 2, and others who study the state-dependence of multipliers, testing the hypothesis that the effect of fiscal

[10] See Coibion (2012) for a comparison on the effects of different approaches to calculating and estimating the effects of monetary policy shocks for the US.

stimulus is larger during recessions. In our analysis, we control for the output gap to account for this form of state-dependence, among other control variables.

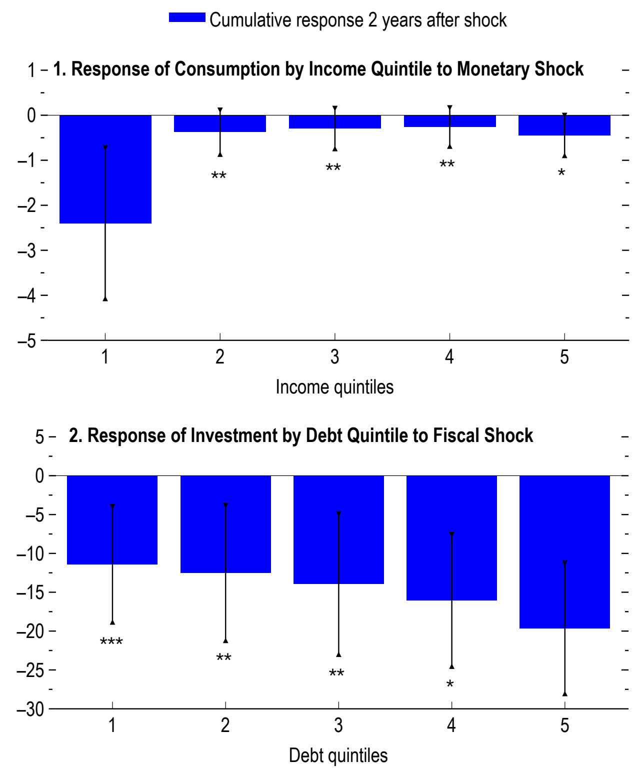
Figure 2.14 in the main text shows that the estimated effects of a fiscal consolidation are larger when private debt-to-GDP is in the top quartile. Annex Figure 2.5.2 shows both the interaction term, β_A^h, following a monetary policy shock, and β_B^h which represents the effect when debt-to-GDP is in the bottom three quartiles The estimated interaction term is negative, suggesting a larger contraction following the shock, but not statistically significant.

Fiscal and monetary transmission: importance of heterogeneity

Transmission of policies to heterogeneous households and firms. Recent studies have more explicitly recognized that the effects of macroeconomic policy will depend on the characteristics of households and firms. See the main chapter text for a discussion of how household and firm heterogeneity affects their responsive to policies.

The empirical analysis in this subsection uses two main datasets. For *households*, data from Allen, Kolerus, and Xu (2022), on consumption by quintiles of income. That is, for each country and year in the sample, the consumption of the lowest income group of households – the lowest quintile of household income – is calculated, and the consumption of the next four income quintiles is calculated. Since the data do not allow for a complete and regular picture of household balance sheets, consumption by debt-quintiles cannot be constructed. There is generally a positive relationship between income level and net worth across households, however (Figure 2.4 in the main text). Once this data is combined with the policy shocks, the sample consists of 13 countries from 1990 onwards. For *firms*, similar data on investment is built using the Bureau van Dijk Orbis dataset. Firms are sorted into quintiles by their leverage (debt-to-assets ratio) and then the real capital stock of firms in each group is aggregated. Once this data is combined with the policy shocks, the sample consists of 20 countries from 1997 onwards for fiscal policy, and 25 countries from 1997 onwards for monetary policy.

Annex Figure 2.5.3. Effects of Macro Policy Tightening on Heterogeneous Households and Firms: Additional Results
(Percent change)



Sources: Allen, Kolerus, and Xu (2022); Bureau van Dijk Orbis; and IMF staff calculations.
Note: In panel 1, the bars represent the estimated effect of a monetary policy tightening shock of 100 basis points on the consumption of five groups of households, according to their income levels, 2 years after the shock. In panel 2, the bars represent the estimated effect of a fiscal consolidation shock of 1 percent of GDP on the real investment of five groups of corporate, according to their leverage ratios. The *x*-axis indicates the quintile of corporate leverage. Error bars denote 90 percent confidence intervals. Statistically significant differences between the lowest income quintile in panel 1 (and highest leverage quintile in panel 2) and other quintiles at the 1, 5, and 10 percent confidence levels are denoted, respectively, by ***, **, *.

The empirical specification is similar to the benchmark specification in equation A.2.5.1 , except that the dependent variables of interest are now (1) household consumption for each income quintile, and (2) corporate investment for each leverage quintile.

$$c_{ij,t+h} - c_{ij,t-1} = \mu_{ij}^h + X_{i,t}\gamma_j^h + s_{i,t}\beta_j^h + v_t + \varepsilon_{ij,t+h} \quad , \quad j = 1,2,3,4,5 \quad \text{(A.2.5.4)}$$

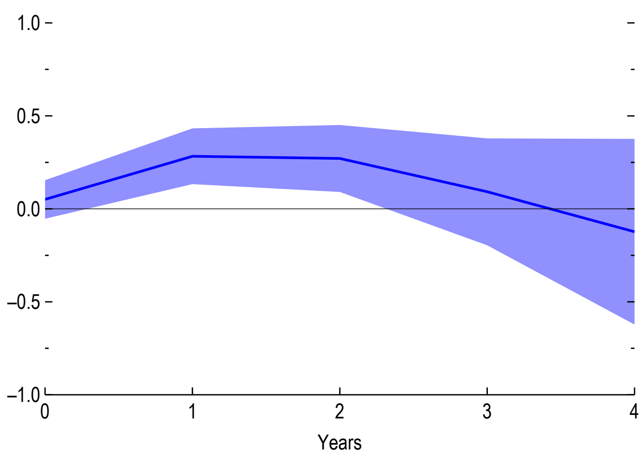
$$k_{ij,t+h} - k_{ij,t-1} = \mu_{ij}^h + X_{i,t}\lambda_j^h + s_{i,t}\delta_j^h + v_t + \eta_{ij,t+h} \quad , \quad j = 1,2,3,4,5 \quad \text{(A.2.5.5)}$$

Equation A.2.5.4 is estimated following a seemingly unrelated regression (SUR) approach, to account for potential correlation of residuals across quintiles, with robust standard errors clustered by country. Equation A.2.5.5 is also estimated as a SUR.

Figure 2.15 in the main text shows that, as expected, fiscal consolidation has the largest effect on the consumption of lower-income households, and monetary tightening negatively affects corporate investment for the most-leveraged corporates. Annex Figure 2.5.3 shows the effects of monetary policy on consumption and fiscal policy on investment. As with fiscal policy, monetary policy has the largest effect on the consumption of the lower-income quintile. Fiscal policy affects corporate investment negatively for all quintiles of leverage, but more so for the most leveraged quintile.

Macroprudential policy interaction. The final part of the analysis assesses how macroprudential settings across countries factor into monetary policy normalization. Macroprudential policies have been shown to mitigate the effects of negative financial shocks, though with a cost in good times (April 2020 WEO Chapter 3; Leduc and Natal 2018). At the country level, the analysis uses the index of macroprudential stringency from the IMF's integrated Macroprudential Policy (iMaPP) database. The index, which captures changes in 17 main macroprudential measures, is cumulated over time to measure the relative level of macroprudential policy across countries. This measure is then interacted with the monetary policy shock, for a sample of 31 countries from 1990 onwards:

Annex Figure 2.5.4. Response of Output to Monetary Shock Interaction with Macroprudential Stringency
(Percent change)



Sources: Consensus Economics Inc.; IMF, iMaPP database; and IMF staff calculations.
Note: The solid line represents the estimated coefficient on the interaction between monetary policy and the level of macroprudential policy; the shaded area represents 90 percent confidence interval. The *x*-axis indicates the number of years after the monetary policy shock.

$$y_{i,t+h} - y_{i,t-1} = \mu_i^h + X_{i,t}\gamma^h + s_{i,t}\beta^h + s_{i,t}MPru_{i,t}\delta^h + v_t + \varepsilon_{i,t+h} \quad \text{(A.2.5.6)}$$

where $MPru_{i,t}$ is the level of macroprudential regulation. The estimated interaction coefficient is reported in Annex Figure 2.5.4, showing that more stringent macroprudential policy mitigates the negative impact of monetary tightening on output.

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