Online Annex 2.1 Data Description and Sources

Online Annex Table 2.1.1. Variable Description and Data Sources

Variable	Description	Source
Global Variables		
Climate Disasters	The number of global climate disasters per year	The International Disaster Database
Excess Bond Premium	A measure of investor sentiment or risk appetite in the corporate bond market to predict the likelihood of a US recession in the next 12 months	Favara, Gilchrist, Lewis, and Zakrajšek (2016)
J.P. Morgan Emerging Markets Bond Index Global (EMBIG)	An index that tracks total returns for traded external debt instruments in the emerging markets	Bloomberg Finance L.P.
Monetary Policy Uncertainty - BBD	Index measuring uncertainty related to US monetary policy based on major newspapers.	Baker, Bloom, and Davis (2016)
Monetary Policy Uncertainty - HRS	Index measuring uncertainty related to US monetary policy based on major newspapers	Husted, Rogers, and Sun (2017)
MSCI All Country World Index (ACWI)	The MSCI All Country World Index (ACWI) is a stock index that tracks nearly 3,000 stocks across 23 Developed Markets and 24 Emerging Markets countries	LSEG Datastream
S&P 500 Index	Price of S&P 500 Index	Haver Analytics
S&P 500 Index Return	One-month return of S&P 500 Index	Haver Analytics; and IMF staff calculation
SKEW Index	The SKEW Index is a measure from the Chicago Board Options Exchange (CBOE) that indicates investor perception of the probability of financial market tail risks	Bloomberg Finance L.P.
Temperature anomalies	Temperature anomalies are average global surface temperature anomalies with respect to the average over 1901-2000	NOAA National Centers for Environmental information
Trade Policy Uncertainty	Index based on frequency of joint occurrences of trade policy and uncertainty terms across major newspaper	Caldara and others (2020)
Trade-Weighted Dollar Indexes	The broad index of the foreign exchange value of the dollar	Federal Reserve Board
US 2-year Government Bond Yield	Interest rate for US government bonds with two-year maturity	Haver Analytics
US Term Spread	Interest spread between US government bonds with ten-year maturity and two-year maturity	Haver Analytics; LSEG Datastream; and IMF staff calculations
VIX	Volatility index measures the market's expectations for volatility over the coming 30 days. The VIX is based on S&P 500 index options and is calculated and disseminated on a real-time basis by the CBOE.	Haver Analytics
VVIX	The VVIX, also known as the CBOE VIX of VIX Index, measures the volatility of the CBOE Volatility Index (VIX) itself	Bloomberg Finance L.P.
Country-level Variables		
10-year Government Bond Yield	Interest rate for government bonds with ten-year maturity	Bloomberg Finance L.P.; LSEG Datastream
3-month Government Bond Yield	Interest rate for government bonds with three-month maturity	Haver Analytics; LSEG Datastream
Consumer Price Index	The price index of a weighted average market basket of consumer goods and services purchased by households	IMF Global Data Source database
Bank Credit Growth	Growth of banks' credits to non-financial private sector, adjusted for inflation	Bank for International Settlements; and IMF staff calculations
Bank Exposure to Government Debt	Government securities holdings of domestic banks as a percentage of total assets	IMF Monetary and Financial Statistics database
Credit to GDP Gap	The gap between the credit-to-GDP ratio and its long-term trend	Bank for International Settlements; and IMF staff calculations.
Earnings Call Uncertainty	Uncertainty measure based on banks' earning calls	LSEG Datastream and IMF staff calculations
Economic Policy Uncertainty Index	Index which quantifies newspaper coverage of policy-related economic uncertainty	Baker, Bloom and Davis (2016); Cerda, Silva and Valente (2016); Baker, Bloom, Davis and Wang (2013); Gil and Silva (2018); Davis (2016); Hardouvelis, Karalas, Karanastasis and Samartzis (2018); Zalla (2016); Arbatli, Davis, Ito and Miake (2019); Kroese, Kok and Parlevliet (2015); Ghirelli, Perez, and Urtasun (2019); Armelius, Hull, and Köhler (2017); and IMF staff calculations

Excess Exchange Rate Return	Three-month exchange rate return in excess of Trade-Weighted Dollar Indexes	LSEG Datastream; Federal Reserve Board; and IMF staff calculations
Excess Stock Return Index	Dividend-adjusted equity price return in excess of S&P 500 returns (local currency)	LSEG Datastream; and IMF staff calculations
Exchange Rate Regime	Classifications on exchange rate arrangement	Ilzetzki, Reinhart, and Rogoff (2019)
Financial Conditions Index	Index measuring a country's financial conditions. A higher index indicates riskier financial conditions. See Chapter 1 of the October 2018 GFSR for further details.	Bloomberg Finance L.P.; LSEG Datastream; and IMF staff calculations
Financial Uncertainty	Time series measures of financial uncertainty	IMF staff calculations
Foreign Currency Denominated Public Debt	Government's borrowing denominated in a currency other than that of the debtor's country	IMF World Economic Outlook database
Foreign Reserves	Foreign assets held by the central bank of a country	IMF Balance of Payments database
Total Credit Growth	Growth of all sectors' credits to non-financial private sector, adjusted for inflation	Bank for International Settlements; and IMF staff calculations
GDP Forecast Standard Deviation	Standard deviation of one-year ahead consensus GDP forecasts	Consensus Economics
GDP Growth	Growth of gross domestic production, inflation-adjusted	IMF Global Data Source database
Geopolitical Uncertainty Measure	Index based adverse geopolitical events based on newspaper articles coverage	Caldara, Dario, and Matteo Iacoviello (2021)
Government Debt Ratio	Government securities holdings as a percentage of GDP	Institute of International Finance; and IMF staff calculations.
Industrial Production	Industrial production index, 2010=100	IMF Global Data Source database
Non-Performing Loans Ratio	Non-performing loans as a percentage of gross loans	IMF Financial Soundness Indicator database; World Bank Global Financial Development Database; and IMF staff calculations
Policy Rate	Policy-related interest rate set by the central bank	IMF Global Data Source database
Real Economic Uncertainty	Time series measures of macroeconomic uncertainty	Jurado, Ludvigson, and Ng (2015); OECD Main Economic Indicators Database; IMF Global Data Source database; IMF International Financial Statistics database; and IMF staff calculations
Regulatory Capital Ratio	Regulatory capital as a percentage of risk-weighted assets	IMF Financial Soundness Indicator database; World Bank Global Financial Development Database; and IMF staff calculations
Return on Assets	Operating profits as a percentage of total assets	IMF Financial Soundness Indicator database; World Bank Global Financial Development Database; and IMF staff calculations
Stock Dividend Yield	Dividend yields of stocks	LSEG Datastream
Stock Price to Earnings Ratio	The price of a stock to its earnings	LSEG Datastream
Stock Return Index	Equity price return, dividend-adjusted	LSEG Datastream
Stock Return Index Standard Deviation	Standard Deviation of dividend-adjusted equity price return within 3 months	LSEG Datastream; and IMF staff calculations
Unemployment Rate	The number of unemployed people as a percentage of the labor force	IMF International Financial Statistics database
US DOLLAR Government Bond Yield	Interest rate for government bonds issued in US DOLLAR	Bloomberg Finance L.P.
World Uncertainty Index	Index that tracks uncertainty based on the country reports of the Economist Intelligence Unit	Ahir, Bloom, and Furceri (2022)

Online Annex Table 2.1.2. List of Countries in the Sample

Advanced economies (AEs)	Emerging market economies (EMs)
Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong SAR, Ireland, Italy, Japan, Korea, Luxembourg, Netherlands, Norway, Singapore, Spain, Sweden, Switzerland, United Kingdom, United States.	Argentina, Brazil, Chile, China, Colombia, Egypt, Hungary, Indonesia, India, Kazakhstan, Lebanon, Mexico, Malaysia, Nigeria, Peru, Philippines, Poland, Russia, South Africa, Türkiye, Ukraine.

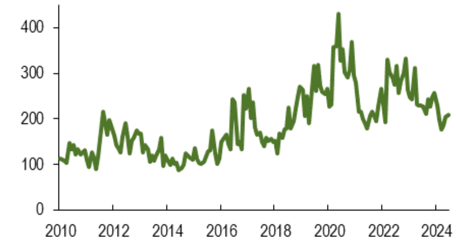
Note: Exact sample composition varies across empirical analyses based on data availability during 1990 to 2024 for the different variables.

A. Additional Stylized Facts

Online Annex Figure A.2.1.1. Macroeconomic Uncertainty and Financial Vulnerabilities

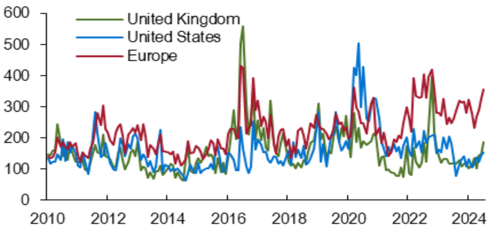
Global economic policy uncertainty declined in 2024 but has increased in recent months…

1. Global Economic Policy Uncertainty, 2010:M1-2024:M6
(Index)



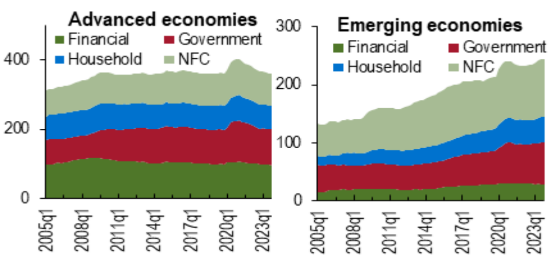
…due to a rise in policy uncertainty in some major economies amid electoral uncertainty.

2. Economic Policy Uncertainty in Europe, United Kingdom, and the US, 2010:M1-2024:M7
(Index)



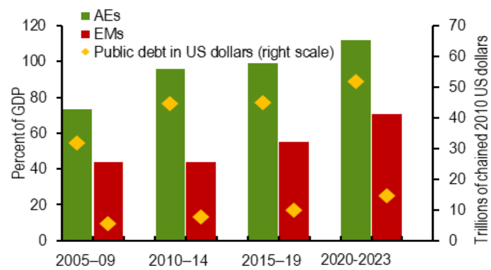
Global debt has increased over the past two decades, particularly during the COVID-19 pandemic.

3. Total Debt Breakdown, 2005-23
(Percent of GDP)



Government debt-to-GDP ratios have increased steadily.

4. Public Debt, 2005–23
(Percent of GDP; trillions of US DOLLAR)

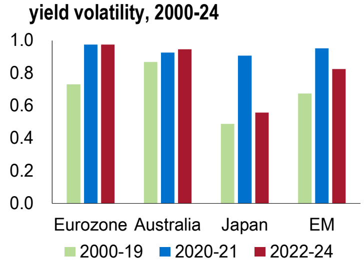


Sources: International Institute of Finance; IMF, World Economic Outlook; Baker, Bloom and Davis (2016); and IMF staff calculations.
Notes: Panels 1 and 2 present the economic policy uncertainty indices for the world and selected advanced economies, respectively. Panel 3 shows the total debt composition in AEs and EMs, respectively. Panel 4 shows the level of public debt in percent of GDP and in US DOLLAR trillions in AEs and EMs. AEs=advanced economies. EMs=emerging markets. NFC=nonfinancial corporate.

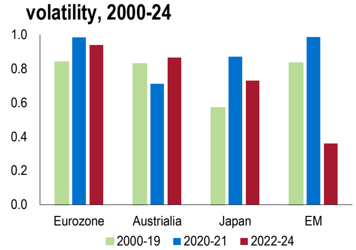
Online Annex Figure A.2.1.2. Spillovers of Market Volatility

Correlation between bond and stock market volatility has generally increased…

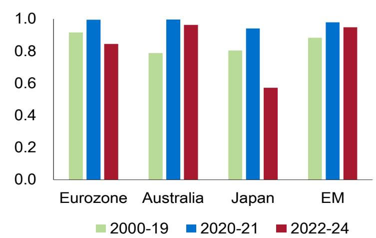
1. Correlation with US government bond yield volatility, 2000-24



2. Correlation with US corporate bond yield volatility, 2000-24

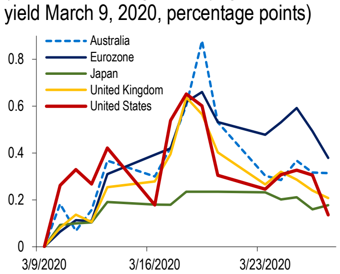


3. Correlation with US stock market volatility, 2000-24

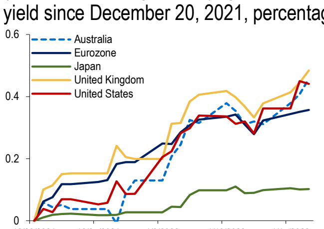


…and recent stress in bond markets has quickly spread across borders.

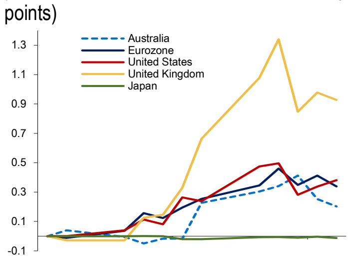
4. March 2020 dash for cash episode
(Cumulative change in 10-yr government bond yield March 9, 2020, percentage points)



5. US Federal Reserve Tapering and Monetary Policy Tightening Announcement
(Cumulative change in 10-yr government bond yield since December 20, 2021, percentage points)



6. U.K. Gilt Crisis 2022
(Cumulative change in 10-yr government bond yields since September 15, 2022, percentage points)



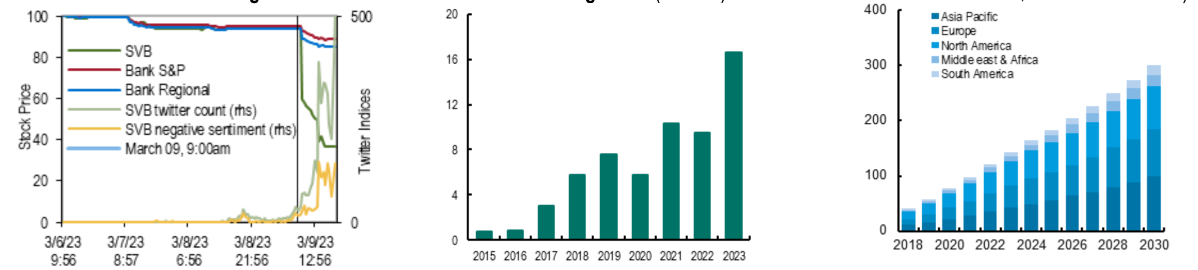
Sources: Barclays; ICAP; Bloomberg Finance L.P.; Fannie Mae; and IMF staff calculations.
Notes: Panels 1 and 2 show the correlation between volatility in US 10-year government bond yields and corporate bond yields and those of specified regions/country groups, respectively. The reported periods in panel 1 partially overlap with the Bank of Japan's Yield Curve Control framework, which might make the observed degree of inward spillovers from global markets to Japanese government bond yields smaller than otherwise. Panel 3 shows the correlation between S&P500 volatility and the stock market volatility of the specified regions. Panels 4-6 show the cumulative changes in the daily 10-year government bond yield for specified regions during recent market stress episodes of: 1) March 9-27, 2020 ("2020 dash for cash"); 2) December 20, 2021-January 19, 2022 (the US Fed announcement of plans to accelerate the tapering of US Treasury and mortgage-based securities asset purchases and in general a more aggressive tightening trajectory of policy rates; and 3) September 15-30, 2022 ("2022 United Kingdom Gilts crisis").

Online Annex Figure A.2.1.3. Social Media, Artificial Intelligence, and Financial Systems

Social media and stock price index during the March 2023 US banking turmoil

Share of companies mentioning AI in Russell 3000 earnings calls (Percent)

Use of AI in the banking industry (Business value derived from AI, billions of US Dollar)



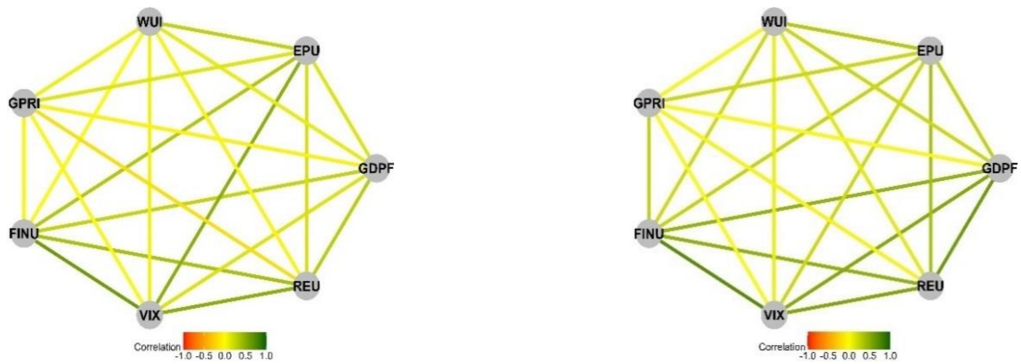
Sources: Bloomberg Finance L.P.; HIS Markit, Statista; and IMF staff calculations.
Notes: In panel 1, the vertical line refers to the time of 9am on March 09, 2023. The green lines represent text-based indices reflecting the mentioning of Silicon Valley Bank (SVB) on twitter ("SVB twitter") and the number of mentions with negative sentiment ("SVB negative sentiment"). The blue lines indicate price indices based on the composite of banks comprised in the S&P 500 ("Bank S&P"), the sub-group of regional banks ("Bank regional") and the stock price of SVB in US DOLLAR. Price indices are rebased with first observation available in March 2006.

Online Annex Figure A.2.1.4. Correlation Between Uncertainty Measures Over Time

Correlation between selected uncertainty measures has increased over time.

1. Correlation Between Selected Measures of Macroeconomic and Financial Uncertainty, 1990–2009 (Index)

2. Correlation Between Selected Measures of Macroeconomic and Financial Uncertainty, 2010–23 (Index)



Sources: See Online Annex 2.1; and IMF staff calculations.

Online Annex 2.2. Measures of Uncertainty

Online Annex Table 2.2.1 summarizes the uncertainty measures used in this chapter, which are described in the main text (paragraph 11), along with the literature sources where detailed methodologies of construction can be found.[1] As also noted in the main text (Box 2.2), this chapter develops a new bank-level measure of uncertainty based on text analysis of banks' earnings calls to capture directly the level of uncertainty perceived by banks that could affect their lending behavior. Section A provides details on the construction of the econometric-based macroeconomic uncertainty measures. Section B examines the extent to which financial variables can span the macroeconomic uncertainty measures. Section C examines episodes of good versus bad uncertainty in the data.

Online Annex Table 2.2.1 Selected Uncertainty Measures

Uncertainty Measure	Type	Description	References/Source
Macroeconomic	Econometric based	Aggregate of the conditional volatility of the unforecastable component of a set of economic variables	Jurado and others (2015)
	Text based	Share of news articles discussing uncertainty about various aspects of economic policy	Baker and others (2016)
	Survey based	Deviations of macroeconomic data projections	Consensus projections
	Text based	Frequency of the word "uncertainty" in the quarterly Economist Intelligence Unit country reports	Ahir and others (2022)
	Text based	Frequency of words referring jointly to "economic" or "economy"; and "uncertain" or "uncertainty"	Banks' earnings calls transcripts.
	Geopolitical (text-based)	Share of news articles discussing risks from geopolitical events	Caldara and Iacoviello (2022)
Financial	Econometric based	Aggregate of the conditional volatility of the unforecastable component of a set of financial variables	Ludvigson and others (2021)

A. Construction of Econometric-based Measures of Uncertainty

Following the methodology in Ludvigon and others (2021) and Londono and others (2024), for each country *i*, $REU_{i,t}$ ($FINU_{i,t}$) combines the uncertainty metrics developed for a wide range of individual macroeconomic (financial) data series referred to as $Y_{i,t.}$ For each series in this set, $y_{i,t} \in Y_{i,t}$, the h-period ahead uncertainty, denoted by $U_{i,t}(h)$, corresponds to the volatility of the unforecastable component of the future value of the series, conditional on the available information set ($I_{i,t}$). Specifically:

$$U_{i,t}(h) \equiv \sqrt{\mathbb{E}\left[(y_{i,t+h} - \mathbb{E}\left[\mathrm{y}_{i,t+h}\middle|\mathrm{I}_{i,t}\right])^2\middle|I_{i,t}\right]}, \quad (1)$$

Where the expectation $\mathbb{E}(\cdot\,|I_{i,t})$ is taken with respect to information $I_{i,t}$ available to economic agents up to time *t* for country *i*. The *h*-period REU (FINU) index is then computed by aggregating the individual uncertainty measures across all economic series, such that:

$$REU_{i,t}(h) \equiv plim_{N_i \to \infty} \frac{1}{N_i} \sum_{j=1}^{N_i} U_{i,t}(h) \equiv \mathbb{E}\left[\mathrm{U_{i,t}}(h)\right], \quad (2)$$

where N_i is the number of series in $Y_{i,t}$. The conditional expectation of the squared forecast errors, ($y_{i,t+h}$ - $\mathbb{E}\left[y_{i,t+h}\middle|I_{i,t}\right])^2$in equation 1) is derived from a stochastic volatility model in which the log volatility of the series $y_{i,t}$ is assumed to be time-varying and to follow an autoregressive model.[2] Furthermore, each economic time series $y_{i,t}$ is assumed to be stationary and follows a factor structure represented by the following form:

$$y_{i,t} \;=\; \Lambda_i^{F'} F_{it} + e_{it} \quad (3)$$

[1] It is worth noting that, empirically, it is often difficult to distinguish macroeconomic uncertainty from risk, which refers to situations in which the outcome is unknown, but the probability distribution governing the outcome is known (or from volatility, a statistical measure of the variation in outcomes to measure risk). The literature often uses these concepts interchangeably (Jefferson 2023; Cascaldi-Garcia and others 2023), and the macroeconomic uncertainty measures considered in this chapter also do not strictly differentiate between them.

[2] The assumption of stochastic volatility is relevant to allow for the constructing of a second-moment shock that is orthogonal to the innovation to the level of $y_{j,t}$.

where F_{it} in country i is a $N_{jF} x\ 1$ vector of latent common factors constructed as the static principal components from a large set of real economic indicators for REU and selected financial indicators for FINU following Ludvigson and others (2021). The estimate of the conditional expectation $\mathbb{E}[y_{i,t+h}|I_{i,t}]$ in equation (1) is the obtained by the forecast of $y_{i,t+h}$using all the factors.[3] Input data are indicated in Table 2.2.2. Note that the sample period used to calculate the uncertainty index varies across countries. Similarly, the indicator FINU is calculated using monthly series indicated in Table 2.2.3. These financial series encompass valuation ratios like dividend-price, Fama-French risk factors and a diverse cross-section of international equity index portfolios.[4] The raw data used to form factors are always transformed to achieve stationarity. In addition, when forming forecasting factors from the large macro and financial datasets, the raw data are standardized before dimension reduction. Estimations are performed separately for each country for one-quarter forecasting horizon to align with the data frequency used in the main analysis discussed in the subsequent sections.

Table 2.2.2 Data Series and Sample Coverage for Real Economic Uncertainty (REU)			
Group A: Output, Trades, Sales, and Orders			
Capacity utilization rate	Order books	Orders inflow	Production tendency
Export order books or demand	Orders, manufacturing	Production, excluding construction	Production, manufacturing consumer goods
Production, manufacturing intermediate goods	Production, manufacturing total	Sales, manufacturing value	Sales, retail trade volume
Sales, retail trade value	Sales, whole trade value	Stocks, Manufacturing	Exports
Imports	Net trade	Industrial production, index	Gross domestic product, constant prices (percent change y/y)
Real imports	Retail sales, percent change (y/y)	Total domestic demand, constant prices, percent change (y/y)	Real exports
Manufacturing PMI	Merchandise trade balance, percent of GDP	National Gross Domestic Product, Constant Price	National Gross Domestic Product, Current Price
Industrial Production, Manufacturing, Index	Industrial Production, Mining, Index	Industrial Production, Index	Oil Production, Crude, Index
Group B: Prices			
CPI, all items, growth	CPI, all items, index	CPI, all Items non-food non-energy	Core CPI, index
Harmonized CPI, index	Producer Price Index	Core producer price index	
Group C: Labor Market Activity			
Hours worked, industry excluding construction	Hours worked, manufacturing	Overtime hours, manufacturing	Earnings, manufacturing
Earnings, private sector	Active population, aged 15+	Employment, agriculture	Employment, construction
Employment, industry	Employment, industry excluding construction	Employment, manufacturing	Employment, services
Employed population, aged 15+	Employment, employees	Harmonized unemployment, aged 15-24	Harmonized unemployment, aged 25 and over
Harmonized unemployment, aged 15+	Unemployed population, aged 15-24	Unemployed population, aged 15-64	Unemployed population, aged 15-74
Unemployed population, aged 15+	Working age population, aged 15-24	Working age population, aged 15-64	Working age population, aged 15-74
Working age population, aged 15+	Job vacancies, Public sector, Unfilled vacancies (stock)	Job vacancies, Private sector, Unfilled vacancies (stock)	Job vacancies, Total, Unfilled vacancies (stock)
Activity rate, aged 15-24	Activity rate, aged 15-64	Activity rate, aged 15-74	Activity rate, aged 15+
Employment rate, aged 15-24	Employment rate, aged 15-64	Employment rate, aged 15-74	Employment rate, aged 15+
Harmonized unemployment, aged 15-24	Harmonized unemployment, aged 25+	Harmonized unemployment, 15+	Unemployment rate, aged 15-24
Unemployment rate, aged 15-64	Unemployment rate, aged 15-74	Unemployment rate, aged 15+	Total labor force
Group D: Monetary Instruments			
Nominal effective exchange rate	Short-term interest rate	Long-term interest rate	Policy-related interest rate
Broad money	Narrow money		
Group E: Consumer and Business Confidence			
Business tendency surveys (manufacturing), business situation	Business tendency surveys (manufacturing), employment	Consumer opinion surveys, confidence indicators	Consumer opinion surveys, economic situation
Business situation	Consumer confidence Units		
Group F: Stock Market			
MSCI stock price index	Benchmark stock market index	Share Prices, broad	
Group G: Residential and non-residential investment			
Construction permit issued	Production, construction		
Sources: OECD Main Economic Indicators database; IMF Global Data Source database; and IMF IFS database.			

[3] Note that utilizing large datasets within each country is crucial for minimizing biases, especially when important predictive information is overlooked or cannot be included due to the absence of sufficient time series data.

[4] Indicators are included in the computation if observations are available since 1998 (or earlier). Missing data for series included before the cut-off date are imputed using multiple imputation by chained equations. Data series used in the construction of the indicators vary depending on data availability for each country. The use of long time series is relevant to cover both global as well as country-specific events featuring large changes in macroeconomic and financial uncertainty across countries.

Table 2.2.3 Data Series for Financial Uncertainty Index (FINU)

Type of indicator	Indicator	Sources
Financial series	Log price-to-dividend ratio	LSEG Datastream and IMF staff calculations
Financial series	Change in stock price (raw and seasonally adjusted for dividend payments)	
Risk factor	Risk-free rate (3-month government bond yield)	
Risk factor	Market return - risk free rate (MKT_RF)	
Risk factor	Small-minus-big (SMB) factor	
Risk factor	High-minus-low (HML) factor	
Risk factor	Small stock value spread	
25 portfolios formed on size and book market (5x5)	Value-weighted return by portfolio	
6 portfolios formed on size and book market (2x3)	Value-weighted return by portfolio	
23 Industry portfolios	Value-weighted return by industries	
16 country portfolios formed across different reference ratios	Value and growth portfolios' returns using four ratios: Book-to-market (B/M); earnings-price (E/P); cash earnings to price (CE/P); and dividend yield (D/P). The measures are calculate both using local currency and US DOLLAR returns	Data library of Kenneth French Dartmouth website
3 Regional Risk factor	SMB, HML,MKT RF computed in the region of the domestic country	

Note: Portfolio formed on size and book market are either 5x5 or 2x3 depending on the data availability for each country.

B. Financial Spanning of Uncertainty Measures

A potential consideration is that macroeconomic uncertainty measures could capture information spanned by financial variables that may not be directly included in the empirical analysis. To assess formally the degree of financial spanning of different macroeconomic uncertainty measures, these measures are regressed on financial factors based on either the principal component analysis (PCA) components of "risk" variables in Chicago Financial Condition Index from Brave and Butters (2018), or directly the "risk" variables based on data availability for countries besides the United States.[5] Online Annex Table 2.2.4 shows the R-squared from the regressions. Overall, the results indicate that financial indicators, such as asset prices and measures of implied volatility, may not fully capture macroeconomic uncertainty. Financial factors explain around 80 percent of the variation in commonly used macroeconomic uncertainty measures for the United States, and about 40-50 percent of the variation for major emerging market economies such as Brazil.

Online Annex Table 2.2.4. Financial Spanning of Macroeconomic Uncertainty Measures

United States

Uncertainty measure	Financial spanning factors	R-squared
Economic policy uncertainty	PCA 1-10 CFCI (Risk factors)	0.38
Real economic uncertainty	PCA 1-10 CFCI (Risk factors)	0.53
Financial uncertainty	PCA 1-10 CFCI (Risk factors)	0.42
Uncertainty, bag-of-words	PCA 1-10 CFCI (Risk factors)	0.35
Dispersion GDP forecasts	PCA 1-10 CFCI (Risk factors)	0.27
Geopolitical uncertainty	PCA 1-10 CFCI (Risk factors)	0.19
Uncertainty, PCA	PCA 1-10 CFCI (Risk factors)	0.38
Uncertainty, PCA macro	PCA 1-10 CFCI (Risk factors)	0.38
Economic policy uncertainty	Risk variables in CFCI	0.78
Real economic uncertainty	Risk variables in CFCI	0.79
Financial uncertainty	Risk variables in CFCI	0.87
Uncertainty, bag-of-words	Risk variables in CFCI	0.59
Dispersion GDP forecasts	Risk variables in CFCI	0.49
Geopolitical uncertainty	Risk variables in CFCI	0.52
Uncertainty, PCA	Risk variables in CFCI	0.78

Brazil

Uncertainty measure	Financial spanning factors	R-squared
Economic policy uncertainty	PCA 1-3 CFCI (Risk factors)	0.12
Real economic uncertainty	PCA 1-3 CFCI (Risk factors)	0.01
Uncertainty, bag-of-words	PCA 1-3 CFCI (Risk factors)	0.09
Dispersion GDP forecasts	PCA 1-3 CFCI (Risk factors)	0.22
Geopolitical uncertainty	PCA 1-3 CFCI (Risk factors)	0.05
Uncertainty, PCA	PCA 1-3 CFCI (Risk factors)	0.10
Uncertainty, PCA macro	PCA 1-3 CFCI (Risk factors)	0.10
Economic policy uncertainty	Risk variables in CFCI	0.54
Real economic uncertainty	Risk variables in CFCI	0.43
Uncertainty, bag-of-words	Risk variables in CFCI	0.34
Dispersion GDP forecasts	Risk variables in CFCI	0.72
Geopolitical uncertainty	Risk variables in CFCI	0.31
Uncertainty, PCA	Risk variables in CFCI	0.51

Notes: The second column in the tables indicate the number of principal components used in the regressions to verify the degree of financial spanning of different uncertainty measures or whether all input variables are directly considered. For instance, "PCA 1-10 CFCI" indicates that the reference model has been estimated using the first ten components computed from the risk indicators as per definition used in the Chicago Fed FCI. Indicators for Brazil use similar variables with data availability. The number of PCA components is selected to cover around 90 percent of the variation across underlying risk indicators. "Variable in CFCI" indicates instead that the individual risk indicators (not PCA factors) are used in the regressions. The third column shows the R2 over the full sample period of estimation when regressing a given uncertainty measure on the financial spanning factors. Economic policy uncertainty refers to text-based measure in Baker and others (2016). Real economic uncertainty and financial uncertainty are based on Ludvigson and others (2021). "Uncertainty, bag-of-words" is an uncertainty text-based measure computed from banks' earning calls. "Uncertainty, PCA" is the first PCA component computed across all uncertainty measures available. CFCI = Chicago Financial Condition Index (Brave and Butters, 2018).

This underscores the importance of incorporating measures of macroeconomic uncertainty into systemic risk assessments and forecasting frameworks to better predict tail risks to markets and economic activity, particularly in countries with less developed financial markets. Recent academic studies support the notion that financial indicators alone do not fully encompass macroeconomic uncertainty (Valkanov and Zhang 2018, Dew-Becker and Giglio 2023).

[5] See for details on the full list of variables used in the Fed Chicago index are here: https://www.chicagofed.org/-/media/publications/nfci/nfci-indicators-list-pdf.pdf?sc_lang=en&hash=2BAA83FA5155FFEBDF4A3448814090C8. Results are similar when using as alternative set of financial factors components computed from the risk indicators in Adrian, Duarte and Iyer (2023).

C. "Good" and "bad" Uncertainty

Macroeconomic uncertainty can arise from various sources and its impact on output and asset prices can be positive or negative depending on how individuals perceive the source. In this vein, studies categorize episodes of uncertainty as "good" or "bad" (Segal, Shaliastovich, and Yaron 2015; Dew-Becker and Giglio 2023). To examine episodes of good versus bad uncertainty in the data, the analysis utilizes the method proposed by Segal and others (2015), which provide a framework to decompose the realized variance into two components; namely the variances associated with negative (bad) and positive (good) movements in the industrial production growth rate within a given year. Then, realized negative and positive semivariances in annual terms for country i are given by:

$$RV_{i,t+1}^{n} = \sum_{j=1}^{N} \mathbb{I}\left(\Delta y_{i,t+\frac{j}{N}} < 0\right) \Delta y_{i,t+j/N}^{2} \qquad \text{and} \qquad RV_{i,t+1}^{p} = \sum_{j=1}^{N} \mathbb{I}\left(\Delta y_{i,t+\frac{j}{N}} \geq 0\right) \Delta y_{i,t+j/N}^{2}$$

Where $\mathbb{I}(\cdot)$ is an indicator function, Δy_i is the demeaned monthly growth rate in industrial production of country *i,* and *N* represents the number of observations of *y* available in one period (i.e. twelve months). The positive and negative semivariances provide insight into the realized variation associated with movements in the right and left tails, respectively, of the underlying variable. Positive semivariance corresponds to favorable realized variance states, while negative semivariance reflects unfavorable states. Consequently, the predictable component of these measures can be used as empirical proxies for ex ante good and bad uncertainty. To construct these predictive components, the logarithm of future average h-period realized semivariance is projected onto a set of time *t* predictors X_t:

$$\log\left(\frac{1}{h}\sum_{j=1}^{h} RV_{i,t+j}^{s}\right) = \beta_i^s + \nu_i^s X_{i,t} + \epsilon_i, \qquad (5)$$

Where $\beta_i{}^s$ is a country-specific constant and s={p, n} refers to positive and negative semivariances. Ex-ante proxies for good (V_i^g) and bad uncertainty (V_i^b) are derived from exponential fitted values of equation (5):

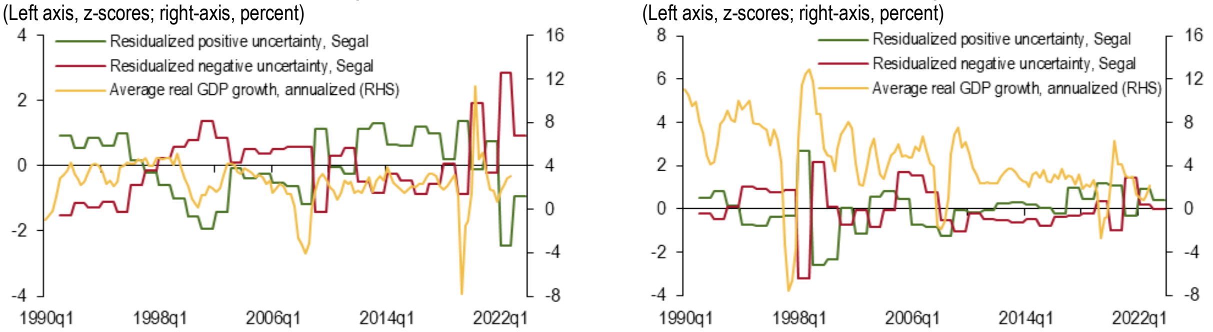
$$V_{i,t}^{g} = \exp\left(\beta_i^p + \nu_i^p X_{i,t}\right), \quad \text{and} \quad V_{i,t}^{b} = \exp\left(\beta_i^n + \nu_i^n X_{i,t}\right), \qquad (6)$$

In the empirical applications, monthly observations are used to allow for multiple good and bad shocks within a given year. To minimize measurement noise, the forecast window *h* is set to three years. Following Segal and others (2015), the benchmark predictors $X_{i,t}$ include positive and negative realized semivariances, consumption growth, the real market return, the market price–dividend ratio, the real risk-free rate, and the default spread. Residual positive (negative) variance is obtained by isolating the orthogonal component of positive (negative) variance from the negative (positive) variance of industrial production growth. Estimations of good and bad uncertainty are conducted separately for each country. Online Annex Figure 2.2.1 shows the results from the analysis, along with four-quarter ahead realized GDP growth for selected countries such as the US and Korea. As can be seen, 'bad' uncertainty (red line) in both cases increases (is above the mean) before the global financial crisis as well as during the COVID-19 pandemic (also before the Asian Financial Crisis in the case of Korea). 'Good' uncertainty (green line) is higher during tech revolutions such as the US dot-com bubble in the 1990s, and during the post-crisis reform period in Korea (1998).

Online Annex Figure 2.2.1 Good and Bad Uncertainty

1. United States: Good and Bad Uncertainty across Time
(Left axis, z-scores; right-axis, percent)

2. Korea: Good and Bad Uncertainty across Time
(Left axis, z-scores; right-axis, percent)



Source: Haver Analytics; LSEG Datastream; and IMF staff calculations.
Note: The panels show the orthogonalized measures of positive and negative uncertainty, calculated using the method from Segal and others (2015). The uncertainty measures are standardized with mean zero.

Online Annex 2.3 Does macroeconomic uncertainty help to predict downside risks to output?

This section describes in detail the econometric and machine learning methods used in the chapter to perform the growth-at-risk (GaR) analysis.[1] Note that the models are primarily estimated or trained using panel data to attain sufficiently large sample sizes for tail risk analysis.[2]

Standard econometric approach. The growth-at-risk model (GaR) for a panel of countries is defined as:

$$y_{i,t+h}^{(\tau)} = \beta_{h,i}^{(\tau)} + \beta_{h,y}^{(\tau)} y_{i,t} + \beta_{h,FCI}^{(\tau)} FCI_{i,t} + \epsilon_{i,t+h}^{(\tau)}, \tag{7}$$

where $y_{i,t+h}^{(\tau)}$ represents *h*-quarter ahead GDP growth for country *i* realized at *t*+*h* (annualized), $\beta_{h,i}^{(\tau)}$ indicates a country-specific constant term, $y_{i,t}$ is realized GDP growth at *t*, $FCI_{i,t}$ is the country's financial conditions index, τ denotes the quantile level ($\tau = 0.05, 0.10, \dots, 0.95$),[3] and *h* is the forecasting horizon in quarters (e.g. h=1,..,12). The model is extended to include uncertainty measures as follows:

$$y_{i,t+h}^{(\tau)} = \beta_{h,i}^{(\tau)} + \beta_{h,y}^{(\tau)} y_{i,t} + \beta_{h,FCI}^{(\tau)} FCI_{i,t} + \beta_{h,u}^{(\tau)} U_{i,t} + \epsilon_{i,t+h}^{(\tau)}, \tag{8}$$

where $U_{i,t}$ is a vector of uncertainty measures (defined earlier), and $\epsilon_{i,t+h}^{(\tau)}$ is the error term. The models are estimated for the full panel of countries with available data from 1990 (or earliest) to 2023. Standard errors are bootstrapped.

As discussed in the previous section, a relevant concern in estimating (8) is that economic uncertainty might already be reflected in financial conditions—particularly if the latter can be measured through a broad set of indicators—given a potential observational similarity between economic uncertainty and the skewness of future GDP growth distributions (Adrian and others 2019).[4] Note that the chapter's main focus is on prediction of future downside tail risks to output growth, conditioning on relevant variables such as financial conditions and macroeconomic uncertainty. The chapter does not aim to specifically identify causal effects of uncertainty shocks on these variables.

That said, different empirical exercises are carried out to address potential endogeneity concerns. Specifically, the analysis is repeated using measures of economic uncertainty that are orthogonalized with respect to financial indicators,[5] and using an instrumental variable (IV) approach that exploits possible variation in uncertainty due to exogenous shocks such as natural disasters, terrorist attacks, political coups, and revolutions (Baker and others 2016). The results are robust to these exercises.[6]

In addition, the measure of overall macroeconomic uncertainty in eq. (8) is replaced with individual measures of good and bad uncertainty described earlier, to study their specific implications for the lower and upper

[1] The chapter extends the literature on systemic risk and macroeconomic uncertainty in several dimensions. As noted earlier, existing studies on systemic risks have focused mainly on the predictive role of financial conditions, ignoring the possible impact of macroeconomic uncertainty. In addition, a burgeoning literature has focused on the effect of macroeconomic uncertainty on mean GDP growth and asset returns (for example, Caldara and others 2020; Alessandri and Mumtaz 2019; Dew-Becker and Giglio 2019; and Londono, Ma, and Wilson 2024), paying scant attention to its association with tail risks to markets and output (Jovanovic and Ma 2022). By contrast, this chapter considers the role of both financial factors and macroeconomic uncertainty in predicting tail risks to future output, asset returns, and bank lending. It also considers a wide sample of countries in the analysis, integrating the two strands of literature on systemic risk and uncertainty from a cross-country perspective.

[2] According to our estimation results, panel data models outperform time-series models in terms of out-of-sample forecast accuracy.

[3] Note that forecasts of upper tails of future GDP growth distributions help identify "good" uncertainty—instances in which uncertainty has a positive impact of future GDP growth.

[4] Jovanovic and Ma (2022) show that higher economic uncertainty in the US increases downside risks to output growth, similar to the role of financial conditions in Adrian and others (2019). Both studies highlight that economic uncertainty or financial conditions impact the mean and volatility of future GDP growth, leading to a distribution skewed towards downside risk. Jovanovic and Ma (2022) also provide a theoretical model linking GDP growth and uncertainty, rooted in technological innovation and adoption (similar to Bloom 2009).

[5] This involves two stages. The first stage involves running a regression of uncertainty measures against an expanded (large dimensional) array of financial conditions (or their principal components), while the second stage consists of using the residuals of the first stage regressions as measures of economic uncertainty in equation 8 (to reflect the part of economic uncertainty not spanned by financial conditions).

[6] The coefficient on the real economic uncertainty index obtained from the IV approach is only slightly smaller than that obtained from the baseline growth-at-risk model and remains statistically significant. For example, based on the IV approach, an increase in the real economic uncertainty index by one standard deviation is associated with an increase in downside real GDP risk (decline in the 10th percentile of one-period ahead GDP growth distribution) of 1.8 percentage points compared to 2 percentage points in the baseline analysis. Results are available upon request.

quantiles of the future GDP growth distribution, respectively. The findings confirm that positive (negative) uncertainty have a stronger association with the upper and lower quantiles compared to the overall real economic uncertainty measure considered in the baseline that combines both types of uncertainty.[7]

The main findings of the GaR analysis are also robust to the following alternative specifications: i) estimating the GaR model by jointly incorporating different macroeconomic uncertainty measures along with the financial uncertainty measure; ii) constructing confidence intervals based on percentile bootstrap with pairwise resampling; iii) controlling for the global financial crisis using a dummy variable; iv) using alternative panel quantile estimators such as Machado and Silva (2019) and Powell (2021); v) controlling for additional factors (such as inflation, policy rate, unemployment) in eq. (8) that could also affect future downside risks; and vi) estimating the model for the pre-COVID 19 period only (or by excluding the first three quarters of 2020).

Machine learning approach: This section describes the machine learning models of growth-at-risk (ML-GaR) used in the chapter, based on quantile random forest (QRF) and quantile neural network (QNN).

Quantile Random Forest

To estimate the QRF model on a panel of advanced or emerging market economies, the chapter follows the approach of Meinshausen (2006). The QRF model is an extension of the popular random forest (RF) regression algorithm developed by Breiman (2001). In both cases, the process begins with estimating the trees in the random forest. To make a prediction for GDP growth in country i at time $t+h$, both models use the time-t vector of country-specific predictors $x_{i,t}$ to assign a particular weight $w_{i,t+h}(x_{i,t})$ for every observation (across all time and countries) in the training sample. Collecting all training-sample realizations of the GDP growth for country i from period t to $t+h$, $y_{i,t+h}$, together with their weights produces pairs $\{y_{i,t+h}, w_{i,t+h}(x_{i,t})\}$ which form the distribution of $y_{i,t+h}$ conditional on $x_{i,t}$. The simple RF algorithm then calculates the expectation of this distribution to produce the forecast. The QRF instead computes the conditional quantile $Q_\tau(y_{i,t+h}|x_{i,t})$ defined as

$$Q_\tau(y_{i,t+h}|x_{i,t}) = inf\left\{y_{i,t+h}: \sum_{s\in I}\sum_{j\in T(i)} w_{s,j+h}(x_{s,j})\ 1_{y_{s,j+h}\leq y_{i,t+h}} \geq \tau\right\}, \tag{9}$$

where I is a set of countries, $T(i)$ is a set of time periods in country i, and $1_{a>b}$ is an indicator function equal to 1 if $a>b$. The vector $x_{i,t}$ consists of country-specific time-t lagged one-quarter GDP growth, financial conditions index, country dummies and an uncertainty measure.[8]

Neural Network

The conditional quantile predictor of future GDP growth (at horizon h=1,4) of the model is obtained by solving the following optimization problem based on country-level panel data:

$$w^* = arg\min_w \frac{1}{I}\sum_{i=1}^{I}\frac{1}{T(i)}\sum_{t=1}^{T(i)}\rho_\tau\left(\Delta y_{i,t+h} - G(x_{i,t}, w)\right), \tag{10}$$

where $\rho_\tau(\cdot)$ is the 10th percentile quantile loss function; $x_{i,t}$=($y_{i,t-1}, FCI_{i,t}, U_{i,t}, \alpha_i$) is the vector of predictors observed at time t in country *i*,[9] consistent with the previous exercise.[10] $G(x_{i,t}, w)$ is the conditional prediction of the h-quarter ahead GDP growth rate (a deep feed-forward neural network or a non-linear

[7] To estimate the impact of bad versus good uncertainty and compare it with the baseline results in this section, the analysis proceeds in two steps. First, proxies for good and bad uncertainty are constructed for each country in the sample at quarterly frequency, following the methodology detailed in Online Annex 2.2.C. Next, the real economic uncertainty index is regressed on these measures to isolate the predicted values arising from positive (good) and negative (bad) macroeconomic uncertainty. These predicted values are then used to estimate the 90th (10th) percentile of future GDP growth.

[8] Like many other machine learning methods, the QRF has several hyperparameters that must be chosen before estimating the model. However, the machine learning literature shows that in case of the RF, one set of hyperparameters works reasonably well across different applications and datasets (Weerts and others 2020, Probst and others 2019). The chapter takes advantage of this unique property of the RF and uses the same pre-specified values of hyperparameters across all specifications. In particular, the number of trees in the forest is set to be 1,000, the minimum number of samples in each node is 5, and the number of predictors considered when searching for the best split equals the square root of the total number of predictors.

[9] These variables are standardized across all samples in in-sample estimation and across each training sample in out-of-sample estimation.

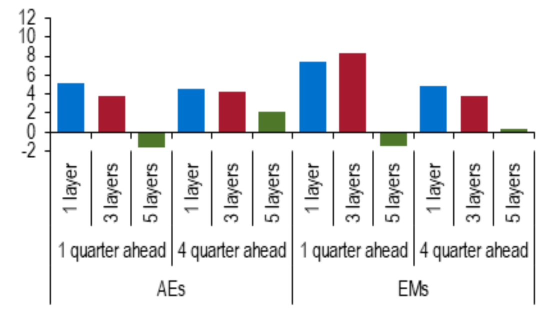
[10] Because neural network models are highly non-linear, including these country-level fixed effect dummies allows the models to account for not only the heterogeneity in average growth rates but also the heterogeneous sensitivity of the predictors to other variables.

mapping from the predictors $x_{i,t}$ to the τ-quantile of the future GDP growth distribution); and $y_{i,t+h}$ is the realized value of average GDP growth from t to $t+h$ (annualized). I and $T(i)$, respectively, represent the number of samples countries in each group and the number of sample periods in country i in the group. The optimal predicted quantile function is thus given by: $Q_\tau(y_{i,t+h}|x_{i,t}) = G(x_{i,t}, w^*)$.

Hyperparameter selection is carried out using three-fold cross-validation with a grid search algorithm, following the approach of Chronopoulos and others (2023) and Gu and others (2020).[11] Specifically, for out-of-sample forecasting in each fold, block cross-validation is used to choose a set of hyperparameters that minimizes the pseudo out-of-sample loss $\sum_{i\in I}\sum_{t=1}^{T(i)-h}\rho\left(y_{i,t+h} - \widehat{y_{\iota,t+h,QNN}}\right)$ across all training samples. Out-of-sample forecasts are then generated using the selected hyperparameters. Overall, the cross-validation results indicate that simpler models with a single hidden layer can often match the out-of-sample forecast accuracy of more complex, deeper networks (i.e., those with additional hidden layers) while using significantly fewer parameters (Online Annex Figure 2.3.1). Based on these findings, network structures with one hidden layer are used in the baseline analysis.[12]

Online Annex Figure 2.3.1 The Number of Layers and Out-of-Sample Forecast Accuracy

(Accuracy change relative to the benchmark model, in percent)



Sources: Haver Analytics; OECD, Main Economic Indicators Database; LSEG Datastream; and IMF staff calculations.
Note: The chart compares the predictive accuracy of the panel quantile neural network (QNN) model against the benchmark GaR model. The specification of the benchmark GaR model includes country-level fixed effects, autoregressive term, and FCI. The accuracy improvement is defined as one minus the percentage change in realized quantile loss for the 10 percentiles when moving from benchmark GaR to QNN-GaR prediction. The out-of-sample analysis is performed by estimating the model on block K-folds, with K=3. The hyperparameters except for the number of layers are chosen based on three block cross validation for each country group. AEs=advanced economies, EMs=emerging market economies, GaR=growth-at-risk.

Forecast Accuracy Evaluation. The analysis compares the forecasting performance of the machine learning models with that of the benchmark model in equation (7). Specifically, the change in the forecast accuracy is evaluated using the following metric:

$$\left(1 - \frac{\sum_{i\in I}\sum_{t=1}^{T(i)-h}\rho_\tau\left(y_{i,t+h} - \widehat{y_{\iota,t+h,ML}}\right)}{\sum_{i\in I}\sum_{t=1}^{T(i)-h}\rho_\tau\left(y_{i,t+h} - \widehat{y_{\iota,t+h,QR}}\right)}\right) * 100\% \tag{11}$$

where $y_{i,t+h}$ is either 1- or 4-quarter GDP growth in country i (from a list of countries I) realized in quarter $t+h$, $\widehat{y_{\iota,t+h,ML}}$ is the corresponding prediction from a machine learning model made from quarter t, $\widehat{y_{\iota,t+h,QR}}$ is the prediction using the benchmark GaR quantile regression model, and ρ_τ is the quantile loss function for quantile τ.

Out-of-Sample Forecasts with Machine Learning. Following an approach common in the literature (Bergmeir and Benítez, 2012; Bergmeir, Hyndman and Koo, 2018), the out-of-sample forecasts are performed on a block basis using a similar specification as in equation (8). The timeline is divided into three equal blocks. The model is estimated using two blocks for training, with out-of-sample predictions made on the hold-out block.[13] This process is repeated until predictions are obtained for each block. Overall, out-of-sample accuracy is then calculated across all periods and countries. Note that despite using future data to predict past outcomes for some observations, the results remain robust when using an expanding window estimation

[11] For all models, the learning rate is set to 0.001, and the dropout rate is set to zero.

[12] The results align with recent empirical evidence, such as Gu and others (2020), showing that simple networks with only a few layers often perform best. This is particularly relevant because training very deep neural networks can be challenging, as they involve a large number of parameters, increasing the risk of overfitting, especially when working with relatively small datasets at a quarterly frequency.

[13] The hyperparameters used to predict each block are chosen separately, while the grids of hyperparameters remain fixed. To avoid spillovers of information between the training and the test samples, the last 4 quarters preceding the beginning of the test sample and the next quarter immediately after its end are dropped from the training sample. To improve stability of the models, the training sample excludes all observations which overlap with the COVID period (2020Q2 and 2020Q3). Note, however, that the COVID period is still included into the test subsample.

scheme.[14] An extension of the analysis also considers combining lower frequency indicators with high frequency measures of uncertainty using mixed data sampling (MIDAS) models.[15]

Variable Importance. The importance and marginal contributions of different input variables to model predictions are evaluated using Shapley values (SHAP). Shapley values explain a model prediction by estimating each feature's contribution to the outcome (see Lundberg and Lee, 2017).

Robustness. The main results of the ML-GaR analysis are robust to the following tests:

i. Prediction at longer horizons and across different macroeconomic uncertainty measures. Online Annex Table 2.3.1 shows the ML-GaR results for different horizons and alternative macroeconomic uncertainty measures. The results include two alternative versions of real economic uncertainty. The first set uses the orthogonal component of the measure relative to a set of financial factors (similar to the previous exercises) and a second set is constructed by projecting the uncertainty measure onto the current values and lags of the cross-sectional mean of squared errors used in the construction of the indicators in equation (1) of Annex 2.2 using a stochastic volatility model ('forward-looking bias corrected REU').[16]

Online Annex Table 2.3.1 Accuracy Change in Out-of-Sample Forecast Using Uncertainty Measures

1. Quantile Random Forest

(Accuracy change from the benchmark model, in percent)

	Advanced Economies				Emerging Market Economies			
	One Quarter Ahead		Four Quarters Ahead		One Quarter Ahead		Four Quarters Ahead	
	Excluding uncertainty	Including uncertainty	Excluding uncertainty	Including uncertainty	Excluding uncertainty	Including uncertainty	Excluding uncertainty	Including uncertainty
Real economic uncertainty	7.4	11.7	2.2	9.4	-0.1	4.7	5.7	12.2
Orthogonal component	7.4	8.2	2.2	5.8	-0.1	4.5	5.7	11.9
w/o forward looking bias	7.2	8.0	3.2	4.4	1.8	3.0	1.8	3.7
Financial uncertainty	10.3	8.2	4.8	5.9	6.9	5.0	5.1	1.1
Economic policy uncertainty	7.1	5.9	9.0	9.1	7.7	7.6	6.4	11.4
Geopolitical uncertainty	13.5	13.8	5.4	5.1	8.1	8.5	0.6	0.2
GDP Forecast dispersion	15.9	15.1	3.4	5.2	9.3	8.6	2.4	4.1
World uncertainty index	12.3	10.8	4.8	3.7	8.1	8.7	0.6	2.6
Text-based uncertainty	3.7	4.3	1.5	1.7	5.1	4.3	3.6	5.5

Online Annex Table 2.3.1 Accuracy Change in Out-of-Sample Forecast Using Uncertainty Measures (concluded)

2. Quantile Neural Network

(Accuracy change from the benchmark model, in percent)

	Advanced Economies				Emerging Market Economies			
	One Quarter Ahead		Four Quarters Ahead		One Quarter Ahead		Four Quarters Ahead	
	Excluding uncertainty	Including uncertainty	Excluding uncertainty	Including uncertainty	Excluding uncertainty	Including uncertainty	Excluding uncertainty	Including uncertainty
Real economic uncertainty	3.6	12.5	4.8	9.1	1.0	6.4	3.9	11.6
Orthogonal component	3.6	6.3	4.8	5.7	1.0	2.1	3.9	5.2
w/o forward-looking bias	6.1	6.2	6.0	5.9	3.1	3.4	2.5	4.9
Financial uncertainty	-0.8	-1.2	2.1	4.8	-1.5	-0.2	2.3	0.3
Economic policy uncertainty	-4.3	-4.2	5.7	7.0	4.4	5.7	3.8	1.9
Geopolitical uncertainty	2.0	2.3	3.6	3.1	0.8	-0.5	2.1	0.5
GDP Forecast dispersion	3.2	3.1	3.5	4.8	1.3	2.1	2.2	4.3
World uncertainty index	1.7	1.0	4.5	3.0	0.8	1.6	2.1	2.5
Text-based uncertainty	-6.3	-3.8	3.2	1.2	1.2	-2.2	-0.7	0.9

Note: The tables show the percentage improvements of the out-of-sample quantile loss function when moving from the benchmark GaR without an uncertainty index to the ML-GaR without or with one of the uncertainty indices. The out-of-sample analysis is performed by estimating the model on block K-folds, with K=3. The hyperparameters for the neural network models are chosen based on three block cross validation.

[14] Expanding window refers to a forecasting method that gradually expands the training dataset by incorporating only the data available up to a specific point in time to test out-of-sample accuracy of the predictions. In the analysis, the forecast accuracy of quantile random forest ML-GaR remains broadly the same, while that of quantile neural network ML-GaR marginally decreases, likely due to its sensitivity to sample size.

[15] Preliminary country-level analysis indicates that MIDAS enhances the out-of-sample performance by efficiently mixing daily uncertainty measures with quarterly data on other predictors. For example, incorporating seven of the most recent daily observations of the economic policy uncertainty index into the standard QRF ML-GaR improves the four-quarter-ahead forecast accuracy for the US by up to 2.5 percent and for the UK by 9.0 percent compared to a similar model using quarterly economic policy uncertainty index.

[16] The fitted values from this estimation provide a test for potential forward-looking bias in the indicator.

ii. Comparison of predictive accuracy of panel data models versus time series models. Online Annex Table 2.3.2 compares the out-of-sample forecast accuracy of panel- and country-level ML-GaR models. While the results are similar for major advanced and emerging market economies,[17] the panel ML-GaR approach generally outperforms the country-level approach in terms of forecast accuracy. Neural network models particularly benefit from the larger panel data, showing significant improvement over country-level estimations due to their sensitivity to sample size. However, panel models may overlook country-specific nuances, which can reduce accuracy in certain cases.

Online Annex Table 2.3.2. Change in Out-of-Sample Forecast Accuracy from Country-Level to Panel ML-GaR

1. Quantile Random Forest

(Accuracy change from the country-level model, in percent)

	Advanced Economies				Emerging Market Economies			
	One Quarter Ahead		Four Quarters Ahead		One Quarter Ahead		Four Quarters Ahead	
	Excluding uncertainty	Including uncertainty	Excluding uncertainty	Including uncertainty	Excluding uncertainty	Including uncertainty	Excluding uncertainty	Including uncertainty
First quartile	-0.3	0.3	-1.1	-3.6	-2.9	-1.5	-1.1	0.2
Median	1.8	3.4	3.3	2.2	0.1	2.7	0.4	4.5
Third quartile	6.8	5.2	6.8	10.9	6.8	4.8	6.3	6.6

2. Quantile Neural Network

(Accuracy change from the country-level model, in percent)

	Advanced Economies				Emerging Market Economies			
	One Quarter Ahead		Four Quarters Ahead		One Quarter Ahead		Four Quarters Ahead	
	Excluding uncertainty	Including uncertainty	Excluding uncertainty	Including uncertainty	Excluding uncertainty	Including uncertainty	Excluding uncertainty	Including uncertainty
First quartile	-4.3	-1.5	-2.7	-1.1	-0.2	8.7	-0.5	1.3
Median	-1.7	6.4	4.0	5.7	2.4	16.2	1.7	8.3
Third quartile	8.5	9.2	10.5	9.2	9.8	16.9	11.8	11.7

Sources: Haver Analytics; OECD, Main Economic Indicators database; LSEG Datastream; and IMF staff calculations.
Note: The tables compare the predictive accuracy of panel ML-GaR relative to country-level time series ML-GaR with and without real economic uncertainty. The out-of-sample analysis is performed by estimating the model on block K-folds, with K=3. The accuracy improvement is defined as one minus the percentage change in realized quantile loss for the 10 percentile, where the accuracy is calculated to each sample country. For the QNN, the hyperparameters for the neural network models are chosen based on three block cross validation. GaR = growth-at-risk.

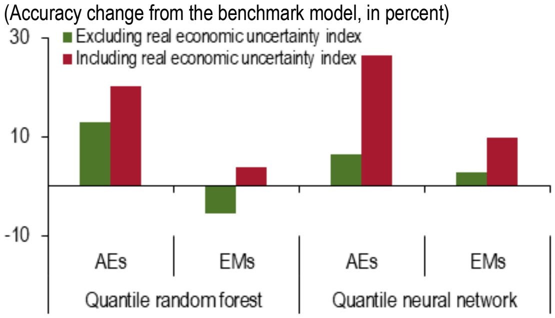
iii. Prediction Accuracy of ML-GaR for Past Crisis Episodes. Online Annex Figure 2.3.2 shows the out-of-sample forecast accuracy of ML-GaRs, by focusing on the accuracy to predict past crisis episodes: (a) the Global Financial Crisis and (b) COVID-19 pandemic. For (a), the evaluation period includes all forecasts made for the realizations between 2007Q4 and 2009Q2, and (b) includes all forecasts made for realizations in 2020Q2 and 2020Q3. Because it is unlikely that uncertainty measure could predict COVID-19 pandemic in 2019Q2, only one-quarter ahead forecast is evaluated for (b). As shown in the figure, the machine learning approach, when considering the real economic uncertainty measure, is generally useful to predict past crisis episodes. Similar results are obtained for GaR estimated over a longer time horizon.

Online Annex Figure 2.3.2 Robustness: Out-of-Sample Forecast Accuracy for the Past Crisis Episodes

a) Global Financial Crisis

1. Machine Learning GaR: One-quarter Ahead Forecasts

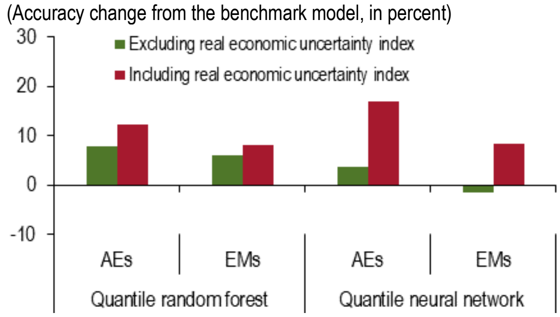
(Accuracy change from the benchmark model, in percent)



b) COVID-19 pandemic

2. Machine Learning GaR: One-quarter Ahead Forecasts

(Accuracy change from the benchmark model, in percent)

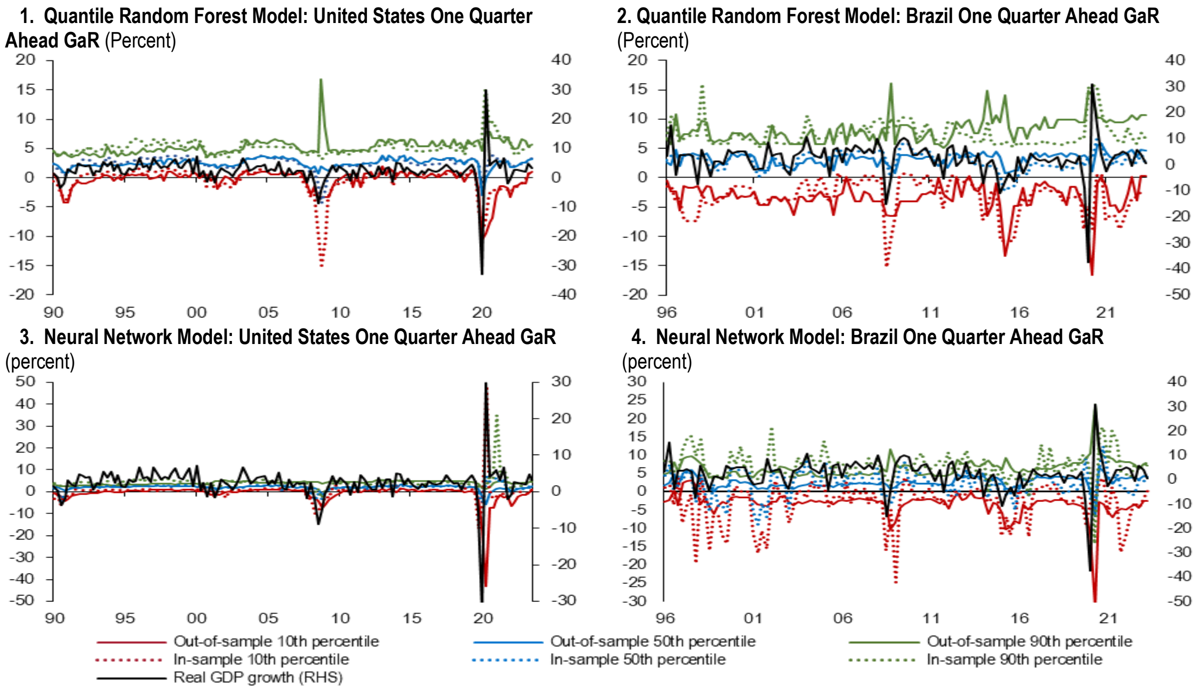


Sources: Haver Analytics; OECD, Main Economic Indicators database; LSEG Datastream; and IMF staff calculations.
Note: The panels compare the accuracy improvements of two ML-GaR models compared with the benchmark GaR model, with and without uncertainty index (the red and green bars, respectively). The models are estimated on a panel of advanced or emerging market economies. The accuracy improvement is defined as one minus the percentage change in the realized quantile less function for 0.10 quantile when moving from the benchmark GaR without the uncertainty index to an alternative model. The out-of-sample accuracy is calculated separately for the global financial crisis and the COVID period. The global financial crisis includes all forecasts made for the realizations over 2007Q4-2009Q2, and the COVID period includes all forecasts made for realizations in 2020Q2-2020Q3. The out-of-sample analysis is performed by estimating the model on block K-folds, with K=3. AEs = advanced economies, EMs = emerging market economies, GaR = growth-at-risk.

[17] For instance, tests for the United States and Brazil show very similar performance across panel and country-level estimations.

iv. Comparison of In-Sample and Out-of-Sample Predictions of Future GDP Growth. Online Annex Figure 2.3.3 displays the in-sample and out-of-sample forecasts generated by the QRF and QNN ML-GaR models across different percentiles of the distribution (i.e., 10th, 50th, and 90th). For in-sample forecasts, the 10th-90th percentile band effectively captures GDP growth realizations. Even in out-of-sample forecasts, this range broadly encompasses the actual GDP growth, including during the Global Financial Crisis. In addition, in-sample and out-of-sample broadly track each other.

Online Annex Figure 2.3.3 ML GaR: In-Sample and Out-of-Sample Forecasts



Sources: Haver Analytics; OECD, Main Economic Indicators database; LSEG Datastream; and IMF staff calculations.
Notes: The graphs show the in-sample and out-of-sample forecast of the one- and four-quarter-ahead GDP growth (the black line) from the panel Random Forest Network ML-GaR model (panels 1-2) and using a neural network model (panels 3-4). The model specifications include real economic uncertainty index as well as the lagged GDP growth and FCI (AEs and EMs model applies to the United States and Brazil, respectively). One-quarter ahead GDP growth forecasts are annualized. The out-of-sample analysis is performed by estimating the model on block K-folds, with K=3. GaR = growth-at-risk.

Online Annex 2.4 How does macroeconomic uncertainty interact with macrofinancial vulnerabilities to affect downside risks to output?

To study the relevance of interaction effects between uncertainty and vulnerability measures, the linear quantile model is extended as follows:

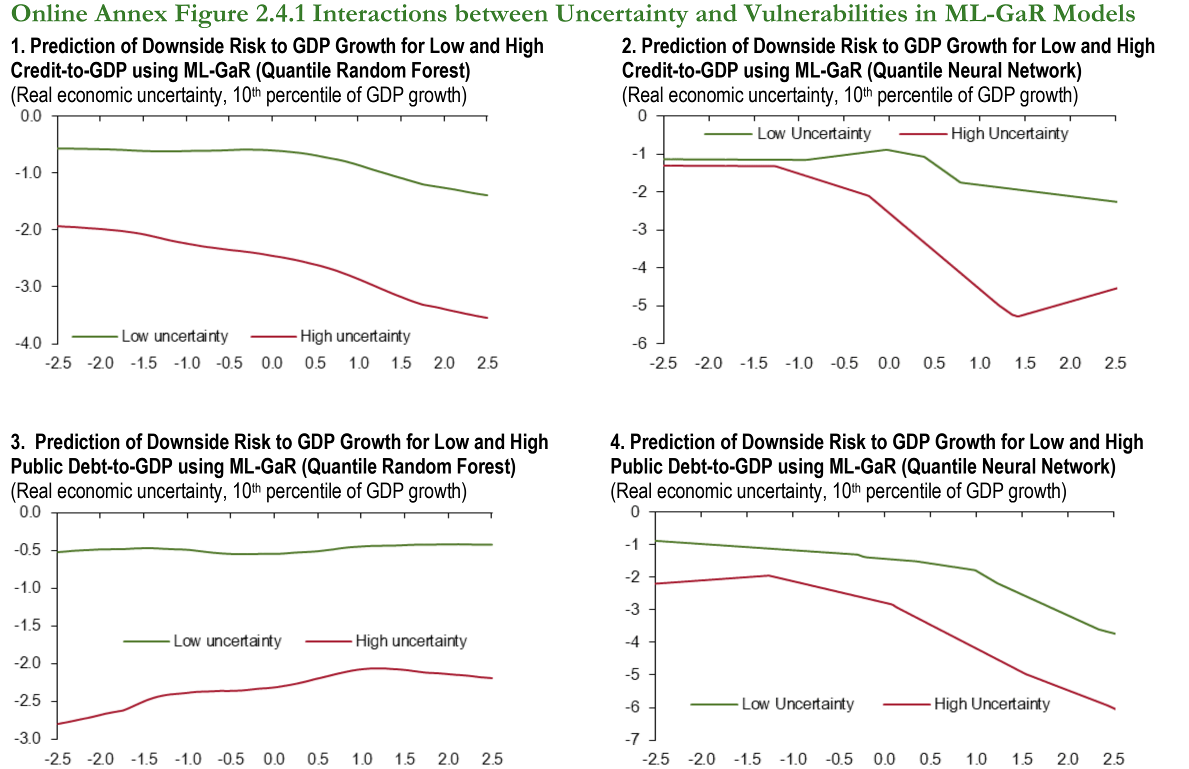
$$y_{i,t+h}^{(\tau)} = \beta_h^{(\tau)} + \beta_{h,y}^{(\tau)} y_{i,t} + \beta_{h,FCI}^{(\tau)} FCI_{i,t} + \beta_{h,u}^{(\tau)} High\ Uncertainty_{i,t} + \beta_{h,v}^{(\tau)} V_{i,t} + \beta_{h,uv}^{(\tau)} High\ Uncertainty_{i,t}\ x\ V_{i,t} + \epsilon_{i,t+h}^{(\tau)}, \qquad (12)$$

where $V_{i,t}$ represents a vector of vulnerabilities, $High\ Uncertainty_{i,t}\ x\ V_{i,t}$ represent interaction terms between uncertainty and vulnerability measures, and the coefficient of interest are $\beta_{h,v}^{(\tau)}$ and $\beta_{h,uv}^{(\tau)}$. "$High\ Uncertainty_{i,t}$" is a dummy that takes the value one when real economic uncertainty is above the median, while V_t comprises different proxies for one-sided HP-filtered credit-to-GDP gap and public debt-to-GDP gap.

Estimations are conducted using panel quantile regressions for countries in the sample, depending on data availability. For machine learning models (ML-GaR), the conditional predictions of h-quarter ahead GDP growth rates $G(x_{i,t}, w^*)$ are now determined by an expanded set of predictors x_t=($FCI_{i,t}$,$U_{i,t}$, $V_{i,t}$)—which includes the vulnerability measures. Results from the linear quantile model estimation are presented in Figure 2.6 (panel 1) of the main text.

Online Annex Figure 2.4.1 presents the estimation results of the interaction effects between real economic uncertainty and vulnerability measures. The figure indicates that higher uncertainty generally predicts lower values for the 10th percentile of the future GDP growth distribution. More importantly, the impact of increased uncertainty on downside tail risk to future GDP growth is amplified when credit-to-GDP and public debt-to-GDP gaps are high, indicating that uncertainty interacts with these vulnerabilities.

Online Annex Figure 2.4.1 Interactions between Uncertainty and Vulnerabilities in ML-GaR Models



Sources: Haver Analytics; OECD, Main Economic Indicators database; LSEG Datastream; and IMF staff calculations.
Notes: Panels 1 and 2 are generated based on ML-GaR that include the autoregressive term, FCI, and high credit-to-GDP gap (standardized). Figures 3 and 4 are generated based on ML-GaR that includes the autoregressive term, FCI, and high public debt-to-GDP gap (standardized). In both figures, input variables except for the variable of interest) are set to the median of the sample. 'Low' and 'High' uncertainty represent below and above median for the sample, respectively. The neural network models have one layer with eight neurons where the number of epochs is 300, and batch size is 32.

A. Uncertainty, Macro-Market Disconnect and Financial Conditions

A high-uncertainty regime can be considered a potential vulnerability that can interact with other macrofinancial vulnerabilities to amplify the effect of adverse shocks to the economy through the channels discussed earlier. Extensions of the model explore therefore potential interaction effects between uncertainty and the financial condition index (FCI). Specifically, the following model is estimated:

$$y_{i,t+h}^{(\tau)} = \beta_h^{(\tau)} + \beta_{h,y}^{(\tau)} y_{i,t} + \beta_{h,FCI}^{(\tau)} FCI_{i,t} + \beta_{h,u}^{(\tau)} High\ Uncertainty_{i,t} + \beta_{h,uf}^{(\tau)} High\ Uncertainty_{i,t}\ x\ FCI_{i,t} + \epsilon_{i,t+h}^{(\tau)}, \quad (13)$$

where $High\ Uncertainty_{i,t}\ x\ FCI_{i,t}$ represents the interaction term between uncertainty and FCI. The coefficients of interest are $\beta_{h,FCI}^{(\tau)}$, which captures the effect of a one-standard deviation change in FCI in low uncertainty regime (i.e., when the "High Uncertainty" dummy is equal to zero); and the coefficient $\beta_{h,uf}^{(\tau)}$, which reflects the additional impact of a change in FCI under a high uncertainty regime (i.e. when the "High Uncertainty" dummy is equal to one). Based on this analysis, Figure 2.6 (panel 2) in the main text shows the impact of a one standard deviation easing shock to financial conditions on the term-structure of GaR amid low real economic uncertainty and the overall effect during periods of high macroeconomic uncertainty ($\beta_{h,FCI}^{(\tau)} + \beta_{h,uf}^{(\tau)}$).

A similar analysis is conducted by replacing the high uncertainty dummy with a dummy that identifies periods of large macro-market disconnect:

$$y_{i,t+h}^{(\tau)} = \beta_h^{(\tau)} + \beta_{h,y}^{(\tau)} y_{i,t} + \beta_{h,FCI}^{(\tau)} FCI_{i,t} + \beta_{h,u}^{(\tau)} HighDisy_{i,t} + \beta_{h,uf}^{(\tau)} HighDis_{i,t}\ x\ FCI_{i,t} + \epsilon_{i,t+h}^{(\tau)}, \quad (14)$$

where $HighDis_{i,t}$ is a dummy variable that takes the value one in periods in which the ratio between real economic uncertainty and realized market volatility is above its mean. Results from this analysis are presented in Figure 2.6 (panel 3) of the main text. The main findings are robust to the following alternative specifications: i) estimating the GaR model by jointly incorporating different macroeconomic uncertainty measures along with the financial uncertainty measure; ii) constructing confidence intervals based on percentile bootstrap with pairwise resampling; iii) controlling for the global financial crisis using a dummy variable; iv) using alternative panel quantile estimators such as Machado and Silva (2019) and Powell (2021), v) controlling for additional confounding factors (such as inflation, policy rate, unemployment, vi) using instrumented uncertainty as described in Online Annex 2.3, vii) estimating the model on the pre-COVID period or by excluding the first three quarters of 2020.[1]

B. Effect of Macroprudential Policies on the Intertemporal Risk-Return Tradeoff

The following specification is used to examine the effectiveness of macroprudential measures in curbing the buildup of sector-specific leverage and mitigating downside risks to economic growth:

$$y_{i,t+h}^{(\tau)} = \theta_{i,t}\left[\alpha_{i,h}^{(\tau,tight)} + \beta_{h,y}^{(\tau,tight)} FCI_{i,t} + \beta_{h,d}^{(\tau,tight)} HighDis_{i,t} + \beta_{h,df}^{(\tau,tight)} HighDis_{i,t} x\ FCI_{i,t} + \lambda_{h,x}^{(\tau,tight)} y_{i,t}\right] \quad (15)$$

$$+(1-\theta_{i,t})\left[\alpha_{i,h}^{(\tau,no\_tight)} + \beta_{h,y}^{(\tau,no\_tight)} FCI_{i,t} + \beta_{h,d}^{(\tau,no\_tight)} HighDis_{i,t} + \beta_{h,df}^{(\tau,no\_tight)} HighDis_{i,t} x\ FCI_{i,t} + \lambda_{h,x}^{(\tau,no\_tight)} y_{i,t}\right] + \epsilon_{i,t+h}^{(\tau)}$$

where $HighDis_{i,t}$ is a dummy variable equal to one when the ratio between real economic uncertainty and realized market volatility is above its mean, consistently with the previous exercise. In the specification, the parameter $\theta_{i,t}$ is a regime dummy that takes a value one if the sum of net macroprudential policy tightening in the past 4 quarters is positive, and zero otherwise. A variety of macroprudential tools are considered to define the macroprudential policy regime. These include borrower-based measures, as well as measures targeting bank lenders—such as capital adequacy requirements, liquidity regulations, and controls on foreign currency exposure. The data on macroprudential measures is sourced from the IMF's Integrated

[1] Note that results from a baseline model including only $HighDisy_{i,t}$ indicate that the disconnect can increase downside risks by up to 0.3 percentage points (annualized) over the next five quarters.

Macroprudential Policy Database, covering the period 1990-2021 (for further details, see Alam and others, 2019).[2]

The empirical methodology and results in this section are aligned with the approach and findings presented in Chapter 2 of the April 2021 GFSR. Figure 2.6 (panel 4) in the main text illustrates the impact of a one standard deviation easing in financial conditions during a period of 'macroprudential tightening' amidst high macro-market disconnect, compared to the effect of FCI loosening without macroprudential tightening in a similar context. In addition to the previous robustness tests discussed in Online Annex 2.3, the conclusions of the analysis in this section are also robust to: i) directly interacting the macroprudential measures with the interaction effects of disconnect and financial conditions; ii) using macroprudential policy shocks as in Brandao-Marques and others (2020), iii) controlling for the global financial crisis using a dummy variable; and iv) controlling for additional factors (such as inflation, policy rate, unemployment) that could also affect future downside risks.

[2] These measures are referred as SUM_{17} in the iMapp database. This is a discrete variable, which indicates the net number of macroprudential tightening actions undertaken in a given quarter The measure included in the indicator can be categorized into six main groups: (1) borrower-based measures, including loan-to-value (LTV) and debt-service-to-income (DSTI) limits; (2) bank capital measures, encompassing capital requirements, leverage limits, loan-loss provisioning, countercyclical capital buffers, capital conservation buffers, and regulations targeting systemically important banks; (3) banks' foreign currency exposure measures, involving limits on foreign currency lending, restrictions on gross open foreign currency positions, and reserve requirements on foreign currency assets; (4) bank liquidity measures, including reserve requirements, liquidity mandates, and limits on the loan-to-deposit ratio; (5) credit measures, covering limits on credit growth and loan restrictions; and (6) other measures, such as stress testing, restrictions on profit distribution, and limits on exposures between financial institutions.

Online Annex 2.5 Does macroeconomic uncertainty influence activity through the market tail risk and bank lending channels?

A. Market tail risk

The following dynamic panel quantile regression specifications are used to examine the association between macroeconomic uncertainty and future tail risks sovereign bond and stock markets:

$$R_{i,t+h}^{(\tau)} = \beta_i^{(\tau)} + \gamma_t^{(\tau)} + R_{i,t} + \beta_u^{(\tau)} U_{i,t} + \beta_v^{(\tau)} V_{i,t} + \beta_{uv}^{(\tau)} U_{i,t} V_{i,t} + \beta_z^{(\tau)} Z_{i,t} + \epsilon_{i,t+h}^{(\tau)}, \quad (16)$$

where $R_{i,t+h}^{(\tau)}$ denotes the τ quantile of the h-period ahead distribution of average stock returns between month *t* and *t+h*, or change in sovereign bond spreads between month *t* and *t+h* in country $i \in [1, \ldots, C]$;[1] $R_{i,t}$ denotes the asset return/bond spread observed in period *t*; $U_{i,t}$ is a measure of macroeconomic uncertainty (monthly change); $V_{i,t}$ denotes financial or fiscal vulnerabilities; and the cross-term $U_{i,t}V_{i,t}$ captures possible interactions between the uncertainty and vulnerability measures; $Z_{i,t}$ denotes additional predictor (control) variables described below; and $\epsilon_{i,t+h}^{(\tau)}$ is the error term. In equation (16), $\beta_i^{(\tau)}$ denotes country-level fixed effects and the parameters $\theta^{*(\tau)} \equiv \left\{\beta_i^{(\tau)}, \beta_u^{(\tau)}, \beta_v^{(\tau)}, \beta_{uv}^{(\tau)}, \beta_z^{(\tau)}\right\}$ minimize the quantile loss function.[2]

The uncertainty measures included in the analysis are the Real Economic Uncertainty index (REU), the financial economic uncertainty measure, the Economic Policy Uncertainty index (EPU), and the World Uncertainty Index (WUI).[3] Equation (16) is estimated using monthly data for a sample of 19 advanced and 9 emerging market economies applying the quantile panel regression approach of Canay (2011) with bootstrapped standard errors.

Robustness is assessed considering measures of implied volatility at time *t* for countries with available data, and restricting the analysis to the pre-COVID-19 pandemic period.

Tail risk in sovereign spreads

The sovereign bond spreads used in equation (16) is defined as the difference between the yields on domestic government bonds and the US or German government bonds of the same maturity, in basis points.[4] The dependent variable is then the 90th percentile of the change in spreads (over different time horizons such as 1, 3, 6 and 12 months) to capture upside tail risk in sovereign bond markets.

The set of control variables ($Z_{i,t}$) when estimating equation (16) for sovereign bond spreads follows Gilchrist and others (2009) and includes: the VIX index, the excess bond premium (EBP) of Gilchrist and Zakrajšek (2012), benchmark economy ('foreign') real 2y Treasury Yield based on TIPS, benchmark economy ('foreign') term spread constructed as the difference between 10-year and 2-year government bond yields, one-month S&P500 stock index return, 3-month daily domestic stock market returns (not correlated with the S&P500 stock return), constructed as the residual from a panel regression of the daily domestic stock market index returns on the S&P500 index returns, controlling for country fixed effects, 3-month daily domestic stock return volatility, 3-month change in the local currency exchange rate vis-à-vis the US DOLLAR in excess of changes in the broad nominal US DOLLAR index from the FRED during the same period, and 3-month exchange rate volatility.[5] All control variables are measured at end-of-period.

[1] Robust predictability of mean returns in stock and bond markets has been difficult to establish empirically (for example, Campbell and Thomson 2007; Goyal and Welch 2008). However, studies have shown the predictability of higher moments of return distributions, as well as of downside tail risks (for example, Adrian, Crump, and Vogt 2019; Hung, Liu, and Yang 2020).

[2] It satisfies the following: $\theta^{*(\tau)} = \arg\min_{\theta^{(\tau)}} \frac{1}{I} \sum_{i=1}^{I} \frac{1}{T} \sum_{t=1}^{T} \rho_\tau\left(\epsilon_{i,t+h}^{(\tau)}\right)$, where $\rho_\tau\left(\epsilon_{i,t+h}^{(\tau)}\right) = \begin{cases} \tau\epsilon_{i,t+h}^{(\tau)} & if\ \epsilon_{i,t+h}^{(\tau)} \geq 0 \\ (1-\tau)\epsilon_{i,t+h}^{(\tau)} & if\ \epsilon_{i,t+h}^{(\tau)} < 0 \end{cases}$, where *I* denotes the number of countries.

[3] The REU is available at a quarterly frequency and is interpolated to a monthly frequency for this analysis.

[4] The choice of the benchmark country (US or Germany) depends on the domestic issuer country—for countries in Euro Area, spread with Germany is computed.

[5] Stock market and exchange rate volatilities are computed as the monthly average of standard deviation of the daily returns of stock returns/ exchange rate over a rolling window of 62 days (3months).

Online Annex Table 2.5.1 Regression Results for Changes in Sovereign Bond Spreads

	Advanced Economies				Emerging Markets			
	1-month	3-month	6-month	12-month	1-month	3-month	6-month	12-month
Real Economic Uncertainty (REU)	102.016**	281.735***	278.996**	-54.443	196.296**	501.164**	926.044***	292.725
	45.958	75.608	114.810	192.208	97.584	199.039	237.837	277.033
Lagged Spread Change	-0.021	0.018	0.117*	0.278**	-0.097	0.070	-0.018	0.170
	0.037	0.070	0.069	0.130	0.097	0.095	0.160	0.213
Excess Bond Premium	1.381	2.933	3.917	7.275	1.125	23.919***	42.811***	26.632**
	1.341	2.147	3.027	4.601	4.259	9.128	12.005	11.908
VIX	0.539***	1.180***	1.382***	1.338***	0.993***	-0.802	-3.570***	-4.098***
	0.123	0.196	0.255	0.418	0.380	0.542	0.658	0.960
Foreign Real 2y Treasury Yield	1.305***	3.121***	6.187***	12.530***	0.033	-2.426	-5.699*	1.552
	0.197	0.293	0.501	0.581	1.018	2.120	3.295	3.817
Foreign Term Spread (10y-2y)	0.899*	-1.049	-3.464***	-19.493***	0.924	2.709	2.582	-10.660
	0.488	0.924	1.269	2.376	1.616	3.369	5.053	6.853
Foreign Stocks 1-month Return	-0.044	-0.111	0.481	0.517	-1.974***	-0.822	-2.250*	-0.399
	0.143	0.213	0.296	0.318	0.511	0.706	1.254	1.523
3-month Stocks Daily Return	-6.566	-36.200**	-49.786**	-16.337	-23.519	-1.285	5.885	-72.124
	8.469	16.789	19.488	33.832	18.426	28.202	50.302	74.489
3-month Stocks Daily Return Volatility	39.106	-50.590	-0.363	507.326	1070.187**	3302.768***	3995.723***	4911.088**
	153.817	224.605	434.650	508.939	490.084	615.723	1279.151	2065.910
3-month Exch. Rate Daily Return	-8.914	-58.719***	-55.550**	-38.021	26.644	-99.062***	-147.665***	-336.712***
	7.215	16.787	27.277	29.191	21.331	37.504	55.801	72.386
3-month Exch. Rate Daily Return Volatility	-387.953*	-950.107**	-3402.273***	-4893.858***	-142.565	-1101.531	-1157.138	-1305.740
	223.500	374.457	666.955	786.686	595.896	783.943	1506.595	1860.931
N	5714	5714	5712	5615	2551	2549	2546	2505
Pseudo R2	0.038	0.06	0.074	0.121	0.049	0.043	0.041	0.041
Percentile	90th	90th	90th	90th	90th	90th	90th	90th
Estimator Method	Canay	Canay	Canay	Canay	Canay	Canay	Canay	Canay
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Sources: FRED, Federal Reserve Bank of St. Louis; Haver Analytics; OECD, Main Economic Indicators database; ICE BoFA; LSEG Datastream; and IMF staff calculations.
Note: Table shows results of quantile panel regressions of sovereign bond spread changes from time t to different horizons (t+1, 3, 6 and 12 months) using country fixed effects and estimated at the 90th percentile of the distribution of the change in spreads. Estimates based on the Canay estimator. The separate samples consist of monthly data for 20 AEs and 9 EMs from 1990m1 to 2023m12. The underlying regressions include relevant controls for the sovereign bond market at the country and global levels following Gilchrist and others (2022), as well as the lagged dependent variable. Spreads are calculated relative to a benchmark economy for each country (Germany for Euro area countries and the United States for all others) and using only debt denominated in the same currency of the benchmark economy. Standard errors presented below the coefficient. *, ** and *** denote statistical significance at the 10, 5 and 1 percent levels, respectively.

The estimation results for equation (16) for REU are presented in Online Annex Table 2.5.1[6], and show that an increase in REU significantly raises upside tail risks to sovereign bond spreads in both advanced and emerging market economies for up to six months. The effect of REU is amplified for high levels of macro-financial and fiscal vulnerabilities in emerging market economies, specifically, debt service to GDP (defined as the ratio of nominal general government debt service payments as a percentage of nominal GDP, interpolated from an annual to a monthly frequency); and domestic banks' exposure to sovereign debt (defined as the value of domestic sovereign debt held by banks as a percentage of banks' total assets) interpolated from quarterly data to monthly frequency (Online Annex Table 2.5.2). In advanced economies, the result is opposite, although with a much lower magnitude and only borderline significant—note that the result becomes insignificant when the sample is restricted to the pre-COVID period.[7]

Tail risk in stock returns

To estimate the effect of macroeconomic uncertainty on tail risk in stock market returns, a panel quantile regression is estimated with the 10th percentile of average future stock returns (over 1, 3, 6 and 12-month horizons) considered as the dependent variable in equation (16). The resulting coefficient for changes in uncertainty is rescaled using the standard deviation in the level of the respective uncertainty measure to improve interpretability.

The set of baseline control variables ($Z_{i,t}$) in this case follows Schmeling (2009) and Goyal and Welch (2008). These are standardized at a country level and include: 3-month domestic CPI inflation; 3-month percentage change in real industrial production; average stock market dividend yield; detrended short (3-month) rate. Constructed using HP filter; domestic term spread, computed as the difference between 10-year and 3-month government bond yields; 3-month daily stock market volatility; and price to earnings ratio for the overall stock market.

[6] Across all uncertainty measures, results for REU are the strongest and most consistent across time horizons and alternative specifications.

[7] The result for the sample that includes the COVID period is possibly capturing the effect of central bank interventions in sovereign bond markets in advanced economies. During the COVID period, spreads in many countries, after initially spiking in March, quickly returned to pre- COVID levels while uncertainty was still on the rise.

The results show that an increase in real economic uncertainty significantly reduces stock returns in both advanced and emerging market economies by up to 12 months (Online Annex Table 2.5.3). The effect is stronger in the first month in advanced economies, but it is of similar magnitude at 3 and 6 month horizons. Unlike with sovereign spreads, fiscal and financial vulnerabilities do not appear to significantly magnify the effect of uncertainty on stock market returns.

Online Annex Table 2.5.2 Regression Results for Changes in Sovereign Spreads in AEs and EMs

	Debt Service		Banks' Sovereign Exposure	
	Advanced Economies	Emerging Markets	Advanced Economies	Emerging Markets
Real Economic Uncertainty (REU)	625.324***	-273.672*	550.033***	-387.527
	134.543	150.648	104.233	309.284
Debt Service	-3.889***	5.450***		
	0.630	1.552		
(Debt Service)*REU	-142.126**	478.789***		
	57.946	110.760		
Banks' Sovereign Exposure			0.562***	-0.613
			0.179	0.411
(Banks' Sovereign Exposure)*REU			-23.443*	101.177***
			13.342	28.895
Lagged Spread Change	0.020	-0.024	-0.016	0.085
	0.071	0.138	0.091	0.162
Excess Bond Premium	-3.889***	5.450***	0.562***	-0.613
	0.630	1.552	0.179	0.411
VIX	2.277	18.534***	-3.970	16.264
	2.041	7.013	2.634	11.068
Foreign Real 2y Treasury Yield	1.189***	0.039	1.659***	-0.521
	0.188	0.512	0.215	0.567
Foreign Term Spread (10y-2y)	3.730***	-4.977**	3.941***	-4.885**
	0.294	2.004	0.294	2.253
Foreign Stocks 1-month Return	-0.065	-0.830	0.804	1.396
	0.955	3.575	0.977	2.958
3-month Stocks Daily Return	-0.083	0.263	0.250	-1.090
	0.236	0.745	0.238	0.900
3-month Stocks Daily Return Volatility	-29.606**	-44.415**	-28.111**	3.266
	14.437	19.889	13.872	31.848
3-month Exch. Rate Daily Return	40.480	2174.453***	-197.893	2824.686***
	222.990	618.024	283.373	893.766
3-month Exch. Rate Daily Return Volatility	-61.017***	-97.005**	-102.419***	-135.161***
	15.211	40.171	16.771	33.480
N	5679	2526	4177	2184
Pseudo R2	0.067	0.067	0.079	0.0545
Percentile	90th	90th	90th	90th
Estimator Method	Canay	Canay	Canay	Canay
Country Fixed Effects	Yes	Yes	Yes	Yes

Sources: FRED, Federal Reserve Bank of St. Louis; Haver Analytics; OECD, Main Economic Indicators database; ICE BoFA; LSEG Datastream; and IMF staff calculations.
Note: Table shows results of quantile panel regressions of sovereign bond spread changes from time t to t+3 using country fixed effects and estimated at the 90th percentile of the distribution of the change in spreads. Specifications include interaction terms between REU and relevant country level vulnerabilities. Estimates based on the Canay estimator. The separate samples consist of unbalanced monthly data for 20 AEs and 9 EMs from 1990m1 to 2024m02. The underlying regressions include relevant controls for the sovereign bond market at the country and global levels following Gilchrist and others (2022), as well as the lagged dependent variable. Spreads are calculated relative to a benchmark economy for each country (Germany for Euro area countries and the United States for all others) and using only debt denominated in the same currency of the benchmark economy. Standard errors presented below the coefficient. *, ** and *** denote statistical significance at the 10, 5 and 1 percent levels, respectively.

Online Annex Table 2.5.3 Regression Results for Tail Risk to Stock Returns

	Advanced Economies				Emerging Markets			
	1-month	3-month	6-month	12-month	1-month	3-month	6-month	12-month
Real Economic Uncertainty (REU)	-70.152***	-200.844***	-297.457***	-329.899***	-39.883	-213.213***	-255.304***	-213.773***
	14.611	23.952	24.999	44.506	30.075	58.393	72.833	56.223
Lagged Stocked Returns	0.017***	0.022***	0.019***	0.028***	0.017***	0.009**	0.013	0.022*
	0.002	0.003	0.006	0.008	0.004	0.005	0.010	0.012
Inflation (3m)	-0.454***	-1.771***	-2.798***	-3.929***	-0.249	1.014	4.332***	7.032***
	0.123	0.215	0.348	0.553	0.621	0.926	1.363	2.464
Ind. Prod. (3m)	0.147	0.914***	0.884**	-0.603	0.089	0.688	-2.426**	-6.542***
	0.093	0.258	0.406	0.534	0.333	0.609	1.107	1.017
3m Interest rate (detrended)	-0.295**	-1.454***	-1.946***	0.896	0.478*	2.176***	2.973***	7.679***
	0.149	0.308	0.422	0.588	0.283	0.690	0.872	1.091
Term Spread	0.255*	0.208	0.928**	4.158***	0.262	1.196**	3.119***	5.667***
	0.134	0.324	0.393	0.625	0.276	0.599	0.848	1.066
Dividend Yield	0.141	0.893***	2.809***	7.990***	0.461*	1.895***	4.961***	7.356***
	0.141	0.304	0.542	0.481	0.256	0.482	1.090	1.285
Stock Return Volatility (3m)	-1.164***	-1.317***	-1.922***	-2.464***	-0.815*	-0.021	-0.052	6.249***
	0.196	0.382	0.436	0.644	0.482	0.747	1.248	0.669
Price/Earnings	-0.027	-0.311	0.006	2.460***	0.492***	1.133***	3.921***	6.356***
	0.131	0.293	0.541	0.482	0.175	0.382	0.731	1.056
N	4761	4761	4761	4671	981	981	981	951
Pseudo R2	0.088	0.105	0.107	0.122	0.066	0.086	0.132	0.251
Percentile	10th	10th	10th	10th	10th	10th	10th	10th
Estimator Method	Canay	Canay	Canay	Canay	Canay	Canay	Canay	Canay
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Sources: Sources: FRED, Federal Reserve Bank of St. Louis; Haver Analytics; OECD, Main Economic Indicators database; LSEG Datastream; and IMF Staff Calculations.
Notes: Table shows results for regressions of national stock total average annualized returns at different horizons (1, 3, 6 and 12 months) relative to month t, measured at the 10th percentile of the returns distribution using panel quantile regressions with country fixed effects. Estimates based on the Canay estimator. The panel is comprised of 20 AEs and 9 EMs and the sample period ranges from 1990m1 to 2023m12, with the panel being unbalanced due to data availability across countries. The underlying monthly unbalanced panel regressions include country fixed effects, lagged returns, and relevant stock market controls at the country levels, following Schmeling (2009) and Goyal and Welch (2008). *, ** and *** denote statistical significance at the 10, 5 and 1 percent levels, respectively.

B. Tail risk in bank lending

To study the impact of uncertainty measures on bank lending tail risk, the following specification is estimated:

$$Lending_{i,t+h}^{(\tau)} = \beta_i^{(\tau)} + \gamma_t^{(\tau)} + \beta_l^{(\tau)}\, Lending_{i,t}^{(\tau)} + \beta_u^{(\tau)} U_{i,t} + \beta_v^{(\tau)}\, V_{i,t} + \beta_{uv}^{(\tau)}\, U_{i,t} V_{i,t} + \beta_z^{(\tau)} Z_{i,t} + \epsilon_{i,t+h}^{(\tau)}, \quad (17)$$

where $Lending_{i,t+h}^{(\tau)}$ denotes the τ^{th} percentile of the distribution of real credit growth in country i between quarter t and $t+h$; credit growth is defined as the average annualized real rate of growth of the stock of bank credit (to firms and households) over the considered horizon; $U_{i,t}$, $V_{i,t}$ and $U_{i,t}V_{i,t}$ denote uncertainty measures, macrofinancial vulnerabilities (described below) and uncertainty-vulnerability interaction terms, respectively; $Z_{i,t}$ includes other relevant control variables (such as real GDP growth and domestic FCI); and $\beta_i^{(\tau)}$ and $\gamma_t^{(\tau)}$ denote country-specific and time effects, respectively.

More specifically, $V_{i,t}$ denotes the credit-to-GDP gap and several banking sector fundamentals that can potentially influence credit growth dynamics, such as the deviation of regulatory capital-to-asset ratio from its country-specific trend, return on assets, non-performing loans (NPLs) ratio, and banks' government debt exposure measured as the share of domestic sovereign bond holdings in banks' total assets.[8] Other variables that may have an impact on aggregate credit dynamics (such as house price growth, changes in stock market index, broad money-to-GDP ratio, US Fed Funds Rate, policy rate and the slope of the yield curve for each country, bank lending rate, changes in nominal exchange rate, etc. (e.g. Magud and others 2014; Miranda-Agrippino and Rey, 2022)) are captured by the FCI and time effects.

Online Annex Figure 2.5.1. Text-based Uncertainty Indicator Constructed from Banks' Earnings Calls

The text-based measure of uncertainty is not strongly correlated with other measures of macroeconomic uncertainty...

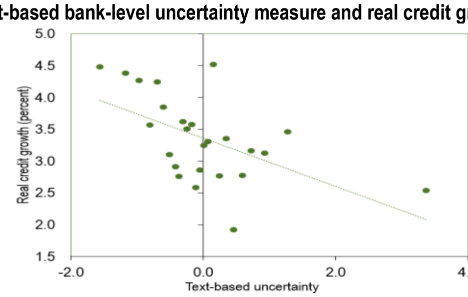
1. Correlations between measures of uncertainty

	Forecast dispersion	REU	EPU	Text-based
Forecast dispersion	1.00			
REU	0.61***	1.00		
EPU	0.24***	0.37***	1.00	
Text-based	0.02	0.03	-0.05	1.00
Alternative text-based	0.12***	0.17***	0.04	0.77***

* p < 0.05, ** p < 0.01, *** p < 0.001

…but is negatively correlated with real credit growth.

2. Text-based bank-level uncertainty measure and real credit growth



Sources: IMF staff calculations.
Notes: Panel 1 presents the correlations between measures of uncertainty used in the bank lending analysis. "Text-based" refers to the measure of uncertainty constructed from banks' earnings calls. "Alternative text-based" refers to an additional measure of uncertainty, which is constructed from the same earnings calls but based on a narrow list of key words (see footnote 10). Panel 2 presents a binscatter plot of the text-based uncertainty measure and real credit growth used in the country-level bank lending analysis. Real credit growth is the average quarterly annualized growth of real credit over the next four quarters. Following the methodology of Cattaneo, Crump, Farrell and Feng (2024), the (standardized) text-based uncertainty is ordered and grouped into 25 bins. The fitted line has a slope of -0.38 (statistically significant at the 1 percent level).

$U_{i,t}$ includes four measures of uncertainty: the Economic Policy Uncertainty index (EPU), the Real Economic Uncertainty index (REU), dispersion of the forecast of one-year ahead real GDP growth, and a text-based measure constructed using banks' earnings call reports. The text-based measure is constructed by first scaling the number of sentences that contain uncertainty-related words by the number of sentences in earnings calls for each bank, using the list of words provided by the Loughran-McDonald Master Dictionary (2024).[9] At each time point, the country-level measure used in this analysis is a simple average of the above bank-specific scores. This measure of uncertainty has little correlation with the other indicators considered in this section (Online Annex Figure 2.5.1, panel 1).[10] Nevertheless, it is negatively correlated with credit growth

[8] The regulatory capital-to-asset ratio exhibits an upward trend, likely reflecting more stringent capital requirements. In this analysis, the deviation of regulatory capital-to-asset ratio from country-specific trends is used (the trend is computed using a two-sided HP filter). The credit-to-GDP gap is also calculated as the deviation of the credit-to-GDP ratio from country-specific trends (based on a two-sided HP filter).

[9] Soto (2021) also constructs bank-level measures of uncertainty by counting the frequency of words in earnings calls, but only for US banks. It also uses a machine learning approach to construct a dictionary of words related to uncertainty.

[10] The low correlation with the EPU (which is also constructed using a text-based approach by Baker and others (2016)) can partly be explained by the different lists of key words. The EPU index reflects the frequency of articles in newspapers that contain the following triple: "economic" or "economy"; "uncertain" or "uncertainty"; and one of more of "congress", "deficit", "Federal Reserve", "legislation", "regulation" or "White House".

(Online Annex Figure 2.5.1, panel 2). Putting together, these suggest that uncertainty conveyed in banks' earnings calls may reflect aspects of uncertainty that are not measured by other indicators and therefore can be an additional determinant of bank loan supply.

Equation (17) is estimated using quarterly data for a panel of 18 advanced economies and 13 emerging market economies from 2001 to 2023. The findings suggest that higher macroeconomic uncertainty is negatively associated with downside risks to future (four-quarter ahead) credit growth across the different measures of uncertainty considered (Online Annex Table 2.5.4).[11] Notably, when the four measures of uncertainty are considered together in the same specification (i.e., col. 5), the coefficients on forecast dispersion, real economic uncertainty and the text-based bank-level indicator are all negative and statistically significant, confirming that these measures capture different aspects of uncertainty that are all useful for forecasting tail risks to lending.[12]

Online Annex Table 2.5.4. Regression Results for Tail Risk in Bank Lending

	(1)	(2)	(3)	(4)	(5)
FCI	-1.43^{***}	-1.28^{***}	-1.53^{***}	-1.31^{***}	-1.28^{***}
	(-5.86)	(-5.58)	(-4.55)	(-5.43)	(-3.31)
Real gdp growth	0.056^{*}	0.021	0.045^{*}	0.052^{*}	0.043
	(1.80)	(0.86)	(1.78)	(1.90)	(1.46)
Real credit growth	0.13^{***}	0.11^{***}	0.18^{***}	0.16^{***}	0.23^{***}
	(5.09)	(3.70)	(5.39)	(5.09)	(5.33)
Credit-to-GDP gap	-0.18^{***}	-0.12^{***}	-0.21^{***}	-0.22^{***}	-0.16^{***}
	(-3.76)	(-3.52)	(-4.08)	(-4.13)	(-2.61)
NPL ratios	-0.38^{***}	-0.46^{***}	-0.53^{***}	-0.58^{***}	-0.53^{***}
	(-5.12)	(-7.10)	(-5.28)	(-4.39)	(-5.36)
Return on assets	1.74^{***}	2.54^{***}	1.79^{***}	1.20^{***}	1.42^{***}
	(8.51)	(9.43)	(6.22)	(3.99)	(4.27)
Reg. cap. to asset (detrended)	1.58^{***}	1.01^{***}	1.13^{***}	1.75^{***}	1.03^{***}
	(7.92)	(6.63)	(4.64)	(7.20)	(3.84)
Bank sovereign exposures	0.13^{***}	-0.061^{**}	-0.019	0.10^{***}	0.12^{***}
	(4.30)	(-2.35)	(-0.78)	(3.13)	(3.72)
Dispersion of 1-y ahead growth forecast	-1.47^{***}				-0.99^{**}
	(-4.13)				(-2.30)
Real Economic Uncertainty		-0.87^{***}			-1.45^{***}
		(-4.42)			(-4.38)
Economic Policy Uncertainty Index			-0.41^{**}		-0.0054
			(-2.07)		(-0.03)
Text-based Indicator				-0.59^{***}	-0.43^{**}
				(-3.07)	(-1.97)
N	2178	1949	1179	1753	929
Pseudo R2	0.24	0.27	0.33	0.23	0.40

t statistics in parentheses
* $p < 0.12$, ** $p < 0.05$, *** $p < 0.01$

Sources: IMF staff calculations.

Notes: Table shows the estimated coefficients for the panel quantile regression of the 10th percentile of the distribution of country-level real credit growth on the measure of uncertainty and a number of covariates (i.e., equation (17)). Real credit growth is the average quarterly annualized growth over the next 4 quarters.

It is noteworthy that the stock of credit in this analysis measures the amount of credit extended by domestic banks to the private non-financial sector. As discussed in IMF (2024), private credit as an alternative to bank financing has been growing rapidly and now rivals other major credit markets in size. Therefore, bank credit may only capture part of the credit channel in certain markets. To address this concern, a robustness test with the Bank for International Settlements total credit data is used, which comprises of financing from all sources, including domestic banks, other domestic financial corporations, non-financial corporations, and non-residents. The results are similar (Online Annex Figure 2.5.2), which is not surprising given the high

Thus, a narrow list of uncertainty-related words is used in the construction of EPU. In contrast, the Loughran-McDonald Master Dictionary (2024) used in this analysis contains around 300 words that convey a sense of uncertainty. The very different list of words may explain the low correlation between the text-based measure here and EPU. To explore this point, an alternative indicator is constructed using three, precise words pertaining to uncertainty ("uncertain", "uncertainty", "uncertainties"). As shown in Panel 1 of Online Appendix Figure 2.5.1, the correlation of this alternative text-based indicator with other indicators increases. However, the correlation of this indicator with real credit growth does not improve and results from the associated empirical analysis tends to underperform those using the baseline text-based indicator.

[11] The baseline results presented in the main text are estimated through a two-step procedure for panel quantile regressions, following Canay (2011). For all measures of uncertainty considered in this section, the results are robust to an alternative estimation method proposed by Powell (2022), which tends to generate tighter confidence intervals compared with Canay (2011). Results for three out of four measures of uncertainty (except the text-based uncertainty) are robust to another estimation method proposed by Machado and Silva (2019). Different from Power (2022), the approach of Machado and Silva (2019) tends to generate larger confidence intervals, compared with Canay (2011).

[12] The coefficients on the covariates are largely as expected. Across all specifications, there is consistent finding that tighter financial conditions, larger credit-to-GDP gap, and higher banking system NPL ratios are associated with lower future credit growth, while stronger banking system profitability and capital position are associated with higher future credit growth.

correlation between total credit and bank credit (99.6 percent). The estimations using total credit in general point to larger and more persistent effects of uncertainty on tail risks of lending.

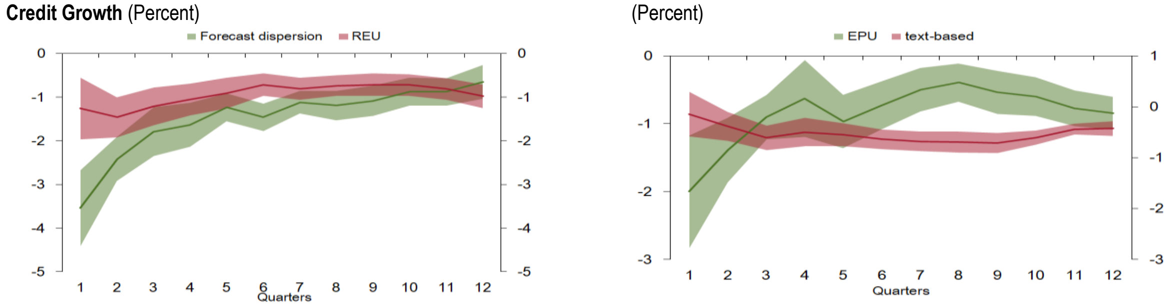
Online Annex Figure 2.5.3 presents the estimation results for eq. (17) for the sub-samples of advanced and emerging market economies.[13] Overall, the main findings hold, though some measures of uncertainty are more significant for certain country groups.

Online Annex Figure 2.5.2. Uncertainty and Tail Risk to Total Credit (Bank and Nonbank)

Higher uncertainty is associated with persistent downside risks to total credit growth in the economy.

1. Real GDP Forecast Dispersion, REU, and Downside Risk to Total Credit Growth (Percent)

2. EPU and the text-based indicator (Percent)



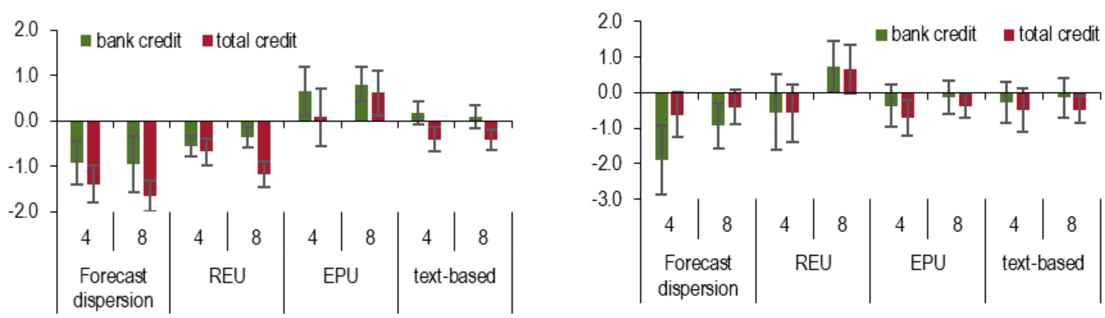
Sources: IMF staff calculations.

Note: The charts plot the estimated impact of one standard deviation increase in uncertainty measures (real GDP forecast dispersion, REU, EPU and the text-based indicator) on the 10th percentile of future real credit growth distribution. Real credit growth is the average quarterly annualized growth of bank and nonbank credit in the future over a specific horizon indicated on the x-axis.

Online Annex Figure 2.5.3. Uncertainty and Tail Risk to Lending by AEs and EMs

1. Bank Lending and Macroeconomic Uncertainty in Advanced economies (Percent)

2. Bank Lending and Macroeconomic Uncertainty in Emerging Market Economies (Percent)



Sources: IMF staff calculations.

Note: The charts plot the estimated impact of one standard deviation increase in uncertainty (measured by forecast dispersion, REU, EPU and the text-based indicator) on the 10th percentile of future real credit growth distribution. Real credit growth is the average quarterly annualized growth over the next 4 or 8 quarters.

[13] While considering subsamples helps maintain some homogeneity in the characteristics of countries in each group, it comes with the cost that the results may be less precisely estimated due to a more limited sample size, especially for the EPU and text-based indicators.

Online Annex 2.6. Does the impact of macroeconomic uncertainty spill over across borders to affect downside risks to economic activity in major financial and trading partners?

To examine the cross-border spillover effects of macroeconomic uncertainty, the standard GaR model is extended to include a measure of foreign uncertainty (i.e., macroeconomic uncertainty in major trading and financial partners), along with a measure of domestic macroeconomic uncertainty and other control variables.[1] Thus, a panel quantile model is estimated as follows:

$$y_{i,t+h}^{(\tau)} = \beta_h^{(\tau)} + \beta_{h,y}^{(\tau)} y_{i,t} + \beta_{h,FCI}^{(\tau)} FCI_{i,t} + \beta_{h,u}^{(\tau)} U_{i,t} + \beta_{h,v}^{(\tau)} Z_{i,t} + \beta_{h,o}^{(\tau)} U_{-i,t} + \epsilon_{i,t+h}^{(\tau)}, \qquad (18)$$

where $U_{-i,t}$ denotes foreign uncertainty measures computed as weighted average of uncertainty of major financial and trading partners of country i, with weights corresponding to the total trade (exports and imports) between country *i* and other countries, normalized by country's *i* GDP. Similar measures are constructed for the banking relationship (sum of assets and liabilities to domestic GDP) and portfolio investment between *i* and *j* (as a share of country *i*'s GDP). $Z_{i,t}$ indicates other relevant control variables, e.g., global real GDP growth, global financial conditions, a domestic financial uncertainty index (based on Ludvigson and others 2021), and a dummy variable equal to one for the GFC (and zero otherwise). The definition of the other variables in equation (18) is the same as in equation (8).

The main results of the analysis are robust to the use of: i) alternative measures of uncertainty (e.g. see results using the economic policy index in the Online Annex Figure 2.6.1); ii) alternative panel quantile estimators; iii) total credit growth as dependent variable $y_{t+h}^{(\tau)}$ in the regressions. iv) controlling for additional confounding factors (such as inflation, policy rate, unemployment, v) estimating the model on the pre-COVID period or by excluding the first three quarters of 2020.[2]

To assess the role of international reserves in mitigating spillover effects from foreign uncertainty, equation (18) is extended to include an indicator variable for these measures along with their interaction term with indicators of foreign macroeconomic uncertainty. The panel quantile model is then estimated as follows:

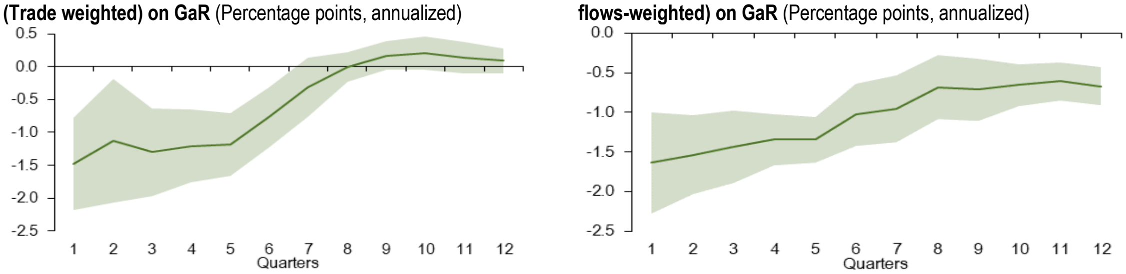
$$y_{t+h}^{(\tau)} = \beta_h^{(\tau)} + \beta_{h,y}^{(\tau)} y_t + \beta_{h,FCI}^{(\tau)} FCI_t + \beta_{h,u}^{(\tau)} U_{i,t} + \beta_{h,z}^{(\tau)} Z_{i,t} + \beta_{h,o}^{(\tau)} U_{-i,t} + \beta_{h,b}^{(\tau)} High\ Buffer_{i,t} + \beta_{h,ob}^{(\tau)} U_{-i,t_t} x\ High\ Buffer_{i,t} + \epsilon_{t+h}^{(\tau)}, \qquad (19)$$

where $High\ Buffer_{i,t}$ a dummy that takes the value one when international reserves-to-GDP is above the median, and $High\ Buffer_t\ x\ V_{i,t}$ represent interaction terms between foreign uncertainty and indicator variable. The coefficients of interest are $\beta_{h,o}^{(\tau)}$ and $\beta_{h,ob}^{(\tau)}$.

Online Annex Figure 2.6.1. Cross-border Spillover Effects of Foreign Uncertainty

1. Effect of an Increase in Foreign Economic Policy Index (Trade weighted) on GaR (Percentage points, annualized)

2. Effect of an Increase in Foreign Economic Policy Index (Portfolio flows-weighted) on GaR (Percentage points, annualized)



Sources: Haver Analytics; OECD, Main Economic Indicators database; LSEG Datastream; and IMF staff calculations.
Notes: Panels 1-2 illustrate the impact of a one standard deviation increase in various foreign uncertainty measures on the 10th percentile of future quarterly real GDP growth (annualized) over time. In panel 1, the foreign uncertainty measure is calculated as a weighted average of the economic policy index in trading partners with weights computed as the sum of bilateral exports and imports to domestic GDP. In panels 2, the foreign uncertainty measure is calculated as a weighted average of the economic policy index in financial partners with weights computed as the sum of portfolio assets and liabilities to domestic GDP. The model controls for current GDP growth, domestic financial conditions index, domestic real economic and financial uncertainty measures (based on Ludvigson and others 2021), global real GDP growth, a global financial condition index and a dummy variable for the global financial crisis. Estimations are conducted using a panel quantile regression framework for the full sample of advanced and emerging market economies. Shaded area around estimated coefficients (solid line) correspond to 90 percent confidence intervals. Standard errors are bootstrapped.

[1] Note also that the transmission of macroeconomic uncertainty across borders often involves carry trades (financed through the cross-border credit channel) that influence the risk of currency crashes (Brunnermeier and others 2009).
[2] The foreign uncertainty measures are constructed using an approach similar to that of Londono and others (2021). Additionally, further analysis was conducted to evaluate the significance of trade and financial linkages, building on the methodology described in Ahir and others (2022). In line with previous findings based on the World Uncertainty Index, the results suggest that trade and financial linkages are positively correlated with REU synchronization, defined as the negative absolute difference between domestic and foreign uncertainty. This relationship holds even after accounting for business cycle synchronization. Detailed results are available upon request from the authors.

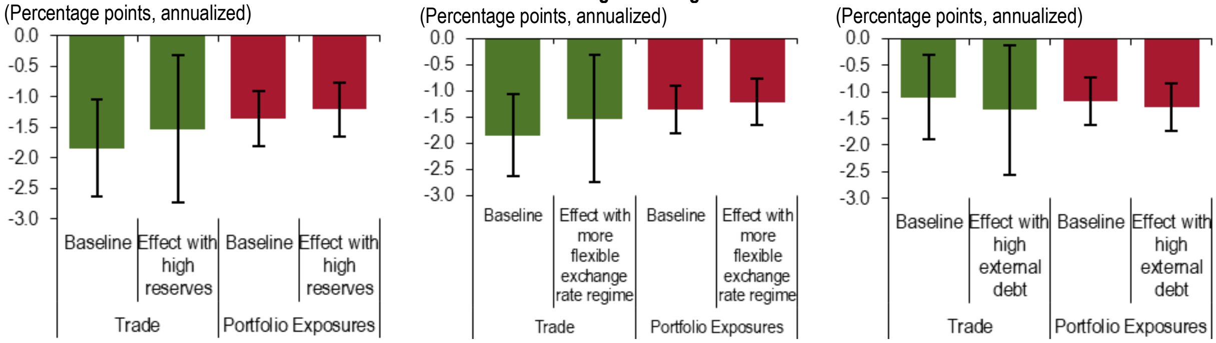
A similar, specification is also tested substituting the $High\ Buffer_{i,t}$ with a dummy variable that identifies flexible exchange rate regimes and a dummy that identifies countries with large external debt-to-GDP. The dummy reflecting the flexibility of exchange rate regime is based on the coarse classification by Ilzetzki and others (2021), where a value of 3 or higher (on a scale from 1 to 6) indicates more flexible exchange rate regimes. The indicator variable for external debt-to-GDP takes value one when the latter is above median. Results are presented in Online Annex Figure 2.6.2. Overall, the findings indicate that international buffers and flexible exchange rate regimes help mitigate spillover effects from foreign uncertainty, while larger external debt amplifies these effects.

Online Annex Figure 2.6.2. Spillover Analysis: Effect of Buffers, Exchange Rate Regimes and External Debt

1. Effect of an Increase in Foreign Real Economic Uncertainty on GaR for Economies with Different International Reserves
(Percentage points, annualized)

2. Effect of an Increase in Foreign Real Economic Uncertainty on GaR for Economies with Different Exchange Rate Regime
(Percentage points, annualized)

3. Effect of an Increase in Foreign Real Economic Uncertainty on GaR for Economies with Different External Debt
(Percentage points, annualized)



Sources: Haver Analytics; OECD, Main Economic Indicators database; LSEG Datastream; and IMF staff calculations.
Panels 1-3 illustrate the impact of a one standard deviation increase in various foreign real economic uncertainty on the 10th percentile of one-quarter ahead real GDP growth (annualized) for different levels of international reserves-to-GDP, for more flexible exchange rate regimes and external debt-to-GDP (respectively). The "High (low) international reserves (external debt)" dummy is equal to 1 for values of the variable (normalized by GDP) above (below) the median. The "more flexible exchange rate regimes" dummy is based on the coarse classification by Ilzetzki and others (2021), where a value of 3 or higher (on a scale from 1 to 6) indicates more flexible exchange rate regimes. Estimations are conducted using panel quantile regressions for the economies in the sample, depending on data availability. The model controls for current GDP growth, domestic financial conditions index, domestic real economic and financial uncertainty measures (based on Ludvigson and others 2021), global real GDP growth, a global financial condition index and a dummy variable for the global financial crisis. Results are presented using both trade-weighted and portfolio exposures-weighed foreign uncertainties. Error bars (solid color) indicate 90 percent confidence intervals.

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