Online Annex: Riding the Waves: Building Resilience in an Era of High Uncertainty

2.1. Measures of Uncertainty

There are several different approaches to measuring uncertainty, which all differ in their interpretation. First, text-based measures use computer algorithms to search for the number of times the word “uncertainty” and related terms are mentioned in newspapers and economic reports. These capture expert perceptions of uncertainty. Second, uncertainty can be proxied by the volatility of price-based market indicators (for example, the US Volatility Index, VIX). These are market-based perceptions of uncertainty, reflecting bets by market participants on financial asset price movements. Third, forecast error behavior-based estimates can also be used to measure uncertainty (for example, large/small errors). These error-based measures are, in effect, measures of expert forecasters’ *ex-post* uncertainty. To ensure a sufficient country and time coverage in the analysis, this chapter relies on text-based measures, which are the most widely available.[1]

Text-Based Measures

The World Uncertainty Index (WUI) database was developed by Ahir, Bloom, and Furceri (2022). In addition to being timely and one of the most heavily cited indicators of global uncertainty, it also has broad country coverage (143 countries), including for the Middle East and Central Asia regions (27 countries). In each quarter, the index is constructed by counting the number of times the word “uncertainty” (or uncertainty synonyms) appears in each country’s Economist Intelligence Unit report. It is then scaled by the total number of words in each report. The database also includes uncertainty related to trade—the World Trade Uncertainty (WTU) index—by counting the number of times the word “trade” (or its synonyms) appears in close proximity to the overall uncertainty word count.

The Economic Policy Uncertainty (EPU) index is constructed similarly to the WUI and counts the number of times a trio of terms related to the economy, policy, and uncertainty appear in major newspaper articles across 22 countries (see Baker and others 2016). The Trade Policy Uncertainty (TPU) index (Caldara and others 2020) follows a similar approach by measuring the joint occurrences of terms related to trade policy uncertainty in major newspapers. Similarly, the Monetary Policy Uncertainty (MPU) index (Husted and others 2020) counts the frequency of terms related to US monetary policy and uncertainty.

2.2. A Dynamic Factor Model of Uncertainty

Methodology

A dynamic factor model (DFM) is used to decompose each country's uncertainty index (WUI) into global, regional, and idiosyncratic factors (see Stock and Watson [2011] for a detailed description of DFMs). The global factor reflects common sources of uncertainty across all countries, regional factors reflect common sources of uncertainty across countries within a particular region (after taking account of common global variation), and the idiosyncratic factor is specific to each country. Specifically:

$$X_{i,t} = A_i F_t + B_i G_{j,t} + \varphi_{i,t}$$

where $X_{i,t}$ is the (standardized) uncertainty index for country *i* ; F_t is a global factor; $G_{j,t}$ is an orthogonal regional factor for country *i* in region *j*; $\varphi_{i,t}$ is an idiosyncratic shock to uncertainty in country *i*; and A_i and B_i are constant over time but differ across countries. Finally, F_t, $G_{j,t}$, and $\varphi_{i,t}$ are assumed to follow AR(1) processes:

$$F_t = CF_{t-1} + \mu_t$$

[1] The correlation between text-based measures of uncertainty and market-based indicators is low. However, according to Pastor and Veronesi (2016), this could be partly due to political news being more unreliable and difficult for financial investors to interpret. Another reason could be that the expansionary US monetary policy may have contributed to reducing the VIX in the post-global financial crisis period (Bekaert, Hoerova, and Lo Duca 2013).

$$G_{j,t} = D_j G_{j,t-1} + \mu_{j,t}$$
$$\varphi_{i,t} = E_i \varphi_{i,t-1} + \mu_{i,t}$$

Uncertainty in each country is thus driven by three orthogonal shocks, μ_t, $\mu_{j,t}$, and $\mu_{i,t}$: the global shock (μ_t) impacts global uncertainty; the regional shock ($\mu_{j,t}$) impacts regional uncertainty in each region *j*; and the idiosyncratic shock ($\mu_{i,t}$) is specific to each country.

Aggregation Equations

Aggregation equations are used to examine the contributors to uncertainty at the regional and global levels. These US dollar GDP-weighted aggregates are treated as observable (measurement variables) in estimation. For each region *j*, the aggregate uncertainty index is:

$$X_{j,t} = \frac{1}{\delta_j} \sum_{i=1}^{N_j} (\delta_i w_i X_{i,t}) + \xi_{j,t}$$

where δ_j is the standard deviation of aggregate uncertainty in region *j,* δ_i and w_i are the standard deviation of country-level uncertainty and the average U.S. dollar GDP weight of country *i* in region *j*, respectively, $\xi_{j,t}$ is a measurement error for the regional aggregate (associated with the US dollar GDP weights being fixed in the specification but time-varying in the data), and N_j is the number of countries in region *j*.[2] Likewise, global uncertainty is the weighted average of the regional uncertainty aggregates:

$$X_t = \frac{1}{\delta} \sum_{j=1}^{N} (\delta_j w_j X_{j,t}) + \xi_t$$

where *N* is the number of regions.

Estimation

The state-space representation of the model outlined above is estimated with maximum likelihood using the Expectation Maximization (EM) algorithm. The EM algorithm consists of iterating the two-step procedure proposed by Doz, Giannone, and Reichlin (2011): the factors and parameters are first estimated using principal components and Ordinary Least Squares (OLS), then the factors and parameters are re-estimated using the Kalman Filter and OLS. The algorithm repeats the second step until the likelihood function is maximized.

Data

All data are sourced from the WUI database. The sample used in estimation begins in 2000Q1 and ends in 2025Q1 and spans 143 countries. The countries are categorized into seven regions: Africa, Asia Pacific, Western Hemisphere, Europe, Middle East and North Africa (MENA)[3] (excluding Gulf Cooperation Council countries), Gulf Cooperation Council countries, and the Caucasus and Central Asia.

2.3. Domestic Drivers of Uncertainty

Methodology

The empirical analysis aims to quantify the relative contributions of domestic factors to the variation of WUIs across countries. These contributions are estimated using a panel regression with an annual sample of 140 countries (19 MENA and 8 CCA countries) spanning 1996−2021 (reflecting data availability).[4] The panel regression is:

[2] Allowing for time-varying weights significantly increases the computational cost of estimation. Since the weights are relatively stable over the sample period for most countries, the weights are assumed to be fixed. Experimentation with time-varying weights and fewer countries suggests that relaxing this assumption would have very little impact on the empirical results. Since the uncertainty indexes for each country are standardized, aggregation requires multiplying each country's index by its standard deviation in aggregation.
[3] For analytical purposes, the Middle East and North Africa (MENA) region includes Pakistan in this annex and the main chapter.
[4] The Middle East and Central Asia countries in the sample are Afghanistan, Algeria, Armenia, Azerbaijan, Egypt, Georgia, Iraq, the Islamic Republic of Iran, Jordan, Kazakhstan, Kuwait, the Kyrgyz Republic, Lebanon, Libya, Mauritania, Morocco, Oman, Pakistan,

$$WUI_{j,t} = \sum_k \beta_k x_{k,j,t} + \delta_j + \varepsilon_{j,t}$$

where δ_j represents country-fixed effects, and $x_{k,j,t}$ represents a common global factor, a common regional factor, or a country-specific determinant of uncertainty. Regressions are run separately for MENA, CCA and the rest of the world.

The global and regional factors included in the regression are those estimated in Annex Section 2.2. The country-level determinants are: (1) Climate (absolute temperature differences from each country's 1950–90 temperature average); (2) Epidemics (the count of infectious disease outbreaks); (3) Political Instability (the number of successful and attempted coups, self-coups, assassinations or coerced resignations of the executive power, eviction of leadership by rebel or foreign forces, but not alleged coup plots or coup plots); (4) Conflict (a dummy variable that is equal to 1 when the number of conflict-related deaths exceeds the 75th percentile worldwide); and (5) Trade Uncertainty (from the WUI database). All these drivers can be considered shocks that are expected to be positively associated with uncertainty, $\beta_k > 0$. Throughout the analysis, standard errors are clustered at the country level to account for autocorrelation of the error term.

The economic significance of each driver is computed according to Sterck (2019):

$$c_k = \frac{d_k}{d_\varepsilon + \sum_k d_k} \qquad \text{where} \qquad d_k = |\widehat{\beta_k}| \sum_{j,t} |x_{k,j,t} - \overline{x_k}|, \quad \beta_\varepsilon = 1$$

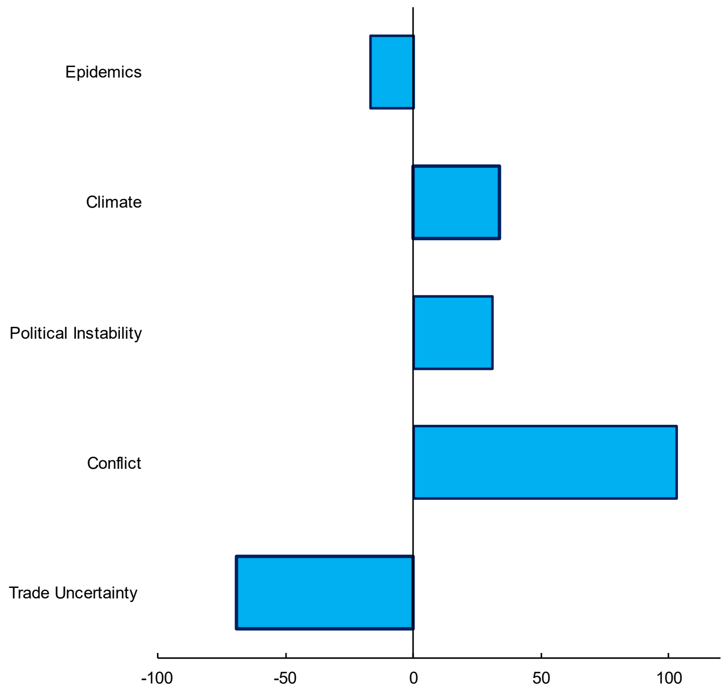
where d_k represents the effect size of each determinant on uncertainty and is the product of the coefficient estimate $\widehat{\beta_k}$ and the sum of mean absolute deviations of driver *k*. c_k measures the absolute economic importance of driver *k*, effectively the proportion of the variation of country-level uncertainty explained by driver *k*. Using the estimated idiosyncratic component of uncertainty instead as a dependent variable would give qualitatively similar results.

Data sources

The data sources are the global and regional factors described in Annex Section 2.2 (Global and Regional Uncertainty); the WUI database (Dependent Variable and Trade Uncertainty); Copernicus Climate Change Service information (2025) processed by Our World in Data (Climate); the Torres Munguía and others (2022) global database on infectious disease outbreaks (Epidemics); the Coups D'état events dataset from the Center of Systemic Peace's Integrated Network for Societal Conflict Research (Political Instability); and the Uppsala Georeferenced Event Database on conflict-related deaths (Conflict).

Qatar, Saudi Arabia, Sudan, Tajikistan, Tunisia, Turkmenistan, the United Arab Emirates, Uzbekistan, and Yemen. Trade Uncertainty and Infectious Diseases data is available from 1996, while data on Political Instability is available through 2021.

Annex Figure 2.3.1. Domestic Drivers of Uncertainty: MENA and CCA compared to the Rest of the World (1990–2023)
(Percent difference; positive means higher occurrence in MENA and CCA regions)



Sources: Ahir, Bloom, and Furceri 2022; World Uncertainty Index (WUI); Our World in Data; Center for Systemic Peace, Integrated Network for Societal Conflict Research; Torres Munguía and others 2022; Uppsala Conflict Data Program, Georeferenced Event dataset; and IMF staff calculations.
Note: The relative occurrence of a domestic driver of uncertainty is computed as the percentage difference between the average value of the uncertainty driver for MENA and CCA countries and the average value of that variable in the rest of the world.

Annex Figure 2.3.1 shows the relative occurrence of these shocks in the MENA and CCA regions compared to the rest of the world. Climate, Political Instability, and Conflict occur more frequently in the MENA and CCA regions than in the rest of the world, while Trade Uncertainty is lower in the MENA and CCA regions than elsewhere.

Annex Table 2.3.1. Regression Results – Baseline Specification

	(1) Rest of the World	(2) MENAP	(3) CCA
Global Uncertainty	0.0461***	0.0179	0.0289
	(0.0055)	(0.0117)	(0.0182)
Regional Uncertainty	-0.0001	0.0450***	0.0566**
	(0.0065)	(0.0141)	(0.0164)
Climate	0.0071	0.0211	0.0090
	(0.0066)	(0.0124)	(0.0122)
Epidemics	-0.0045	0.0000	0.0691***
	(0.0041)	(0.0083)	(0.0143)
Trade Uncertainty	0.0138***	0.0192*	0.0316**
	(0.0020)	(0.0097)	(0.0096)

Political Instability	0.0361**	0.0760**	0.0316
	(0.0182)	(0.0309)	(0.0365)
Conflict	-0.0094	0.0429	0.0252
	(0.0114)	(0.0294)	(0.0224)
Observations	2934	482	208
R2	0.312	0.356	0.292
Number of Countries	113	19	8

Sources: Ahir, Bloom, and Furceri 2022; World Uncertainty Index (WUI); Our World in Data; Center for Systemic Peace, Integrated Network for Societal Conflict Research; Torres Munguía and others 2022; Uppsala Conflict Data Program, Georeferenced Event dataset; and IMF staff calculations.
Note: The relative contributions are computed according to Sterck (2019) using the sum of mean absolute deviations as a distance measure. Clustered standard errors at the country-level in parentheses. * *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

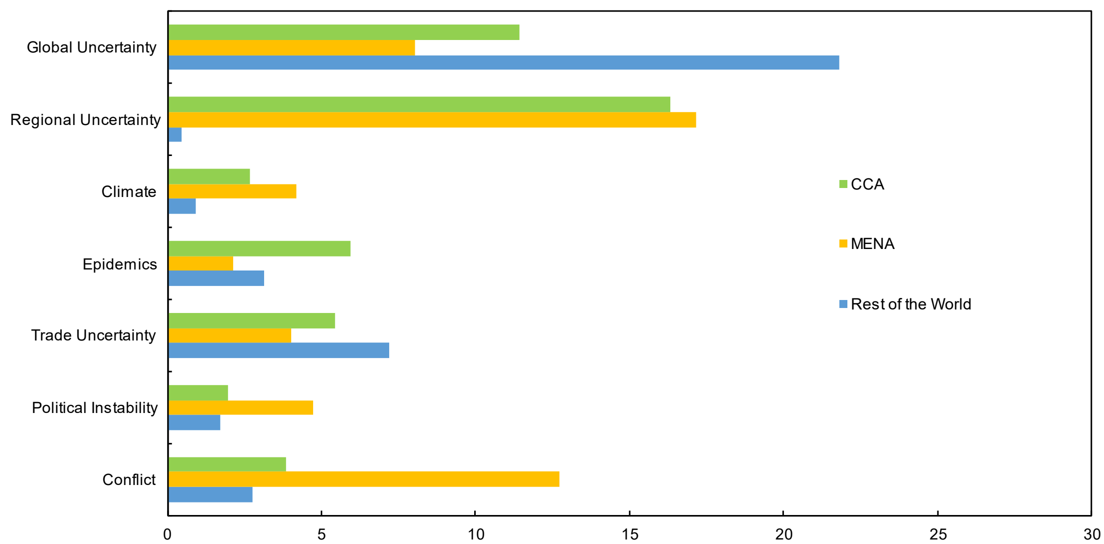
Annex Table 2.3.1 presents the regression estimates for the MENA and CCA regions, the MENA region, the CCA region, and the rest of the world, used to calculate the relative contributions shown in Figure 2.4 of the main text.

Robustness Exercises

Epidemics

The consequences of the COVID-19 pandemic could explain the outsized impact of uncertainty related to Epidemics on the variation of uncertainty in CCA countries. To alleviate this concern, Annex Table 2.3.2 and Annex Figure 2.3.2 show regression estimates and relative contributions excluding the last two years of the sample (2020 and 2021) for the MENA and CCA regions and for the rest of the world. Epidemic uncertainty (excluding COVID-19) contributes to about 6 percent of the variation of uncertainty across CCA countries, still much higher than in the rest of the world and in the MENA region.

Annex Figure 2.3.2. Domestic Drivers of Uncertainty, excluding COVID-19 years (2020 and 2021)
(Percent)



Sources: Ahir, Bloom, and Furceri 2022; World Uncertainty Index (WUI); Our World in Data; Center for Systemic Peace, Integrated Network for Societal Conflict Research; Torres Munguía and others 2022; Uppsala Conflict Data Program, Georeferenced Event dataset; and IMF staff calculations.
Note: The relative contributions add up to less than 100 because the error term contributes between 47 and 62 percent of the total variation. The relative contributions are computed according to Sterck (2019) using the sum of mean absolute deviations as a distance measure.

Annex Table 2.3.2. Regression Results – excluding COVID-19 years (2020 and 2021)

	(1) Rest of the World	(2) MENA	(3) CCA
Global Uncertainty	0.0447***	0.0174	0.0263
	(0.0057)	*(0.0119)*	*(0.0203)*
Regional Uncertainty	0.0013	0.0452***	0.0595***
	(0.0070)	*(0.0141)*	*(0.0167)*
Climate	0.0035	0.0172	0.0096
	(0.0069)	*(0.0144)*	*(0.0143)*
Epidemics	-0.0085**	-0.0073	0.0594**
	(0.0041)	*(0.0086)*	*(0.0187)*
Trade Uncertainty	0.0129***	0.0193*	0.0323**
	(0.0020)	*(0.0094)*	*(0.0099)*
Political Instability	0.0336*	0.0884**	0.0375
	(0.0188)	*(0.0326)*	*(0.0392)*
Conflict	-0.0104	0.0413	0.0158
	(0.0121)	(0.0296)	(0.0218)
Observations	2710	444	192
R2	0.310	0.364	0.276
Number of Countries	113	19	8

Sources: Ahir, Bloom, and Furceri 2022; World Uncertainty Index (WUI); Our World in Data; Center for Systemic Peace, Integrated Network for Societal Conflict Research; Torres Munguía and others 2022; Uppsala Conflict Data Program, Georeferenced Event dataset; and IMF staff calculations.
Note: The relative contributions are computed according to Sterck (2019) using the sum of mean absolute deviations as a distance measure. Years 2020 and 2021 are excluded from the estimation. Clustered standard errors at the country-level in parentheses.
* *p < 0.10,* ** *p < 0.05,* *** *p < 0.01*

2.4. Economic Cost of Uncertainty

Methodology

The economic costs of uncertainty are estimated using local projections following Jordà (2005) using the following baseline specification:

$$y_{i,t+h} - y_{i,t-1} = \beta_1^h UNC_{i,t} + \beta_2^h UNC_{i,t} * MECAdummy_i + \sum_{j=1}^{l} \beta_{3,j}^h UNC_{i,t-j} + \sum_{j=1}^{l} \gamma_{1,j}^h (y_{i,t-j} - y_{i,t-j-1}) + \theta_j^h X_{i,t} + \alpha_i^h + \alpha_t^h + \epsilon_{i,t}^h$$

$MECAdummy$ is an indicator variable equal to 1 if the country is part of the Middle East and Central Asia region.

Quarterly Data

Quarterly data is used to estimate the impact of uncertainty on stock market volatility and sovereign spreads. $y_{i,t}$ is the dependent variable of interest (log of stock market price volatility or sovereign spreads), $UNC_{i,t}$ is the standardized uncertainty index (WUI), and *h* is the impulse response horizon. α_i^h and α_t^h are country or stock market indices and time fixed effects, respectively. Three lags of the dependent variable and the uncertainty variable are included. Standard errors are clustered at the country or stock market index level are robust to double clustering. The coefficient β_1^h directly estimates the impulse response of the variable of interest for horizon *h* in response to a one standard deviation increase in the uncertainty variable among all economies excluding MENA and CCA countries. The coefficient β_2^h estimates the differential impulse response of the variable of interest for horizon *h* in response to a one standard deviation increase in the uncertainty variable among MENA and CCA countries. The average impulse response for MENA and CCA countries is the sum of β_1^h and β_2^h.

When looking at global shocks, time-fixed effects are removed and replaced by year and quarter fixed effects while controlling for domestic uncertainty.

Annual Data

Annual data is used to estimate impact of uncertainty on output growth and additional macroeconomic variables. $y_{i,t}$ is the dependent variable of interest, $UNC_{i,t}$ is the standardized uncertainty variable (WUI), $X_{i,\,t}^{j}$is a set of control variables: (log) trade openness, terms of trade (percent change), and export partners' growth, investment as a share of GDP, epidemic outbreaks, conflict shocks, control of corruption, and natural disaster shocks (estimated damage as a share of GDP) and *h* is the impulse response horizon. α_i^h and α_t^h are country- and time-fixed effects, respectively. Two lags of GDP growth and the uncertainty variable are included. Standard errors are clustered at the country level and are robust to double clustering.

The coefficient β_1^h directly estimates the impulse response of variable of interest for horizon *h* in response to a one standard deviation increase in the uncertainty variable among all economies excluding MENA and CCA countries. The coefficient β_2^h estimates the differential impulse response of the variable of interest for horizon *h* in response to a one standard deviation increase in the uncertainty variable among MENA and CCA countries. The average impulse response for MENA and CCA countries is the sum of β_1^h and β_2^h. These results are displayed in Annex Figure 2.4.1.

When looking at global shocks (Annex Figure 2.4.2), time-fixed effects are removed and additional controls include global oil prices, US federal funds rates, an additional lag of each control variable, and the country-level uncertainty index. The results are also robust to controlling for tariff rates and financial crises.

Differential Impacts based on Pre-Existing Conditions

The following specification is used for the differential impacts of pre-existing conditions (the control of corruption and the debt-to-GDP ratio) across MENA countries:

$$y_{i,t+h} - y_{i,t-1} = \beta_1^h UNC_{i,t} + \beta_2^h UNC_{i,t} * MENAdummy_i + \beta_3^h UNC_{i,t} * PreExistingCharateristicDummy_{i,t} + \beta_4^h MENAdummy_i * PreExistingCharateristicDummy_{i,t} + \beta_5^h UNC_{i,t} * MENAdummy_i * PreExistingCharateristicDummy_{i,t} + \sum_{j=1}^{l} \beta_{6,j}^h UNC_{i,t-j} + \sum_{j=1}^{l} \gamma_{1,j}^h \left(y_{i,t-j} - y_{i,t-j-1}\right) + \sum_{j=1}^{l} \theta_j^h X_{i,t-j} + \alpha_i^h + \alpha_t^h + \epsilon_{i,t}^h$$

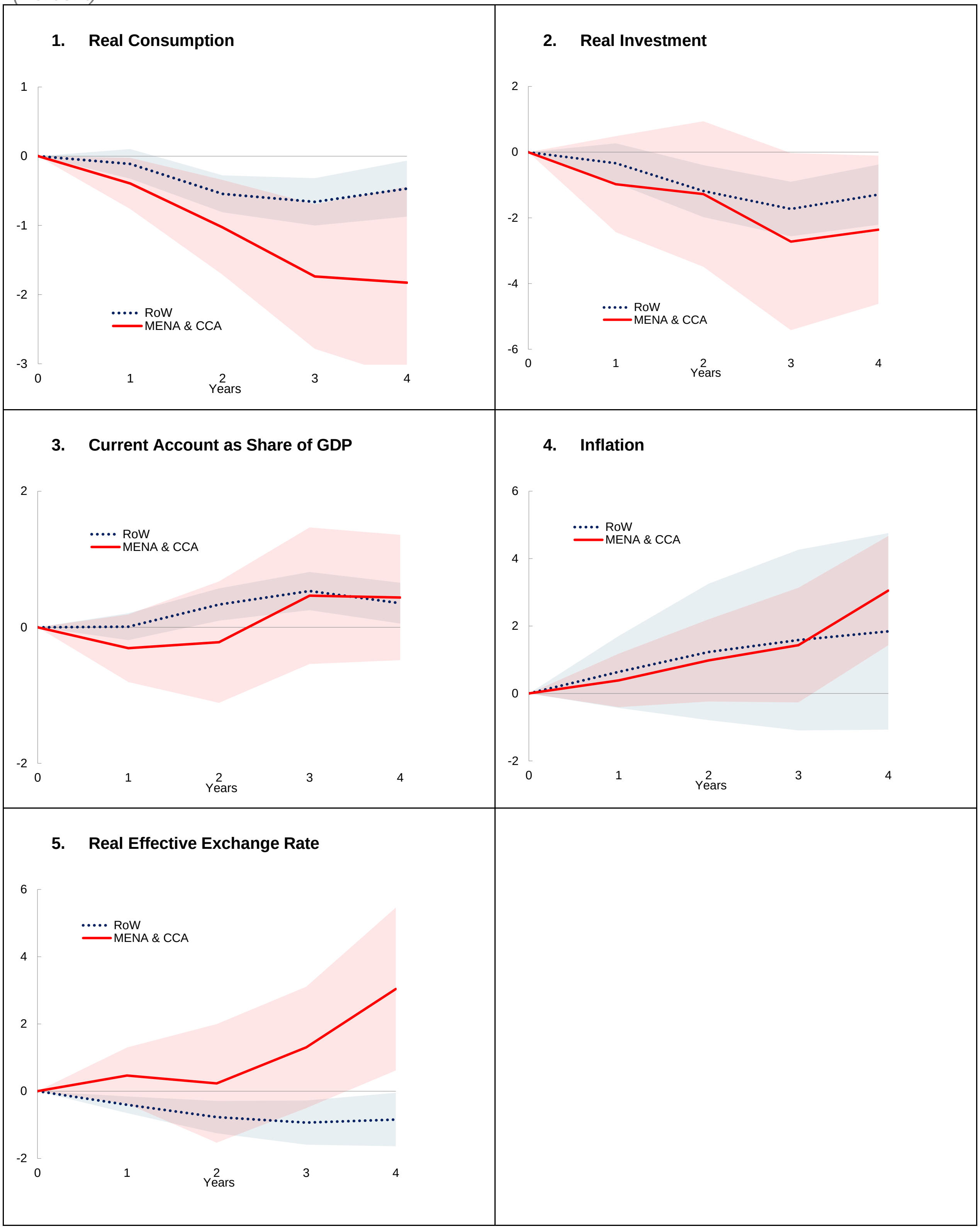
$MENAdummy$ is an indicator variable equal to 1 if the country is part of the Middle East and North Africa subregion (including Pakistan). The sum of β_1^h, β_2^h, β_3^h and β_5^h estimates the differential impulse response of real GDP for horizon h in response to a one standard deviation increase in uncertainty among MENA countries with the specific preexisting characteristic of interest. Preexisting characteristics of interest include control of corruption from the World Bank Worldwide Governance Indicators and public debt (general government debt as a percent of fiscal year GDP) from the IMF World Economic Outlook database. Control of corruption is considered low if it is in the bottom 15 percent of the world distribution. Debt is considered high if it is in the top 25 percent of the distribution of the country's corresponding economic grouping (low-income country, emerging market and developing economy, or advanced economy). Our average impulse response for other countries in the MENA and CCA regions is the sum of β_1^h and β_2^h. These results are displayed in Annex Figure 2.4.3.

Data sources

The data sources are the WUI database; the Torres Munguía and others (2022) global database on infectious disease outbreaks (epidemic outbreaks); the Uppsala Georeferenced Event Database on conflict-related deaths (conflict intensity, defined as number of conflict-related deaths as a share of population); the Worldwide Governance Indicators (control of corruption); the Caldara et al. (2020) Trade Policy Uncertainty Index Database; the Husted and others (2020) US Monetary Policy Uncertainty Index Database; the Emergency Events Database EM-DAT (economic damage from natural disasters as a share of GDP); Finaeon (volatility of stock market indices as the standard deviation of daily or weekly stock market prices over the quarter); the IMF Sovereign Spreads Monitor; Bloomberg (oil prices); and the Federal Reserve Bank of St. Louis (FRED) (US Federal Funds rates). Economic variables are from the October 2024 World Economic Outlook database.

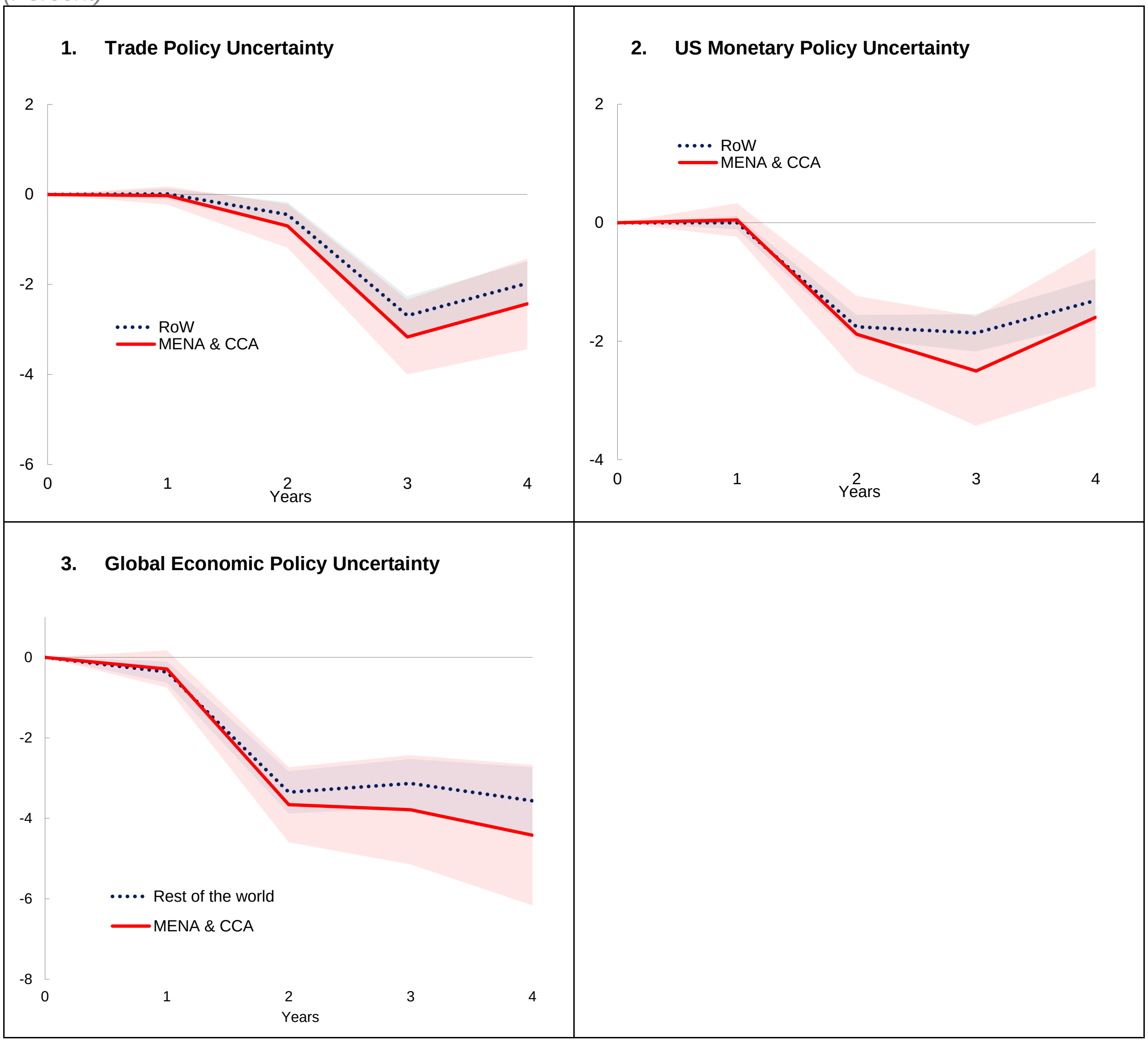
The quarterly dataset on spreads comprises 17 countries in the MENA and CCA regions and 70 countries in the rest of the world. When looking at stock market data, 29 stock market indices from 17 countries in the MENA and CCA regions and 197 stock market indices from 82 countries in the rest of the world are studied. The annual dataset is an unbalanced panel of 31 countries in the MENA and CCA regions and 163 countries in the rest of the world.

Annex Figure 2.4.1. Impact of Domestic Uncertainty on the Macroeconomy
(Percent)



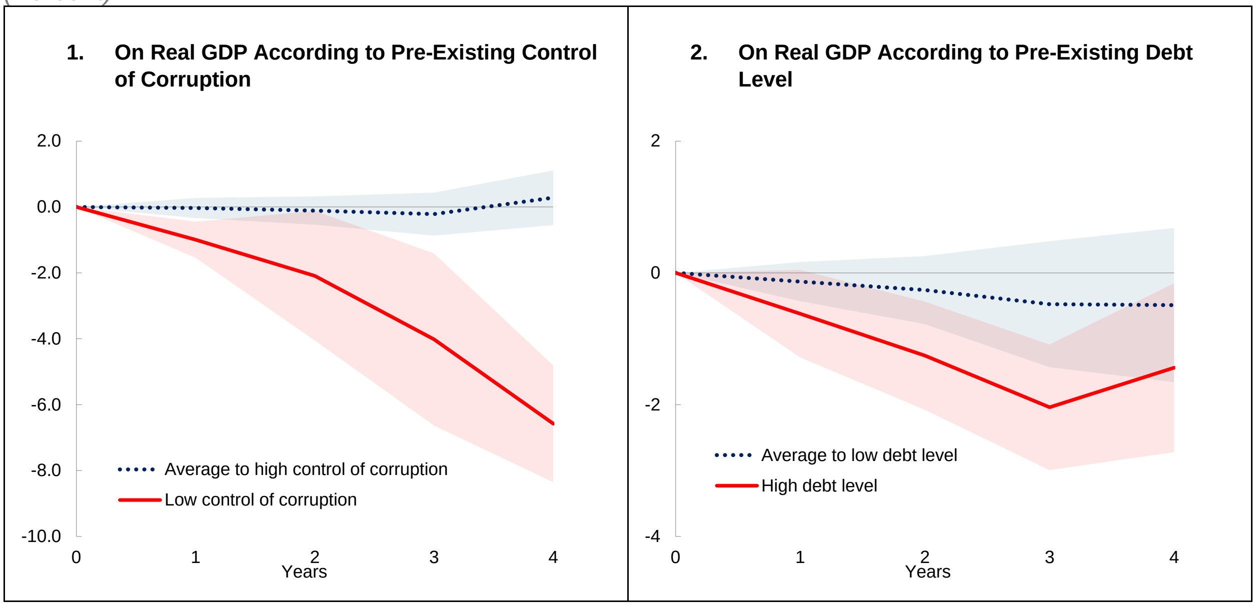
Sources: IMF, World Economic Outlook database; Ahir, Bloom and Furceri 2022; World Uncertainty Index (WUI) database; Torres Munguía and others 2022; Uppsala Georeferenced Event Database; Center for Research on the Epidemiology of Disasters, Emergency Events Database EM-DAT; World Bank, Worldwide Governance Indicators; and IMF staff calculations.
Note: The shock occurs in year one and corresponds to a one standard deviation increase in the country-level uncertainty indicator.

Annex Figure 2.4.2. Impact of Global Trade Policy Uncertainty, US Monetary Policy Uncertainty and Global Economic Policy Uncertainty on Real GDP
(Percent)



Sources: IMF, World Economic Outlook database; Caldara and others 2020, Trade Policy Uncertainty Index Database; Husted and others 2020, US Monetary Policy Uncertainty Index Database; Davis 2016; Global Economic Policy Uncertainty Index; Torres Munguía and others 2022; Uppsala Georeferenced Event Database; Centre for Research on the Epidemiology of Disasters, Emergency Events Database EM-DAT; World Bank, Worldwide Governance Indicators; Federal Reserve Bank of St. Louis, Federal Reserve Economic Data database; Finaeon, Inc., GFDatabase; IMF, Sovereign Spread Monitor; Stock Market Prices, Global Financial Database; and IMF staff calculations.
Note: The shock occurs in year one and corresponds to a one standard deviation increase in the global uncertainty indicator.

Annex Figure 2.4.3. Differential Impact of Uncertainty on Real GDP in MENA countries
(Percent)



Sources: IMF, World Economic Outlook database; Ahir, Bloom, and Furceri 2022; World Uncertainty Index (WUI) database; Torres Munguía and others 2022; Uppsala Georeferenced Event Database; Centre for Research on the Epidemiology of Disasters, Emergency Events Database EM-DAT; World Bank, Worldwide Governance Indicators; and IMF staff calculations.
Note: The shock occurs in year one and corresponds to a one standard deviation increase in the country-level uncertainty indicator. Control of corruption is considered low if it is in the bottom 15 percent of the world distribution. Debt is considered high if it is in the top 25 percent of the distribution of the country's corresponding economic grouping (low-income country, emerging market and developing economy, or advanced economy).

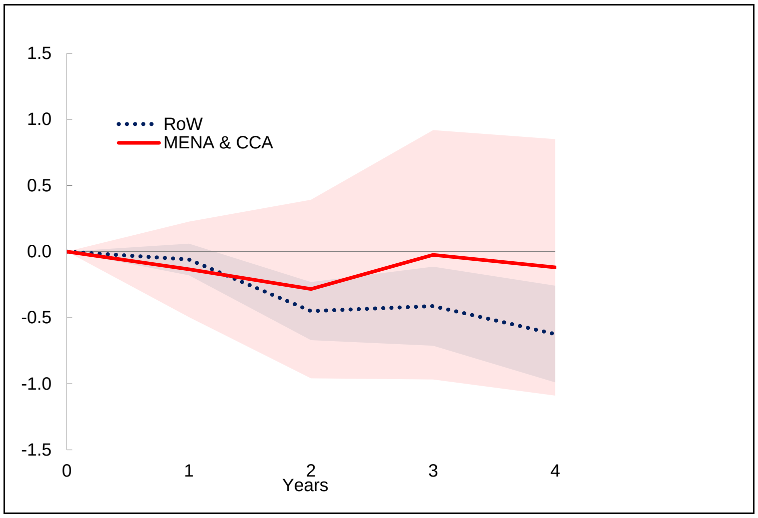
Robustness to the Persistence of Uncertainty Shocks

A potential criticism of the Jordà (2005) specification is that shocks could be persistent over time and lead to bias in point estimates. Following Teulings and Zubanov (2014), this leads to the following variant of the baseline specification:

$$y_{i,t+h} - y_{i,t-1} = \beta_1^h UNC_{i,t} + \beta_2^h UNC_{i,t} * MECAdummy_i + \sum_{j=-h,j\neq 0}^{l} \beta_{3,j}^h UNC_{i,t-j} + \sum_{j=1}^{h} \gamma_{1,j}^h \left(y_{i,t-j} - y_{i,t-j-1}\right) + \sum_{j=1}^{l} \theta_j^h X_{i,t-j} + \alpha_i^h + \alpha_t^h + \epsilon_{i,t}^h$$

Results from this specification (Annex Figure 2.4.4) suggest that the impact of uncertainty on real GDP in the rest of the world remains unchanged but those for the MENA and CCA regions become smaller and not significant. This is not surprising given the smaller sample size for countries in the MENA and CCA regions, especially once future shocks are included in the specification.

Annex Figure 2.4.4. Impact of Domestic Uncertainty on Real GDP
(Percent)



Sources: IMF, World Economic Outlook database; Ahir, Bloom and Furceri 2022; World Uncertainty Index (WUI) database; Torres Munguía and others 2022; Uppsala Georeferenced Event Database; Center for Research on the Epidemiology of Disasters, Emergency Events Database EM-DAT; World Bank, Worldwide Governance Indicators; and IMF staff calculations.
Note: The shock occurs in year one and corresponds to a one standard deviation increase in the country-level uncertainty indicator.

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