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# Foreign Vulnerabilities, Domestic Risks: The Global Drivers of GDP-at-Risk*

Simon Lloyd† Ed Manuel‡ Konstantin Panchev §

July 29, 2021

**Abstract**

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# 1 Introduction

It is well established that *domestic* financial developments can generate downside risks to *domestic* economic growth (Adrian, Boyarchenko, and Giannone, 2019; Aikman, Bridges, Hacioglu Hoke, O'Neill, and Raja, 2019) and, in turn, can influence the probability of crises (Schularick and Taylor, 2012). But not all crises have domestic origins. In a highly interconnected and increasingly synchronised global economy, international vulnerabilities can spill over to the domestic risk environment. But how, and to what extent, does this occur?

In this paper, we document the crucial role of *foreign* vulnerabilities in determining downside risks to *domestic* economic growth. Tighter foreign financial conditions and faster foreign credit-to-GDP growth can generate significant macroeconomic tail risks, even when controlling for domestic indicators. In particular, we show that they weigh heavily on 'GDP-at-Risk'—the 5th percentile of the GDP-growth distribution. A summary measure of downside macroeconomic risks, GDP-at-Risk is a now widely used concept in financial stability monitoring and cost-benefit analysis informing macroprudential policy (Carney, 2020).

Foreign financial developments can influence domestic GDP-at-Risk, and the conditional distribution of domestic GDP growth more generally, through a number of channels. First, consistent with evidence of a global financial cycle (Rey, 2013; Miranda-Agrippino and Rey, 2020) characterised by strong cross-country comovement in asset prices, a substantial portion of variation in domestic financial conditions can arise from global sources. Tighter global financial conditions can instantaneously impact domestic funding costs and risky asset prices, and, in turn, the conditional distribution of future GDP growth outturns. Second, with financial institutions increasingly holding foreign claims, excessive credit growth and risk-taking abroad can generate losses for domestic financial institutions and cause spillovers to the wider economy. Third, a build-up in foreign vulnerabilities that triggers a downturn abroad can spill over to the domestic economy through broader macroeconomic channels—for instance by lowering demand for domestic exports. While the influence of foreign factors on the *mean* of domestic GDP growth is widely studied in the international business-cycle literature (see Corsetti, 2008, and the references within), their influence on the *tails* of the domestic GDP growth distribution is the subject of this paper.

In our key methodological contribution, we propose a general and parsimonious approach to account for the influence of foreign vulnerabilities on the conditional distribution of domestic GDP growth. We do so within a quantile regression setup (Koenker and Bassett, 1978) that allows us to estimate the relationship between a range of indicators and the GDP-growth distribution over time and across countries. We account for foreign vulnerabilities by defining a weighted average of indicators in the rest of the world using bilateral-exposure weights. This approach has the advantage of capturing country-specific exposures to foreign vulnerabilities, while also limiting the number of additional regressors—a particular computational challenge for quantile regression.

We then employ this methodology to a cross-country panel dataset of advanced economies. Doing so provides novel empirical evidence demonstrating the link between foreign vulnerabilities and domestic GDP-at-Risk, as well as the conditional distribution of GDP growth more generally. We emphasise four main findings.

First, we show that foreign vulnerabilities significantly influence the conditional distribution of future domestic GDP growth, even when controlling for domestic indicators. Higher foreign equity volatility is associated with significant reductions in the left tail of domestic GDP in the near term—i.e. less than 1 year. Faster foreign credit-to-GDP growth weighs on the 5th percentile of domestic GDP growth out to longer horizons—i.e. up to 5 years. Moreover, the influence of foreign credit-to-GDP on the distribution of domestic GDP growth, in particular, is significantly larger at the 5th percentile than at the median, indicating that global credit conditions can have non-linear impacts on domestic GDP.

Second, we demonstrate that the inclusion of foreign vulnerabilities significantly improves estimates of domestic GDP-at-Risk. The goodness-of-fit for estimates of the 5th percentile of domestic GDP are materially higher when foreign-weighted variables are included in the quantile regression specification. Foreign indicators provide information relevant for estimating domestic GDP-at-Risk, over and above domestic ones.

Third, we break down the predictive power of foreign indicators in terms of their ability to estimate different moments of the GDP-growth distribution. We demonstrate that the inclusion of foreign indicators yields time-varying estimates of higher moments (over and above the mean) that are more interpretable than from a model with domestic covariates only. In the run-up to crises, the model with foreign covariates estimates a reduction in the skew of GDP growth and an increase in kurtosis, in addition to a lower mean and higher variance. By capturing vulnerabilities relevant for the tails of the GDP-growth distribution, foreign indicators help to improve the narrative around moments estimated within a quantile regression framework.

Finally, by orthogonalising domestic and foreign variables, we identify the contribution of foreign shocks to historical estimates of GDP-at-Risk. We show that foreign vulnerabilities are a key driver of domestic macroeconomic tail risks. On average, foreign shocks explain up to around 71% of variation in the estimated 5th percentile of advanced-economy GDP growth at the 3-year horizon, more than the comparable figure for the median.

Our results have important implications for financial stability policy. By highlighting the additional explanatory power of foreign variables to domestic GDP-at-Risk, we show the importance of accounting for foreign indicators when monitoring risks to domestic financial stability. In addition, by demonstrating the substantial contribution of foreign shocks to domestic tail risks, we highlight the importance of international macroprudential policy frameworks that foster cooperation between national authorities when forming regulatory responses to global shocks.

**Related Literature** Our paper is related to four main strands of literature. First, and most directly, our work builds on studies applying quantile regression techniques to assess the drivers of macroeconomic tail risks (see, e.g., Adrian, Grinberg, Liang, and Malik, 2018; Adrian, Boyarchenko, and Giannone, 2019; Aikman, Bridges, Burgess, Galletly, Levina, O'Neill, and Varadi, 2018; Aikman, Bridges, Hacioglu Hoke, O'Neill, and Raja, 2019). Using data on advanced economies, these papers identify a strong relationship between *domestic* vulnerabilities, such as financial conditions and credit growth, and the tails of the conditional GDP growth distribution. But they do not explicitly account for the influence of *foreign* vulnerabilities. These will only be implicitly captured insofar as foreign vulnerabilities are reflected within domestic indicators. We contribute to this body of work by exploring the independent influence of foreign vulnerabilities, and propose a novel methodological framework for doing so.

Second, our study relates to a literature on financial crisis warning indicators. Building on Schularick and Taylor (2012), who find credit-to-GDP to be a robust predictor of financial crises, others have shown that foreign variables can have significant predictive power. For instance, Cesa-Bianchi, Eguren-Martin, and Thwaites (2019) and Bluwstein, Buckmann, Joseph, Kang, Kapadia, and Simsek (2020) find that *global* financial developments influence the probability of *domestic* crises, over and above domestic indicators. Our analysis extends this literature by documenting the influence of foreign factors on the whole conditional distribution of GDP growth—not just crisis events.

Third, our work contributes to a growing literature assessing the ability of econometric models to estimate higher moments of the GDP distribution. Recently, Plagborg-Møller, Reichlin, Ricco, and Hasenzagl (2020) argue that conditional moments of US GDP growth other than the mean are poorly estimated by domestic financial conditions. In contrast, Delle Monache, De Polis, and Petrella (2021) estimate interpretable time-varying moves in the variance and skewness of US GDP growth, finding excess leverage and household credit to be significant drivers of downside risks. We contribute to this literature by emphasising the role of foreign indicators in delivering interpretable estimates of higher GDP moments over time.

Finally, our paper has links with the broad literature on disaster risks and economic growth (see, e.g., Barro, 2009; Barro and Ursúa, 2012; Gabaix, 2012; Gourio, 2012; Wachter, 2013). In particular, our evidence emphasising the importance of foreign vulnerabilities for domestic downside risks contributes to recent work highlighting the cross-border transmission of macroeconomic disasters (Gourio, Siemer, and Verdelhan, 2013; Farhi and Gabaix, 2016).

The remainder of this paper is structured as follows. Section 2 presents our general methodology. Section 3 describes the results from a specific application, emphasising the additional information foreign variables provide over and above domestic ones. Section 4 demonstrates the contribution of foreign indicators to estimates of time-varying GDP moments. In Section 5, we decompose GDP-at-Risk estimates into domestic and foreign shocks. Section 6 concludes.

## 2 Methodology to Account for Global Drivers

In this section, we outline our general methodology to account for global drivers of GDP-at-Risk, and the conditional distribution of GDP growth more generally. As in previous studies, we employ a quantile regression framework (Koenker and Bassett, 1978) to study how changes in a set of conditioning variables are associated with the distribution of future GDP growth. We present our approach within a panel setting, where time is denoted by $t = 1, ..., T$ and the countries for whom we estimate the conditional distribution of GDP are labelled with $i = 1, ..., N$.[1]

We specify the following local-projection model (Jordà, 2005) for the conditional quantile function $Q$ of $h$-period-ahead GDP growth $\Delta^h y_{i,t+h}$:

$$Q_{\Delta^h y_{i,t+h}}(\tau|\mathbf{X}_{i,t}, \mathbf{X}^*_{i,t}) = \alpha_i^h(\tau) + \beta^h(\tau)\mathbf{X}_{i,t} + \vartheta^h(\tau)\mathbf{X}^*_{i,t} \tag{1}$$

where $Q$ computes quantiles $\tau$ of the distribution of $\Delta^h y_{i,t+h}$ given two sets of covariates: $\mathbf{X}_{i,t}$ and $\mathbf{X}^*_{i,t}$. $\alpha_i^h(\tau)$ represents a potentially country- and quantile-specific constant.[2]

**Domestic Covariates** The domestic covariates in equation (1) are denoted by $\mathbf{X}_{i,t}$. They include domestic indicators that may influence the conditional distribution of domestic GDP, such as credit growth or proxies for financial conditions (see, e.g., Adrian et al., 2019; Aikman et al., 2019). The coefficients $\beta^h(\tau)$ denote the average association between domestic covariates

[1] Our general approach to accounting for global factors can also be applied to country-specific regressions.

[2] When we estimate the model in subsequent sections, we follow the approach of Canay (2011), which is best suited to the dimensions of our panel dataset. This splits the constant into (i) a quantile-specific constant for all countries $\alpha^h(\tau)$ and (ii) a country-specific fixed effect for all quantiles $f_i^h$. This approach permits a two-stage estimation procedure, whereby country fixed effects are first estimated in a linear pooled panel model via OLS and then quantile regressions are estimated given these fixed effects. Nevertheless, our approach to account for foreign vulnerabilities does not depend on these specific assumptions about the constant term.

and quantiles $\tau$ of the GDP-growth distribution.

**Foreign Covariates** The key novelty in equation (1) is the inclusion of foreign covariates $\mathbf{X}^*_{i,t}$. The coefficients $\vartheta^h(\tau)$ represent the average association between *foreign* indicators and the conditional distribution of *domestic* GDP growth, holding domestic factors fixed. However, as we explain in the next sub-section, the construction of these foreign variables is not trivial.

## 2.1 Constructing Foreign Covariates

To appreciate these challenges, consider a country $i \in [1, N]$ for whom we estimate the conditional distribution of GDP growth using equation (1). The $\tau$-th quantile of GDP growth in country $i$ can depend on domestic covariates $\mathbf{X}_{i,t}$, but also a set of indicators $\mathbf{X}_{j,t}$ in a range of other countries $j = 1, ..., N^*$.

In order to account for the influence of a single foreign indicator (e.g. credit-to-GDP) on the conditional distribution of domestic (country-$i$) GDP, one approach could be to individually add this indicator for each foreign country $j = 1, ..., N^*$, where $j \neq i$, to the foreign-covariate set $\mathbf{X}^*_{i,t}$ in equation (1). However, this would lead to a proliferation of regressors, adding an extra $N^* - 1$ explanatory variables. This could pose computational challenges for quantile regression methods—especially if scaled up to more than one foreign indicator—and, in the limit, would exhaust available degrees of freedom.

To circumvent this 'curse of dimensionality', for each indicator (e.g. credit-to-GDP) we define a single foreign covariate $x^*_{i,t} \subset \mathbf{X}^*_{i,t}$ as the weighted sum of the indicator $x_{j,t}$ in all other countries $j = 1, ..., N^*$. Defining $\omega_{i,j,t}$ as a time-varying weight capturing the 'bilateral exposure' of country $i$ to country $j$ at time $t$, we construct the foreign-weighted sum for each indicator using:

$$x^*_{i,t} = \sum_{j=1}^{N^*} \omega_{i,j,t} x_{j,t} \tag{2}$$

where $\sum_{j=1}^{N^*} \omega_{i,j,t} = 1$ and $\omega_{i,i,t} = 0$, for all $i, t$. With this definition, each additional foreign indicator (e.g. credit-to-GDP) adds a single regressor (e.g. foreign-weighted credit-to-GDP) to equation (1), offering a parsimonious solution to the curse of dimensionality. Furthermore, by constructing the foreign covariates in this way, we can extend the number of foreign countries $N^*$ that we account for, without increasing dimensionality. There is also no restriction that the number of foreign countries $N^*$ needs to be the same as the number of domestic ones $N$.[3]

[3]For instance, we may estimate GDP-at-Risk for a set of $N$ advanced economies, but want to account for spillover channels from a broader set of countries $N^* > N$, which may include major emerging markets in addition to the $N$ advanced economies.

Moreover, by using weights $\omega_{i,j,t}$ that capture *country-specific* bilateral exposures to the rest of the world, we can account for heterogeneity in countries' cross-border links. For instance, we can ensure that countries with stronger ties to country $i$ through trade or financial linkages (i.e. larger $\omega_{i,j,t}$) comprise a larger share of the foreign-weighted covariate and therefore can have a stronger association with the conditional distribution of country-$i$ GDP growth. This desirable economic intuition would be lost were we to specify each $x^*_{i,t}$ as a simple global aggregate (e.g. global credit-to-GDP), i.e. the sum (or unweighted average) of country-$j$ indicators.

So, our approach is parsimonious, while also maintaining a meaningful economic narrative around cross-country links. As in the global vector autoregression (GVAR) literature, where similar weighting schemes are applied to account for the influence of foreign factors at the mean (Pesaran et al., 2004; Eickmeier and Ng, 2015), there are a number of candidate weighting schemes that can be used too, depending on practitioners' focus, including: bilateral trade weights, bilateral financial linkages and combinations thereof.

# 3 Documenting the Global Drivers

In this section, we estimate the global drivers of the conditional distribution of GDP growth, emphasising the additional information provided by foreign indicators.

## 3.1 Specific Empirical Model

We illustrate our general methodology using a specific empirical model. This model is deliberately pared back, in order to highlight the influence of the key global drivers of the conditional distribution of GDP growth. However, as we emphasise in Section 3.4, our key findings are robust to a range of alternative model specifications, reflecting the generality of our approach.

We estimate the conditional distribution of GDP growth for $15$ advanced economies: Australia, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Norway, the Netherlands, Spain, Sweden, Switzerland, the United Kingdom (UK) and the United States (US). The dataset spans the period 1981Q1 to 2018Q4.[4] Our dependent variable is formally defined as annual average real GDP growth over $h$ quarters, i.e. $\Delta^h y_{i,t+h} \equiv (y_{i,t+h} - y_{i,t})/(h/4)$.

**Domestic Covariates** We include three domestic indicators in the variable set $\mathbf{X}_{i,t}$: the one-quarter realised volatility of equity prices; the three-year percentage point change in the aggregate private non-financial credit-to-GDP ratio; and the lagged one-quarter growth of real

[4]See Appendix A for a full description of data sources.

GDP.[5] This variable choice is motivated by existing studies focusing on domestic GDP-at-Risk (see, e.g., Adrian et al., 2019; Aikman et al., 2019). As in Aikman et al. (2019) specifically, we use equity price volatility as a proxy for financial market conditions, while the change in credit-to-GDP captures the evolution of the quantity of credit. We favour the three-year change in this quantity to capture *persistent* changes in credit, which are thought to pose risks to financial stability and are leading indicators of macroeconomic crises (Schularick and Taylor, 2012). Moreover, we choose to separate these two 'vulnerability' indicators—rather than use a single aggregated indicator of price- and quantity-based vulnerabilities—to capture the differing influence of risk factors across horizons. As Adrian et al. (2018) and Aikman et al. (2019) show, financial market prices tend to have a negative near-term influence on the left-tail of GDP growth, while growth in the quantity of credit relative to GDP is associated with a medium-term deterioration in GDP-at-Risk. Lagged quarterly real GDP growth is included as a control for the prevailing state of the macroeconomy.

**Foreign Covariates** We include the foreign-weighted counterparts of each of the indicators in the foreign variable set $\mathbf{X}^*_{i,t}$.[6] This variable choice is, in part, motivated by evidence that global financial market indicators and credit quantities tend to predict domestic financial crises (Cesa-Bianchi et al., 2019; Bluwstein et al., 2020). For our baseline results, we construct foreign-weighted variables using data on bilateral trade linkages. Using data from IMF Direction of Trade Statistics, we define the weights $\omega_{i,j,t}$ as the fraction of country $i$'s exports to country $j$ at time $t$. This scheme will place higher weight on countries that country $i$ exports more extensively to, reflecting the fact that a downturn in one country $j$ may spill over to another $i$ through reduced demand for country-$i$ exports. Compared to the bilateral financial weights from BIS International Banking Statistics we use in robustness analyses in Section 3.4, these trade weights have the advantage of running back to 1980, enabling us to use time-varying weights in the baseline specification. However, as we discuss there, our key results are robust to different combinations of country weights. Moreover, owing to constraints on data availability, we focus on the same set of *foreign* countries used in the *domestic* variable set, i.e. $N = N^* = 15$.[7]

**Interpretation and Inference** For presentational purposes, we standardise all regressors by the country-level mean and standard deviation. So, all coefficients can be interpreted as the association between a one standard deviation change in an indicator and the $\tau$-th quantile

[5]We discuss the robustness of our findings to different specifications of domestic risk factors in Section 3.4.
[6]We include alternative foreign risk indicators in robustness analyses reported in Section 3.4.
[7]We discuss the robustness of our findings to a broader specification of foreign countries in Section 3.4.

of GDP growth. We estimate the local projection regression (1) for $h = 1, 2, ..., 20$ quarters. For inference, we follow the block bootstrap procedure of Kapetanios (2008), resampling the data over blocks of different time series dimensions to generate coefficient standard errors for respective quantiles. As in Aikman et al. (2019), we resample time series observations using $8$ blocks, replicating the bootstrap $5000$ times.

## 3.2 Coefficient Estimates

We present coefficient estimates in two ways. First, we show the relationship between indicators and GDP-at-Risk—i.e. the $\tau = 0.05$-th quantile of GDP—across horizons $h$. Second, we present the relationship between indicators across GDP quantiles $\tau$ at a given horizon $h$.

### 3.2.1 Coefficients Across Horizons

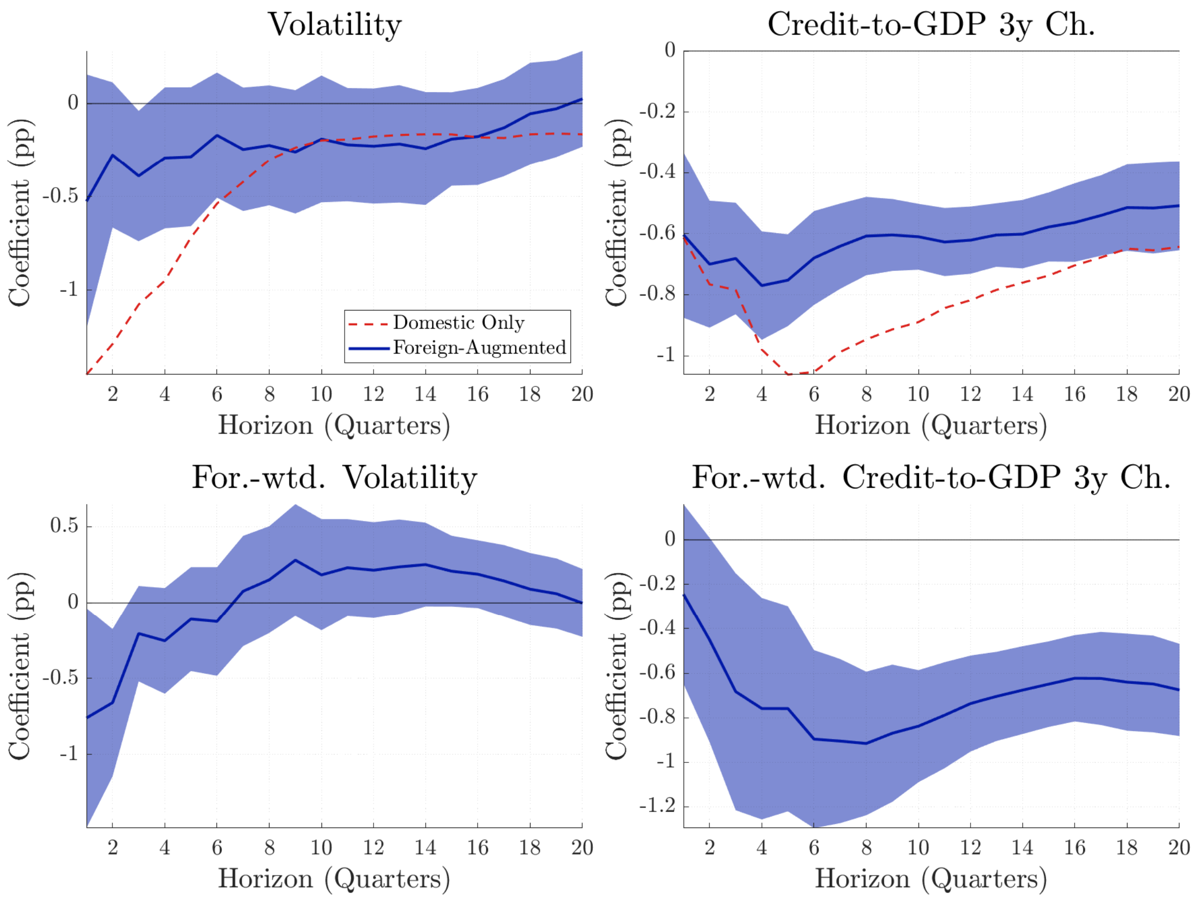
Figure 1 presents coefficient estimates at the 5th percentile of GDP across horizons $h$ for equity volatility and the 3-year change in credit-to-GDP—both domestic and foreign-weighted—from our specific model (solid blue lines).[8] These results highlight the differing association between indicators and GDP-at-Risk over time.

**Domestic Covariates** The upper panels demonstrate the association between domestic indicators and domestic GDP-at-Risk. Here, for comparison, we also present coefficient estimates from a domestic-only specification (dashed red lines), which excludes the foreign-weighted variables from the regressor set. The domestic-only model results are similar to those in Adrian et al. (2018) and Aikman et al. (2019). Heightened equity volatility weighs negatively on the left tail of GDP growth (i.e. GDP-at-Risk) in the near term—with the effect peaking in the first quarter, then waning over time. Higher credit-to-GDP also has detrimental effects on the left-tail of GDP in the near-to-medium term—the effect peaks around year 1 and persists out to year 5.

The addition of foreign-weighted variables significantly alters the coefficient on domestic equity volatility. Its magnitude is much reduced and generally insignificant across horizons. At the 1-quarter horizon, a one standard deviation increase in domestic volatility is associated with a $0.5$pp deterioration in the $5$th percentile of GDP growth—an estimate which is not statistically different from 0—compared to a $1.5$pp reduction in the domestic-only specification. This suggests that risks to the domestic macroeconomy reflected in domestic financial markets tend to have global origins, mirroring findings in Eguren-Martin and Sokol (2019). While the

[8] Coefficient estimates for the macroeconomic control variables—domestic and foreign-weighted lagged quarterly GDP growth—are presented in Appendix B.1.

Figure 1: Association between indicators and the 5th percentile of GDP growth across horizons




*Note*: Estimated association between one standard deviation change in each indicator at time $t$ with 5th percentile of annual average real GDP growth at each quarterly horizon. Red dashed lines denote coefficient estimates from model that excludes foreign covariates. Solid blue lines denote coefficient estimates from model that includes foreign covariates, and blue-shaded areas represent 68% confidence bands from block bootstrap procedure. Additional macroeconomic controls: domestic and foreign-weighted lagged quarterly real GDP growth.

coefficient on domestic credit growth is also smaller in the specification with foreign-weighted indicators, it remains negative and statistically significant across horizons,[9] suggesting that global credit conditions have an impact on GDP-at-Risk over and above domestic one. At its peak, a one standard deviation increase in domestic credit-to-GDP is associated with a 0.8pp reduction in GDP-at-Risk, compared to a reduction of around 1.1pp in the domestic-only specification.

**Foreign Covariates** The lower panels illustrate the strong association between foreign indicators and the left tail of domestic GDP growth. We find that higher foreign equity volatility is associated with a significant near-term reduction in the left-tail of annual average domestic GDP

[9] As Table 2 shows, these point estimates are statistically significant at the 99% level for $h = 4, 12, 20$.

growth. The 1-quarter coefficient indicates that a one standard deviation increase in foreign-weighted equity volatility is linked with a 0.7pp fall in the 5th percentile of GDP growth, larger than the corresponding estimate for domestic equity volatility. This suggests that, on average, foreign financial risk factors have more substantial effects on domestic macroeconomic tail risks than domestic financial markets, highlighting an important role for financial spillovers.

At longer horizons, the point estimates for the coefficient on foreign-weighted equity volatility turn positive, indicating that financial conditions can pose an intertemporal trade-off for GDP-at-Risk. Loose financial conditions can reduce tail risk in the near term, but generate vulnerabilities that increase tail risk further out. This mirrors a finding in Adrian et al. (2018). While this finding is neither strongly significant nor robust across different model specifications, the results in Figure 1 suggest that the trade-off—to the extent it exists—arises from *global* financial conditions rather than domestic ones.

We also find that foreign-weighted credit-to-GDP weighs significantly on GDP-at-Risk in the near-to-medium term. The coefficient is significantly negative from the third quarter onward.[10] At its peak, a one standard deviation increase in foreign-weighted credit-to-GDP is associated with a 0.9pp reduction in the 5th percentile of GDP growth. Foreign credit growth (relative to GDP) appears to have similar effects on the domestic macroeconomic risk outlook as domestic credit-to-GDP.

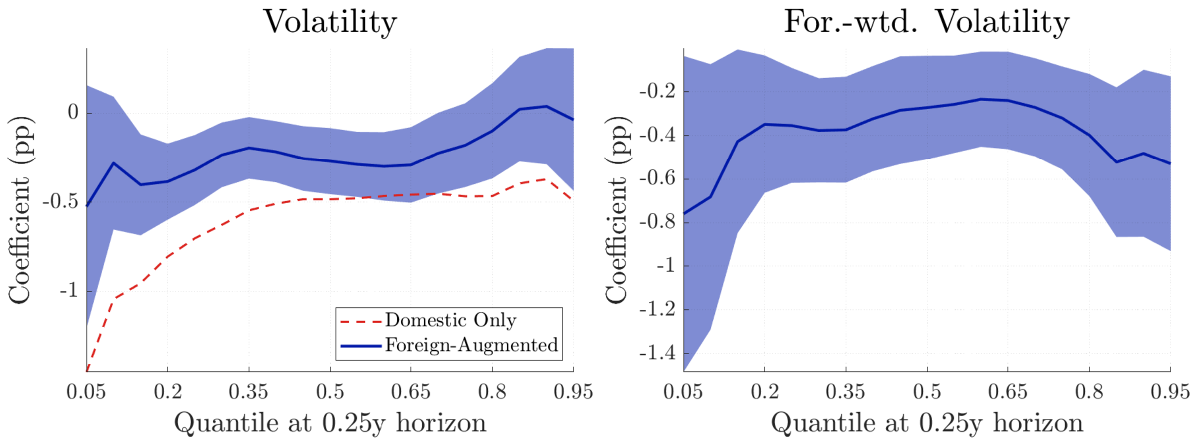
#### 3.2.2 Coefficients Across Quantiles

In Figures 2 and 3, we show complementary coefficient estimates to Figure 1. Focusing on the horizons at which the foreign-weighted indicators have their peak effects on the left tail of GDP growth, we present coefficient estimates across quantiles $\tau$ to assess the extent to which there is a non-linear association between indicators and the conditional distribution of GDP growth.

**Equity Volatility** Figure 2 plots the coefficient estimates for domestic and foreign-weighted realised equity volatility across quantiles at $h = 1$. The left-hand plot demonstrates that the addition of foreign-weighted variables has a significant impact on coefficient estimates for domestic equity volatility across quantiles. At all quantiles, the magnitude of estimated coefficients is smaller in the foreign-augmented model. Although the coefficient is still most negative at the 5th percentile, coefficient estimates are not significantly different across quantiles.

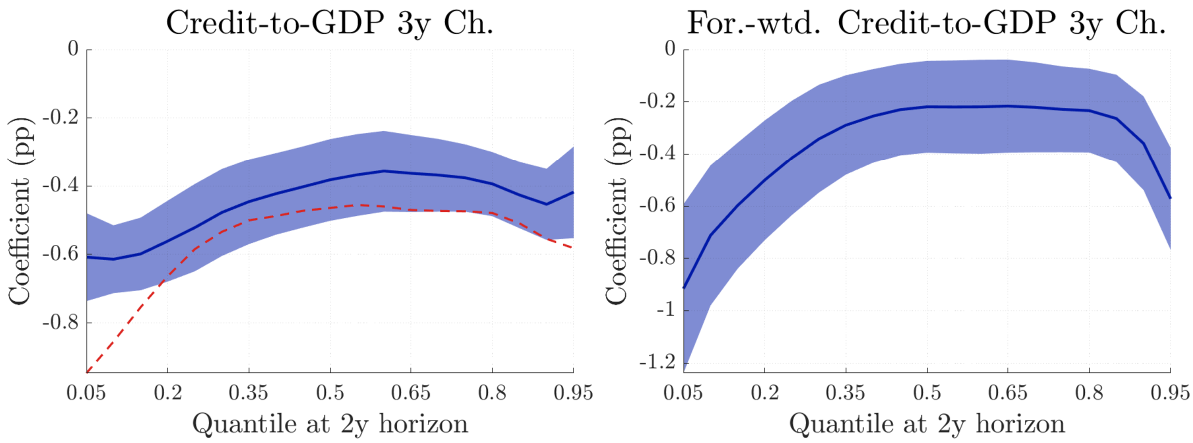
[10] These point estimates are statistically significant at the 99% for $h = 12, 20$, as Table 2 shows.

Figure 2: Association between domestic and foreign-equity volatility across quantiles at $h = 1$




*Note*: Estimated association between one standard deviation change in domestic or foreign-weighted realised equity volatility at time $t$ with each quantile $\tau$ of average annual real GDP growth at horizon $h = 1$. Red dashed lines denote coefficient estimates from model that excludes foreign covariates. Solid blue lines denote coefficient estimates from model that includes foreign covariates, and blue-shaded areas represent 68% confidence bands from block bootstrap procedure.

Figure 3: Association between domestic and foreign-equity credit-to-GDP across quantiles at $h = 8$




*Note*: Estimated association between one standard deviation innovation to 3-year change in credit-to-GDP at time $t$ with each quantile $\tau$ of average annual real GDP growth at horizon $h = 8$. Red dashed lines denote coefficient estimates from model that excludes foreign covariates. Solid blue lines denote coefficient estimates from model that includes foreign covariates, and blue-shaded areas represent 68% confidence bands from block bootstrap procedure.

The right-hand panel illustrates that foreign-weighted equity volatility has its strongest association with tails of the GDP growth distribution. Although coefficient estimates are significantly different from zero at all quantiles, they are not significantly different across quantiles.

**Credit-to-GDP** Coefficient estimates for the domestic and foreign-weighted 3-year change in credit-to-GDP across quantiles at $h = 8$ are presented in Figure 3. The plots highlight a strong non-linear association between the GDP growth distribution and credit-to-GDP growth. Higher credit growth, relative to GDP, is associated with a significantly more left-skewed distribution. This is most strongly the case for foreign-weighted credit-to-GDP, whose coefficient at the 5th percentile—of around $0.9$pp—is around four-times larger than the coefficient estimate at the median.

While domestic credit-to-GDP is also associated with a more left-skewed distribution of GDP, the left-hand plot shows that the addition of foreign indicators reduces the extent to which this is the case. Taken together, these findings indicate that faster global credit-to-GDP growth is associated with more severe left-tail risk for domestic GDP.

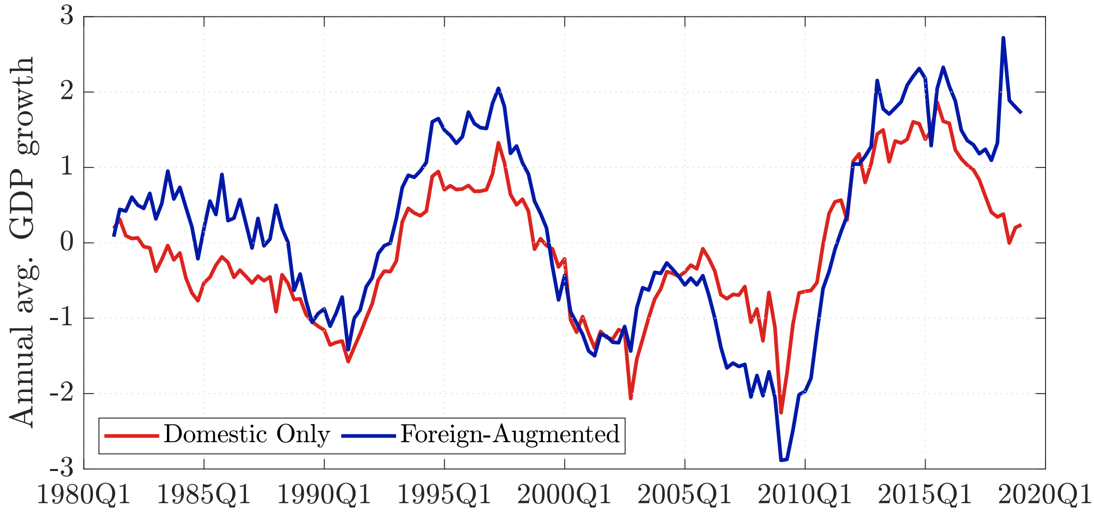
These findings have some parallels with the early-warning literature, where faster global credit growth is found to be a significant predictor of crises (Cesa-Bianchi et al., 2019; Bluwstein et al., 2020). However, our results are more general, suggesting that this predictability arises specifically from the association between foreign variables and the left tail of the domestic GDP growth distribution.

### 3.3 Additional Information from Foreign Variables

Our coefficient estimates indicate that, holding domestic factors fixed, changes in foreign factors can significantly influence the conditional distribution of future real GDP growth. However, a natural and complementary question is whether the inclusion of foreign covariates in equation (1) significantly improves estimates of the predicted conditional distribution of GDP growth.

Figure 4 helps motivate this question further, using the UK as an example. This compares the estimated level of UK GDP-at-Risk at the 3-year horizon from the foreign-augmented and domestic-only models set out in Section 3.1. Both models estimate a substantial fall in UK GDP-at-Risk in the years proceeding both the 1990-1991 recession and the Global Financial Crisis (GFC). This illustrates both models' predictive power for tail events and potential usefulness as an early-warning indicator. The foreign-augmented model picks up a sharper decline in UK GDP-at-Risk from early 2005, with estimated the estimated value reaching $-1.8\%$ by 2006Q1, compared to an estimate of $-0.6\%$ in the domestic-only model. This suggests that the foreign

Figure 4: Estimated UK GDP-at-Risk at 3-year horizon for domestic-only and foreign-augmented models




*Note*: Blue and red lines denote the estimated forecast for the 5th percentile of annual average 3-year-ahead UK GDP growth at each point in time using estimates from the foreign-augmented and domestic-only models (set out in Section 3.1) respectively.

variables in the model—i.e. foreign financial conditions and foreign credit-to-GDP growth—provide additional explanatory power over and above their domestic counterparts.

Next, we assess whether foreign variables add explanatory power to our quantile regression model more systematically. To do so, we draw on Koenker and Machado (1999), who introduce a quantile-specific $R^1(\tau)$ statistic, a 'goodness-of-fit' measure for quantile regression analogous to the conventional $R^2$ statistic for OLS regression. While the $R^2$ quantifies the success of one model relative to another—typically a constant-only model—at the conditional mean, the $R^1(\tau)$ provides information on the relative performance of models at the $\tau$-th quantile.

To focus on the additional information from foreign variables, we compare the full ('unrestricted') foreign-augmented model (1) with the ('restricted') domestic-only model, i.e. one in which $\vartheta^h(\tau)$ is set to 0 at all quantiles $\tau$ and horizons $h$. Defining $\hat{V}^h(\tau)$ as the sum of weighted absolute residuals from the unrestricted model at the $\tau$-th quantile and $h$-th horizon, and $\tilde{V}^h(\tau)$ equivalently for the restricted model, we calculate the $R^1_h(\tau)$ using:[11]

$$R^1_h(\tau) = 1 - \frac{\hat{V}^h(\tau)}{\tilde{V}^h(\tau)} \tag{3}$$

As for $R^2$, $R^1_h(\tau) \in [0, 1]$. We can then interpret $R^1_h(\tau)$ as a measure of how much foreign aug-

[11] Note that, in our local projections setup, the $R^1_h(\tau)$ statistic is horizon-specific, as well as quantile-specific.

mentation alters the goodness-of-fit of the estimated $\tau$-th quantile of $h$-quarter-ahead real GDP growth relative to the domestic-only model. Here, a higher $R_h^1(\tau)$ denotes a larger increase in goodness-of-fit arising from the addition of foreign variables.

We present the $R_h^1(\tau)$ statistics at the 5th percentile, the median and the 95th percentile from our specific model in Figure 5. The horizontal axis denotes the horizon at which each model is estimated. Table 1 details $R_1^h(\tau)$ statistics across a range of quantiles and horizons, alongside their statistical significance—assessed using the likelihood ratio test described in Koenker and Machado (1999).

Three observations are noteworthy. First, at all horizons, the $R_h^1(\tau)$ is highest for the 5th percentile of real GDP growth, relative to both the median and the 95th percentile. So, the inclusion of foreign variables in equation (1) improves estimates of the left tail of the conditional GDP growth distribution most materially.

Second, $R_h^1(0.05)$ grows over short-to-medium-term horizons, peaking for 17-quarter-ahead real GDP growth. So, the inclusion of foreign variables has the largest impact on estimates of GDP-at-Risk at roughly the 4-year horizon.

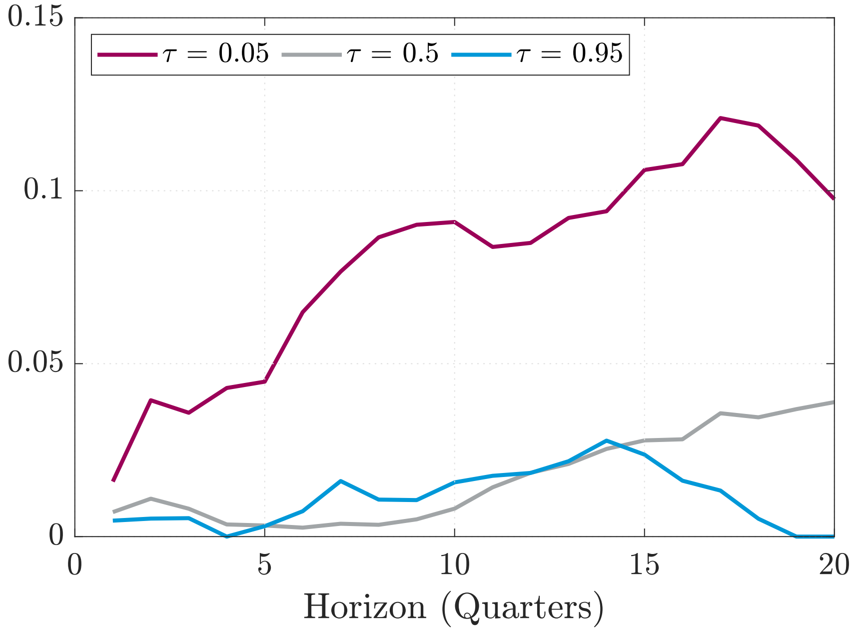
Third, and consistent with the coefficient estimates across quantiles presented in Section 3.2, when carrying out a likelihood ratio test on the $R_h^1(\tau)$ statistic—as presented in Table 1—we find the test statistics for the 5th percentile of GDP growth to be statistically significant at the 1% level (at least) for all 20 horizons. As such, the inclusion of foreign variables has a *significant* impact on estimates of the left tail of the conditional GDP distribution in particular, improving the goodness-of-fit, mirroring the discussion in Section 3.2.2. This highlights the importance of accounting for foreign variables when monitoring tail risks to domestic GDP growth.

### 3.4 Robustness

As explained in Section 3.1, we have so far used a pared back model to focus on the key insights gained from using our general methodology to account for the global drivers of GDP-at-Risk, and the distribution of GDP growth more generally. Using this specific model, we have shown that: (i) foreign-weighted variables exert a significant influence on domestic GDP-at-Risk, even when accounting for domestic variables; (ii) foreign-weighted variables, in particular changes in credit-to-GDP, have a larger influence on the left tail of the conditional GDP growth distribution than at the median; and (iii) foreign-augmentation can significantly improve the goodness-of-fit of estimates of conditional quantiles of GDP growth, especially at the left tail of the distribution.

As Table 2 summarises, these headline results are robust to a range of alternative model

Figure 5: Additional variation in fitted quantiles from foreign augmentation across horizons measured by $R^1_h(\tau)$




*Note*: $R^1_h(\tau)$ statistics (Koenker and Machado, 1999) comparing the foreign-augmented ('unrestricted') model to the domestic-only ('restricted') model at the 5th percentile, median and 95th percentile of real GDP growth across horizons.

Table 1: $R^1_h(\tau)$ across horizons and quantiles

| | Quantiles | | | | |
|---|---|---|---|---|---|
| Horizons | $\tau = 0.05$ | $\tau = 0.25$ | $\tau = 0.5$ | $\tau = 0.75$ | $\tau = 0.95$ |
| $h = 1$ | 0.015*** | 0.009 | 0.007 | 0.008 | 0.004* |
| $h = 4$ | 0.042*** | 0.007 | 0.003 | 0.006 | 0.000 |
| $h = 8$ | 0.086*** | 0.026*** | 0.003 | 0.004 | 0.010*** |
| $h = 12$ | 0.084*** | 0.035*** | 0.018** | 0.015 | 0.018*** |
| $h = 20$ | 0.097*** | 0.036*** | 0.038*** | 0.035*** | 0.000 |

*Note*: $R^1_h(\tau)$ statistics comparing the foreign-augmented ('unrestricted') model to the domestic-only ('restricted') across horizons and quantiles. Significance at 10%, 5% and 1% levels denoted by $*$, $**$ and $***$ respectively. Statistical significance assessed using likelihood ratio test from Koenker and Machado (1999).

specifications. Across all specifications, the estimated coefficient on foreign-weighted credit-to-GDP at the 5th percentile for medium-term horizons (i.e. 3-5 years) is significantly negative at the 10% level at least. The estimate coefficient on foreign equity price volatility (or alternative measures of financial conditions) at the 5th percentile is significantly negative at near-term horizons across all specifications at the 32% level at least. These coefficients are substantially more negative than coefficients estimates for the median—typically by around a factor 2-3 at the peak effect—indicating the influence of these foreign variables on the left tail of the conditional GDP growth distribution in particular. Finally, across all specifications, $R^1_h(0.05)$ is significant at the 10% level, at least, for near-term horizons, and at the 1% level for medium-term horizons—and is consistently larger than $R^1_h(0.5)$. This indicates a robust and significant improvement in the goodness-of-fit for estimates of the left tail of GDP growth from the inclusion of foreign variables.

We discuss each of the robustness exercises summarised in Table 2 in more detail below.

**Domestic Covariates** In column 2 of Table 2, we present results from a specification with additional domestic covariates. In this specification, we include domestic 3-year house price growth, the capital ratio (a measure of overall banking system resilience), the current account, the 1-year change in headline central bank policy rates and 1-year inflation in our domestic covariate set—as in Aikman et al. (2019). In the this specification, the foreign variables we construct continue to have explanatory power, as shown by the significant coefficient and $R^1_h(\tau)$ estimates. This is particularly noteworthy given the inclusion of the current account in the domestic covariate set.[12] The current account is a measure of external imbalances, so could be perceived as a sufficient proxy for risks emanating from abroad. However, our results indicate that the current account is insufficient for capturing all foreign risks when monitoring financial stability, with foreign financial conditions and credit growth having additional explanatory power.

**Financial Conditions Index** In column 3 of Table 2, we present results from a specification using a financial conditions index (FCI), as in Eguren-Martin and Sokol (2019), in place of equity price volatility. The FCI is a summary measure that extracts common variation across a range of asset prices—including term spreads, interbank spreads, corporate spreads, sovereign spreads, policy rates, equity returns and equity volatility. As our FCI data only begins in 1995, we shorten the sample for this robustness exercise. We find that a rise in weighted foreign

[12]For the purposes of this paper, we formally distinguish between 'domestic' and 'foreign' covariates in relation to the dimensionality challenges discussed in Section 2.1. As there is a single current account series per domestic country in our dataset, we do not need to construct a weighted measure using equation (2). Therefore, we define the current account as a 'domestic' variable.

Table 2: Coefficient estimates for benchmark model and robustness exercises

| | (1) Baseline | | | | (2) Additional Domestic Covariates | | | | (3) Alternative Financial Conditions | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $h=1$ | $h=4$ | $h=12$ | $h=20$ | $h=1$ | $h=4$ | $h=12$ | $h=20$ | $h=1$ | $h=4$ | $h=12$ | $h=20$ |
| **Foreign variables** | | | | | | | | | | | | |
| For. Credit-to GDP | -0.26 | -0.75^ | -0.74*** | -0.66*** | -0.28^ | -0.62* | -0.56*** | -0.56** | -0.46^ | -0.62* | -0.64** | -0.49* |
| | (0.09) | (-0.05) | (-0.38*) | (-0.42***) | (0.11) | (-0.04) | (-0.38**) | (-0.38***) | (-0.1) | (-0.19^) | (-0.31^) | (-0.25^) |
| For. Volatility | -0.8^ | -0.26 | 0.22 | 0.00 | -1.11^ | -0.46^ | 0.27^ | 0.07 | | | | |
| | (-0.28^) | (-0.25^) | (0.02) | (0.01) | (-0.27^) | (-0.27*) | (0.02) | (0.05) | | | | |
| For. FCI | | | | | | | | | -2.02** | -1.95*** | -0.29 | 0.13 |
| | | | | | | | | | (-0.97***) | (-0.89***) | (-0.41**) | (-0.07) |
| For. Lag. GDP gr. | 0.58 | 0.36 | 0.01 | 0.08 | 0.5 | 0.36 | 0.12 | 0.06 | 0.05 | -0.17 | -0.09 | 0.03 |
| | (0.34**) | (0.21^) | (0.00) | (-0.04) | (0.39***) | (0.29**) | (0.07) | (0.02) | (0.05) | (-0.07) | (-0.15^) | (-0.06) |
| **Domestic variables** | | | | | | | | | | | | |
| Credit-to-GDP | -0.61** | -0.77*** | -0.63*** | -0.5*** | -0.36^ | -0.56*** | -0.44*** | -0.26*** | -0.43^ | -0.63** | -0.68*** | -0.52*** |
| | (-0.13^) | (-0.27**) | (-0.45***) | (-0.45***) | (-0.07) | (-0.21**) | (-0.35***) | (-0.29***) | (-0.13^) | (-0.24**) | (-0.3***) | (-0.28**) |
| Volatility | -0.55 | -0.29 | -0.23 | 0.03 | -0.54^ | -0.3^ | -0.31^ | -0.11 | | | | |
| | (-0.27^) | (-0.05) | (-0.03) | (0.02) | (-0.33*) | (-0.08) | (-0.08) | (-0.03) | | | | |
| FCI | | | | | | | | | -0.26 | 0.14 | -0.05 | -0.53^ |
| | | | | | | | | | (-0.1) | (-0.12) | (-0.07) | (-0.08) |
| Lag. GDP gr. | 0.09 | 0.38* | 0.21^ | 0.00 | -0.09 | 0.21^ | 0.12^ | 0.02 | -0.17 | 0.15 | 0.11 | 0.05 |
| | (0.57***) | (0.27**) | (0.06^) | (0.00) | (0.53***) | (0.26***) | (0.08^) | (0.03) | (0.39***) | (0.07) | (0.03) | (-0.01) |
| House price gr. | | | | | 0.55* | 0.45** | -0.01 | -0.15^ | | | | |
| | | | | | (0.14^) | (0.15^) | (-0.02) | (-0.19*) | | | | |
| Capital ratio | | | | | -0.52^ | -0.13 | 0.12 | 0.25^ | | | | |
| | | | | | (-0.03) | (-0.13) | (-0.12) | (-0.04) | | | | |
| Current acc. | | | | | -0.94*** | -0.45** | -0.46*** | -0.41*** | | | | |
| | | | | | (-0.21***) | (-0.23***) | (-0.2**) | (-0.16**) | | | | |
| Inflation | | | | | -0.76* | -0.66^ | -0.07 | -0.01 | | | | |
| | | | | | (-0.29^) | (-0.25^) | (-0.06) | (0.07) | | | | |
| Policy rate | | | | | -0.11 | -0.6*** | -0.46** | -0.25** | | | | |
| | | | | | (-0.23*) | (-0.4***) | (-0.32***) | (-0.16*) | | | | |
| $R_h^1(\tau)$ | 0.02*** | 0.04*** | 0.09*** | 0.08*** | | | | | 0.1*** | 0.18*** | 0.12*** | 0.11*** |
| | (0.01) | (0.00) | (0.00) | (0.02**) | | | | | (0.03*) | (0.07***) | (0.05***) | (0.05***) |
| $N$ ($N^*$) | 15 (15) | | | | 15 (15) | | | | 15 (15) | | | |
| Weights (Sample) | Trade (1981Q1-2018Q4) | | | | Trade (1981Q1-2018Q4) | | | | Trade (1995Q1-2018Q5) | | | |

| | | | | | (4) Financial Weights | | | | (5) Extended Foreign Country Set | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | $h=1$ | $h=4$ | $h=12$ | $h=20$ | $h=1$ | $h=4$ | $h=12$ | $h=20$ |
| **Foreign variables** | | | | | | | | | | | | |
| For. Credit-to GDP | | | | | 0.1 | -0.49 | -0.6** | -0.58** | 0.04 | -0.56 | -0.8*** | -0.79*** |
| | | | | | (0.18^) | (0.1) | (-0.23) | (-0.56**) | (0.09) | (-0.13) | (-0.43**) | (-0.47**) |
| For. Volatility | | | | | -0.94^ | -0.64^ | 0.21 | -0.08 | -1.4* | -0.36 | 0.54* | 0.34^ |
| | | | | | (-0.23) | (-0.14) | (0.04) | (-0.03) | (-0.05) | (-0.06) | (0.18) | (0.2^) |
| For. Lag. GDP gr. | | | | | 0.6 | 0.46 | 0.1 | 0.17 | -0.11 | 0.21 | -0.07 | -0.02 |
| | | | | | (0.35**) | (0.28*) | (0.14^) | (0.04) | (0.07) | (0.05) | (-0.05) | (-0.05) |
| **Domestic variables** | | | | | | | | | | | | |
| Credit-to-GDP | | | | | -0.69** | -0.84*** | -0.65*** | -0.53*** | -0.3^ | -0.74*** | -0.8*** | -0.59*** |
| | | | | | (-0.17*) | (-0.29***) | (-0.44***) | (-0.37***) | (-0.09) | (-0.19^) | (-0.36***) | (-0.4***) |
| Volatility | | | | | -0.41 | -0.06 | -0.25 | 0.06 | -0.72 | -0.52^ | -0.58** | -0.3^ |
| | | | | | (-0.31*) | (-0.15^) | (-0.07) | (0.09^) | (-0.6***) | (-0.36**) | (-0.2^) | (-0.07) |
| Lag. GDP gr. | | | | | 0.39 | 0.45^ | 0.28^ | 0.07 | 0.18 | 0.31^ | 0.17^ | 0.09 |
| | | | | | (0.6***) | (0.28**) | (0.03) | (-0.01) | (0.55***) | (0.19^) | (0.07) | (0.01) |
| $R_h^1(\tau)$ | | | | | 0.02** | 0.04*** | 0.05*** | 0.05*** | 0.02* | 0.05*** | 0.11*** | 0.08*** |
| | | | | | (0.01) | (0.01) | (0.01) | (0.01) | (0.00) | (0.00) | (0.01) | (0.05***) |
| $N$ ($N^*$) | | | | | 13 (13) | | | | 15 (21) | | | |
| Weights (Sample) | | | | | Financial (1981Q1-2018Q4) | | | | Trade (1991Q3-2018Q4) | | | |

*Notes*: Coefficient estimates for 5th percentile and median (in parentheses). Significance, assessed using block bootstrap procedure, at 32%, 10%, 5% and 1% levels denoted by ^, *, ** and ***, respectively.

FCIs (signalling a tightening in foreign financial conditions) has a particularly strong negative effect on the left tail of domestic GDP growth at near-term horizons that is significant at the 5% level. We find limited evidence of a switch in the sign of the coefficient on foreign FCIs at longer horizons—the coefficient remains negative at $h = 12$ and is only just positive (and insignificant from zero) at $h = 20$. Hence, we do not find robust evidence of an intertemporal trade-off for GDP-at-Risk from asset prices alone when separately controlling for credit-to-GDP growth.

**Foreign Weighting Scheme** In our baseline specification, we use trade weights to capture countries' bilateral exposures. These weights have the advantage of running back to 1980, enabling us to use time-varying weights. However, we find similar results when we use bilateral financial weights using BIS International Banking Statistics that capture banks' exposures to the rest of the world (column 4 of Table 2).[13]

**Foreign Country Set** In column 5 of Table 2, we present results from a specification where we extend the set of countries used to define foreign-weighted covariates. We increase our foreign country set ($N^*$) to 21, by including 6 emerging market economies (China, Korea, Indonesia, Mexico, Turkey and Hong Kong) in addition to the 15 advanced economies used in our baseline specification. We maintain our domestic variable set ($N$) at 15, as in the baseline. We shorten the sample for this specification due to limited data availability in some emerging market economies. The results from this model are very similar to our baseline results, although we find slightly larger effects of foreign variables on domestic GDP-at-Risk when we extend the foreign country set.

# 4 Estimating Higher Moments of the GDP Growth Distribution

In this section, we assess the specific contribution of foreign vulnerabilities to higher moments of the distribution of GDP growth using the specific model described in Section 3.1.

Using a different model to ours, the results in Plagborg-Møller et al. (2020) suggest that quantile regression techniques are only able to estimate interpretable changes in the conditional mean of the GDP growth distribution. Yet the motivation for employing a quantile regression methodology, in favour of standard OLS-based techniques, to estimate the entire conditional distribution of GDP growth rests on the belief that the relationship between GDP growth and a set of covariates differs across quantiles. A quantile regression setup can provide estimates specific to the quantiles of the GDP growth distribution, and thus GDP-at-Risk, that

[13]Owing to data limitations, we construct time invariant bilateral financial weights using average values from 2005 to 2018.

could missed by standard forecasting models which focus only on estimating the conditional mean. So, the usefulness of the quantile regression framework rests on its ability to estimate meaningful changes in higher-order moments of the GDP growth distribution.

To test our own model against this challenge, we break down the estimated GDP growth distribution into its moments. We consider whether the changes in the distribution in the run-up to crisis events are driven by changes in the predicted mean—i.e. *locational shifts* of the GDP distribution—or by changes in higher moments—i.e. changes in the *shape* of the GDP distribution. In particular, we focus on the extent to which the addition of foreign variables can improve the narrative around higher moments estimated within a quantile regression framework.

**Method** We construct estimates for the time-varying moments of the GDP growth distribution following the methodology in Adrian et al. (2019). We begin with the quantile regression model set out in Section 3.1, estimated at quantiles $\tau = 0.05, 0.25, 0.5, 0.95$. We use this to estimate conditional quantiles of GDP growth $Q_{\Delta^h y_{i,t+h}}(\tau|\mathbf{X}_{i,t}, \mathbf{X}^*_{i,t})$ for country $i$ at horizon $h$ and time $t$. We then fit a skew-$t$ distribution (Azzalini and Capitanio, 2003) to the estimated quantiles to recover a full estimated probability density function at each point in time. We then calculate the conditional moments of these fitted distributions for GDP growth at each point in time to construct time-varying estimates of the moments.

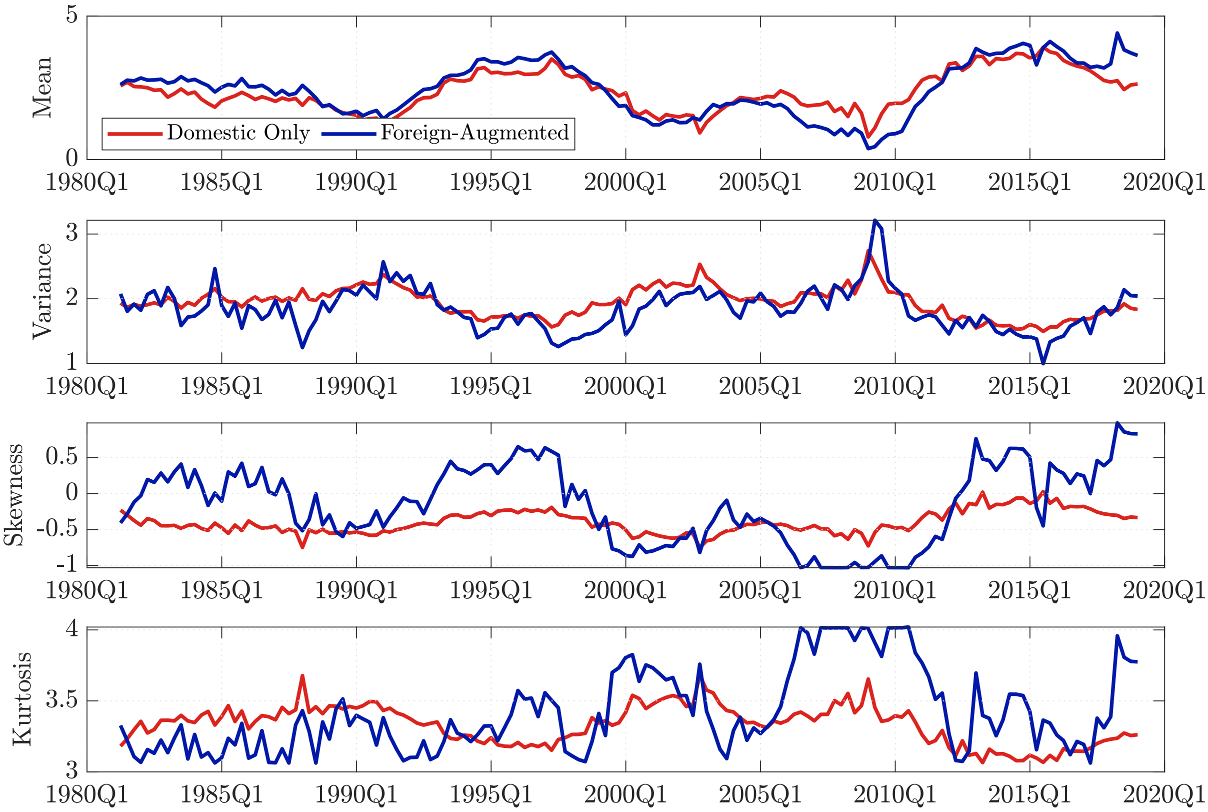
**Results** Figure 6 shows the estimated time-varying moments for UK GDP growth at the 3-year horizon for both our foreign-augmented baseline and the restricted domestic-only model.

As already highlighted in Figure 4, both models estimate a fall in UK GDP-at-Risk in the run-up to the GFC. Figure 6 shows that this estimated fall in the 5th percentile *partly* reflects an estimated fall in the mean from around 2005Q1 across both models—where this fall is more pronounced for the foreign-augmented than the domestic-only model. Both models estimate a sharp rise in variance related to the GFC—although this is with significant delay, with a clear spike only emerging around 2009H2, once the UK was already in a recession.

Crucially, for the foreign-augmented model, the estimates of other higher moments exhibit clear interpretable patterns. In particular, in the run-up to the GFC (2004-2008), the model predicts a notable fall in the skew and a rise in the kurtosis of UK GDP growth—with the distribution becoming most left-skewed and fat-tailed around 2006Q2. Therefore, the model provides a useful advanced warning, not just of a leftward shift in the distribution of future GDP growth, but also a significant fattening in the left-hand tail, well in advance of the GFC.

In contrast, the domestic-only model estimates little change in the skew and kurtosis of

Figure 6: Estimated time-varying moments of UK GDP at the 3-year horizon




*Note*: Estimates of time-varying moments of the UK GDP distribution at the 3-year horizon. The blue line shows the estimates from the foreign-augmented model while the red line shows the estimates from the restricted domestic-only model, as described in Section 3.1.

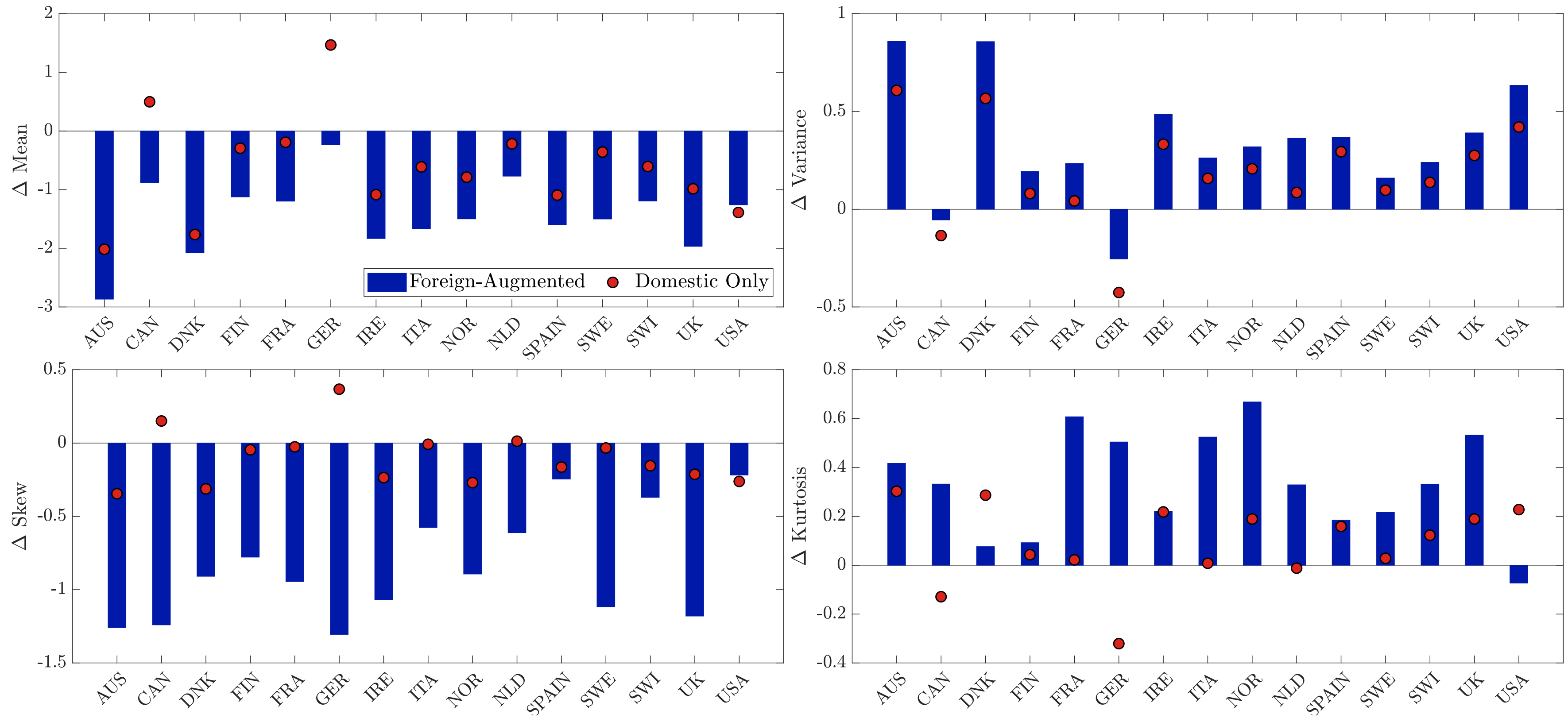
GDP growth over time—and in particular, does not pick-up a noticeable change in these higher moments ahead of the GFC. This suggests that the model outlined in Section 3.1 is able to predict interpretable moves in higher moments of the 3-year ahead UK GDP growth distribution, and that the addition of foreign variables improves these predictions.

Figure 7 assesses the extent to which these results hold more generally across countries. It shows the estimated change in the moments of the GDP growth distribution across countries in the panel in the run-up to the GFC at the 3-year horizon ($h = 12$).

The figure demonstrates that the foreign-augmented model is able to pick up interpretable moves in higher moments of the GDP growth distribution across all countries. In particular, between 1997Q1 and 2006Q1—a full 3-years before the peak macroeconomic impact of the GFC—the model estimates a significant fall in the skew of the 12-quarter-ahead GDP growth distribution for all countries in the panel.[14] The model also estimates a rise in variance and

[14]We look at the change here relative to 1997Q1, a quarter when risks were relatively muted across countries in our panel.

Figure 7: Estimated change in 3-year-ahead GDP moments: 1997Q1 to 2006Q1




*Note*: Estimated change in the moments of 3-year ahead annual average real GDP growth between 1997Q1 and 2006Q1 across countries. Blue bars represent estimates from model that includes foreign covariates. Red dots represent estimates from model that excludes foreign covariates.

kurtosis for most countries—although the results here are more mixed.

Interestingly, as in Figure 6 for the UK, the estimated fall in skew is consistently and substantially larger in the foreign-augmented model than the domestic-only model, by around 4-5 times on average across the panel. This suggests that at longer horizons, the additional predictive power from foreign variables pertains to information about *higher moments* of the GDP growth distribution, other than the mean. This is also consistent with the results discussed in Sections 3.2.2 and 3.3 that highlight the effect of foreign variables on the left tail of the GDP growth distribution in particular.

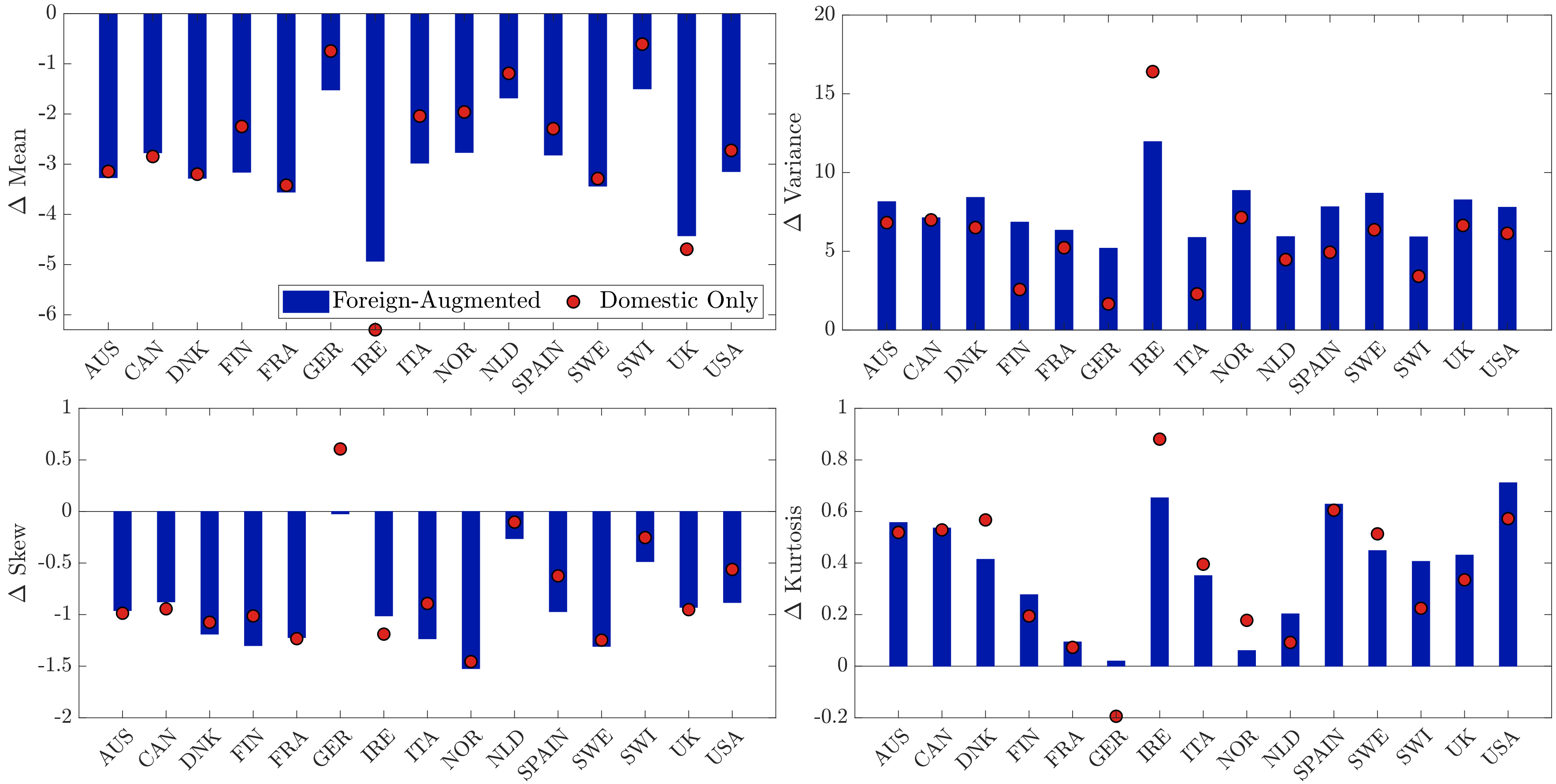
This finding is particularly stark for Germany. The domestic-only model estimates a rise in skew and fall in kurtosis for 12-quarter-ahead GDP growth in the run-up to the GFC, suggesting a reduction in downside risk. However, it is only with the addition of foreign variables that the model picks up intuitive changes in the shape of the German GDP growth distribution in this period, with greater probability mass in the left tail. This reflects the fact that domestic vulnerabilities—particularly domestic credit-to-GDP growth—were relatively low in Germany in the years preceding the GFC. Hence, an assessment of tail risks to German GDP growth reliant on domestic vulnerabilities alone fails to provide an early warning signal of the upcoming crisis.

Figure 8 presents a comparable plot for the 1-quarter-ahead horizon ($h = 1$), focusing on the change in moments between 1997Q1 and 2008Q3, 1 to 2 quarters ahead of the trough in quarterly GDP growth associated with the GFC. As with the 3-year-ahead results in Figure 7, the moves in higher moments are interpretable and there are some differences between the foreign-augmented and domestic-only models. Unlike at the 3-year-ahead horizon, the clearest differences between the models are seen in the estimated conditional variance. For all but one country, the foreign-augmented model identifies a larger rise in the variance of GDP growth up to 2008Q3 than the domestic-only model. At $h = 1$, the differences between the foreign-augmented and domestic-only models are less marked for estimates of skew and kurtosis.

Taken together, these results indicate the addition of foreign-weighted variables within a quantile regression framework can generate more interpretable estimates of time-varying moments of the conditional GDP growth distribution, especially in the run-up to the GFC. At medium-term horizons (i.e. $h = 12$), this manifests in changes in higher moments of the GDP growth distribution—the skew and kurtosis in particular. While at near-term horizons (i.e. $h = 1$), the effect is more pronounced for estimates of the conditional variance.

**Discussion** These conclusions are particularly noteworthy in light of recent work by Plagborg-Møller et al. (2020). Plagborg-Møller et al. (2020) follow a similar methodology to ours above,

Figure 8: Estimated change in 1-quarter-ahead GDP moments: 1997Q1 to 2008Q3




*Note*: Estimated change in the moments of 1-quarter ahead annual average real GDP growth between 1997Q1 and 2008Q3 across countries. Blue bars represent estimates from model that includes foreign covariates. Red dots represent estimates from model that excludes foreign covariates.

focusing their analysis most closely on the US and on near-term horizons (particularly $h = 1$ and $h = 4$).[15] They find that estimated movements in higher moments of US GDP growth are not informative and that, in particular, the estimated skewness and kurtosis do not show any interpretable movement around recessions. This differs from our results discussed above.

For comparison purposes, we present full time-varying estimates of the moments of US GDP growth across horizons in Appendix B.2.[16] In line with our above discussion, and unlike Plagborg-Møller et al. (2020), we find clearly interpretable moves in higher moments of US GDP growth at near-term horizons ($h = 1$ and $h = 4$)—with intuitive moves across all moments of the GDP distribution around crisis events. In general, the mean and skewness of the distribution tend to fall, while the variance and kurtosis tend to rise around the three US recessions in our sample (1990Q1-1991Q1, 2001Q1-2001Q3, 2007Q4-2009Q2).

Moreover, our findings carry over to medium-term horizons. These horizons are likely to be more relevant for macroprudential policymakers when monitoring risks to financial stability given policy implementation and transmission lags. Corroborating with the evidence discussed above, we find that the skewness of 12-quarter-ahead US GDP growth shows a steady decline well in advance of the three US recessions in our sample (see Appendix B.2).

There are two key reasons for the differences in results. First, we do not aggregate macro-financial variables into a single indicator, but rather separate out asset price variables (in our baseline case, equity price volatility) from credit quantities (credit-to-GDP). Our results are consistent with the general conclusion that asset price variables are of limited use in providing advanced warning signals of upcoming crises. This is in line with the intuition that asset prices are largely endogenous and tend to react to negative news around the economic outlook. For example, the largest spike in equity price volatility, which drives a sharp rise in the estimated variance of the US GDP growth distribution at near-term horizons, only occurs in 2008Q4—after the collapse of Lehman Brothers in September 2008. In contrast, we find that credit quantities do provide a useful signal of changes in higher moments of the GDP growth distribution, well in advance of crisis episodes. Second and in line with the key contribution of our paper, unlike Plagborg-Møller et al. (2020), we include foreign-weighted variables in our quantile regression alongside domestic variables. As discussed above, adding these foreign variables aids interpretation of estimated higher moments of the GDP growth distribution, especially at medium-term horizons.

[15] In a specific application in their paper, Plagborg-Møller et al. (2020) estimate a quantile regression for US GDP growth across horizons. They include three regressors in that regression: (i) a single factor of real, financial, monetary, and price variables; (ii) a factor of financial variables only (orthogonal to (i)); and (iii) lagged GDP growth.

[16] As above, we focus on in-sample fit here. Plagborg-Møller et al. (2020) also provide estimates of higher moments from an out-of-sample forecast.

## 5 Decomposing Estimates of GDP-at-Risk

In this section, we decompose historical estimates of GDP-at-Risk, aiming to identify the contribution of foreign shocks to domestic tail risks.

An immediate challenge to constructing this decomposition arises from the potential correlation of domestic and foreign covariates in equation (1). For example, consistent with evidence of a global financial cycle (Rey, 2013; Miranda-Agrippino and Rey, 2020), tighter financial conditions abroad are likely to spill over to the domestic economy, generating a contemporaneous tightening in domestic financial conditions that, in turn, can drive changes in domestic GDP-at-Risk. The estimated coefficient on foreign financial conditions in equation (1) effectively "partials out" this effect however, by controlling for domestic financial conditions. So, simply decomposing the drivers of GDP-at-Risk using the fitted values from equation (1)—i.e. $\hat{\beta}^h(\tau)\mathbf{X}_{i,t}$ representing domestic drivers and $\hat{\vartheta}^h(\tau)\mathbf{X}^*{}_{i,t}$ foreign drivers—will likely only yield a lower bound estimate for the relative importance of foreign shocks.

### 5.1 Towards a Structural Decomposition

To identify the relative contribution of foreign and domestic *shocks* to domestic GDP-at-Risk, we build a decomposition using a two-step procedure.

In the first step, we orthogonalise the domestic variables with respect to their foreign-weighted counterparts. To do this, we estimate the following OLS regression for each domestic indicator $x_{i,t} \subset \mathbf{X}_{i,t}$ and for each country $i = 1, ..., N$:

$$x_{i,t} = a_i + b_i \mathbf{X}^*_{i,t} + u^{\perp}_{i,t} \tag{4}$$

where $a_i$ and $b_i$ denote country- and indicator-specific coefficients, and $u^{\perp}_{i,t}$ represents the component of a domestic indicator $x_{i,t}$ that is orthogonal to contemporaneous variation in foreign-weighted indicators $\mathbf{X}^*_{i,t}$. Given coefficient estimates $\{\hat{a}_i, \hat{b}_i\}$ from equation (4), we define the estimated orthogonal component as the residual:

$$\hat{u}^{\perp}_{i,t} = x_{i,t} - \hat{a}_i - \hat{b}_i \mathbf{X}_{i,t}$$

In the second step, we then estimate a local-projection model for the conditional quantile function of $h$-period-ahead GDP growth using the estimated orthogonal component of domestic indicators, the full set of which is denoted by $\mathbf{u}^{\perp}_{i,t}$, alongside the set of weighted foreign variables $\mathbf{X}^*_{i,t}$:

$$Q_{\Delta^h y_{i,t+h}}(\tau | \mathbf{u}^{\perp}_{i,t}, \mathbf{X}^*_{i,t}) = \tilde{\alpha}^h_i(\tau) + \tilde{\beta}^h(\tau)\hat{\mathbf{u}}^{\perp}_{i,t} + \tilde{\vartheta}^h(\tau)\mathbf{X}^*_{i,t} \tag{5}$$

where we distinguish coefficients in this equation, relative to equation (1), with tildes. We can then decompose estimates of GDP-at-Risk, by labelling $\hat{\tilde{\beta}}^h(\tau)\mathbf{u}^{\perp}_{i,t}$ as 'domestic drivers' and $\hat{\tilde{\vartheta}}^h(\tau)\mathbf{X}^*_{i,t}$ as 'foreign drivers'.

The key assumption in this two-step procedure is that foreign indicators can contemporaneously influence domestic ones, but domestic indicators cannot contemporaneously affect their foreign counterparts. In effect, we treat the domestic country as a small-open economy, by excluding instantaneous feedback from domestic variables to foreign ones. This mirrors the block exogeneity assumption that has been widely used to estimate the transmission of shocks at the mean using structural vector autoregression methods in the empirical international macroeconomics literature (see, e.g., Cesa-Bianchi and Sokol, 2017; Dedola, Rivolta, and Stracca, 2017).

Importantly, while this two-step procedure does orthogonalise foreign-weighted variables with respect to their domestic counterparts, it does not enable a structural decomposition of shocks *within* countries. So, this procedure can isolate the relative importance of foreign shocks for domestic GDP-at-Risk. But it cannot distinguish between, for example, different domestic (or foreign) shocks within that (e.g. shocks to domestic financial conditions versus shocks to domestic credit growth) in a structural sense.

### 5.2 Estimated Decompositions

We now apply this orthogonalisation procedure to our specific empirical model to estimate the relative importance of foreign drivers of GDP-at-Risk. In this sub-section, we present results for the baseline model outlined in Section 3.1, albeit with one change. To justify the 'small-open economy' assumption implicit in the orthogonalisation, we exclude the US from the set of domestic economies when estimating the structural decompositions. Nevertheless, we continue to include the US in the foreign variable set, so we continue to account for its influence in the global economy.

Figure 9 shows the orthogonalised decomposition for the estimated 5th percentile of 3-year-ahead UK real GDP growth. The orthogonalised decomposition suggests that the estimated fall in UK 3-year GDP-at-Risk in the run-up to the 1990-1991 recession was predominantly driven by domestic drivers (red bars), in particular growth in domestic credit-to-GDP. Foreign drivers (blue bars) played a limited role. Following this recession, these factors reversed with the estimated rise in the 5th percentile of UK 3-year GDP growth supported by both domestic and foreign factors.

Tail risks built up substantially over the 2000s though—with estimated GDP-at-Risk becoming more negative from 2005 especially, driven largely by a build-up in foreign-weighted credit-to-GDP. This accords with the well established view that the GFC had global origins, driven by worldwide trends in an increasingly interconnected international financial system.

Since the GFC, these drivers of tail risks have again reversed, likely tempered by enhanced macroprudential policy toolkits and global monitoring of the financial system.

Figure 10 presents the comparable decomposition for German 3-year GDP-at-Risk. The relative evolution of domestic and foreign shocks in the run-up to the GFC is particularly notable for Germany. Domestic factors—in particular domestic credit-to-GDP—are associated with improvements in the left tail of the GDP growth distribution from 2004 to 2008. In contrast, foreign-weighted credit-to-GDP growth is associated with a worsening in tail risk over the same period. In sum, these foreign factors dominate and contribute to an overall fall in fitted GDP-at-Risk over the period, exemplifying the importance of accounting for global influences when monitoring macro-financial risks.

### 5.3 Contribution of Foreign Drivers

As well as provide narrative evidence, this orthogonalised decomposition can be used to assess the role of foreign drivers of tail risk more systematically. Because equation (4) imposes $\text{cov}_t(\mathbf{X}_{i,t}, \mathbf{X}^*_{i,t}) = 0$, then the variance of fitted values of the $\tau$-th percentile of the GDP-growth distribution can be decomposed as:

$$\text{var}_t\left(\Delta^h \hat{y}_{i,t+h}(\tau)\right) = \text{var}_t\left(\hat{\tilde{\beta}}^h(\tau)\hat{\mathbf{u}}^{\perp}_{i,t}\right) + \text{var}_t\left(\hat{\tilde{\vartheta}}^h(\tau)\mathbf{X}^*_{i,t}\right)$$

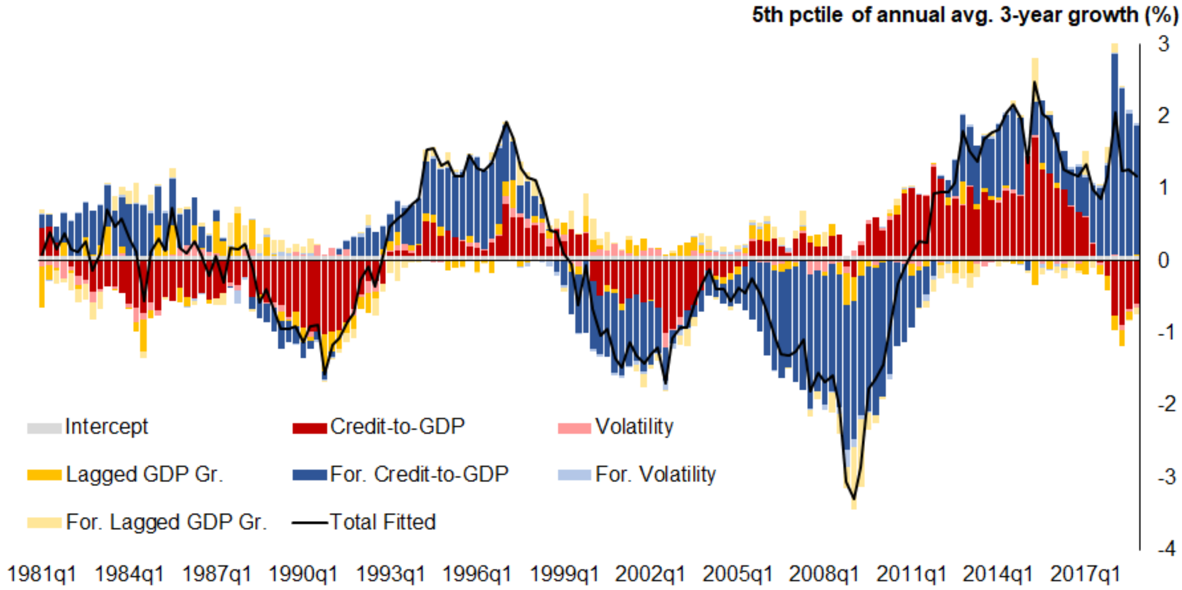
Therefore, the share of variation in the fitted value of country-$i$ GDP growth at the $\tau$-th percentile at horizon $h$ attributable to foreign sources can be defined as:

$$ForShare^h_i(\tau) \equiv 100 \times \left[\frac{\widehat{\text{var}}_t\left(\hat{\tilde{\vartheta}}^h(\tau)\mathbf{X}^*_{i,t}\right)}{\widehat{\text{var}}_t\left(\Delta^h \hat{y}_{i,t+h}(\tau)\right)}\right] \tag{6}$$

The estimated shares $ForShare^h_i(\tau)$ at $h = 1, 4, 12$ and $\tau = 0.05$ for each country in our baseline regression are presented in Figure 11. Due to the stringency of the orthogonalisation assumption imposed by equation (4), we interpret these quantities as upper-bound estimates for the share of variation attributable to foreign sources.

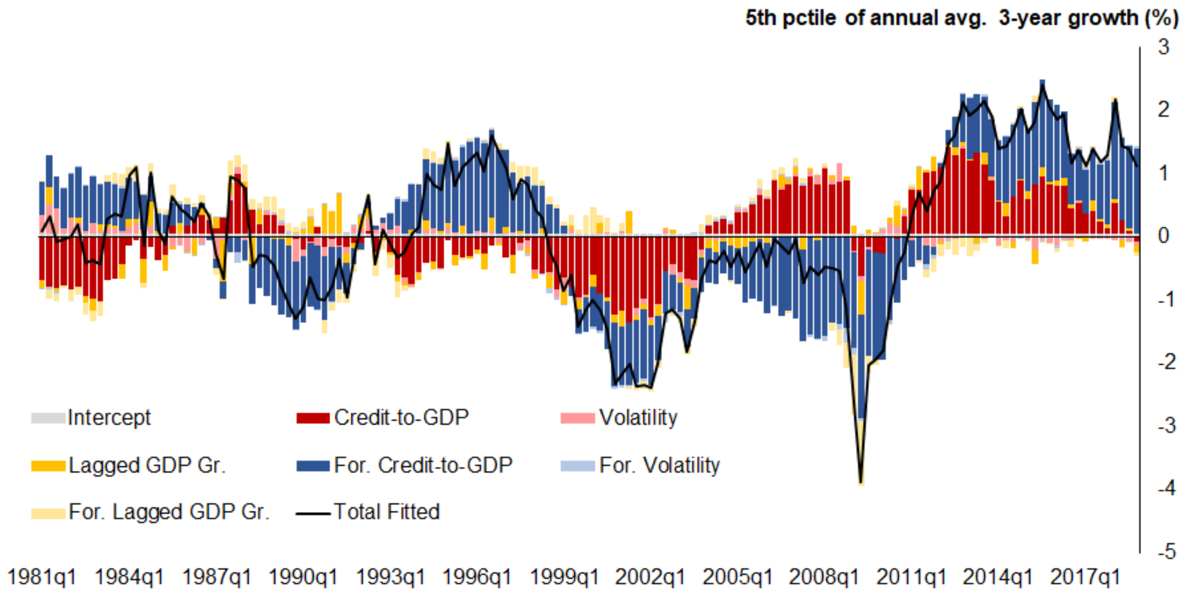
Overall, Figure 4 illustrates that a substantial portion of variation in estimates of the GDP-growth distribution can be attributed to foreign sources for all 14 countries in our sample. At the 1-quarter horizon, the average share of variation in GDP-at-Risk (i.e. $\tau = 0.05$) from foreign sources is 89%, around 13pp more than the variation attributed to foreign sources at the median ($\tau = 0.5$). Although there is variation across countries, this finding emphasises the

Figure 9: Estimated orthogonalised decomposition of UK GDP-at-Risk at the 3-year horizon



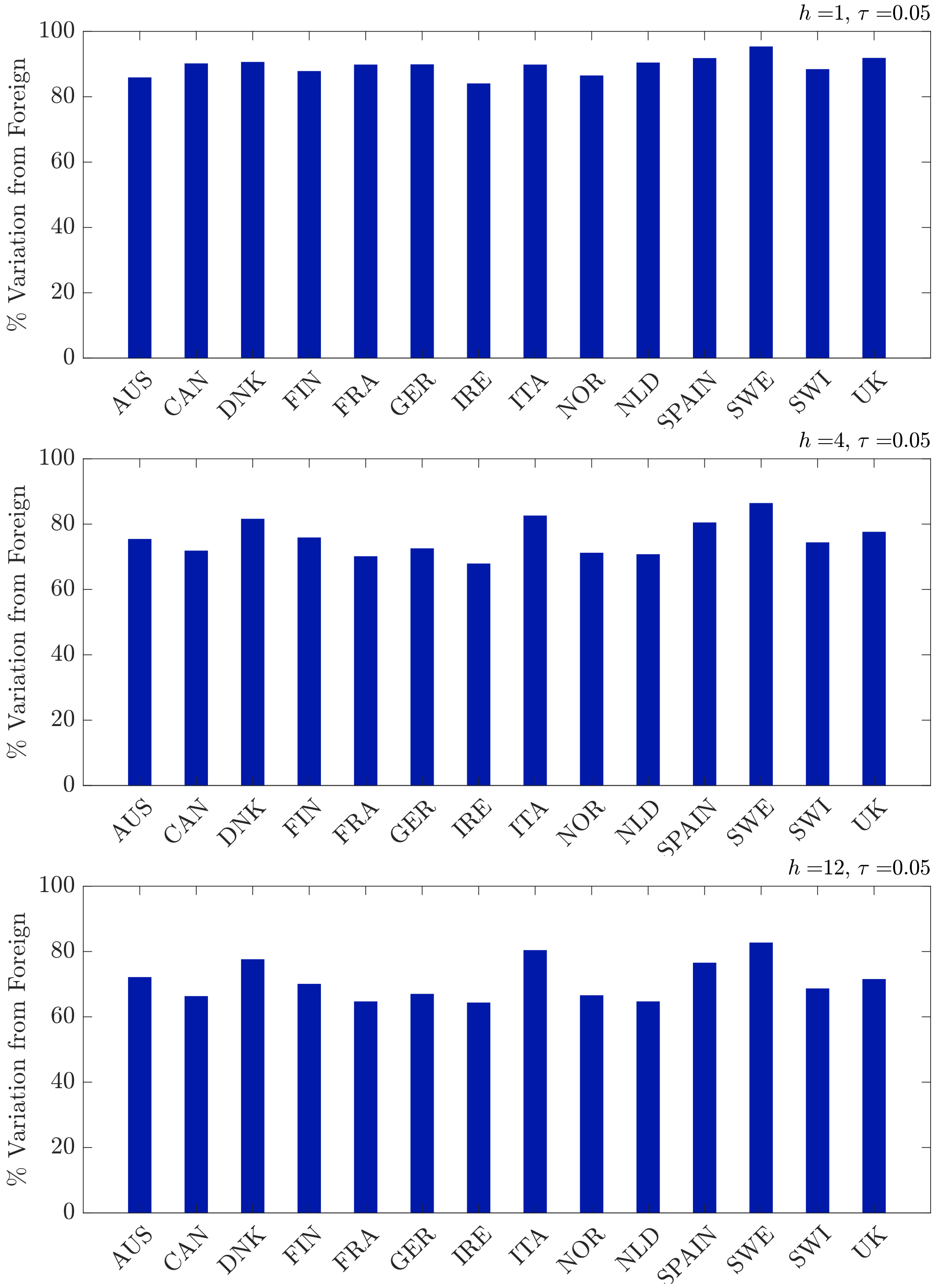

*Note*: Solid black line denotes estimated 5th percentile of annual average 3-year-ahead GDP growth at each point in time. The bars show the contribution of each indicator to that total from estimates of equation (5).

Figure 10: Estimated orthogonalised decomposition of German GDP-at-Risk at the 3-year horizon




*Note*: Solid black line denotes estimated 5th percentile of annual average 3-year-ahead GDP growth at each point in time. The bars show the contribution of each indicator to that total from estimates of equation (5).

Figure 11: Share of variation in fitted values (%) attributed to foreign shocks across horizons at the 5th percentile




*Note*: Share of variation at the 5th percentile ($\tau = 0.05$) of country-GDP distributions at different horizons: $h = 1$ (1 quarter), $h = 4$ (1 year), and $h = 12$ (3 years). Share definition in equation (6). Shares constructed from baseline model in which domestic indicators are orthogonalised with respect to all foreign indicators, akin to a small-open economy assumption for domestic countries.

crucial role for foreign vulnerabilities at the left tail of the GDP growth distribution specifically.

While the share of variation attributable to foreign sources tends to decline as horizons $h$ increase, the relative importance of foreign factors remains substantial. At the 3-year horizon, the average share of GDP-at-Risk variation linked with foreign shocks is 71%, around 8pp more than the corresponding estimate at the median.

**Robustness** We assess the robustness of the results presented in Figure 11 by estimating comparable decompositions for two alternative models. First, we estimate our baseline model, but construct foreign-weighted variables using bilateral financial weights from BIS International Banking Statistics. Second, we estimate a model with more domestic and foreign covariates, mirroring the specification in Aikman et al. (2019). We continue to exclude the US from the domestic variable set when constructing these decompositions. The results are discussed in Appendix B.3. However, our key finding—that foreign factors play a dominant role in explaining variation in the estimated 5th percentile of GDP growth, and more so than for the median—is robust in both alternative model specifications.

## 6 Conclusion

This paper has shown that foreign vulnerabilities matter for domestic macroeconomic tail risks. Faster global credit-to-GDP growth and tighter global financial conditions exert a significant negative influence on the left tail of the GDP-growth distribution. Moreover, these foreign indicators significantly increase the goodness-of-fit for estimates of GDP-at-Risk. In turn, these foreign indicators help to generate estimates of higher GDP moments that are interpretable and provide advanced warnings of crisis episodes. Decomposing historical estimates of GDP-at-Risk into orthogonalised domestic and foreign shocks, we show that foreign vulnerabilities on average explain up to around 71% of variation at the 3-year horizon, more than the comparable figure for the median.

Taken together, our findings have important implications for macroprudential policymakers. By highlighting the relevance of global spillovers, they emphasise the importance of monitoring global variables when assessing risks to domestic financial stability. Moreover, by demonstrating the substantial contribution of foreign shocks to domestic tail risks, they highlight the importance of international macroprudential policy cooperation in response to global shocks.

# Appendix

## A Data Sources

Table 3 presents a full list of data sources used in this paper—both in the main body and the appendices.

Table 3: List of Data Sources

| Variable | Source | Frequency | Notes |
|---|---|---|---|
| *Dependent Variable* | | | |
| Real GDP | OECD | Quarterly | Construct annual average growth across quarterly horizons |
| *Covariates* | | | |
| Equity Volatility | Datastream | Daily | Calculate realised volatility within quarter using standard deviation of daily returns |
| Credit-to-GDP | BIS | Quarterly | Construct 3-year change in ratio |
| Current account | OECD | Quarterly | Percent of real GDP |
| House Prices | OECD | Quarterly | Construct 3-year growth |
| Capital Ratio | Aikman et al. (2019) | Annual | Ratio of tangible common equity to tangible assets |
| Inflation | OECD | Quarterly | Annual growth of CPI |
| Policy Rates | BIS | Quarterly | Annual change in central bank policy rates |
| *Bilateral Weights* | | | |
| Export Weights | IMF DOTS | Quarterly | Construct weights by averaging across each calendar year to smooth seasonal variation |
| Financial Weights | BIS IBS, Tbl. 9D | Quarterly | Construct weights by averaging across each calendar year to smooth seasonal variation |

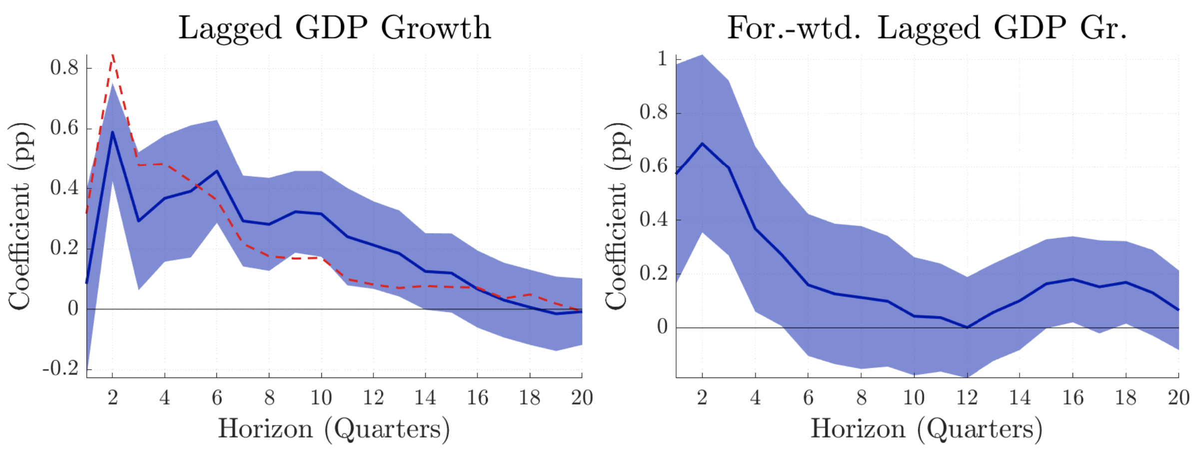
## B Additional Results

### B.1 Baseline Empirical Model

In this Appendix sub-section, we report additional results for our specific model described in Section 3.1.

**Coefficient Estimates for Macroeconomic Controls Across Horizons** Figure 12 presents coefficient estimates for the macroeconomic control variables—domestic and foreign-weighted lagged quarterly real GDP growth—at the $\tau = 0.05$-th quantile across horizons in our specific model described in Section 3. Both domestic and foreign-weighted lagged real GDP growth are associated with higher estimates of the 5th percentile of real GDP growth.

Figure 12: Association between indicators and the 5th percentile of GDP growth across horizons

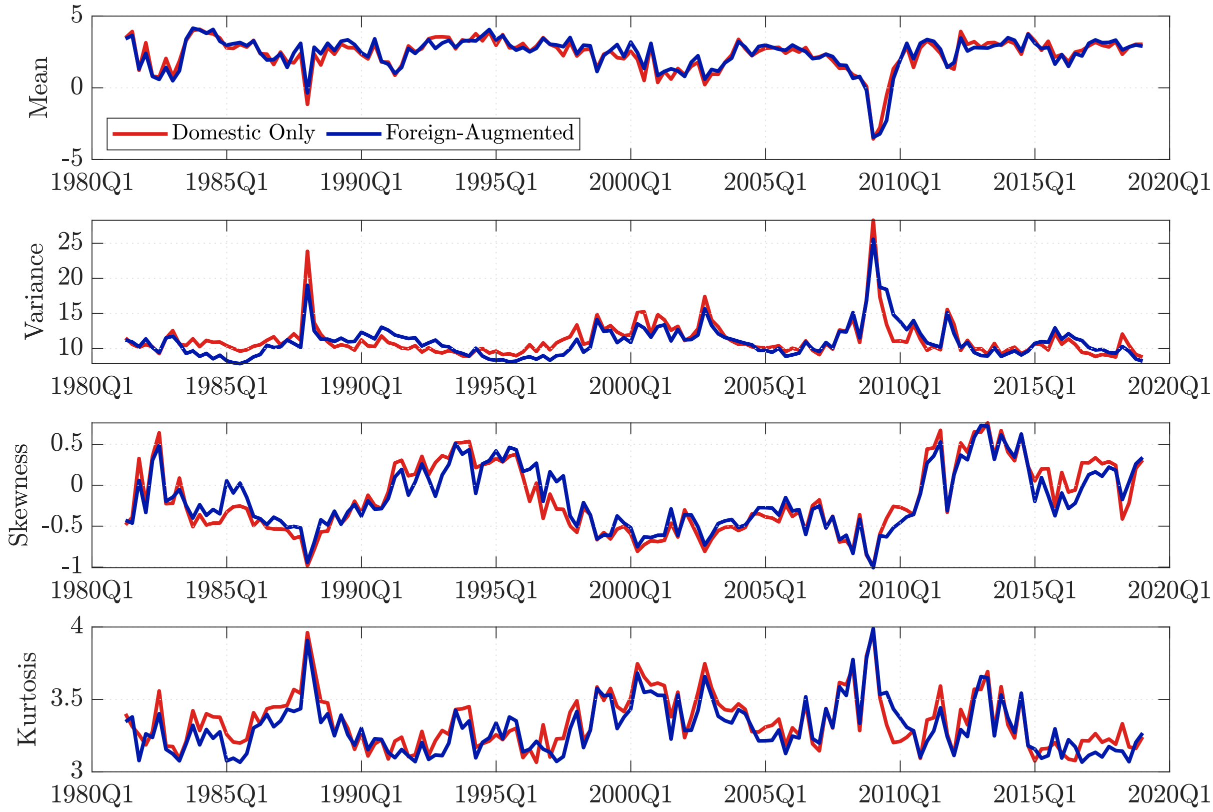



*Note*: Estimated association between one standard deviation change in each indicator at time $t$ with 5th percentile of average annual real GDP growth at each quarterly horizon. Red dashed lines denote coefficient estimates from model that excludes foreign covariates. Solid blue lines denote coefficient estimates from model that includes foreign covariates, and blue-shaded areas represent 68% confidence bands from block bootstrap procedure.

## B.2 US GDP Moments

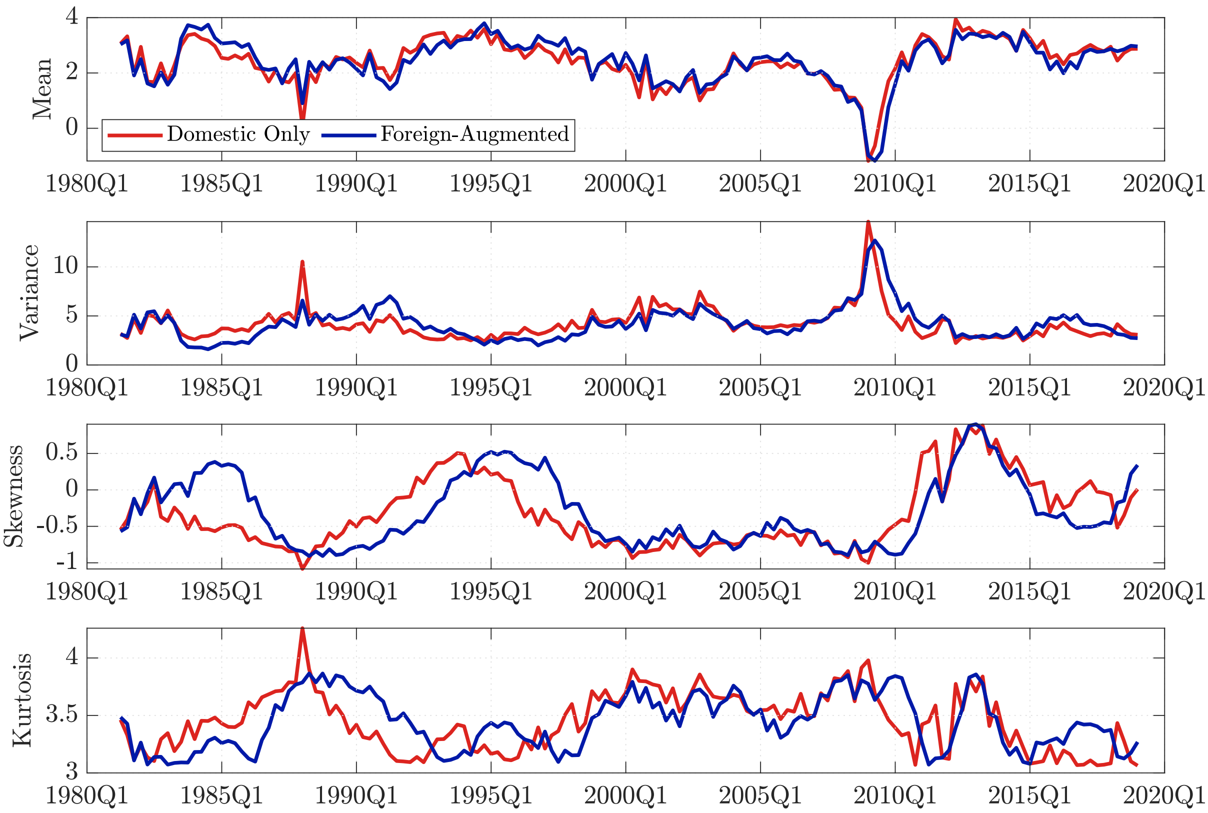
In this Appendix sub-section, we present estimates of time-varying moments of US GDP growth from our baseline specification. These results are described in Section 4.

Figure 13: Estimated time-varying moments of US GDP at the 1-quarter horizon



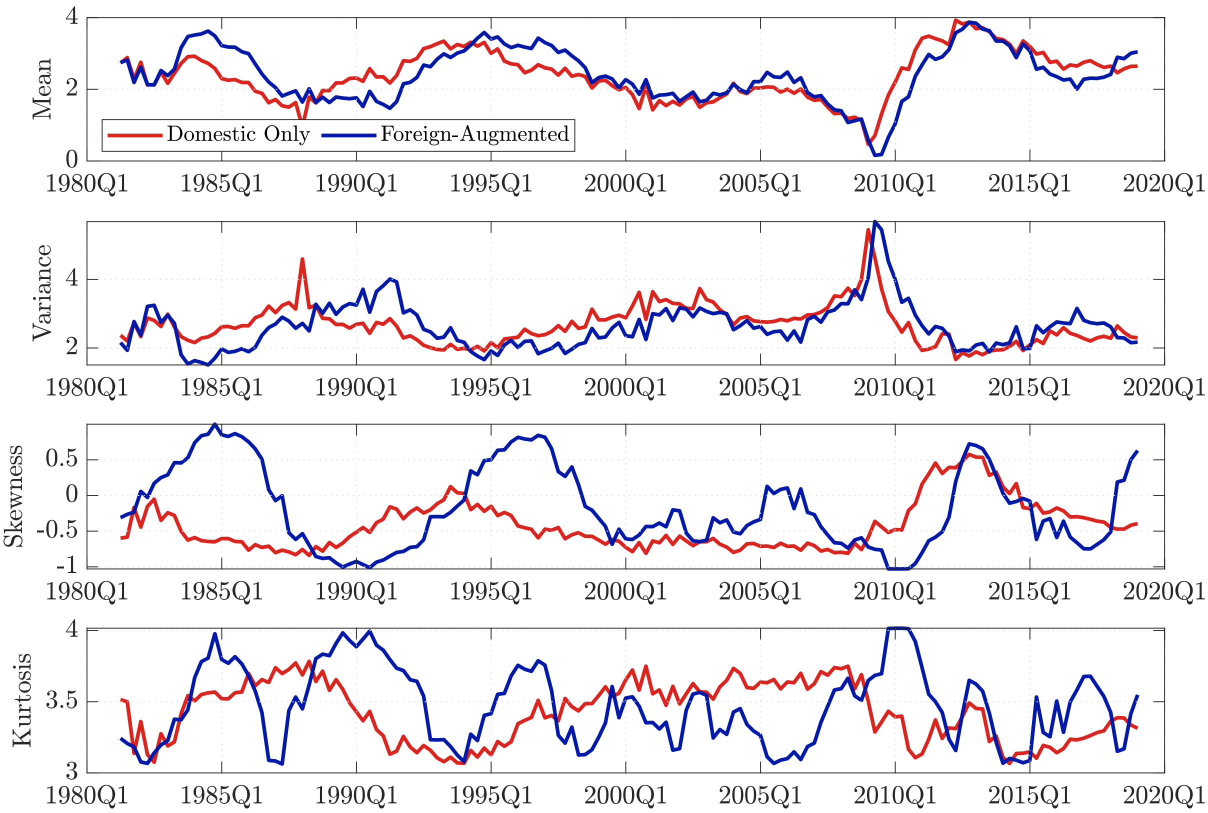

*Note*: Estimates of time-varying moments of the US GDP distribution at the 1-quarter horizon. The blue line shows the estimates from the foreign-augmented model while the red line shows the estimates from the restricted domestic-only model, as described in Section 3.1.

Figure 14: Estimated time-varying moments of US GDP at the 1-year horizon



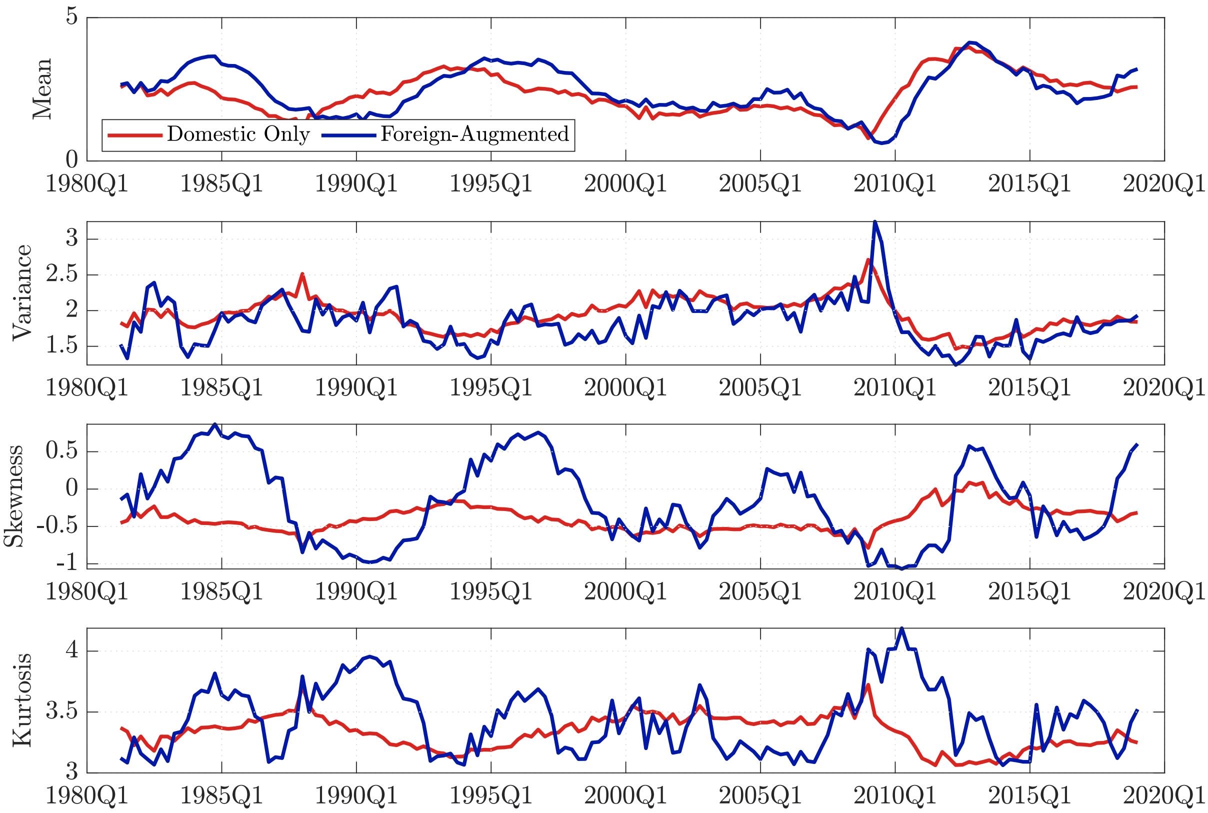

*Note*: Estimates of time-varying moments of the US GDP distribution at the 1-year horizon. The blue line shows the estimates from the foreign-augmented model while the red line shows the estimates from the restricted domestic-only model, as described in Section 3.1.

Figure 15: Estimated time-varying moments of US GDP at the 2-year horizon




*Note*: Estimates of time-varying moments of the US GDP distribution at the 2-year horizon. The blue line shows the estimates from the foreign-augmented model while the red line shows the estimates from the restricted domestic-only model, as described in Section 3.1.

Figure 16: Estimated time-varying moments of US GDP at the 3-year horizon




*Note*: Estimates of time-varying moments of the US GDP distribution at the 3-year horizon. The blue line shows the estimates from the foreign-augmented model while the red line shows the estimates from the restricted domestic-only model, as described in Section 3.1.

### B.3 Structural Decompositions

In this Appendix sub-section, we present details of the robustness exercises we run to complement the structural decompositions in Section 5.

Specifically, we estimate structural decompositions from two model variants, in addition to the baseline model.

First, we re-estimate our baseline model, weighting foreign variables using bilateral financial linkages measured using BIS International Banking Statistics. Compared to our baseline model, which includes $14$ countries in the domestic variable set, this financially-weighted model includes $11$ domestic economies owing to data availability.

Second, we estimate an extended model, akin to that in Aikman et al. (2019). Here, the domestic variable set includes 3-year house price growth, the current account, bank capital ratios, 1-year CPI inflation and the 1-year change in central bank policy rates, in addition to our baseline domestic indicators (3-year change in credit-to-GDP growth and lagged quarterly real GDP growth).

The estimated share of variation in fitted values attributable to foreign shocks $ForShare_i^h(\tau)$, defined in equation (6), at $h = 1, 4, 12$ and $\tau = 0.05, 0.5$ from these two models, alongside the baseline, are presented in Table 4.

In all three models, the majority of of variation in estimated percentiles of GDP growth is attributable to foreign shocks in most cases. Moreover, foreign factors exert a larger influence on fitted values at the left tail of the GDP distribution, i.e. the $5$th percentile, than at the median, corroborating the results in Figure 11. Although the foreign share is lowest for the extended model, this is unsurprising given that it includes more domestic covariates than the baseline or its financially-weighted variant. Even so, the results in Table 4 indicate that, across models, between $54$ and $70\%$ of variation in the $5$th percentile of 3-year GDP growth is attributable to foreign shocks.

Table 4: Share of Variation in Fitted Values (%) Attributes to Foreign Shocks Across Horizons

| | (1) Baseline | | | | | | (2) Financial Weights | | | | | | (3) Extended Specification | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $h=1$ | | $h=4$ | | $h=12$ | | $h=1$ | | $h=4$ | | $h=12$ | | $h=1$ | | $h=4$ | | $h=12$ | |
| Country | $\tau=0.05$ | 0.5 | 0.05 | 0.5 | 0.05 | 0.5 | 0.05 | 0.5 | 0.05 | 0.5 | 0.05 | 0.5 | 0.05 | 0.5 | 0.05 | 0.5 | 0.05 | 0.5 |
| AUS | 85.80 | (73.44) | 75.34 | (75.64) | 72.05 | (68.10) | 86.71 | (72.03) | 75.88 | (73.17) | 61.51 | (59.72) | 64.69 | (60.60) | 48.34 | (44.40) | 49.53 | (51.84) |
| CAN | 90.09 | (78.98) | 71.77 | (71.97) | 66.23 | (57.49) | 88.10 | (77.47) | 68.94 | (70.62) | 53.14 | (50.34) | 69.75 | (72.03) | 53.36 | (47.04) | 53.60 | (40.72) |
| DNK | 90.54 | (74.85) | 81.51 | (78.61) | 77.51 | (72.22) | n/a | n/a | n/a | n/a | n/a | n/a | 50.70 | (62.32) | 51.51 | (42.11) | 63.10 | (55.58) |
| FIN | 87.75 | (76.79) | 75.79 | (73.79) | 69.98 | (61.27) | 88.48 | (73.69) | 74.24 | (71.23) | 60.05 | (57.92) | 60.37 | (63.21) | 45.43 | (35.25) | 55.84 | (42.40) |
| FRA | 89.73 | (83.04) | 70.05 | (72.57) | 64.60 | (54.80) | 88.24 | (80.99) | 70.75 | (73.97) | 54.63 | (50.77) | 67.00 | (71.66) | 49.42 | (45.51) | 49.62 | (42.80) |
| GER | 89.80 | (76.71) | 72.47 | (71.94) | 66.91 | (57.81) | 86.39 | (71.29) | 68.34 | (67.11) | 52.49 | (50.06) | 65.38 | (66.29) | 47.83 | (45.13) | 50.09 | (51.27) |
| IRE | 83.96 | (71.52) | 67.82 | (69.99) | 64.26 | (58.21) | 83.85 | (69.62) | 69.24 | (68.39) | 53.53 | (50.96) | 56.11 | (55.87) | 42.51 | (36.94) | 50.57 | (49.48) |
| ITA | 89.73 | (80.03) | 82.50 | (81.50) | 80.30 | (76.48) | 88.95 | (76.84) | 73.81 | (74.08) | 60.78 | (58.12) | 67.52 | (66.79) | 52.59 | (47.81) | 50.17 | (54.83) |
| NOR | 86.40 | (70.68) | 71.12 | (69.81) | 66.48 | (59.73) | n/a | n/a | n/a | n/a | n/a | n/a | 58.46 | (56.84) | 44.86 | (40.60) | 50.98 | (47.86) |
| NLD | 90.35 | (76.73) | 70.67 | (70.55) | 64.60 | (53.65) | 87.67 | (74.59) | 66.99 | (69.22) | 50.92 | (46.93) | 66.89 | (64.06) | 51.15 | (45.46) | 60.84 | (48.74) |
| SPAIN | 91.72 | (77.84) | 80.39 | (79.52) | 76.45 | (68.95) | 88.95 | (75.17) | 77.38 | (74.85) | 63.91 | (63.00) | 76.96 | (65.39) | 52.75 | (46.27) | 50.47 | (53.54) |
| SWE | 95.28 | (78.10) | 86.33 | (83.14) | 82.61 | (76.47) | 93.21 | (74.46) | 85.61 | (79.91) | 75.27 | (73.95) | 60.90 | (55.18) | 47.06 | (40.35) | 55.35 | (56.41) |
| SWI | 88.33 | (81.47) | 74.30 | (77.88) | 68.57 | (56.21) | n/a | n/a | n/a | n/a | n/a | n/a | 53.78 | (64.36) | 45.61 | (37.51) | 57.45 | (38.07) |
| UK | 91.77 | (76.37) | 77.53 | (76.06) | 71.45 | (63.13) | 91.20 | (74.46) | 79.94 | (79.91) | 66.60 | (73.95) | 76.98 | (66.27) | 64.79 | (52.95) | 58.64 | (54.26) |
| *Avg.* | *89.37* | *(76.90)* | *75.54* | *(75.21)* | *70.86* | *(63.18)* | *88.34* | *(74.56)* | *73.74* | *(72.59)* | *59.35* | *(56.97)* | *63.96* | *(63.63)* | *49.80* | *(43.38)* | *54.02* | *(49.13)* |

Share of variation at the 5th percentile ($\tau = 0.05$) and median ($\tau = 0.5$ in parentheses) of country-GDP distributions at different horizons: $h = 1$ (1 quarter), $h = 4$ (1 year), and $h = 12$ (3 years). Share definition in equation (6). Shares constructed from three models in which domestic indicators are orthogonalised with respect to all foreign indicators, akin to a small-open economy assumption for domestic countries.

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