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Growth in stress

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ABSTRACT

We propose a new global risk index, Growth-in-Stress (GiS), that measures the expected fall in a country's GDP as the global factors, which drive world growth, are subject to stressful conditions. Using the GDP growth rates of 87 countries, we find that, since the 2008 financial crisis, though mainly from 2011 on, the world overall has fallen in a state of complacency, with the cross-sectional average GiS falling quite dramatically; in 2015, the average worst outcome seems to be no growth at the 95% probability factor stress. However, the cross-sectional dispersion within groups is quite variable: it is the smallest among industrialized countries and the largest among emerging and developing countries. We also measure the factor stress on different quantiles of the GDP growth distribution of each country. We calculate an Armageddon-type event as we seek to find the GiS on the 5% quantile of growth under the extreme 95% probability events of the factors, and find that it can be as large as an annual 20% fall in GDP.

1. Introduction

There is a large body of evidence on the presence of cross-country links in macroeconomic fluctuations, with world and regional business cycles having different effects on developing and developed economies. For example, Bjornland, Ravazzolo, and Thorsrud (2017), Imbs (2010), Kose, Otrok, and Prasad (2012) and Kose, Otrok, and Whiteman (2003) conclude that the world factor is more important in explaining fluctuations in developed, stable economies, whereas country-specific factors are more important in developing, volatile economies. Similarly, Ozturk and Sheng (2018) show that some regional recession episodes are associated with higher levels of uncertainty than global recession episodes. For instance, the peaks of uncertainty in Indonesia and South Korea were higher around the 1997 Asian financial crisis than around the recent global recession. The presence of both world and regional business cycles leads to the possibility of exploring a global macroeconomic risk when these common cycles are subject to extreme negative scenarios. The related literature considering common factors and macroeconomic risk has considered the factors as being fixed at their (estimated) expected values. However, if the factors are drivers of economic growth, the potential growth risk must naturally be a function of the factor risk. Thus, we need to consider factors beyond their expected values and instead to explore their lower quantiles, where stress is measured.

The proposed methodology is based on the use of predictive quantile regressions of output growth, augmented with common factors as predictors. The factors are extracted by means of principal components (PC) from a large set of macroeconomic aggregates, modeled using dynamic factor models (DFMs), and their joint probability density is computed by the subsampling method proposed by Maldonado and Ruiz (2017). We construct the risk index for each country by considering the Value-in-Stress (ViS) risk measure proposed by González-Rivera (2003) in the context of monitoring capital requirements for controlling market risk. Adapted to a macroeconometric context, the ViS, denoted by GiS for Growth-in-Stress, is defined as (minus) the lowest expected gross domestic product (GDP) growth (or quantile of growth) in a given

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country when there is extreme stress in the macroeconomic common factors. We calculate each country's risk exposure to extreme changes in the macroeconomic factors, as well as its ability to withstand stressful scenarios, which may eventually generate economic crises. One important advantage of our approach is that, while calculating the GiS, we are able to learn the magnitude of the factor stress concurrently; in other words, the stressful scenarios are determined endogenously, which is very different from the standard practice of stress testing, where stressful scenarios are chosen a priori. We also analyze whether the risk exposure differs across industrialized, emerging and other developing countries. We calculate the GiS values of 87 countries using the annual data on macroeconomic growth from 1985 to 2015, obtained from the World Bank's World Development Indicators and supplemented with the International Monetary Fund's World Economic Outlook (WEO) data base.

The most recent literature on macroeconomic risk analyzes two different but related dimensions of risk. Some works focus on uncertainty indexes, while others consider downside risks to economic growth. The main difference between uncertainty and risk indexes is that the former measure variances (uncertainty) while the latter measure the lower tail (risk) of growth. Although variances take into account deviations from the mean in both directions, a policy maker who wishes to monitor the downside risk would be more interested in the lower quantiles of growth. Our work measures the effect of stressed factors not only on the average growth, but also on different quantiles of growth.

The proposed macroeconomic risk index is related to the macroeconomic uncertainty indexes proposed by Jurado, Ludvigson, and Ng (2015), who use augmented predictive regressions based on PC factors, and by Henzel and Rengel (2017), who implement two-step Kalman filter factors. However, there are two main differences between these studies and our work. First, Henzel and Rengel (2017) and Jurado et al. (2015) construct uncertainty indexes based on weighted combinations of the uncertainty of the idiosyncratic components, whereas we are concerned with the common factors rather than the idiosyncratic noises. Second, instead of focusing on conditional variances, we measure the risk in the tails of the factors' joint distribution; i.e., we consider multivariate quantiles rather than variances. Other uncertainty indexes are proposed by Ozturk and Sheng (2018) and Rossi and Sekhposyan (2015), which are based on survey data from the European Central Bank Survey of Professional Forecasters and the Consensus Forecasts, respectively; see Ozturk and Sheng (2018) for a detailed survey of the literature on economic uncertainty indexes.

More closely related to our proposal is the risk index proposed by Adrian, Boyarchenko, and Giannone (2019), who model the full distribution of future real GDP growth as a function of current financial and economic conditions. They estimate a semi-parametric distribution of growth using quantile regressions. Risk is computed either as the expected shortfall of this distribution or using an entropy measure with respect to the unconditional distribution of growth that is time-invariant and based on quantile regressions in which only the constant term is included. In this latter case, they quantify the upside and downside vulnerability of future GDP growth as the "extra" probability mass that the conditional density assigns to extreme right- and left-tail outcomes relative to the probability of these outcomes under the unconditional density. There are three main differences between our proposed GiS index and that of Adrian et al. (2019). First, the GiS is based on stressed conditions of the common factors and their effects on growth, while Adrian et al. (2019) consider that factors are fixed at their estimated mean values. Second, the factors considered in this paper are world and regional factors, while Adrian et al. (2019) focus on financial local factors. Finally, Adrian et al. (2019) focus their analysis on growth risk in the USA, while we extend our analysis to 87 countries around the world. Our methodology is also related to that proposed by Giglio, Kelly, and Pruitt (2016), who fit factor-augmented quantile regressions in order to evaluate the abilities of various measures of systemic financial risk to predict real activity outcomes. Their study also differs from ours in various important ways. Like Adrian et al. (2019), they consider the effect of financial common factors, which are treated as observable. However, they do not propose a proper risk measure for growth, but only predict it. Furthermore, their empirical application considers US and European countries, but not developing or emerging ones.

The rest of this paper is organized as follows. Section 2 describes the GiS index. Section 3 estimates the common factors and GiS index values for a large number of industrialized, emerging and other developing countries. Section 4 concludes. An online appendix provides detailed results of the estimation of the predictive and quantile regressions.

2. Growth-in-stress index

The choice of key macroeconomic variable(s) is crucial in describing the state of the economy. Following the standard choice in the related macroeconomic literature, we focus on GDP growth as representative of the business cycle. Let GDP_{it} be the GDP of country i at time t, and define the corresponding growth as $y_{it} \equiv \triangle log(GDP_{it})$. For each country, we forecast growth using the following single equation autoregressive model augmented with factors:

$$y_{it+1} = \mu_i + \phi_i y_{it} + \sum_{k=1}^{r} \beta_{ik} F_{kt} + u_{it+1}, \tag{1}$$

where F_{kt}, for $k = 1, \ldots, r$, are the r unobserved common factors, also known as diffusion indexes, that summarize the variation in the large cross-section of growths, and u_{it} is a white noise process; see Forni, Hallin, Lippi, and Reichlin (2000) and Stock and Watson (1999) for the introduction of factor-augmented predictive regressions. Factor-augmented regressions such as that in Eq. (1) have been considered by Jurado et al. (2015) for constructing their uncertainty index.

If the interest is in not only the center of the probability distribution of growth but also its lower or upper tail, we can consider a factor-augmented quantile regression model that estimates the τ quantile of y_{it+1} conditional on y_{it} and F_t; see Ando and Tsay (2011) for factor-augmented quantile regressions. In particular, we consider the following model:

$$q_\tau(y_{it+1}|y_t, F_t) = \mu_i(\tau)+\phi_i(\tau)y_{it}+\sum_{k=1}^{r}\beta_{ik}(\tau)F_{kt}+v_{it+1}, \quad (2)$$

where $q_\tau(y_{it+1}|y_t, F_t)$ is the τth quantile of y_{it+1} conditional on y_{it} and $F_t = (F_{1t}, \ldots, F_{rt})'$, and v_{it} is an uncorrelated sequence such that $q_\tau(v_{it+1}|y_t, F_t) = 0$. Quantile regressions with factors as explanatory variables have also been considered by Adrian et al. (2019) for computing their risk index and by Giglio et al. (2016) for evaluating the ability of various measures of systemic risk to predict real activity outcomes. The quantile approach is appropriate for evaluating the potentially asymmetric and nonlinear association between global and regional factors and economic growth.

The GiS index for country i at time $t+1$ is defined as the minimum expected growth (or quantile of growth) of the country when the underlying factors are subject to α-probability extreme scenarios, that is

$$GiS_{t+1}^{(i)} = -\min h(y_{i,t+1}) \quad (3)$$

$$s.t. \quad g(F_t, \alpha) = 0,$$

and, depending on whether the interest is in the average growth or in a quantile of growth, $h(y_{it+1})$ is given by either the predicted y_{it+1}, as defined in Eq. (1), or the predicted $q_\tau(y_{it+1}|y_t, F_t)$, as defined in Eq. (2), respectively. Note that, for ease of interpretation, we multiply the sign of $h(y_{it+1})$ by -1, so that larger values of GiS mean larger risks. The constraint in Eq. (3) requires us to know the multivariate probability density of the factors, from which the function $g(F_t, \alpha) = 0$ is a contour. The function $g(F_t, \alpha) = 0$ is an ellipsoid that contains the true factor vector, F_t, with probability α. For instance, if $\alpha = 95\%$, the ellipsoid will contain 95% of the factor events. The values of F_t that are on the boundary of the ellipsoid $g(F_t, \alpha) = 0$ are considered to be the extreme events. Therefore, if $\alpha = 0.95$, the GiS measures the minimum expected growth (or quantile of growth) at time $t+1$ when the factors are on the boundary of the ellipsoid $g(F_t, 0.95) = 0$. Fig. 1 illustrates graphically how to obtain the GiS for two different probability contours, $\alpha_1 < \alpha_2$, when the number of factors is two, i.e., $r = 2$. First, we plot the two ellipsoids, $g(F_t, \alpha_1) = 0$ and $g(F_t, \alpha_2) = 0$. Second, we plot the so-called iso-growth curves. These are the combinations of F_1 and F_2 that produce the same predicted value of growth (or quantile of growth), $h(y_{i,t+1})$. For α_1, the GiS is given by the predicted value of growth that corresponds to the iso-growth curve that is tangent to $g(F_t, \alpha_1) = 0$; while for α_2, the GiS is given by the predicted value of the iso-growth curve tangent to $g(F_t, \alpha_2) = 0$. Observe that the minimization exercise gives us not only the GiS, but also the combination of factors that gives rise to this GiS. This combination corresponds to the point at which the ellipsoid and the iso-growth curve are tangent. In Fig. 1, GiS_1 is generated by the combination (F_{11}, F_{21}), while GiS_2 is generated by (F_{12}, F_{22}). This is an important advantage of our approach: once the α-probability level has been chosen, the stressful scenarios are determined endogenously, which is quite different from the standard practice in stress-testing exercises, where the stressful scenarios are chosen a priori.

The factors for calculating the GiS in Eq. (3) are modeled using a dynamic factor model (DFM). The specification of the DFM follows common practice in the literature; see Giglio et al. (2016), Henzel and Rengel (2017) and Jurado et al. (2015), among others.[1] We consider the following DFM:

$$Y_t = PF_t + \varepsilon_t, \quad (4)$$

where $Y_t = (y_{1t}, \ldots, y_{Nt})'$ is the $N \times 1$ vector of growth rates observed at time t for $t = 1, \ldots, T$; P is the $N \times r$ matrix of factor loadings such that $P'P$ is a diagonal matrix with distinct entries arranged in decreasing order; F_t is the vector of unobserved common factors; and $\varepsilon_t = (\varepsilon_{1t}, \ldots, \varepsilon_{Nt})'$ is the $N \times 1$ vector of idiosyncratic noises, which are assumed to be potentially weakly cross-correlated and heteroscedastic; see Bai (2003) for the assumptions on Eq. (4) that guarantee the asymptotic validity of the principal components (PC) factor extraction procedure. The number of factors r is assumed to be known.

We extract the factors using PC, due to its well known computational simplicity and popularity; see Bai and Ng (2008a) for a review of PC factor extraction. For a unique identification of the factors, we assume $\frac{F'F}{T} = I_r$; see Bai and Ng (2013) for a discussion of identification issues in the context of PC factor extraction. The $r \times T$ matrix of extracted factors $\hat{F} = (\hat{F}_1, \ldots, \hat{F}_T)$ is given by $\sqrt{T}$ times the eigenvectors that correspond to the r largest eigenvalues of the $T \times T$ matrix $Y'Y$, where $Y = (Y_1, \ldots, Y_T)$. The matrix of estimated factor loadings, $\hat{P}$, is computed as $\hat{P} = \frac{Y\hat{F}'}{T}$. Bai (2003) shows that, if $\frac{\sqrt{N}}{T} \to 0$ when $N, T \to \infty$, then $\hat{F}$ is a consistent estimator of the space spanned by the true factors. Finally, we obtain the joint probability density of the factors for computing $g(F_t, \alpha)$ in Eq. (3) by following Maldonado and Ruiz (2017), who propose the construction of ellipsoids based on the point-wise asymptotic normality of the PC estimated factors (Bai, 2003), with a covariance matrix computed by using a subsampling procedure that is designed to measure the parameter uncertainty associated with the factor estimation.[2]

The estimated factors are substituted in either Eq. (1) or Eq. (2), depending on whether the interest is in the macroeconomic global risk that affects the center or one

[1] Note that our approach differs from other related DFM models in that we do not specify *a priori* either global and specific factors for industrialized, emerging and other developing countries as per Kose et al. (2012), or global and regional factors as per Aastveit, Bjørnland, and Thorsrud (2016) and Bjornland et al. (2017).

[2] Note that the bootstrap procedure implemented by Aastveit et al. (2016) for computing prediction intervals of the factors underestimates the uncertainty because they do not consider parameter uncertainty; see Maldonado and Ruiz (2017), who show that the subsampling correction of the covariance asymptotic matrix provides point-wise prediction regions for the factors with a coverage that is very close to the nominal.

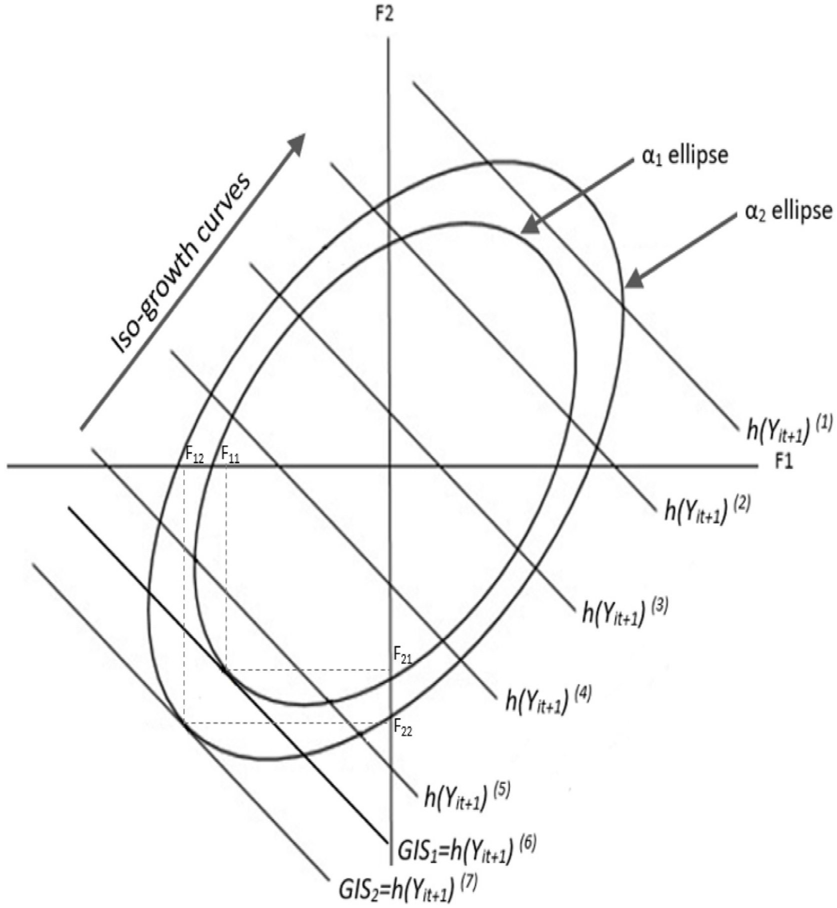


Fig. 1. Graphical illustration of the computation of GiS when the number of common factors is two.

particular quantile of the growth distribution. In the former case, the estimated factors are substituted in Eq. (1) and the predictive regression parameters are estimated by least squares (LS) as per Stock and Watson (1999). When the interest is in a particular quantile of the growth distribution, the parameters of the quantile regressions in Eq. (2) can be estimated as per Koenker and Bassett (1978); see Ando and Tsay (2011).[3] Recently, Ohno and Ando (2018) proposed a shrinkage procedure for estimating the parameters of factor-augmented predictive regressions, which can be implemented in both Eqs. (1) and (2).

Finally, when the estimated ellipsoids contain the true factors, $g(F_t, \alpha) = 0$, and the estimated predictive regression or quantile regression is augmented with the factors $h(y_{t+1})$, it is possible to solve the minimization problem in Eq. (3) numerically by evaluating Eq. (1) or (2) in *all* points of the ellipsoid.[4]

3. Gis indexes in industrialized, emerging and other developing countries

We compute the GiS values of 87 countries.[5] The data consist of the GDP, measured at constant national prices and observed annually from 1985 to 2015 for $N = 87$ countries, obtained from the World Bank's World Development Indicators and supplemented with the International Monetary Fund's WEO database. The same database was considered by Kose et al. (2012) for a larger number of countries (106) and variables (GDP, real private consumption and real fixed asset investment) over the period 1960–2008. Given the dramatic shift in the global landscape since the mid-1980s, we consider only the period starting in 1985, which is defined by Kose et al. (2012) as the wave of globalization. On the other hand, we also extend the sample period with data observed following the 2008 global financial crisis. The GDP is transformed

3 Stock and Watson (2002a) show the consistency of the LS estimator, while Bai and Ng (2006) derive its asymptotic normality. Bai and Ng (2006, 2008b) show that when the generated regressors are the estimated factors, they can be plugged in as if they were observed as far as $\frac{\sqrt{T}}{N} \to 0$ for $N, T \to \infty$ in regression models or $\frac{T^{5/8}}{N} \to 0$ for $N, T \to \infty$ in quantile regressions, respectively.

4 Note that this "brute force" approach of minimizing growth is feasible only when the number of factors is relatively small. When the number of factors is large, one needs to use optimization techniques, such as second-order cone programming (SOCP); see Bertsimas, Brown, and Caramanis (2013) and the references therein. Alternatively, Chassein and Goerigk (2017) proposed using regret combinatorial optimization.

5 The software for estimating the GiS was developed by the third author in the R programming language, and is available upon request.

to growth rates by taking the first differences of the log of GDP. Consequently, the time series length is $T = 30$.

3.1. Estimating the factors

Previous to factor extraction, the growth series are demeaned and standardized. Note that the demeaning procedure eliminates differences in mean growth rates among countries. We identify the number of common factors by implementing the procedure proposed by Alessi, Barigozzi, and Capasso (2010), which selects $r = 3$. After extracting the factors using PC, we obtain the idiosyncratic residuals and identify outliers as those residuals that exceed six times the interquartile range;[6] see Artis, Banerjee, and Massimiliano (2005), Breitung and Eickmeier (2011), Marcellino, Stock, and Watson (2003) and Stock and Watson (2002b) who also use the interquartile range to identify outliers in the context of DFM. We identify the following outliers that are due to exceptional events: (i) the consumer response to the Mexican Peso crisis in 1994, which caused a fall in Mexican growth in 1995, see McKenzie (2006); (ii) Rwanda's fall in growth in 1994 due to the genocide against the Tutsi, see Lopez and Wodon (2005); and (iii) the political crisis in 2002 in Madagascar that seriously hampered economic growth, see Vaillant, Grimm, Lay, and Rouband (2014). Like Breitung and Eickmeier (2011), we replace each outlying original growth with the median of the previous five observations. From now on, the growth rates considered in the analysis, denoted by y_{it}, are the corresponding growth rates corrected by outliers.

After demeaning and standardizing the outlier-corrected growth series y_{it}, Alessi et al. (2010) still selects $r = 3$ common factors that explain 42% of the total growth variability, with the first factor accounting for 20%. These percentages are comparable to those found by other authors in related research. For example, Aastveit et al. (2016) find that global and regional factors respectively explain around 30% and 20% of the business cycle variation in four small open economies (Canada, New Zealand, Norway and United Kingdom). Kose et al. (2003) attribute up to 35% of the variance in GDP across G7 countries to one common international business cycle. Finally, Bjornland et al. (2017), who analyze quarterly real GDP growth from 1978 to 2011 for 33 countries, covering four geographical regions and both developed and emerging economies, report that the common business cycle accounts for between 5% and 45% of the total variability of growth, depending on the particular region of the world and the period of time considered. As a consequence, we extract three factors using PC and compute their confidence bounds, as well as those for the corresponding weights, $\hat{P}$, using the subsampling procedure proposed by Maldonado and Ruiz (2017).[7] Following a visual inspection, the idiosyncratic components are considered to be approximately stationary.[8]

Table 1
List of countries.

Country	Group	Code
Algeria	Other	DZA
Benin	Other	BEN
Botswana	Other	BWA
Burkina Faso	Other	BFA
Cameroon	Other	CMR
Congo, Rep.	Other	COG
Egypt, Arab Rep.	Emerging	EGY
Gabon	Other	GAB
Gambia, The	Other	GMB
Ghana	Other	GHA
Kenya	Other	KEN
Lesotho	Other	LSO
Madagascar	Other	MDG
Mali	Other	MLI
Mauritania	Other	MRT
Mauritius	Other	MUS
Morocco	Emerging	MAR
Mozambique	Other	MOZ
Nigeria	Other	NGA
Rwanda	Other	RWA
Senegal	Other	SEN
Seychelles	Other	SYC
South Africa	Emerging	ZAF
Tanzania	Other	TZA
Togo	Other	TGO
Tunisia	Other	TUN
Uganda	Other	UGA
Zimbabwe	Other	ZWE
Argentina	Emerging	ARG
Bolivia	Other	BOL
Brazil	Emerging	BRA
Canada	Industrialized	CAN
Chile	Emerging	CHL
Colombia	Emerging	COL
Costa Rica	Other	CRI
Dominican Republic	Other	DOM
Ecuador	Other	ECU
El Salvador	Other	SLV
Guatemala	Other	GTM
Honduras	Other	HND
Mexico	Emerging	MEX
Nicaragua	Other	NIC
Panama	Other	PAN
Paraguay	Other	PRY
Peru	Emerging	PER
Trinidad and Tobago	Other	TTO

(*continued on next page*)

6 Kristensen (2014) analyzes the effects of outliers on PC factor extraction and predictive regressions, and proposes a robust factor extraction procedure based on least absolute deviations (LAD). However, this robust procedure cannot be implemented in our context because of the lack of an asymptotic distribution, which is needed to obtain the probability ellipsoids that contain the factors.

7 Kose et al. (2003) and Kose et al. (2012) extract common factors of macroeconomic variables by implementing a data augmentation Bayesian procedure based on the spectral density matrix. Alternatively, Bjornland et al. (2017) implement Bayesian estimation of the corresponding state space model using Gibbs simulation. These procedures also provide predictive densities for the factors.

8 We do not test formally for non-stationarity of the idiosyncratic noises because the temporal dimension is rather small and the lack of power of most popular nonstationarity tests is well known in this case; see for example Kwiatkowski, Phillips, Schmidt, and Shin (1992). Banerjee, Marcellino, and Masten (2008) also point out related problems associated with cointegration tests in the context of non-stationary panels.

Table 1 (*continued*).

Country	Group	Code
United States	Industrialized	USA
Uruguay	Other	URY
Venezuela, RB	Emerging	VEN
Bangladesh	Other	BGD
China	Emerging	CHN
Hong Kong SAR, China	Emerging	HKG
India	Emerging	IND
Indonesia	Emerging	IDN
Iran, Islamic Rep.	Other	IRN
Israel	Emerging	ISR
Japan	Industrialized	JPN
Korea, Rep.	Emerging	KOR
Malaysia	Emerging	MYS
Nepal	Other	NPL
Pakistan	Emerging	PAK
Philippines	Emerging	PHL
Singapore	Emerging	SGP
Sri Lanka	Other	LKA
Syrian Arab Republic	Other	SYR
Thailand	Emerging	THA
Turkey	Emerging	TUR
Austria	Industrialized	AUT
Belgium	Industrialized	BEL
Denmark	Industrialized	DNK
Finland	Industrialized	FIN
France	Industrialized	FRA
Germany	Industrialized	DEU
Greece	Industrialized	GRC
Iceland	Industrialized	ISL
Ireland	Industrialized	IRL
Italy	Industrialized	ITA
Luxembourg	Industrialized	LUX
Netherlands	Industrialized	NLD
Norway	Industrialized	NOR
Portugal	Industrialized	PRT
Spain	Industrialized	ESP
Sweden	Industrialized	SWE
Switzerland	Industrialized	CHE
United Kingdom	Industrialized	GBR
Australia	Industrialized	AUS
New Zealand	Industrialized	NZL

Figs. 2 to 4 plot the estimated factors and weights that correspond to the DFM in Eq. (4), together with their 95% bounds. Following Kose et al. (2012), the countries are classified into three groups: (i) industrial, the weights of which are represented by red bars; (ii) emerging markets, represented by blue bars; and (iii) other developing countries, represented by gray bars. Table 1 reports the classification of each country, with the countries being listed in the same order as their weights are plotted in Figs. 2 to 4. Consider the first factor, which is plotted in Fig. 2, together with its weights and corresponding 95% confidence intervals. This factor can be interpreted as a world growth factor, with all industrial and emerging countries but Morocco, Peru and China having positive weights. In the case of Morocco, the weight is not significant, while the weights for Peru and China are negative, although relatively small in magnitude. We also observe that the weights are negative and relatively small or non-significant in several "other developing countries", mainly in Africa. It is also remarkable that the weights of India and Indonesia, although positive, are relatively small. The dynamic profile of the estimated global factor is very similar to those found by Kose et al. (2012), Aastveit et al. (2016) and Bjornland et al. (2017), with declines in the early 1990s, in 2000/2001 during the bursting of the dot-com bubble, and in 2008–2009 during the Great Recession, with the last being by far the most severe.

Fig. 3 plots the second factor, together with its weights. We observe that this factor is negative until the mid-1990s and then positive, with a relatively weak drop during the Great Recession. This factor has positive weights in most of the "other developing" countries in Africa and America. Furthermore, China's weight is not significant, while India's is positive and large. As far as we know, this factor has not been identified before. Other related works, as that of Aastveit et al. (2016), have not included African countries or developing countries in South America. Only Kose et al. (2012) extracted factors using data from a similar set of countries to those considered here; however, they specified *a priori* common factors that were associated with industrialized, emerging and other developing countries. Our results suggest that the factors are not associated with these groups of countries exactly, but rather with a mixture of these groups and geographic regions.

Finally, the third factor, which is plotted in Fig. 4 together with its weights, is not affected by the 2008 global crisis. Furthermore, its weights are negative for all industrialized countries but Japan (non-significant) and Germany (rather small positive weight). In America and Asia, the weights are positive for all emerging and other developing countries. In particular, China's weight is rather large. This factor is related to an East Asian common factor, and can be compared with the factors estimated by Moneta and Rüffer (2009) for the period 1993–2005 based on quarterly growth from ten East Asian countries, and by Bjornland et al. (2017) for the period 1978–2011. This factor clearly reflects the Asian financial crisis, which affected output in 1998; see for example Cabalu (1999) and Radelet, Sachs, Cooper, and Bosworth (1998).

According to the interpretation of the factors above, the impressive growth performances of emerging market economies, such as China and India, do not seem to be affected by the growth slowdown observed in the world factor. This conclusion is in agreement with the findings of Kose et al. (2012), who conclude that emerging markets have "decoupled" from industrial economies, meaning that their business cycle dynamics are no longer linked tightly to the business cycles of industrial countries.

As an illustration of the joint ellipsoids of the factors obtained by the subsampling procedure, we plot the 95% ellipsoids for 1998 and 2004 for the USA (Fig. 8) and China (Fig. 9). The ellipsoids corresponding to 1998 have larger volumes, meaning that the uncertainty in the underlying factors in 1998 is larger just around and after the Asian financial crisis. Furthermore, we observe that the increase in uncertainty is due mainly to the first and second factors.

3.2. Predictive regressions

For each country's growth, we estimate the predictive regression in Eq. (1) by LS using the estimated factors

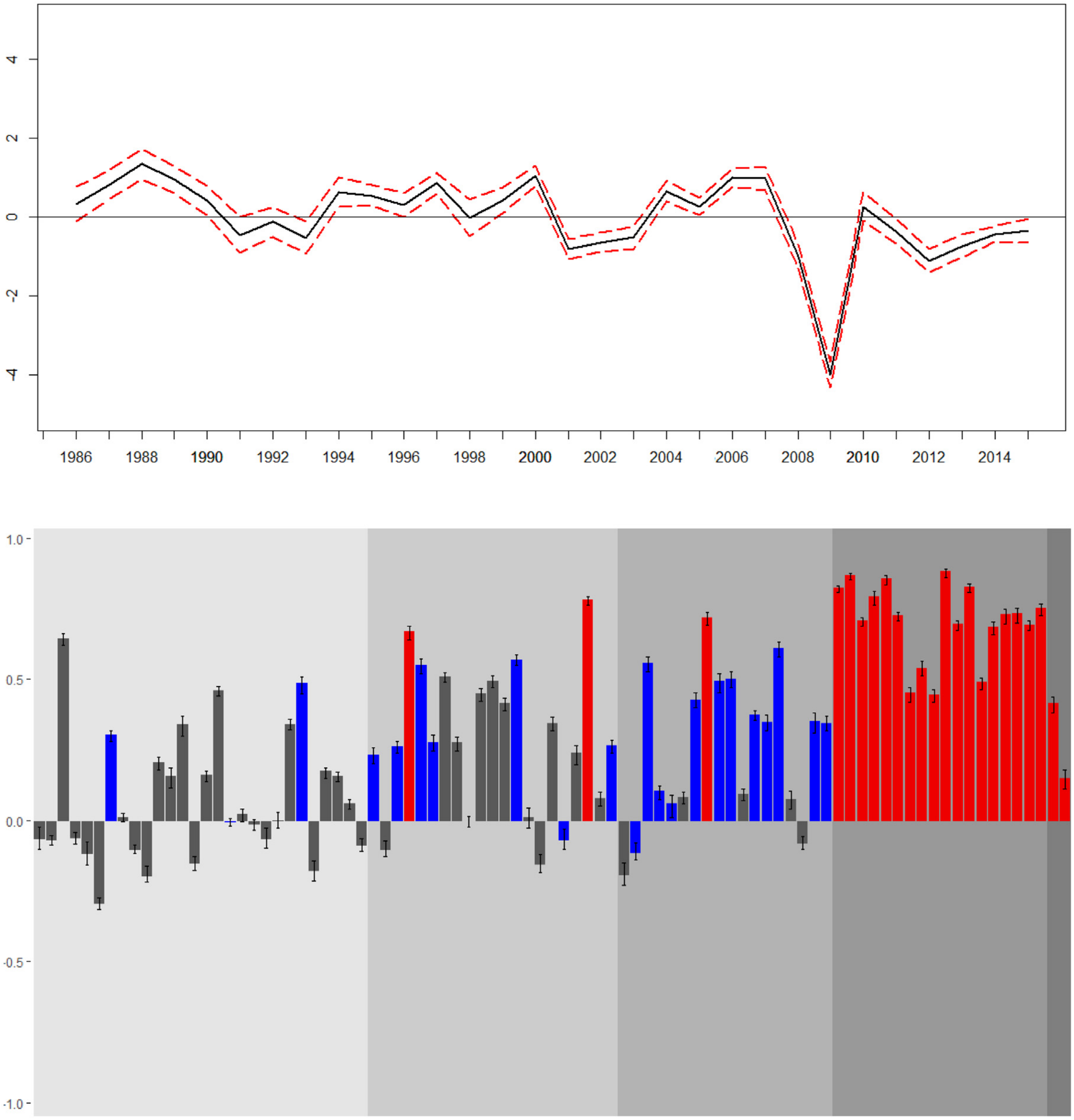


Fig. 2. First world factor. Top panel: Estimated factor together with 95% prediction intervals (in red). Bottom panel: Estimated weights for each country together with 95% confidence intervals. The red, blue, and gray bars correspond to industrialized, emerging, and other developing countries, respectively. The lighter to darker gray areas correspond to African, American, Asian, European and Oceania countries, respectively. Within each continent, the countries appear in the same order as in Table 1. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

$\hat{F}_{1t}, \hat{F}_{2t}$ and $\hat{F}_{3t}$ as regressors. Note that the predictive regressions are estimated using the original growth rates without demeaning and standardizing, in order to enable us to recover information about the average growth. Fig. 5 summarizes the estimated parameters, $\hat{\beta}_{i1}, \hat{\beta}_{i2}$ and $\hat{\beta}_{i3}$, by plotting a histogram of their values across all countries (first row) and across countries in Africa (second row), America (third row), Asia (fourth row) and Europe/Oceania (fifth row). Across all countries (first row), there are no clear patterns in either the signs or the magnitudes of the estimates. Their histograms are centered roughly around zero and have similar ranges, going approximately from −2.5 to 2.5. The marginal effect of the first factor (first column), $\hat{\beta}_{i1}$, on forecast growth is similar across Africa, America and Asia, with values roughly centered around zero, but tends to be mainly positive in the Europe/Oceania group. The marginal effect of the second factor (second column), $\hat{\beta}_{i2}$, tends to be

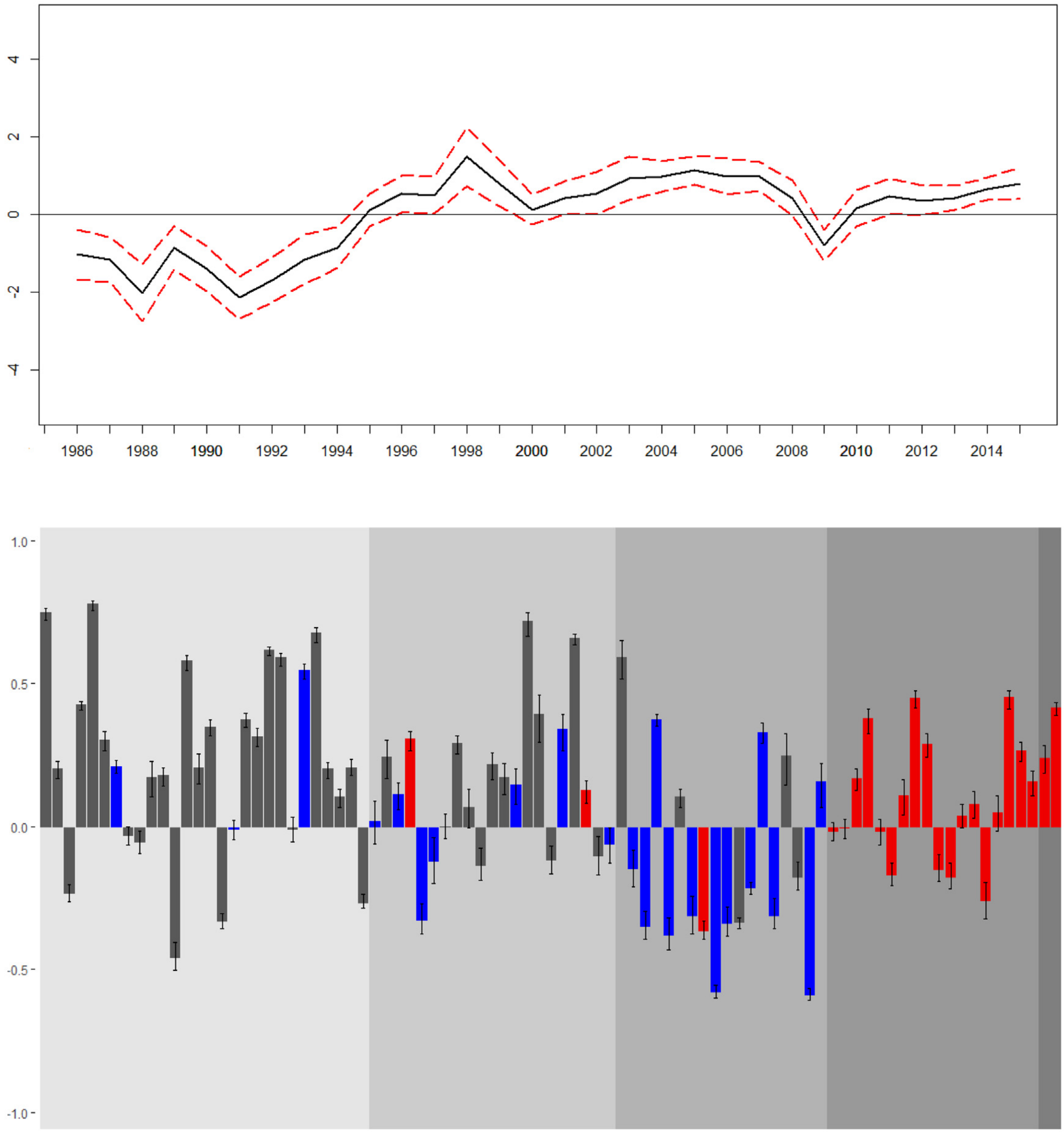


Fig. 3. Second world factor. Top panel: Estimated factor together with 95% prediction intervals (in red). Bottom panel: Estimated weights for each country together with 95% confidence intervals. The red, blue, and gray bars correspond to industrialized, emerging, and other developing countries, respectively. The lighter to darker gray areas correspond to African, American, Asian, European and Oceania countries, respectively. Within each continent, the countries appear in the same order as in Table 1. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

positive in Africa, negative in Asia and virtually zero in Europe/Oceania; while the marginal effect of the third factor (third column), $\hat{\beta}_{i3}$, is positive mainly in America. It is interesting to observe the link between the American continent and the third factor, which is loading mostly in East Asian countries. We should mention that the factors are mildly significant and the estimated magnitudes are rather small.[9]

Table 2 reports the coefficient of determination, R^2, for each factor-augmented predictive regression. Overall, we

9 Note that the results of Bai and Ng (2006) require $\frac{\sqrt{T}}{N} \to 0$ for the asymptotic normality of the LS estimator. In our application, $\frac{\sqrt{30}}{87} = 0.06$. However, Gonąlves and Perron (2014) show that the LS estimator of the parameters of the predictive regressions may be affected by negative biases. In addition, the contemporaneous correlation between growth and the estimated factors is rather large for some countries, and multicolinearity could be severe. Thus, we should be cautious about inference on the parameters of the predictive regressions. The estimated parameters, together with their p-values and the Box-Ljung statistic for the joint significance of the first four autocorrelations of the residuals, $Q(4)$, of each predictive regression, are reported in an online appendix.

Table 2
Goodness of fit: R^2 of factor-augmented predictive regressions and R^1_τ of factor-augmented predictive quantile regressions.

Africa

	DZA	BEN	BWA	BFA	CMR	COG	EGY	GAB	GMB	GHA	KEN	LSO	MDG	MLI	MRT	MUS	MAR	MOZ	NGA	RWA	SEN	SYC	ZAF	TZA	TGO	TUN	UGA	ZWE
R^2	0.39	0.14	0.11	0.43	0.64	0.13	0.23	0.08	0.13	0.29	0.32	0.34	0.40	0.29	0.11	0.14	0.49	0.14	0.17	0.46	0.39	0.19	0.31	0.55	0.06	0.06	0.10	0.26
$R^1_{0.95}$	0.42	0.36	0.34	0.15	0.41	0.40	0.40	0.47	0.23	0.52	0.47	0.37	0.36	0.62	0.29	0.24	0.63	0.21	0.39	0.22	0.24	0.18	0.42	0.28	0.13	0.30	0.24	0.31
$R^1_{0.50}$	0.20	0.15	0.06	0.31	0.37	0.20	0.17	0.17	0.16	0.20	0.29	0.26	0.29	0.23	0.16	0.19	0.35	0.14	0.18	0.29	0.31	0.22	0.18	0.38	0.12	0.18	0.21	0.25
$R^1_{0.05}$	0.54	0.49	0.33	0.49	0.66	0.43	0.28	0.37	0.35	0.21	0.21	0.25	0.55	0.29	0.22	0.37	0.51	0.56	0.49	0.50	0.45	0.24	0.29	0.58	0.47	0.22	0.45	0.36

America

	ARG	BOL	BRA	CAN	CHL	COL	CRI	DOM	ECU	SLV	GTM	HND	MEX	NIC	PAN	PRY	PER	TTO	USA	URY	VEN
R^2	0.20	0.35	0.07	0.24	0.41	0.11	0.08	0.09	0.16	0.38	0.12	0.07	0.09	0.34	0.27	0.21	0.45	0.53	0.44	0.41	0.20
$R^1_{0.95}$	0.21	0.49	0.43	0.27	0.48	0.23	0.44	0.15	0.31	0.55	0.49	0.15	0.25	0.3	0.34	0.54	0.40	0.49	0.27	0.20	0.20
$R^1_{0.50}$	0.21	0.44	0.1	0.12	0.23	0.09	0.08	0.11	0.11	0.24	0.21	0.09	0.23	0.36	0.23	0.09	0.26	0.41	0.28	0.27	0.16
$R^1_{0.05}$	0.43	0.67	0.39	0.36	0.43	0.46	0.29	0.37	0.38	0.29	0.41	0.4	0.33	0.38	0.50	0.33	0.67	0.39	0.58	0.53	0.44

Asia

	BGD	CHN	HKG	IND	IDN	IRN	ISR	JPN	KOR	MYS	NPL	PAK	PHL	SGP	LKA	SYR	THA	TUR
R^2	0.53	0.38	0.22	0.19	0.14	0.35	0.10	0.37	0.33	0.17	0.16	0.21	0.28	0.27	0.22	0.36	0.47	0.03
$R^1_{0.95}$	0.39	0.36	0.57	0.18	0.39	0.53	0.27	0.50	0.48	0.23	0.43	0.40	0.26	0.47	0.35	0.54	0.48	0.1
$R^1_{0.50}$	0.35	0.37	0.22	0.21	0.27	0.28	0.1	0.18	0.34	0.27	0.06	0.27	0.24	0.19	0.17	0.24	0.33	0.08
$R^1_{0.05}$	0.56	0.46	0.34	0.3	0.12	0.47	0.23	0.44	0.23	0.24	0.43	0.17	0.27	0.37	0.39	0.63	0.51	0.12

Europe and Oceania

	AUT	BEL	DNK	FIN	FRA	DEU	GRC	ISL	IRL	ITA	LUX	NLD	NOR	PRT	ESP	SWE	CHE	GBR	AUS	NZL
R^2	0.33	0.37	0.09	0.25	0.42	0.16	0.55	0.37	0.38	0.44	0.24	0.38	0.31	0.54	0.62	0.27	0.16	0.41	0.19	0.39
$R^1_{0.95}$	0.35	0.4	0.22	0.22	0.47	0.27	0.24	0.31	0.43	0.37	0.30	0.46	0.32	0.59	0.39	0.33	0.29	0.48	0.34	0.21
$R^1_{0.50}$	0.21	0.22	0.21	0.22	0.26	0.12	0.34	0.36	0.32	0.25	0.19	0.28	0.23	0.33	0.39	0.13	0.12	0.15	0.14	0.38
$R^1_{0.05}$	0.43	0.44	0.34	0.43	0.49	0.44	0.62	0.36	0.46	0.48	0.43	0.54	0.44	0.55	0.54	0.47	0.42	0.51	0.50	0.39

observe that half of the predictive regressions have R^2 values larger than 30%, and only 10% of the regressions have R^2 values larger than 50%. The results above show that the effects of the factors on the one-step-ahead average growth are very mild.

Next, we analyze the effects of the factors on different growth quantiles by estimating the factor-augmented quantile predictive regressions in Eq. (2) with $\tau = 0.05$, 0.5 and 0.95.[10] Note that when $\tau = 0.5$, the quantile regression reduces to the conditional median regression, which is more robust to outliers than the conditional mean regression in Eq. (1); see Ando and Tsay (2011). Fig. 6 plots the cross-sectional histograms of the estimated parameters $\hat{\beta}_{i1}(\tau)$, $\hat{\beta}_{i2}(\tau)$ and $\hat{\beta}_{i3}(\tau)$ for the lower quantile $\tau = 0.05$.[11] The main difference from the results of the predictive regression for expected growth is that the magnitude of the parameter estimates is much larger for all countries. Across all countries (first row), the histograms are centered roughly around zero, with an approximate range from −5 to 5. The marginal effect of the first factor (first column), $\hat{\beta}_{i1}(\tau)$, on the forecast of the 0.05 quantile of growth tends to be mainly positive in America and the Europe/Oceania group, and negative in Asia. The marginal effect of the second factor (second column), $\hat{\beta}_{i2}(\tau)$, tends to be positive in Africa, and the marginal effect of the third factor (third column), $\hat{\beta}_{i3}(\tau)$ is mainly positive in America and negative in Europe/Oceania. In general, the joint effect of the three factors is more relevant to forecasting the 0.05 quantile of growth than to forecasting the expected growth.

Table 2 reports the goodness of fit measure proposed by Koenker and Machado (1999), denoted by R^1, which is analogous to the coefficient of determination in regression models.[12] We observe that, in general, the fit of the median regression is lower than that of the average growth regression. However, the fit improves dramatically in the tail quantiles. For the lower tail, the 5% quantile, we find that about 30% of the regressions have R^1 coefficients that are larger than 50%. Thus, it seems that the factors are more relevant for explaining future tails than the center of the growth distribution. This conclusion is in agreement with the main findings of Adrian et al. (2019) and Giglio et al. (2016), who conclude that the estimated lower quantile of growth depends on financial conditions, while the upper quantiles are stable over time.[13]

Finally, following Adrian et al. (2019), we use the factor-augmented quantile predictive regressions for different values of τ to compute the growth densities for each country and year.[14] Fig. 7 plots these densities for two countries, namely China and the USA. We observe that the densities are skewed to the left in both countries, with the densities in China having the concentration of mass in the values of growth being larger than those in the USA (less risk). Furthermore, the dispersion (uncertainty) of the densities in China is also smaller than that of the densities for the USA. Finally, note that the effect of the global crisis in the USA densities is very obvious, while there is not any clear effect on the densities in China.

3.3. Forecasting recession risk under stressed factors

We obtain the GiS for each country by solving the optimization problem in Eq. (3), with $h(y_{it+1}) = \hat{y}_{it+1}$ being the predicted expected mean growth, which is calculated by plugging in the LS estimates of the parameters in Eq. (1). The ellipsoid $g(F_t, \alpha) = 0$ is estimated using the resampling procedure of Maldonado and Ruiz (2017). Figs. 8 and 9 illustrate this optimization problem by plotting the 95%-probability ellipsoids $g(F_t, 95\%) = 0$ that correspond to 1998 and 2004 for the USA and China, respectively. The top left panel of each figure also plots the iso-growth surfaces that correspond to the predictive regressions for 1999 and 2005 that are tangential to the ellipsoids. We observe that the surfaces of the predictive regressions for the two countries considered are rather different in both shape and orientation.

After estimating the GiS for each country and year, we observe that, in Africa, the country with the lowest GiS over time is Cameroon, while that with the largest GiS, and, consequently, the highest risk of recession, is Uganda.[15] These two countries also have the smallest and largest risks among the developing countries. In America, the country with the lowest risk of recession is Guatemala, while that with the largest risk is Venezuela. For Asian countries, Syria and China have the largest and smallest risks of recession, respectively. It is also important to note that, among the countries that are classified as emerging, China has the lowest risk, while Venezuela has the largest. Finally, in Europe/Oceania, the largest risk of recession corresponds to Iceland, while Norway has the lowest. These two countries also have the largest and lowest risks among the industrialized countries.

Fig. 10 summarizes the GiS results by plotting the year-by-year cross-sectional average GiS, together with the cross-sectional bounds, constructed as ±2 cross-sectional standard deviations of the GiS when the countries are grouped by continent. Fig. 11 plots the same quantities when the countries are grouped by type. Several conclusions emerge from these figures. We observe that the average risk has decreased slightly over time in all continents, with the Asian continent enjoying the smallest average GiS. The African and American continents offer very similar average risk profiles. Note that the decrease

10 The estimator of the parameters is based on the algorithm by Koenker and d'Orey (1987). Results based on the shrinkage estimator proposed by Ohno and Ando (2018) are similar, and are available upon request.

11 Histograms for $\tau = 0.5$ and 0.95 are available in the online appendix.

12 The estimated parameters and their corresponding p-values are reported in the online appendix.

13 Adrian et al. (2019) show that current economic conditions forecast the median of the distribution of growth, but do not contain information about the other quantiles of the distribution.

14 Adrian et al. (2019) fitted the skewed-t distribution proposed by Azzalini and Capitanio (2003) in order to obtain a density by smoothing the quantile function.

15 Time series plots of the GiS values estimated in each country appear in the online appendix.

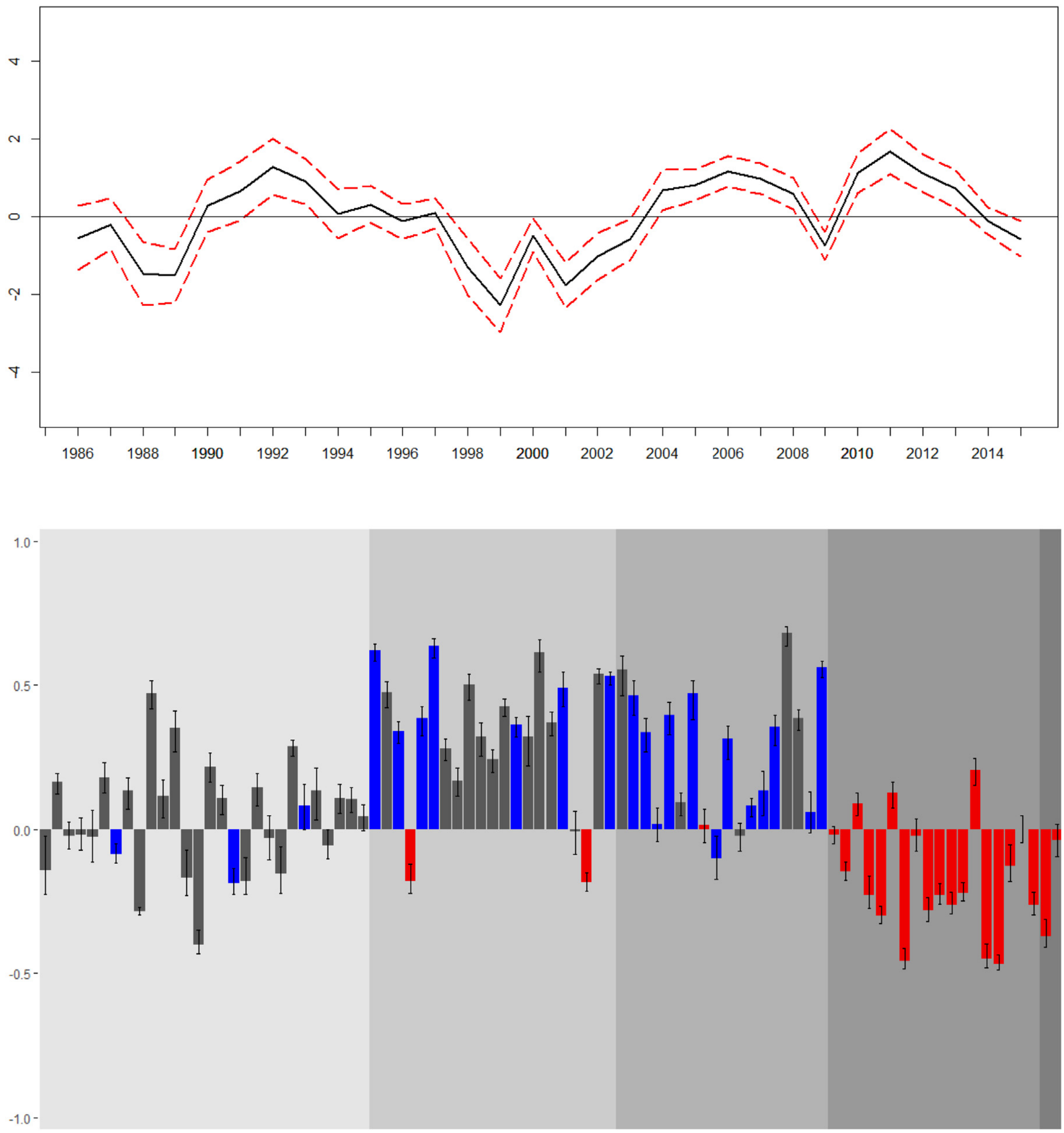


Fig. 4. Third world factor. Top panel: Estimated factor together with 95% prediction intervals (in red). Bottom panel: Estimated weights for each country together with 95% confidence intervals. The red, blue, and gray bars correspond to industrialized, emerging, and other developing countries, respectively. The lighter to darker gray areas correspond to African, American, Asian, European and Oceania countries, respectively. Within each continent, the countries appear in the same order as in Table 1. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

in the average GiS is more pronounced among countries in Africa, America and Asia than among countries in Europe/Oceania. In this latter case, the GiS is more stable over time. This result is in contrast to other macroeconomic uncertainty indexes, which conclude that the risk has been increasing over time. There are two potential explanations for this apparent contradiction. First, note that most uncertainty indexes focus on industrialized countries, while we consider growth in countries all over the world. As was explained above, the decrease in the GiS is more pronounced in emerging and developing countries than in industrialized countries. Second, our index measures the growth risk when the global and regional common factors are stressed, whereas most of the alternative indexes focus on uncertainty. Even if the variance (uncertainty) of the distribution of growth increases, the expected growth under stressed factors can also increase, leading the GiS to decrease. The ± 2 standard deviation bounds are also becoming narrower over time, and have very similar profiles in the African, Asian, and American

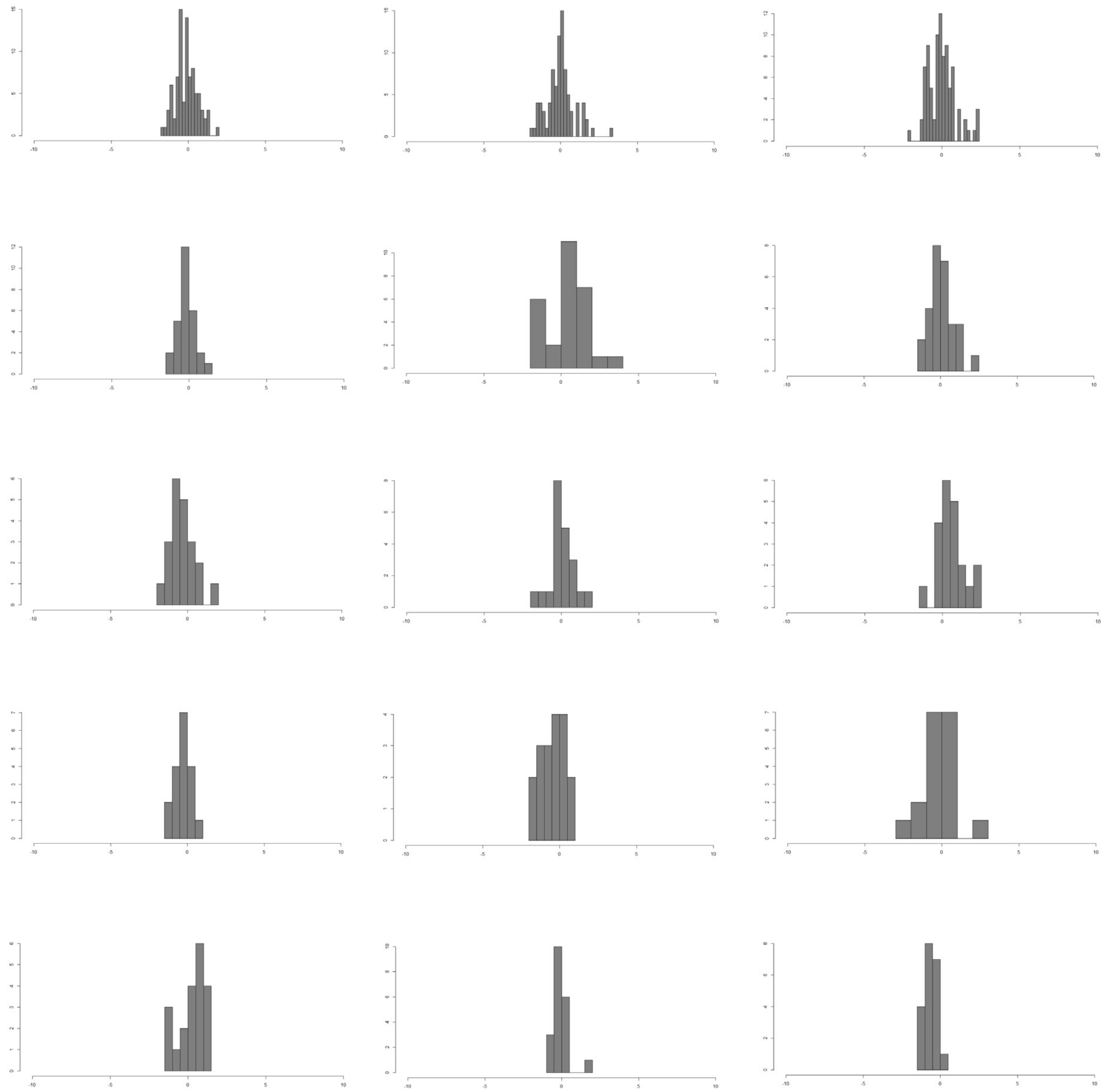


Fig. 5. Cross-sectional histograms of the estimated parameters of the factor-augmented predictive regressions, corresponding to factor 1 (first column), factor 2 (second column) and factor 3 (third column) computed through all countries (first row) and countries in Africa (second row), America (third row), Asia (fourth row) and Europe/Oceania (fifth row).

continents, with a sharp jump in 1999 coinciding with the Asian financial crisis. The lower bound is rather stable relative to the upper bound, which is more volatile over time. This is because the standard deviations during the years with high recession risks are larger than those when the risk is low. The plot for the European/Oceania continents is rather different from the other plots, as the bounds are much narrower, indicating that the risk profiles of these countries are very similar. We observe that, following the 2008 financial crisis, and mainly from 2011 on, the world has fallen into a state of complacency, with the average GiS falling quite dramatically to reach the lowest levels of risk, between 1 and 0%, in 2015. Fig. 8 summarizes the risk among developing, emerging and industrialized countries. We observe that the GiS plots of industrialized and emerging countries coincide with those of Europe/Oceania and Asia, respectively, while the plot corresponding to developing countries is very similar to that of African countries.

In addition to analyzing the effects of stressed factors on the average of growth, we also predict the GiS of each country for the $\tau = 0.05$, 0.5 and 0.95 quantiles of the country growth distribution. We solve the minimization problem in Eq. (3) with $h(y_{it+1}) = \hat{q}_\tau(y_{it+1}|y_t, F_t)$ and compute $\hat{q}_\tau(y_{it+1}|y_t, F_t)$ as in Eq. (2) by plugging in the parameter estimates. As an illustration, Figs. 8 and 9 plot the 95% ellipsoids for the factors in 1998 and 2004, together with the tangent iso-growth surfaces for

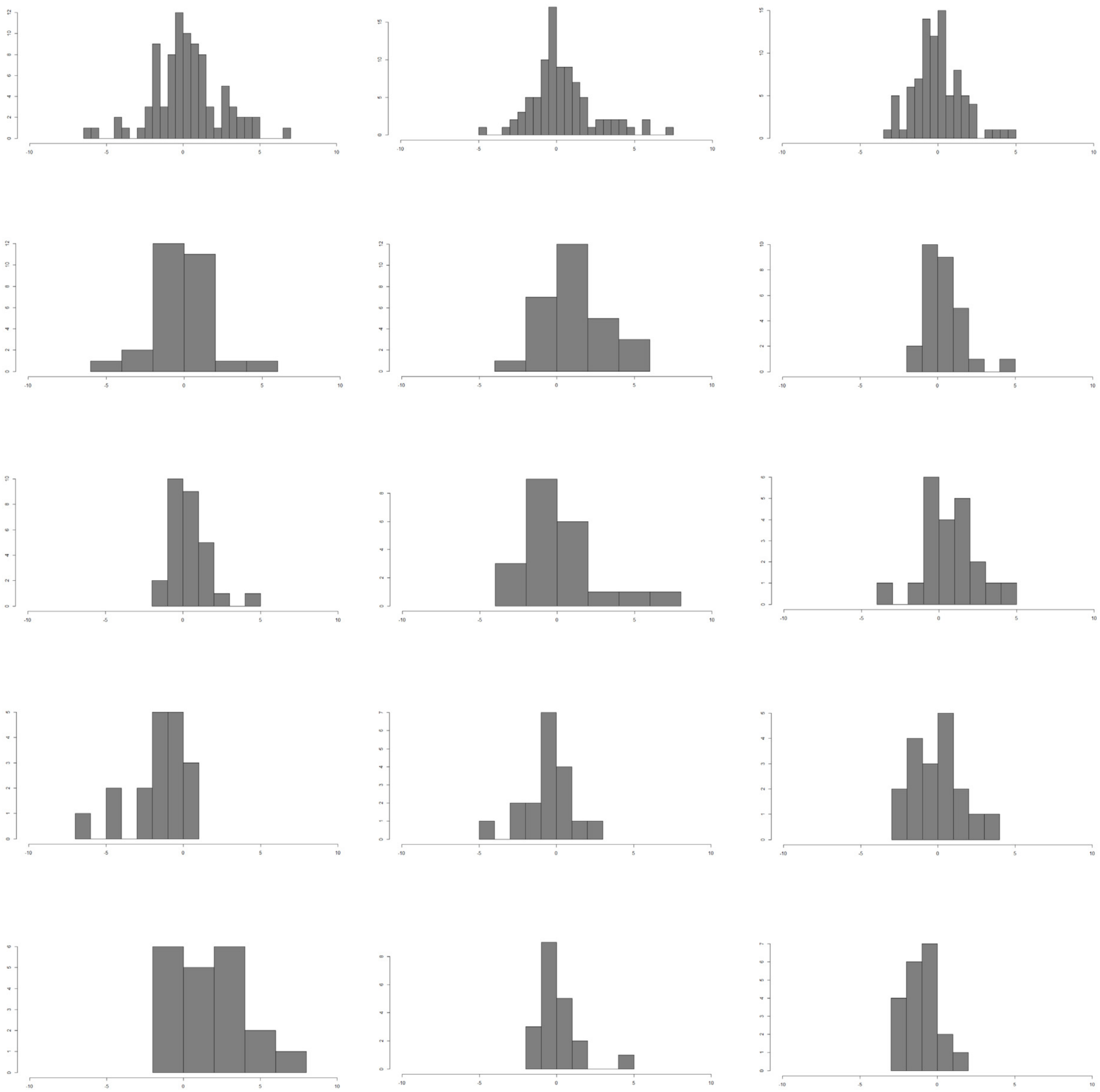
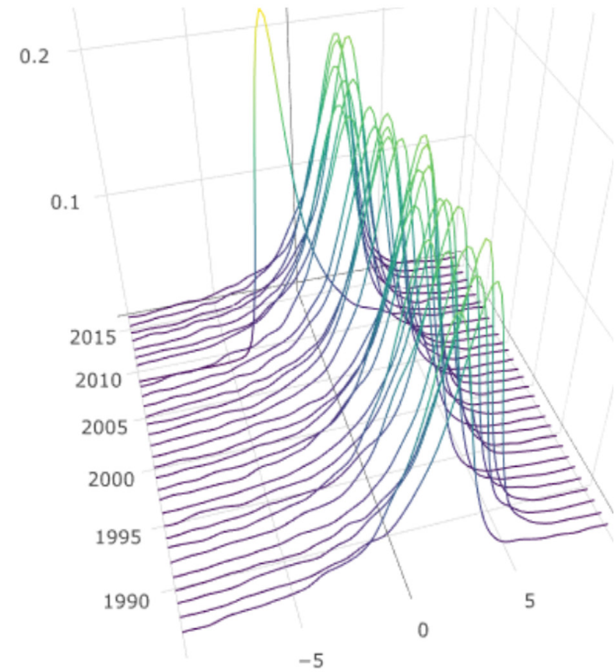


Fig. 6. Cross-sectional histograms of the estimated parameters of the factor-augmented quantile predictive regressions for $\tau = 0.05$, corresponding to factor 1 (first column), factor 2 (second column) and factor 3 (third column) computed through all countries (first row) and countries in Africa (second row), America (third row), Asia (fourth row) and Europe/Oceania (fifth row).

one-step-ahead (1999 and 2005) growth quantiles ($\tau = 0.05, 0.5$ and 0.95) obtained from the estimated factor-augmented predictive regressions, for the USA and China, respectively. We observe that the tangent surfaces based on the mean are rather similar to those based on the median growth. However, the tangent surfaces for the 5% and/or 95% growth quantiles can be very different in shape and orientation from the mean and median surfaces, as we show in the case of China. In summary, the effect of stressed factors can differ quite considerably depending on the specific quantile of the growth distribution being considered.

Fig. 12 plots a summary of the τ-quantile GiS. As before, we plot the cross-country average and ± 2 times the standard deviations of the predicted τ-quantile GiS for all industrialized, emerging and other developing countries. First, compare the GiS results for $\tau = 0.5$ with those plotted in Fig. 11, where GiS is predicted for the mean growth. In both cases, the plots for industrialized and emerging countries are almost identical. However, the bounds for developing countries become narrower, mainly because the upper bound has come down substantially. For the $\tau = 0.05$ quantile of growth, we are looking at catastrophic outcomes. For the three groups, the cross-country average of the predicted 5% quantile GiS is rather high, at 20% (or slightly below 20%), and does not decrease much over time. Obviously, these are the worst outcomes. Extreme events in the three world factors could



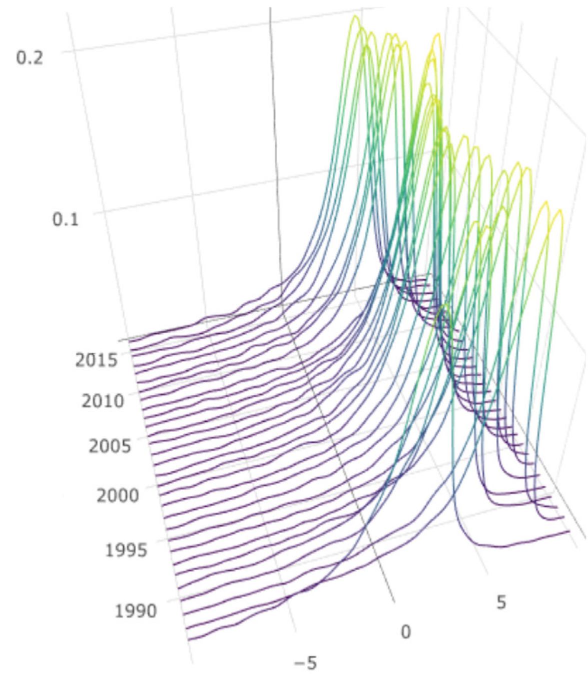


Fig. 7. Estimated densities of growth for the USA (top panel) and China (bottom panel) based on factor-augmented quantile regressions.

wipe out one-fifth of the GDP in those countries, which are already going through deep recessions. On the other hand, when a country is in its 95% growth quantile, it could withstand extreme events in the world factors, as the predicted average GiS for this quantile is close to 0%; that is, no growth on average, and with the bounds becoming narrower over time.

4. Conclusions

The existence of world business cycles raises questions as to the vulnerability of individual country economies which face extreme scenarios in those factors that drive world growth. With this objective in mind, we have proposed a new global risk index, Growth-in-Stress (GiS), that measures the expected fall in a country's GDP when

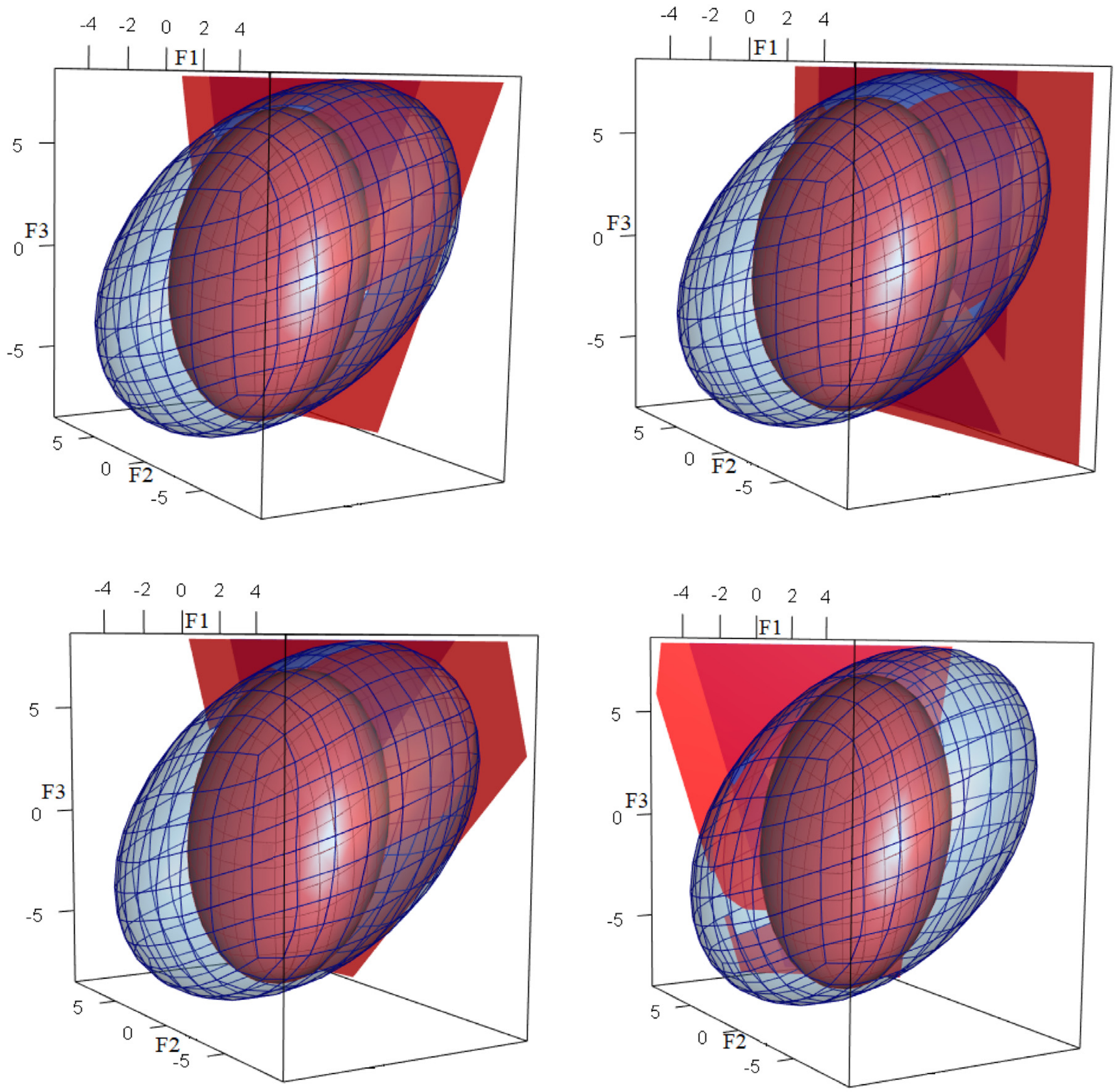


Fig. 8. Resampling ellipsoids for the three factors in 1998 (blue) and 2004 (red). Predicted iso-growth surfaces in the USA for 1999 and 2005 based on predictive regression (top left panel) and quantile regressions with $\tau = 0.05$ (bottom left panel), $\tau = 0.5$ (top right panel) and $\tau = 0.95$ (bottom right panel). For each year, the GiS is the tangency point between the ellipsoid and the corresponding surface. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the global factors are subject to stressful conditions. There are three components to this measure: the existence of global factors, the definition of stress, and the choice of the objective function.

We have extracted three global factors out of a sample of the GDP growths of 87 countries, classified as industrialized, emerging, and other developing, over the period 1985–2015. The first factor, which accounts for 20% of the total variability of growth, is driven by all industrial and emerging countries and is considered a world growth factor; the second factor is driven by other developing countries in Africa and America; and the third factor is related mainly to East Asian economies. The three factors collectively account for 42% of the total growth variability. To the best of our knowledge, the African/American factor has not been reported in the literature previously. We have defined stressful events in the factors by considering the extreme multivariate quantiles of the joint distribution of the three factors. We have constructed 95% probability ellipsoids that contain the true factors so that the extreme events are those on the boundary of the ellipsoid. Obviously, it is up to the researcher to choose the level of risk or stress desired. It is this approach of considering the stress based on the factors directly that makes our index a risk index rather than an uncertainty index. Finally, we have estimated country-specific predictive regressions augmented with the three factors for predicting (i) the one-step-ahead average growth, and (ii) the one-step-ahead τ-quantile growth in each country. With these three elements in place (factors, stress,

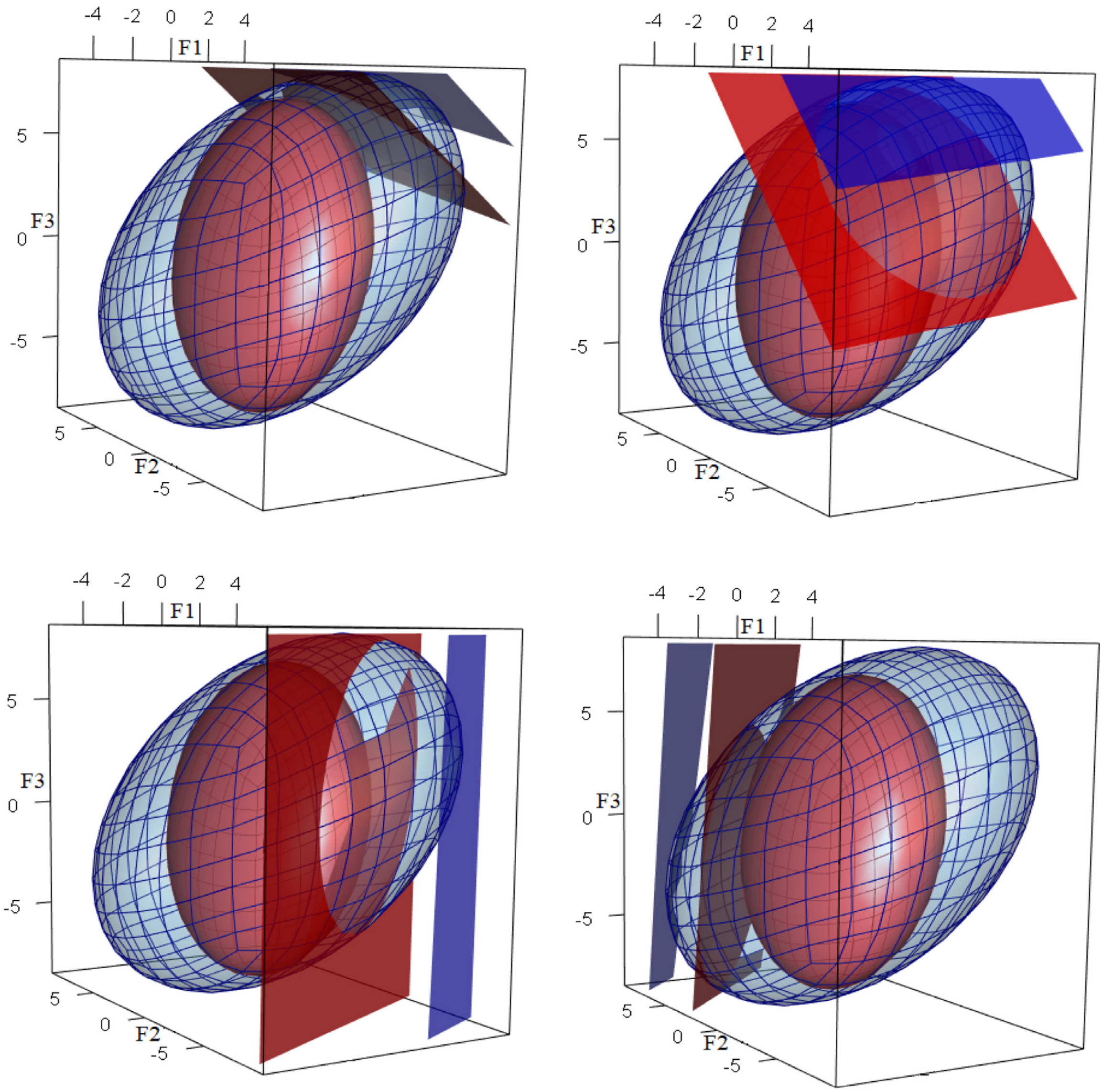


Fig. 9. Resampling ellipsoids for the three factors in 1998 (blue) and 2004 (red). Predicted iso-growth surfaces in China for 1999 and 2005 based on predictive regression (top left panel) and quantile regressions with $\tau = 0.05$ (bottom left panel), $\tau = 0.5$ (top right panel) and $\tau = 0.95$ (bottom right panel). For each year, the GiS is the tangency point between the ellipsoid and the corresponding surface. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

and objective function), we proceed to compute GiS as the predicted minimum growth and minimum τ-quantile generated by the point of tangency between the 95% probability ellipsoid and the properly-oriented surfaces based on the predictive regressions.

Our results confirm that the global risk has been decreasing over time. Not only has the cross-sectional average GiS been going down, but also the ± 2 standard deviation bounds have become narrower over time. The cross-sectional average GiS was about 5% in 1987 and 0%–1% in 2015, considering the 87 countries in Africa, America, Asia and Europe/Oceania. However, there is considerable heterogeneity across countries and continents. Several countries in Africa and America are exposed to very high risks, with GiS values larger than 10%. The countries in the Europe/Oceania group are more homogeneous, as the bounds around the cross-sectional average GiS are the tightest of all continents. From 2011 on, all continents entered into a state of complacency, and by 2015, the average worst outcome seems to be no growth at the 95% factor stress. We also measure the factor stress on different quantiles ($\tau = 0.05$, 0.5 and 0.95) of the GDP growth distribution of each country. Overall, the 50% quantile GiS and the average GiS are quite similar. For those countries that are already in or approaching recession, i.e., those in the 5% quantile of the growth distribution, an extreme event in the factors will have catastrophic consequences, as we have calculated that their GDP may experience a 20% drop.

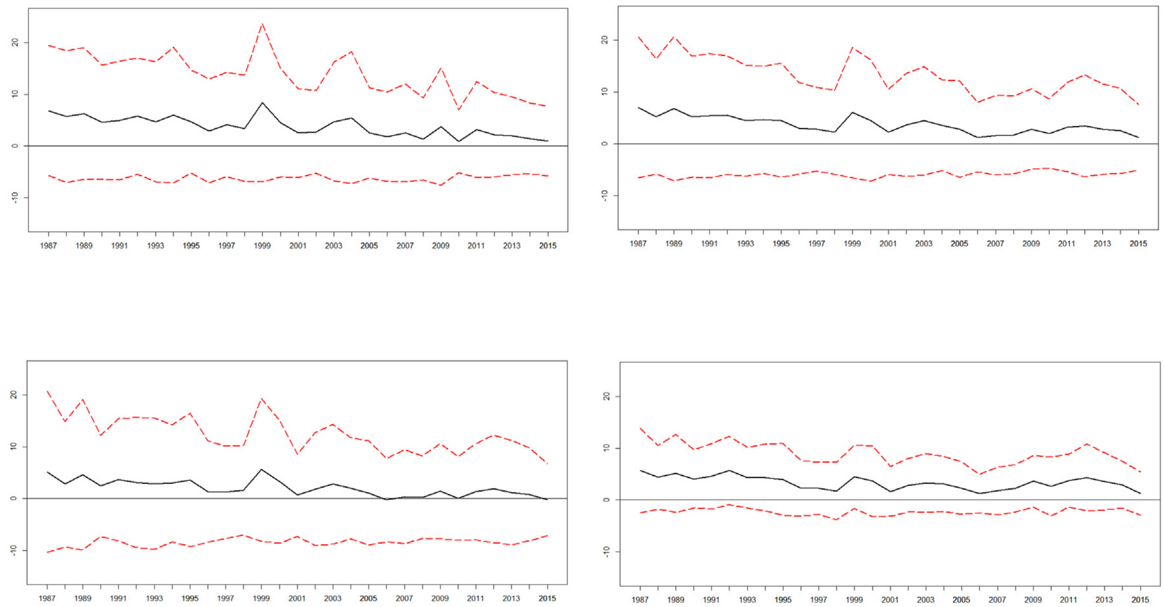


Fig. 10. Cross-sectional average GiS (black line) and ±2 standard deviations (red lines) among countries in Africa (top left panel), America (top right panel), Asia (bottom left panel) and Europe and Oceania (bottom right panel). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 11. Cross-sectional average GiS (black line) and ±2 standard deviations (red lines) among other developing (top panel), emerging (middle panel) and industrialized (bottom panel) countries. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

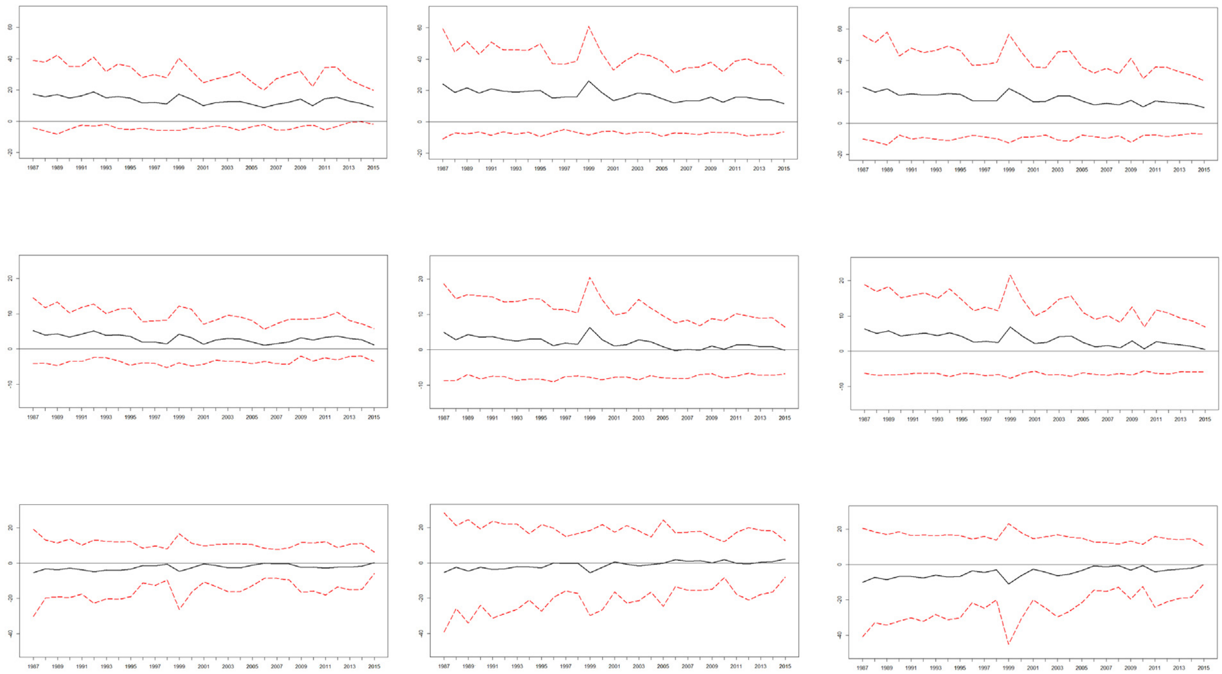


Fig. 12. Cross-sectional average GiS (black line) and ±2 standard deviations (red lines) for $\tau = 0.05$ (first row), 0.5 (second row) and 0.95 quantiles of the growth distribution among industrialized (first column), emerging (second column) and other developing (third column) countries. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The exercise that we have described is predictive, but has been conducted in-sample. This is because the time series is too short to implement an out-of-sample exercise, though it would be possible to increase the frequency of the series to give a larger sample size. The methodology that we propose is general enough to be applicable to any other macroeconomic aggregate beyond GDP growth. Moreover, the factors could also be extracted from systems of macroeconomic/financial variables instead of from the system of growths.

Acknowledgments

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.ijforecast.2019.04.006.

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