Growth in Stress

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Abstract

We propose a new global risk index, Growth-in-Stress (GiS), that measures the decrease in a country expected growth, and in its quantiles, when the factors driving world growth are subject to stressful conditions. Stress is measured as the 95% contours of the factors joint probability distribution. With a sample of 87 countries' growths from 1985 to 2015, we find that the average GiS across industrialized, emerging and other developing countries has been going down from 1987. However, the dispersion within groups is quite wide being the smallest among industrialized countries and the largest among emerging and other developing countries.

Keywords: Business Cycle, Dynamic Factor Model, Factor uncertainty, Predictive regressions, Principal Components, Quantile regressions, Stress Index, Value in Stress.

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1 Introduction

There is a large evidence about the presence of cross-country links in macroeconomic fluctuations with business cycles of developing economies having similar characteristics to those of developed countries; see, for example, Kose et al. (2003), Imbs (2010), Kose et al. (2012) and Bjornland et al. (2017) who 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. The presence of world business cycles leads to the possibility of thinking about a macroeconomic global risk when these common cycles are subject to extreme negative scenarios. The objective of this paper is to analyze whether this global risk affects differently to industrialized, emerging and other developing countries. For this goal, we propose a new risk index to measure growth in a particular country when there is stress in the common factors. The proposed methodology is based on using a predictive regression of output growth of each country augmented with common factors as predictors. The factors are extracted using principal components (PC) from a large set of macroeconomic aggregates modeled using Dynamic Factor Models (DFMs) and computing the factors' uncertainty by the subsampling method proposed by Vicente and Ruiz (2017). To construct the risk index for each country, we consider the Value-in-Stress (ViS) risk measure proposed by González-Rivera (2003) in the context of monitoring capital requirements to control market risk. Adapted to a macroeconometric context, the ViS, denoted as GiS for Growth-in-Stress, is defined as (minus) the smallest expected Gross Domestic Product (GDP) growth in a given country when there is extreme stress in the macroeconomic common factors. In this way, we can assess the risk exposure of each country to extreme changes in the macroeconomic factors and, consequently, the ability of countries to withstand stressful scenarios that eventually may generate economic crises. We analyze whether this ability is different across industrialized, emerging and other developing countries. The GiS is computed for 87 countries using annual data on macroeconomic growth from 1985 to 2015, obtained from the World Bank's World Development Indicators supplemented with the International Monetary Fund's World Economic Outlook (WEO) data base.

Our proposal of a macroeconomic risk index is related to the macroeconomic uncertainty indexes proposed by Jurado et al. (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 with our work. First, Jurado et al. (2015) and Henzel and Rengel (2017) construct uncertainty indexes based on weighted combinations of the uncertainty of the idiosyncratic components while we are concerned with the uncertainty of the common factors themselves. Second, instead of focusing on conditional variances as in Jurado et al. (2015) and Henzel and Rengel (2017), we measure the risk in the tails of the factors' joint distribution, i.e. we consider multivariate quantiles instead of variances. Our proposal is also related to the uncertainty index proposed by Rossi and Sekhposyan (2015) that is based on percentiles of the historical distribution of realized forecast errors. However, as mentioned above, our index is a risk index and not an uncertainty index.

The rest of the paper is organized as follows. In section 2, we describe the GiS index. Section 3 is devoted to estimating the GiS index of a large number of industrialized, emerging and other developing countries. Section 4 contains our conclusions.

2 Growth-in-Stress Index

The choice of a key macroeconomic variable(s) is crucial to describe the state of the economy. Following the standard choice in the 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 $y_{it} = \triangle log(GDP_{it})$. For each country, we forecast growth by 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 $k = 1, ..., r$ are the r unobserved common factors, also known as diffusion indexes, that summarize the variations of the large cross-section of growths and u_{it} is a white noise process; see Stock and Watson (1999) and Forni et al. (2000) for the introduction of factor-augmented predictive regressions.

If the interest is not only the center of the distribution of growth but also its lower or upper tails, we can consider a factor-augmented quantile regression model that estimates the

τ quantile of y_{it+1} given 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, and v_{ti} is an uncorrelated sequence such that $q_\tau(v_{it+1}|y_t, F_t) = 0$.

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, i.e.,

$$GiS^{(i)}_{t+1} = -\min h(y_{it+1}) \quad (3)$$
$$s.t. \quad g(F_t, \alpha) = 0$$

where $h(y_{it+1})$ is either the expected growth y_{it+1} as defined in equation (1) or expected $q_\tau(y_{it+1}|y_t, F_t)$ as defined in (2), $F_t = (F_{1t}, ..., F_{rt})'$ is the $r \times 1$ vector of unobservable factors, $g(F_t, \alpha)$ is the α-probability ellipsoid that contains the true factor vector, F_t. For instance, if $\alpha = 95\%$, the ellipsoid will contain 95% of the factor events and those values of F_t on the boundary of the ellipsoid are considered the extreme events. Note that the sign of $h(y_{it+1})$ is multiplied by -1 so that GiS can be interpreted as an uncertainty index with larger values of GiS meaning larger risk. Figure 1 illustrates the location of the GiS for two different probability contours, $\alpha_1 < \alpha_2$, when the number of factors is two, i.e. $r = 2$. Observe that, as result of the minimization exercise, we will obtain not only the optimizer GiS but also the optimal combination of factors that gives rise to GiS.

The factors are modeled using a dynamic factor model (DFM). The specification of the DFM follows common practice in the literature; see Jurado et al. (2015) and Henzel and Rengel (2017), among others.[1] In particular, we consider, the following DFM

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

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

$$F_t = \Phi F_{t-1} + \eta_t, \tag{5}$$

$$\varepsilon_t = \Gamma \varepsilon_{t-1} + a_t \tag{6}$$

where $Y_t = (y_{1t}, ..., y_{Nt})'$ is the $N \times 1$ vector of growth rates observed at time t for $t = 1, ..., T$; 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 and $\varepsilon_t = (\varepsilon_{1t}, ..., \varepsilon_{Nt})'$ is the $N \times 1$ vector of idiosyncratic noises, which are assumed to be potentially weakly cross-correlated and heteroscedastic. The disturbances $\eta_t = (\eta_{1t}, ..., \eta_{rt})'$ and $a_t = (a_{1t}, ..., a_{Nt})'$ are mutually independent Gaussian white noise vectors with positive covariance matrices Σ_η and Σ_a, respectively. The matrices Φ and Γ are diagonal with their parameters restricted so that Y_t is stationary. The number of factors r is assumed to be known.

We extract the factors using Principal Components (PC) due to its well known computational simplicity and popularity. For a unique identification of the factors, we assume $\frac{F'F}{T} = I_r$; see Bai and Ng (2013) for a discussion on identification issues in the context of PC factor extraction in DFM in equations (4) to (6). The $r \times T$ matrix of extracted factors $\hat{F} = (\hat{F}_1, ..., \hat{F}_T)$ is given by $\sqrt{T}$ times the eigenvectors corresponding to the r largest eigenvalues of the $T \times T$ matrix $Y'Y$ where $Y = (Y_1, ..., Y_T)$. The matrix of estimated factor loadings, $\hat{P}$, is computed by $\hat{P} = \frac{Y\hat{F}'}{T}$; see Bai and Ng (2008a) for a review of PC factor extraction. Bai (2003) shows that, if the data generating process is the DFM in equations (4) to (6) and $\frac{\sqrt{N}}{T} \to 0$ when $N, T \to \infty$, then $\hat{F}$ is a consistent estimator of the space spanned by the true factors. Finally, in order to obtain the joint distribution of the factors needed to compute $g(F_t, \alpha)$ and the GiS in (3), we follow Vicente and Ruiz (2017) who propose constructing 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 parameter uncertainty in the context of the DFM in equations (4) to (6).[2]

The estimated factors are substituted either in equation (1) or in equation (2) depending on whether the interest is on the macroeconomic global risk affecting the center of the growth

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

distribution or affecting one particular quantile of this distribution. In the former case, the estimated factors are substituted in equation (1) and the predictive regression parameters are estimated by Least Squares (LS). Stock and Watson (1999) introduced factor-augmented regressions estimated by LS and Stock and Watson (2002a) showed the consistency of this estimator. In the context of stationary systems, Bai and Ng (2006) derived the asymptotic normality of the estimator when the underlying factors are substituted by estimates obtained using PC. They showed that these estimates can be treated as if the factors were known when $\frac{\sqrt{T}}{N} \to 0$ for $N, T \to \infty$. They also presented analytical formulas for prediction intervals that can be useful in forecasting.

When the interest is on measuring the effect of the global risk on a particular quantile of the growth distribution, the parameters of the quantile regressions in equation (2) can be estimated as in Koenker and Bassett (1978); see Ando and Tsay (2011). The asymptotic normality of the estimator is derived by Bai and Ng (2008b) who showed that, when the generated regressors are the estimated factors, they can be plugged in as if they were observed as far as $\frac{T^{5/8}}{N} \to 0$ for $N, T \to \infty$. [3] Recently, Ohno and Ando (2018) proposed a shrinkage procedure to estimate the parameters of factor augmented predictive regressions, which can be implemented in both (1) and (2).

Finally, using the ellipsoids containing the true factors and the estimated predictive regressions augmented with the factors, it is possible to solve numerically the minimization problem in (3) by evaluating (1) or (2) in *all* points of the ellipsoid[4].

[3] Ando and Tsay (2011) proposed a criteria to select the number of factors. In an empirical application to forecast Japan growth, they showed that the number of factors may vary over time and can be different for different quantiles.

[4] Note that this "brute force" way of minimizing growth is only feasible if the number of factors is relatively small. When the number of factors is large, one needs to use optimization techniques, for example, second-order cone programming (SOCP); see Bertsimas et al. (2013) and the references there in. Alternatively, Chassein and Goerigk (2017) proposed using regret combinatorial optimization.

3 GiS indexes in industrialized, emerging and other developing countries

We compute the GiS of 87 countries.[5] The data consists of 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 supplemented with the International Monetary Fund's World Economic Outlook (WEO) data base. The same data base has been 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 of the global landscape since the mid-1980s, we only consider the period defined by Kose et al. (2012) as the wave of globalization starting in 1985. On the other hand, we extend the sample period with data observed after the 2008 global financial crisis. Previous to the analysis, GDP is transformed to growth by taking first differences of logs. Consequently, the time series length is $T = 30$.

3.1 Estimating the factors

Previous to factor extraction, the growth series are demeaned and standardized. Notice that the demeaning procedure eliminates differences in mean growth rates among countries. To identify the number of common factors, we implement the procedure proposed by Alessi et al. (2010), which selects $r = 3$. After extracting the factors using PC, we obtain the idiosyncratic residuals and identify outliers as those residuals exceeding six times the interquartile range[6]; see Marcellino et al. (2003), Artis et al. (2005), Stock and Watson (2002b) and Breitung and Eickmeier (2011) for the use of the interquartile range to identify outliers in the context of DFM. We identify the following outliers due to exceptional events: i) the consumer

[5] All the software in this paper to estimate the GiS has been developed by the third author in R programming language.

[6] Kristensen (2014) analyzes the effects of outliers on PC factor extraction and predictive regressions. He 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 containing the factors.

response to the Mexican Peso crisis in 1994 that caused a drop in Mexican growth in 1995, see McKenzie (2006); ii) in 1994 Rwanda's growth dropped due to the genocide against the Tutsi, see Lopez and Wodon (2005); iii) the political crisis of 2002 in Madagascar that seriously hampered economic growth, see Vaillant et al. (2014). As in Breitung and Eickmeier (2011), we substitute each outlying original growth by the median of the last 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 explaining 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 explain around 30% and 20% respectively 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) analyze quarterly real GDP growth from 1978 to 2011 for 33 countries covering four geographical regions and both developed and emerging economies. They report that the common business cycle accounts for 5% to 45% of the total variability of growth depending on the particular region of the world and the period of time considered. Consequently, we extract three factors by PC and compute their confidence bounds as well as those for the corresponding weights using the subsampling procedure proposed by Vicente and Ruiz (2017).[7] After visual inspection, the idiosyncratic components are considered approximately stationary.[8]

In Figures 2 to 4, we plot the estimated factors and the corresponding weights together

[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 formally test 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; see, for example, Kwiatkowski et al. (1992). Banerjee et al. (2008) also point out related problems associated with cointegration tests in the context of non-stationary panels.

with their 95% bounds for each of the three factors. Following Kose et al. (2012), the countries are classified in three groups: i) Industrial whose weights are represented by red bars; ii) Emerging markets represented by blue bars; and iii) Other developing countries represented by gray bars. In Table 1, we list the countries classified within each of these three categories. Consider the first factor plotted in Figure 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 in Peru and China the weights are negative although relatively small in magnitude. We also observe that the weights are also 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 evolution of the estimated global factor is very similar to that found in related works 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, which is by far the most severe; compare with estimates obtained by Kose et al. (2012) using annual data up to 2008 for 106 countries, Aastveit et al. (2016) using quarterly data on macroeconomic aggregates of four small open economies and Bjornland et al. (2017) for results based on 33 countries.

We plot the second factor together with its weights in Figure 3. We observe that this factor is negative until the mid-1990s and then is positive with a relatively weak drop during the Great Recession. This factor has positive weights in most "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, for example, Aastveit et al. (2016), have not included African countries or developing countries in South America. Only Kose et al. (2012) extract factors using data from a similar set of countries as those considered in this paper. However, they specified *a priori* common factors associated with industrialized, emerging and other developing countries. According to our results, the factors are not exactly associated with these groups of countries but with a mixture of these groups and geographic regions.

Finally, the third factor, plotted in Figure 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; compare with the factor estimated by Moneta and Ruffer (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, Radelet and Sachs (1998) and Cabalu (1999).

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

In Figure 5, as an illustration of the joint ellipsoids of the factors obtained by the subsampling procedure, we plot the 95% ellipsoids for 1998 and 2004. The ellipsoid corresponding to 2004 has less volume, meaning that in 1998 the uncertainty of the underlying factors is larger just around and after the Asian financial crisis. Furthermore, we observe that the increase in uncertainty is mainly due to the first and second factors.

3.2 Predictive regressions

After estimating the factors, we estimate first the predictive regressions in equation (1) by LS, for each country growth. Note that the predictive regressions are estimated using the original growth rates without demeaning and standardizing so that we can recover information about the average growth. In Table 2, we report the estimated parameters together with their corresponding p-values computed as if the factors were observable. We also report the determination coefficient, R^2, and the Box-Ljung statistic for the joint significance of the first four autocorrelations of the residuals, $Q(4)$, of each predictive regression.[9] We observe

[9]Note that the results in Bai (2003) require $\frac{\sqrt{N}}{T} \to 0$ for the asymptotic normality of the factors. However, in our application, $\frac{\sqrt{89}}{30} = 0.31$ and, consequently, the finite sample properties of the asymptotic approach

that most countries have significant positive average growth rates as $\hat{\mu} > 0$. In the countries in which this is not the case, the average growth is not significantly different from zero. In Africa, growth in most countries is positively correlated with the African factor. In industrialized countries, growth is mostly positively correlated with the world factor and negatively correlated with the Asian factor. For most countries, it is a combination of factors that help to predict growth. Overall, we find a good fit in the predictive regressions, of which half have R-squared of about 30% and larger, and about 10% of the regressions have an R-squared of 50% and larger.

To analyze the effect of the factors not only on the average level of growth but also on its quantiles, we estimate the factor augmented quantile predictive regressions in equation (2)[10]. The quantile regressions are estimated for $\tau = 0.05, 0.5$ and 0.95. 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 equation (1); see Ando and Tsay (2011).

In Table 3, we report the estimated parameters together with their corresponding p-values and the goodness of fit measure proposed by Koenker and Machado (1999), denoted as R^1, which is the analogous counterpart to the coefficient of determination in quantile regression models. The fit of the median regression is in general 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 larger than 50%. Therefore, it seems that the factors are more relevant to explain future tails than the center of the growth distribution.

can be poor. Furthermore, Goncalves and Perron (2014) show that the LS estimator of the parameters of the predictive regressions may be affected by negative biases. Finally, the correlation between growth and estimated factors can be rather large in some countries, so the corresponding regressions are affected by a severe multicolinearity problem. Therefore, we should be cautious about inference on the parameters of the predictive regressions.

[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. They are available upon request.

3.3 Forecasting recession risk under stressed factors

To obtain the GiS for each country, we solve the optimization problem in (3) where $h(y_{it+1}) = \hat{y}_{it+1}$ with $\hat{y}_{it+1}$ obtained from equation (1) by plugging in the LS estimates of the parameters reported in Table 2. The ellipsoid $g(F_t, \alpha)$ is estimated using the resampling procedure of Vicente and Ruiz (2017). In Figure 5, we illustrate this optimization problem by plotting the 95%-probability ellipsoids $g(F_t, 95\%)$ corresponding to 1998 and 2004. In each panel of Figure 5, we also plot the surfaces corresponding to the predictive regressions that are tangent to the ellipsoids, in three industrialized countries (US, Germany and Greece), three emerging countries (Brazil, China and India), and three other developing countries (Bolivia, Uganda and Nepal). We observe that the surfaces of the predictive regressions in the years 1999 and 2005 are rather different in shape and orientation in the six countries considered.

In each panel of Figure 6, we plot the estimated GiS for the countries in each continent (in the fourth panel, European and Oceania countries are plotted together). In Africa, the country with the lowest GiS over time is Cameroon while the country with the largest GiS and, consequently, the highest risk of recession is Uganda. These two countries also have the smallest and the largest risk among the developing countries. In America, the country with the lowest risk of recession when the factors are stressed is Guatemala while the country with the largest risk is Venezuela. For Asian countries, Syria and China have the largest and the smallest risk of recession, respectively. It is also important to note that among the countries 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 the lowest risks among the industrialized countries.

In Figure 7, we summarize the GiS results by plotting the average GiS together with the bounds constructed as ± 2 standard deviations of the risks across countries in each continent and in each year. In Figure 8, we plot the same quantities when countries are grouped by type. Several conclusions emerge from Figure 7. First, we observe that in all continents, the average risk has been slightly decreasing over time, with the Asian continent enjoying the smallest average GiS. The African and American continents offer very similar average risk profiles. The ± 2 standard deviations bounds are also becoming narrower over time and have very similar profiles in the African, Asian, and American continents with a sharp jump in 1999 coinciding with the Asian financial crisis. The lower bound is rather stable when compared with the upper bound that is more volatile over time. This is because the standard deviations during the years with high recession risk are larger than the standard deviations 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 these countries are very similar in risk profile. We observe that post 2008 financial crisis, mainly from 2011 on, the world has fallen in a state-of-complacency with the average GiS falling quite dramatically to reach the lowest levels of risk, between 1 and 0%, in 2015. In Figure 8, we summarize 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, and the plot corresponding to developing countries is very similar to that of African countries.

In addition to analyzing the effects of stressed factors on mean 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 by solving the minimization problem in (3) with $h(y_{it+1}) = \hat{q}_\tau(y_{it+1}|y_t, F_t)$. We compute $\hat{q}_\tau(y_{it+1}|y_t, F_t)$ as in equation (2) by plugging in the parameter estimates reported in Table 3. As an illustration, in Figures 9 to 11 we plot the 95% ellipsoids for the factors in 1998 and 2004 together with the tangent surfaces for one-step-ahead growth based on the mean and quantile ($\tau = 0.05, 0.5$ and 0.95) factor augmented predictive regressions for USA, China and Uganda, respectively. Regardless of a particular country, we observe that the tangent surfaces based on the mean and those based on the median growth are rather similar. 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 in the case of China and Uganda. In summary, the effect of stressed factors can be rather different depending on the particular quantile of the growth distribution considered.

In Figure 12, we plot a summary of the τ-quantile GiS. As before, we plot the cross-country average and ± 2 times the standard deviations of the τ-quantile GiS predicted for all industrialized, emerging and other developing countries. First, compare the GiS results for

$\tau = 0.5$ with those plotted in Figure 8 where GiS is predicted for the mean growth. The plots in both cases are almost identical for industrialized and emerging countries. However, for developing countries, the bounds become narrower mainly because the upper bound has coming 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 it does not decrease much over time. Obviously, these are the worst outcomes. Extreme events in the three world factors could wipe out one-fifth of GDP in those countries that are already going through deep recessions. On the contrary, 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 bounds becoming narrower over time.

4 Conclusions

The existence of world business cycles prompts the question about the vulnerability of individual country economies when facing extreme events 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 drop in a country GDP growth when 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 GDP growth 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 it is considered a world growth factor; the second factor is driven by other developing countries in Africa and America; and the third factor is mainly related to East Asian economies. All three factors account for 42% of the total growth variability. To our knowledge, the African/American factor has not been reported in the literature yet. 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% ellipsoids that contain the true factors so that the extreme events are those seating 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 stress directly on the factors that makes our index a risk index instead of an uncertainty index. Finally, we have estimated country-specific predictive regressions augmented with the three factors to predict (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, and objective function), we proceed to compute GiS as the minimum expected growth and minimum expected τ-quantile provided by the point of tangency between the 95% ellipsoid and the properly oriented surfaces generated by the predictive regressions.

Our results confirm that global risk has been decreasing over time. Not only the average GiS has been going doing but also the ± 2 standard deviation bounds have become narrower over time. The cross-sectional average GiS was about 5% in 1987 and between 0-1% in 2015 considering the 87 countries in Africa, America, Asia and Europe/Oceania. However, there is a lot of heterogeneity across countries and continents. Several countries in Africa and America are exposed to very high risks with GiS 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 have entered in a state-of-complacency and by 2015 the average worst scenario seem 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 DGP growth distribution of each country. Overall, the 50% quantile GiS and the average GiS are quite similar. For those countries that are on recession, those in the 5% quantile of the growth distribution, an extreme event in the factors has catastrophic consequences as we have calculated that GDP growth may experience a 20% drop.

The exercise that we have described is predictive but it has been conducted in-sample. 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 so that we have a larger sample size. The methodology that we propose is general enough to be applicable to any other macroeconomic aggregate beyond GDP growth.

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Table 1: List of Countries

Conuntry	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
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

Table 2: LS estimates of the parameters of factor augmented predictive regressions (p-values in parenthesis), coefficient of determination, R^2, and Box-Ljung statistic for the joint significance of the first four autocorrelations of the corresponding residuals.

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
μ	2.97	4.56	4.99	7.05	1.94	2.91	2.87	2.22	4.21	3.50	1.82	5.29	3.92	6.57	3.95	5.52	6.65	8.77	4.01	5.58	5.25	2.68	1.43	3.44	2.54	4.33	5.56	0.68
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.07)	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.05)	(0.00)	(0.04)	(0.00)	(0.00)	(0.65)
ϕ	-0.12	-0.16	0.08	-0.41	0.06	0.02	0.32	-0.06	-0.25	0.34	0.51	-0.30	-0.36	-0.56	-0.10	-0.16	-0.67	-0.20	0.21	-0.01	-0.54	0.33	0.43	0.31	0.07	-0.12	0.13	0.35
	(0.64)	(0.43)	(0.78)	(0.02)	(0.78)	(0.93)	(0.11)	(0.78)	(0.22)	(0.12)	(0.01)	(0.16)	(0.12)	(0.01)	(0.66)	(0.47)	(0.00)	(0.31)	(0.28)	(0.96)	(0.01)	(0.12)	(0.1)	(0.13)	(0.75)	(0.54)	(0.47)	(0.07)
β_1	-0.25	0.08	0.50	0.14	-0.95	-0.77	0.17	-0.12	-0.42	-0.18	-0.69	0.36	1.18	-0.02	-0.07	0.59	0.25	0.63	-0.78	-0.40	-0.07	0.24	-0.19	-0.24	-0.47	0.26	0.42	-1.15
	(0.47)	(0.86)	(0.69)	(0.74)	(0.07)	(0.23)	(0.55)	(0.91)	(0.44)	(0.63)	(0.09)	(0.31)	(0.03)	(0.98)	(0.93)	(0.15)	(0.65)	(0.48)	(0.49)	(0.59)	(0.84)	(0.79)	(0.63)	(0.44)	(0.67)	(0.55)	(0.29)	(0.43)
β_2	1.38	0.84	-1.06	1.73	2.95	0.78	0.31	-1.11	0.14	0.20	0.13	-1.22	2.06	1.14	1.07	-0.46	0.52	1.71	1.43	3.33	1.59	-0.70	0.40	1.02	1.10	0.27	0.16	-1.51
	(0.02)	(0.07)	(0.27)	(0)	(0)	(0.23)	(0.28)	(0.33)	(0.8)	(0.59)	(0.74)	(0.00)	(0.00)	(0.09)	(0.23)	(0.23)	(0.35)	(0.09)	(0.25)	(0.00)	(0.00)	(0.39)	(0.36)	(0.02)	(0.32)	(0.55)	(0.69)	(0.33)
β_3	-0.67	0.25	-0.59	0.65	0.15	-0.19	-0.18	1.16	-0.85	0.50	0.16	0.74	-0.78	-0.82	1.01	-0.23	-0.10	0.21	-1.03	0.04	-0.33	0.57	-0.14	-0.32	0.20	-0.28	0.22	1.50
	(0.07)	(0.58)	(0.52)	(0.12)	(0.77)	(0.76)	(0.51)	(0.31)	(0.14)	(0.23)	(0.68)	(0.06)	(0.12)	(0.25)	(0.23)	(0.51)	(0.85)	(0.81)	(0.37)	(0.95)	(0.33)	(0.5)	(0.67)	(0.3)	(0.85)	(0.53)	(0.58)	(0.31)
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
$Q(4)$	4.95	2.09	2.27	1.37	5.27	3.05	3.92	3.05	4.92	2.02	3.34	0.73	1.71	3.29	2.10	0.93	5.52	5.25	0.96	6.74	1.94	7.13	7.97	0.95	8.05	0.32	0.39	2.92
	(0.29)	(0.72)	(0.69)	(0.85)	(0.26)	(0.55)	(0.42)	(0.55)	(0.30)	(0.73)	(0.5)	(0.95)	(0.79)	(0.51)	(0.72)	(0.92)	(0.24)	(0.26)	(0.92)	(0.15)	(0.75)	(0.13)	(0.09)	(0.92)	(0.09)	(0.99)	(0.98)	(0.57)

America

	ARG	BOL	BRA	CAN	CHL	COL	CRI	DOM	ECU	SLV	GTM	HND	MEX	NIC	PAN	PRY	PER	TTO	USA	URY	VEN
μ	2.25	3.46	2.11	0.83	5.61	3.51	4.47	4.13	3.79	1.46	3.60	4.39	2.15	2.19	3.19	3.75	2.54	1.54	-0.15	2.31	2.50
	(0.09)	(0.00)	(0.02)	(0.29)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)	(0.01)	(0.03)	(0.04)	(0.00)	(0.02)	(0.11)	(0.84)	(0.01)	(0.05)
ϕ	0.11	0.13	0.11	0.64	-0.11	0.04	-0.02	0.16	-0.19	0.50	0.02	-0.23	0.31	0.16	0.34	-0.04	0.24	0.57	1.05	0.23	-0.13
	(0.65)	(0.39)	(0.63)	(0.04)	(0.65)	(0.88)	(0.95)	(0.47)	(0.40)	(0.02)	(0.94)	(0.37)	(0.21)	(0.58)	(0.22)	(0.84)	(0.22)	(0.01)	(0.00)	(0.23)	(0.56)
β_1	-1.12	0.01	-0.56	-0.72	0.68	0.00	0.28	-0.62	-0.01	-0.08	0.28	0.58	-0.27	-0.63	-0.18	-1.01	-1.72	-0.54	-1.16	-0.61	1.82
	(0.33)	(0.95)	(0.28)	(0.14)	(0.21)	(1.00)	(0.53)	(0.40)	(0.98)	(0.83)	(0.23)	(0.27)	(0.63)	(0.34)	(0.84)	(0.18)	(0.04)	(0.42)	(0.01)	(0.32)	(0.12)
β_2	-0.20	0.06	0.04	-0.10	-1.64	-0.37	-0.40	0.17	0.14	-0.64	-0.05	0.01	-0.41	1.63	0.77	-1.22	1.49	0.72	-0.31	-0.34	0.53
	(0.86)	(0.81)	(0.94)	(0.79)	(0.00)	(0.39)	(0.3)	(0.81)	(0.77)	(0.07)	(0.79)	(0.99)	(0.37)	(0.13)	(0.43)	(0.09)	(0.10)	(0.45)	(0.21)	(0.58)	(0.64)
β_3	2.02	0.65	0.30	-0.21	0.33	0.52	0.30	0.64	1.13	-0.03	0.18	0.44	-0.36	0.40	0.68	0.69	1.47	-1.03	-0.15	1.76	2.37
	(0.17)	(0.02)	(0.57)	(0.54)	(0.49)	(0.36)	(0.46)	(0.37)	(0.05)	(0.94)	(0.37)	(0.40)	(0.47)	(0.6)	(0.55)	(0.37)	(0.13)	(0.12)	(0.57)	(0.02)	(0.08)
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
Q(4)	2.44	1.57	0.89	3.42	2.79	1.04	4.37	2.18	1.33	2.82	4.78	1.32	2.61	0.27	5.01	3.83	0.67	0.36	3.56	1.33	1.89
	(0.65)	(0.81)	(0.93)	(0.49)	(0.59)	(0.90)	(0.36)	(0.70)	(0.86)	(0.59)	(0.31)	(0.86)	(0.63)	(0.99)	(0.29)	(0.43)	(0.95)	(0.99)	(0.47)	(0.86)	(0.76)

Table 2 cont.: LS estimates of the parameters of factor augmented predictive regressions (p-values in parenthesis), coefficient of determination, R^2, and Box-Ljung statistic for the joint significance of the first four autocorrelations of the corresponding residuals.

Europe and Oceania																				
	AUT	BEL	DNK	FIN	FRA	DEU	GRC	ISL	IRL	ITA	LUX	NLD	NOR	PRT	ESP	SWE	CHE	GBR	AUS	NZL
μ	2.52	3.42	0.90	1.21	2.71	1.93	0.39	2.53	1.14	1.35	4.36	2.07	0.86	1.25	1.66	1.11	1.69	-0.04	3.03	0.95
	(0.00)	(0.00)	(0.12)	(0.31)	(0.00)	(0.01)	(0.50)	(0.01)	(0.51)	(0.02)	(0.00)	(0.01)	(0.11)	(0.08)	(0.03)	(0.24)	(0.01)	(0.96)	(0.00)	(0.09)
ϕ	-0.24	-0.75	0.36	0.34	-0.50	-0.11	0.58	0.02	0.93	-0.34	-0.09	0.05	0.60	0.33	0.29	0.51	0.04	1.01	0.04	0.62
	(0.45)	(0.06)	(0.21)	(0.51)	(0.24)	(0.71)	(0.00)	(0.95)	(0.01)	(0.47)	(0.74)	(0.88)	(0.01)	(0.26)	(0.30)	(0.22)	(0.89)	(0.00)	(0.86)	(0.00)
β_1	0.99	1.30	-0.36	0.02	1.18	0.62	0.53	1.38	-1.50	1.26	0.88	0.85	-0.14	0.47	0.65	-1.09	0.34	-1.11	0.32	-0.52
	(0.05)	(0.02)	(0.48)	(0.99)	(0.06)	(0.30)	(0.39)	(0.07)	(0.19)	(0.16)	(0.29)	(0.16)	(0.63)	(0.48)	(0.26)	(0.20)	(0.44)	(0.03)	(0.21)	(0.10)
β_2	-0.18	-0.04	0.00	0.22	-0.16	-0.55	0.14	1.56	-0.19	-0.61	-0.52	-0.10	-0.16	-0.47	0.09	0.12	0.30	-0.28	0.30	-0.03
	(0.51)	(0.85)	(1.00)	(0.81)	(0.49)	(0.18)	(0.80)	(0.03)	(0.83)	(0.08)	(0.36)	(0.75)	(0.54)	(0.28)	(0.77)	(0.84)	(0.36)	(0.37)	(0.21)	(0.94)
β_3	-0.51	-0.83	-0.30	-0.90	-0.97	-0.40	-0.62	0.00	-0.76	-1.11	-1.28	-0.60	-0.05	-1.02	-1.08	-0.75	-0.36	0.03	-0.22	0.00
	(0.06)	(0.00)	(0.40)	(0.23)	(0.00)	(0.32)	(0.33)	(1.00)	(0.38)	(0.01)	(0.04)	(0.08)	(0.85)	(0.06)	(0.02)	(0.09)	(0.23)	(0.92)	(0.38)	(1.00)
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
Q(4)	4.55	4.22	1.17	3.80	7.76	4.40	2.64	2.81	1.75	5.35	5.89	1.21	0.28	3.77	2.09	2.89	1.75	1.66	7.52	0.11
	(0.34)	(0.38)	(0.88)	(0.43)	(0.10)	(0.35)	(0.62)	(0.59)	(0.78)	(0.25)	(0.21)	(0.88)	(0.99)	(0.44)	(0.72)	(0.58)	(0.78)	(0.80)	(0.11)	(1.00)
Asia																				
	BGD	CHN	HKG	IND	IDN	IRN	ISR	JPN	KOR	MYS	NPL	PAK	PHL	SGP	LKA	SYR	THA	TUR		
μ	5.40	3.18	1.59	5.72	3.87	2.11	3.51	1.03	6.56	5.68	5.86	2.38	2.29	4.72	5.18	6.36	3.12	4.79		
	(0.00)	(0.08)	(0.23)	(0.00)	(0.01)	(0.02)	(0.01)	(0.09)	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.02)	(0.00)	(0.00)	(0.02)	(0.00)		
ϕ	-0.08	0.64	0.58	0.10	0.20	0.35	0.15	0.34	-0.16	0.03	-0.35	0.43	0.47	0.26	-0.04	-0.46	0.37	-0.07		
	(0.78)	(0.00)	(0.03)	(0.61)	(0.4)	(0.03)	(0.59)	(0.24)	(0.56)	(0.89)	(0.1)	(0.04)	(0.03)	(0.35)	(0.87)	(0.01)	(0.09)	(0.81)		
β_1	-0.17	-0.11	-1.39	-0.60	-0.42	0.06	-0.08	-0.27	0.64	0.04	0.11	0.05	-0.87	-1.30	-0.56	-0.44	-0.49	-0.56		
	(0.31)	(0.78)	(0.10)	(0.13)	(0.56)	(0.94)	(0.88)	(0.67)	(0.41)	(0.96)	(0.69)	(0.89)	(0.04)	(0.17)	(0.15)	(0.5)	(0.49)	(0.58)		
β_2	0.66	0.02	-0.04	0.53	-0.85	-0.24	-0.52	-0.71	-1.83	-1.46	-0.44	-0.08	0.20	-1.34	0.47	-1.05	-1.55	0.23		
	(0.01)	(0.96)	(0.95)	(0.21)	(0.30)	(0.75)	(0.29)	(0.13)	(0.03)	(0.07)	(0.16)	(0.82)	(0.61)	(0.08)	(0.25)	(0.13)	(0.07)	(0.81)		
β_3	0.52	-0.12	-0.87	0.25	0.08	-2.15	0.03	-0.82	-1.35	-0.34	0.20	-0.13	-0.17	-0.91	0.70	2.21	-1.04	0.22		
	((0.04)	(0.78)	(0.22)	(0.51)	(0.92)	(0.01)	(0.95)	(0.04)	(0.03)	(0.65)	(0.48)	(0.69)	(0.64)	(0.24)	(0.20)	(0.00)	(0.11)	(0.85)		
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		
$Q(4)$	4.01	5.43	5.41	2.82	1.41	3.52	3.27	3.55	4.05	4.11	3.59	2.99	5.38	3.18	1.88	2.50	0.59	4.69		
	(0.41)	(0.25)	(0.25)	(0.59)	(0.84)	(0.48)	(0.51)	(0.47)	(0.40)	(0.39)	(0.46)	(0.56)	(0.25)	(0.53)	(0.76)	(0.64)	(0.96)	(0.32)		

Table 3: Estimated parameters of factor augmented quantile predictive regressions with p-values in parenthesis and fit measure, R^1

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
$\tau = 0.95$	μ	5.05	6.72	12.61	7.87	4.70	6.41	5.89	6.83	6.06	8.48	5.84	6.42	6.71	7.84	11.58	8.04	6.76	18.36	17.23	11.42	5.81	9.10	4.25	7.30	12.56	6.70	9.89	10.27
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
	ϕ	0.26	-0.39	1.14	-0.49	0.13	0.09	0.12	-0.15	0.01	1.29	0.26	-0.27	0.15	-0.95	0.33	0.17	-0.78	-0.70	-0.04	0.00	0.03	0.12	0.75	-0.01	0.17	-0.04	-0.41	0.01
		(0.10)	(0.00)	(0.00)	(0.07)	(0.00)	(0.30)	(0.41)	(0.00)	(0.91)	(0.00)	(0.00)	(0.05)	(0.51)	(0.00)	(0.19)	(0.29)	(0.00)	(0.02)	(0.76)	(0.97)	(0.88)	(0.14)	(0.00)	(0.94)	(0.47)	(0.69)	(0.00)	(0.94)
	β_1	0.36	-0.91	-2.31	0.28	-0.62	-0.66	0.12	0.27	-0.32	-0.36	-0.71	0.28	-0.81	0.90	0.50	0.78	0.79	1.73	-7.71	0.66	-0.14	0.75	-0.34	0.16	0.91	0.38	1.03	-0.41
		(0.1)	(0.00)	(0.01)	(0.65)	(0.00)	(0.03)	(0.57)	(0.1)	(0.16)	(0.14)	(0.00)	(0.21)	(0.13)	(0.00)	(0.58)	(0.01)	(0.00)	(0.17)	(0.00)	(0.00)	(0.62)	(0.04)	(0.01)	(0.33)	(0.45)	(0.14)	(0.00)	(0.69)
	β_2	0.70	0.23	-0.41	1.81	1.04	1.56	0.55	-1.87	0.30	0.47	-0.39	-0.71	1.73	0.94	0.71	0.57	-0.32	6.11	4.78	2.44	0.38	0.51	-0.33	0.46	0.67	-0.48	-0.37	-3.81
		(0.04)	(0.12)	(0.51)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.19)	(0.05)	(0.00)	(0.01)	(0.01)	(0.00)	(0.47)	(0.05)	(0.16)	(0.00)	(0.00)	(0.00)	(0.29)	(0.12)	(0.01)	(0.05)	(0.58)	(0.07)	(0.01)	(0.00)
	β_3	-0.98	-0.20	-2.33	1.54	-0.43	-0.17	0.05	0.87	-0.47	1.57	1.05	0.68	-1.22	-3.00	3.80	-0.09	0.04	1.07	-6.32	-0.24	-1.00	-0.93	-0.13	0.17	6.28	-0.05	0.57	4.24
		(0.00)	(0.16)	(0.00)	(0.02)	(0.00)	(0.54)	(0.79)	(0.00)	(0.05)	(0.00)	(0.00)	(0.01)	(0.02)	(0.00)	(0.00)	(0.71)	(0.85)	(0.4)	(0.00)	(0.25)	(0.00)	(0.01)	(0.17)	(0.29)	(0.00)	(0.84)	(0.00)	(0.00)
	R^1	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
$\tau = 0.50$	μ	2.40	4.08	5.59	5.15	2.57	3.58	4.03	3.40	4.18	5.11	4.44	4.29	3.02	5.29	3.36	4.94	4.04	7.01	4.40	6.00	3.63	4.33	2.64	4.76	1.98	3.84	5.95	1.30
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.09)
	ϕ	-0.22	0.10	-0.09	-0.45	0.41	-0.01	0.37	0.22	-0.17	0.40	0.56	-0.45	-0.12	-0.63	0.04	0.21	-0.80	0.17	-0.11	0.23	-0.55	0.40	0.27	0.03	0.54	-0.04	0.34	0.32
		(0.60)	(0.56)	(0.83)	(0.04)	(0.02)	(0.97)	(0.18)	(0.02)	(0.22)	(0.02)	(0.01)	(0.13)	(0.51)	(0.00)	(0.86)	(0.47)	(0.00)	(0.02)	(0.39)	(0.34)	(0.07)	(0.14)	(0.44)	(0.89)	(0.00)	(0.86)	(0.06)	(0.00)
	β_1	-0.53	0.44	0.69	0.14	-0.59	-0.34	0.44	-0.16	-0.62	-0.33	-0.42	0.95	0.80	0.08	-0.72	0.50	-0.02	0.02	-0.84	-0.68	-0.20	-0.21	-0.38	-0.59	-0.56	0.02	0.13	-1.46
		(0.38)	(0.24)	(0.7)	(0.77)	(0.16)	(0.67)	(0.28)	(0.73)	(0.1)	(0.26)	(0.35)	(0.05)	(0.06)	(0.84)	(0.41)	(0.35)	(0.98)	(0.95)	(0.29)	(0.45)	(0.67)	(0.85)	(0.49)	(0.12)	(0.14)	(0.96)	(0.74)	(0.05)
	β_2	2.21	0.37	-0.72	1.66	1.78	0.74	0.36	-1.35	0.45	0.07	0.22	-1.58	1.12	1.23	0.67	-0.33	0.73	0.57	2.05	2.60	1.63	-0.88	0.12	1.72	0.35	0.69	0.18	-1.85
		(0.03)	(0.34)	(0.6)	(0.01)	(0.01)	(0.36)	(0.36)	(0.01)	(0.22)	(0.8)	(0.62)	(0.01)	(0.03)	(0.01)	(0.47)	(0.51)	(0.28)	(0.11)	(0.02)	(0.03)	(0.01)	(0.4)	(0.84)	(0.00)	(0.36)	(0.22)	(0.64)	(0.02)
	β_3	-0.79	-0.30	-0.39	0.51	0.34	-0.18	-0.38	0.74	-0.69	0.25	0.13	0.88	-0.26	-2.12	1.14	-0.59	-0.35	-0.18	0.43	-0.21	-0.59	0.54	-0.01	-0.50	0.70	-0.28	-0.07	-0.05
		(0.20)	(0.43)	(0.76)	(0.3)	(0.4)	(0.81)	(0.32)	(0.13)	(0.08)	(0.43)	(0.78)	(0.09)	(0.5)	(0.00)	(0.20)	(0.21)	(0.60)	(0.59)	(0.6)	(0.82)	(0.21)	(0.62)	(0.98)	(0.18)	(0.07)	(0.6)	(0.85)	(0.94)
	R^1	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
$\tau = 0.05$	μ	0.59	0.58	-2.63	2.05	-1.52	-2.56	2.08	-9.24	-1.65	3.63	0.24	1.30	-1.03	-1.04	-2.42	2.51	-0.29	2.20	-2.88	-0.58	1.15	-3.07	-0.71	3.14	-5.28	-0.53	3.58	-12.23
		(0.01)	(0.02)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.51)	(0.00)	(0.00)	(0.17)	(0.00)	(0.00)	(0.34)	(0.00)	(0.01)	(0.48)	(0.00)	(0.00)	(0.08)	(0.00)	(0.00)	(0.12)	(0.00)	(0.00)
	ϕ	-0.01	0.46	0.27	-0.06	0.34	1.12	-0.34	0.63	-0.85	0.08	-0.28	-0.44	-0.92	-0.12	-0.63	-0.04	-0.37	0.30	0.12	-0.50	-0.58	0.08	-0.40	0.23	0.23	-0.01	-0.07	1.58
		(0.95)	(0.00)	(0.34)	(0.31)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.19)	(0.1)	(0.00)	(0.00)	(0.59)	(0.00)	(0.59)	(0.00)	(0.00)	(0.43)	(0.03)	(0.00)	(0.54)	(0.2)	(0.03)	(0.02)	(0.96)	(0.48)	(0.00)
	β_1	-0.76	-0.48	4.27	0.47	-1.84	0.26	1.06	-5.79	-1.15	0.11	-0.70	0.02	0.63	-1.66	-0.45	-0.22	-1.54	-1.40	-3.78	2.53	0.47	1.50	0.85	-0.88	-2.70	-0.65	0.55	0.95
		(0.00)	(0.05)	(0.00)	(0.00)	(0.00)	(0.5)	(0.00)	(0.00)	(0.00)	(0.30)	(0.07)	(0.88)	(0.02)	(0.03)	(0.14)	(0.13)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.01)	(0.08)	(0.00)	(0.00)	(0.06)	(0.01)	(0.27)
	β_2	1.30	0.56	-3.18	1.55	3.24	-1.85	0.63	3.24	-0.63	0.33	1.08	-0.27	3.86	0.83	-0.80	-1.18	2.59	3.97	4.25	5.54	1.96	-1.87	1.20	1.01	5.56	-0.85	0.11	1.14
		(0.00)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.03)	(0.00)	(0.01)	(0.15)	(0.00)	(0.28)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)	(0.02)	(0.62)	(0.21)
	β_3	-0.49	1.00	0.36	1.28	-0.04	-1.16	-0.36	4.61	0.19	0.10	0.43	1.23	-0.63	-0.53	-0.64	0.10	1.13	1.46	2.18	1.46	0.17	0.81	-0.39	-0.25	-0.41	-0.97	0.31	-1.56
		(0.04)	(0.00)	(0.69)	(0.00)	(0.89)	(0.00)	(0.03)	(0.00)	(0.50)	(0.39)	(0.25)	(0.00)	(0.02)	(0.52)	(0.04)	(0.43)	(0.00)	(0.00)	(0.03)	(0.08)	(0.37)	(0.12)	(0.31)	(0.11)	(0.40)	(0.01)	(0.15)	(0.08)
	R^1	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

Table 3 cont.: Estimated parameters of factor augmented quantile predictive regressions with p-values in parenthesis and fit measure, R^1

America		ARG	BOL	BRA	CAN	CHL	COL	CRI	DOM	ECU	SLV	GTM	HND	MEX	NIC	PAN	PRY	PER	TTO	USA	URY	VEN
$\tau = 0.95$	μ	9.91	5.34	5.36	4.39	7.83	5.95	6.72	9.47	6.47	4.87	4.85	6.03	5.84	5.61	9.19	7.9	7.83	8.72	4.00	7.31	12.07
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
	ϕ	0.04	0.43	-0.17	0.26	0.06	-0.11	-0.12	0.18	-0.65	0.27	0.32	0.14	0.14	0.46	-0.23	-0.49	0.51	0.26	0.71	0.47	-0.79
		(0.81)	(0.00)	(0.26)	(0.05)	(0.56)	(0.36)	(0.37)	(0.2)	(0.00)	(0.00)	(0.05)	(0.29)	(0.41)	(0.00)	(0.06)	(0.00)	(0.00)	(0.07)	(0.00)	(0.00)	(0.00)
	β_1	0.32	-0.10	-0.57	-0.31	-0.40	0.48	0.51	0.16	0.51	0.72	0.16	0.41	-0.16	-0.29	0.72	-0.84	-1.76	-1.39	-0.44	-0.35	2.55
		(0.70)	(0.34)	(0.09)	(0.14)	(0.08)	(0.02)	(0.04)	(0.72)	(0.00)	(0.00)	(0.34)	(0.13)	(0.68)	(0.29)	(0.07)	(0.01)	(0.00)	(0.01)	(0.05)	(0.34)	(0.04)
	β_2	-1.57	-0.16	0.36	0.19	-1.22	0.25	-0.58	-1.06	1.79	-1.20	0.14	0.01	0.91	0.12	0.19	-2.75	-0.88	3.46	-0.59	0.44	2.18
		(0.06)	(0.15)	(0.26)	(0.22)	(0.00)	(0.17)	(0.01)	(0.02)	(0.00)	(0.00)	(0.35)	(0.96)	(0.01)	(0.78)	(0.65)	(0.00)	(0.00)	(0.00)	(0.00)	(0.23)	(0.06)
	β_3	-0.23	0.56	0.78	0.01	-0.25	0.24	1.27	1.36	0.69	-0.05	0.34	-0.15	-0.36	-0.31	1.75	2.60	1.17	-0.81	-0.14	1.61	7.55
		(0.83)	(0.00)	(0.03)	(0.93)	(0.21)	(0.32)	(0.00)	(0.00)	(0.00)	(0.61)	(0.03)	(0.58)	(0.30)	(0.33)	(0.00)	(0.00)	(0.00)	(0.08)	(0.28)	(0.00)	(0.00)
	R^1	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
$\tau = 0.50$	μ	3.05	4.22	2.84	2.48	5.17	4.11	4.28	5.26	3.43	3.02	3.71	3.97	3.15	3.24	5.24	3.46	4.15	3.25	2.58	3.01	2.11
		(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.27)
	ϕ	0.44	0.29	0.18	0.33	-0.43	-0.20	-0.02	0.39	-0.11	0.46	0.07	0.03	0.30	0.01	-0.02	0.12	0.46	0.35	1.26	0.00	0.09
		(0.12)	(0.02)	(0.68)	(0.42)	(0.21)	(0.50)	(0.90)	(0.22)	(0.71)	(0.08)	(0.73)	(0.91)	(0.22)	(0.95)	(0.90)	(0.73)	(0.07)	(0.20)	(0.00)	(0.99)	(0.81)
	β_1	-2.90	-0.02	-0.31	-0.58	0.80	0.06	-0.15	-0.8	-0.17	-0.14	0.15	0.04	0.12	-0.67	0.43	-0.58	-1.28	-0.74	-1.63	-0.18	2.03
		(0.03)	(0.91)	(0.74)	(0.38)	(0.29)	(0.90)	(0.59)	(0.44)	(0.78)	(0.78)	(0.47)	(0.94)	(0.84)	(0.05)	(0.36)	(0.63)	(0.23)	(0.4)	(0.00)	(0.85)	(0.31)
	β_2	1.07	-0.11	0.09	0.13	-1.63	-0.05	-0.05	-0.18	0.30	-0.70	0.00	-0.15	-0.51	1.81	1.14	-1.06	-0.07	1.14	-0.25	-0.51	-1.33
		(0.39)	(0.56)	(0.92)	(0.8)	(0.02)	(0.91)	(0.81)	(0.86)	(0.62)	(0.12)	(0.99)	(0.77)	(0.26)	(0.00)	(0.04)	(0.36)	(0.95)	(0.35)	(0.3)	(0.58)	(0.48)
	β_3	0.31	0.3	-0.08	-0.15	0.71	0.61	0.23	-0.55	0.93	0	0.11	0.09	-0.18	0.19	1.62	0.09	0.25	-0.9	0.00	1.96	1.81
		(0.85)	(0.15)	(0.93)	(0.74)	(0.29)	(0.32)	(0.35)	(0.58)	(0.19)	(1)	(0.56)	(0.88)	(0.71)	(0.61)	(0.02)	(0.94)	(0.84)	(0.28)	(0.99)	(0.08)	(0.43)
	R^1	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
$\tau = 0.05$	μ	-5.12	2.14	-1.57	-1.03	1.27	0.1	0.94	-0.72	-1.06	-0.69	1.62	-0.06	-2.14	-5.21	-2.98	-1.4	-1.98	-1.52	0.61	-1.74	-4.58
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.71)	(0.03)	(0.27)	(0.01)	(0.08)	(0.00)	(0.83)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.00)	(0.00)	(0.00)
	ϕ	0.56	-0.30	0.6	0.77	-0.26	1.15	0.30	0.45	0.63	0.48	0.38	-0.39	0.40	0.31	2.25	0.32	-0.30	0.89	1.79	0.33	-0.21
		(0.00)	(0.04)	(0.00)	(0.00)	(0.18)	(0.00)	(0.25)	(0.04)	(0.00)	(0.04)	(0.11)	(0.02)	(0.26)	(0.28)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.11)
	β_1	2.51	-0.10	0.85	0.60	2.89	-1.57	1.26	-0.71	1.17	1.63	0.94	3.36	0.75	1.28	0.95	2.68	-0.37	1.42	-2.26	0.47	4.85
		(0.00)	(0.64)	(0.02)	(0.04)	(0.00)	(0.00)	(0.01)	(0.29)	(0.00)	(0.00)	(0.00)	(0.00)	(0.36)	(0.06)	(0.28)	(0.00)	(0.29)	(0.07)	(0.00)	(0.17)	(0.00)
	β_2	1.21	0.61	-0.45	-0.31	-2.96	-0.25	-0.88	0.91	-0.86	0.51	-0.77	0.13	-2.68	7.26	-1.67	-2.00	4.67	-1.09	-0.52	1.70	2.17
		(0.13)	(0.01)	(0.21)	(0.17)	(0.00)	(0.37)	(0.04)	(0.18)	(0.04)	(0.18)	(0.00)	(0.64)	(0.00)	(0.00)	(0.1)	(0.00)	(0.00)	(0.3)	(0.01)	(0.00)	(0.00)
	β_3	0.51	1.76	1.99	-0.28	1.44	0.26	-0.52	2.13	1.91	-0.63	0.46	1.76	-0.34	-0.63	-3.05	0.13	3.64	-1.97	-0.53	2.41	4.06
		(0.62)	(0.00)	(0.00)	(0.18)	(0.00)	(0.5)	(0.22)	(0.00)	(0.00)	(0.12)	(0.05)	(0.00)	(0.64)	(0.41)	(0.01)	(0.65)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)
	R^1	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

Table 3 cont.: Estimated parameters of factor augmented quantile predictive regressions with p-values in parenthesis and fit measure, R^1

	Asia																		
		BGD	CHN	HKG	IND	IDN	IRN	ISR	JPN	KOR	MYS	NPL	PAK	PHL	SGP	LKA	SYR	THA	TUR
$\tau = 0.95$	μ	6.09	11.79	7.54	9.16	6.65	7.92	6.80	3.99	8.68	8.91	6.31	6.18	6.51	10.17	7.35	8.45	8.74	9.62
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
	ϕ	0.33	0.91	0.75	0.27	0.29	0.52	-0.33	0.18	-0.31	0.12	-0.91	0.82	0.49	0.07	0.6	-0.32	0.05	0.28
		(0.14)	(0.00)	(0.00)	(0.14)	(0.00)	(0.00)	(0.05)	(0.24)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.48)	(0.00)	(0.00)	(0.73)	(0.07)
	β_1	0.15	0.98	-1.04	0.09	0.27	0.62	1.01	0.10	1.91	0.32	-0.10	-0.99	-0.56	-1.01	-0.2	0.67	0.81	-0.15
		(0.25)	(0.00)	(0.00)	(0.79)	(0.01)	(0.27)	(0.00)	(0.77)	(0.00)	(0.04)	(0.69)	(0.00)	(0.02)	(0.01)	(0.29)	(0.02)	(0.08)	(0.78)
	β_2	0.10	-1.01	0.23	-0.50	-0.49	0.52	-1.21	-2.04	-2.75	-0.34	-1.03	-0.22	-0.46	-0.85	-0.33	-2.45	-2.5	-0.76
		(0.59)	(0.00)	(0.24)	(0.18)	(0.00)	(0.36)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)	(0.13)	(0.06)	(0.00)	(0.1)	(0.00)	(0.00)	(0.13)
	β_3	-0.02	-0.12	-1.92	-0.10	-0.23	-1.99	-0.61	-0.31	-1.98	0.13	-0.22	-0.39	0.38	0.22	-0.24	0.48	-0.06	0.06
		(0.92)	(0.66)	(0.00)	(0.77)	(0.04)	(0.00)	(0.06)	(0.13)	(0.00)	(0.33)	(0.39)	(0.01)	(0.09)	(0.43)	(0.38)	(0.12)	(0.88)	(0.92)
	R^1	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
$\tau = 0.50$	μ	4.87	8.94	4.7	6.56	5.48	2.82	5.08	1.64	5.82	6.69	4.41	4.57	4.45	6.35	4.98	4.94	5.22	5.30
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
	ϕ	-0.21	0.98	0.48	0.04	0.20	0.09	-0.01	0.45	0.15	-0.12	-0.4	0.57	0.45	0.22	0.07	-0.23	0.41	-0.29
		(0.55)	(0.00)	(0.20)	(0.87)	(0.00)	(0.66)	(0.96)	(0.32)	(0.52)	(0.52)	(0.21)	(0.00)	(0.03)	(0.64)	(0.86)	(0.13)	(0.03)	(0.31)
	β_1	-0.09	0.03	-1.12	-0.88	0.32	-0.3	0.32	-0.74	0.25	0.59	0.02	-0.07	-1.06	-0.91	-0.46	0.27	-0.67	-0.38
		(0.67)	(0.93)	(0.34)	(0.09)	(0.13)	(0.77)	(0.45)	(0.45)	(0.71)	(0.33)	(0.96)	(0.75)	(0.01)	(0.56)	(0.39)	(0.63)	(0.28)	(0.71)
	β_2	0.64	0.23	-0.32	0.61	-0.42	-0.37	-1.31	-0.38	-1.57	-1.69	-0.48	-0.25	0.23	-0.78	0.46	-1.3	-1.43	1.04
		(0.03)	(0.43)	(0.75)	(0.26)	(0.07)	(0.72)	(0.00)	(0.60)	(0.04)	(0.00)	(0.31)	(0.22)	(0.56)	(0.53)	(0.42)	(0.04)	(0.06)	(0.28)
	β_3	0.83	-0.23	-0.59	-0.13	0.22	-2.01	-0.34	-1.00	-1.40	-0.17	-0.04	-0.09	-0.29	-1.45	0.7	1.36	-0.89	0.83
		(0.01)	(0.49)	(0.55)	(0.79)	(0.35)	(0.06)	(0.44)	(0.1)	(0.02)	(0.75)	(0.92)	(0.64)	(0.44)	(0.25)	(0.36)	(0.04)	(0.12)	(0.49)
	R^1	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
$\tau = 0.05$	μ	3.9	6.21	-2.19	3.25	4.18	-3.52	0.90	-1.67	-1.71	-0.87	2.14	1.57	0.67	1.15	1.54	-0.2	1.62	-4.83
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.08)	(0.16)	(0.00)	(0.00)	(0.04)	(0.00)	(0.01)	(0.56)	(0.00)	(0.00)
	ϕ	0.58	0.53	1.38	0.27	0.17	0.73	-0.16	1.31	2.19	-0.19	0.00	-0.36	0.66	0.87	-0.64	-0.43	0.86	-0.13
		(0.01)	(0.00)	(0.00)	(0.22)	(0.00)	(0.00)	(0.08)	(0.00)	(0.00)	(0.40)	(0.95)	(0.01)	(0.00)	(0.00)	(0.10)	(0.00)	(0.00)	(0.58)
	β_1	-0.05	-0.97	-4.09	-1.8	-0.38	-2.01	0.07	-0.23	-6.04	-0.42	0.04	0.36	-1.67	-4.1	-1.58	-1.38	-1.97	-2.05
		(0.67)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.67)	(0.53)	(0.00)	(0.58)	(0.59)	(0.08)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.02)
	β_2	0.63	1.8	-2.1	0.97	-0.71	-0.42	-0.2	1	2.73	-4.84	-0.13	-0.99	-0.49	-2.19	-0.29	0.22	-1.79	-1.73
		(0.00)	(0.00)	(0.01)	(0.04)	(0.00)	(0.33)	(0.19)	(0.00)	(0.04)	(0.00)	(0.09)	(0.00)	(0.16)	(0.00)	(0.61)	(0.53)	(0.00)	(0.03)
	β_3	0.27	0.03	-0.41	0.55	0.19	-2.78	0.72	-1.59	3.38	-0.78	1.1	-0.24	-1.51	-1.41	1.73	2.28	-1.83	-2.85
		(0.11)	(0.92)	(0.58)	(0.19)	(0.07)	(0.00)	(0.00)	(0.00)	(0.00)	(0.25)	(0.00)	(0.20)	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)	(0.01)
	R^1	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

Table 3 cont.: Estimated parameters of factor augmented quantile predictive regressions with p-values in parenthesis and fit measure, R^1

		Europe and Oceania																			
		AUT	BEL	DNK	FIN	FRA	DEU	GRC	ISL	IRL	ITA	LUX	NLD	NOR	PRT	ESP	SWE	CHE	GBR	AUS	NZL
$\tau = 0.95$	μ	3.42	3.40	4.32	5.10	3.28	4.2	4.62	6.88	13.47	2.90	7.79	3.62	4.23	3.94	4.18	4.40	3.54	3.94	4.64	5.26
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
	ϕ	0.16	-1.02	0.1	1.27	-0.66	-0.36	-0.03	0.77	1.47	0.52	0.24	0.4	0.77	0.51	0.54	0.06	0.53	0.51	-0.05	-0.26
		(-0.26)	(0.00)	(-0.52)	(0.00)	(-0.03)	(-0.2)	(-0.8)	(0.00)	(0.00)	(0.00)	(-0.15)	(-0.02)	(0.00)	(0.00)	(0.00)	(-0.55)	(-0.01)	(0)	(-0.72)	(-0.07)
	β_1	0.17	1.41	-2.46	-2.85	1.44	0.92	0.86	-0.88	-5.63	-0.42	0.30	-0.01	-1.1	0.13	0.15	-0.51	-0.34	-0.04	0.80	-0.81
		(-0.42)	(0.00)	(0.00)	(0.00)	(0.00)	(-0.1)	(-0.03)	(-0.09)	(0.00)	(-0.16)	(-0.54)	(-0.98)	(0.00)	(-0.67)	(-0.49)	(-0.01)	(-0.26)	(-0.82)	(0.00)	(0.00)
	β_2	0.25	-0.23	0.15	-0.38	-0.33	-1.12	1.23	0.85	2.09	-0.34	-0.13	0.07	0.03	-0.86	-0.42	0.28	-0.02	-0.38	-0.17	-0.72
		(-0.04)	(0.00)	(-0.45)	(-0.43)	(-0.05)	(-0.01)	(0.00)	(-0.08)	(0.00)	(-0.01)	(-0.71)	(-0.6)	(-0.86)	(0.00)	(0.00)	(-0.05)	(-0.92)	(0.00)	(-0.25)	(-0.01)
	β_3	-0.4	-0.58	-0.07	0.51	-1.32	0.12	-0.95	0.32	-4.64	-0.42	-0.12	-0.27	-0.22	-0.46	-0.45	-0.04	-0.24	-0.78	-0.45	-0.54
		(0.00)	(0.00)	(-0.71)	(-0.19)	(0.00)	(-0.75)	(-0.02)	(-0.43)	(0.00)	(0.00)	(-0.74)	(-0.09)	(-0.27)	(-0.06)	(-0.01)	(-0.68)	(-0.25)	(0.00)	(-0.01)	(-0.03)
	R^1	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
$\tau = 0.50$	μ	1.94	2.27	1.58	2.10	2.07	1.85	0.69	2.53	5.37	1.24	4.17	2.25	2.40	2.50	2.60	2.69	2.05	2.37	3.40	2.31
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(-0.23)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
	ϕ	0.06	-0.79	0.55	0.81	-0.48	-0.05	0.7	-0.25	0.55	-0.13	-0.42	0.09	0.57	0.57	0.20	0.18	0.13	0.74	-0.22	0.68
		(-0.84)	(-0.17)	(-0.01)	(-0.03)	(-0.27)	(-0.82)	(0)	(-0.19)	(-0.03)	(-0.76)	(-0.28)	(-0.8)	(-0.04)	(-0.13)	(-0.44)	(-0.77)	(-0.71)	(-0.04)	(-0.4)	(0.00)
	β_1	1.03	1.31	-0.85	-0.57	0.77	0.29	0.65	1.63	-0.28	0.73	1.18	0.68	-0.13	-0.42	0.74	-0.41	0.04	-0.91	0.47	-0.25
		(-0.03)	(-0.12)	(-0.02)	(-0.59)	(-0.21)	(-0.56)	(-0.33)	(-0.01)	(-0.72)	(-0.35)	(-0.31)	(-0.29)	(-0.76)	(-0.62)	(-0.18)	(-0.74)	(-0.94)	(-0.14)	(-0.10)	(-0.36)
	β_2	-0.24	-0.08	0.00	-0.44	0.05	-0.43	0.4	2.12	0.14	-0.22	-0.65	-0.07	-0.25	-0.43	0.35	0.40	0.63	-0.10	0.02	0.00
		(-0.32)	(-0.82)	(-0.99)	(-0.51)	(-0.82)	(-0.21)	(-0.49)	(0.00)	(-0.82)	(-0.48)	(-0.42)	(-0.83)	(-0.49)	(-0.45)	(-0.23)	(-0.65)	(-0.1)	(-0.80)	(-0.93)	(-0.99)
	β_3	-0.46	-0.89	-0.75	-0.14	-0.92	-0.57	-0.48	0.62	-0.73	-0.73	-1.56	-0.63	0.15	-0.30	-0.7	-0.60	-0.57	-0.23	-0.24	-0.04
		(-0.07)	(-0.03)	(0.00)	(-0.79)	(-0.01)	(-0.09)	(-0.47)	(-0.19)	(-0.24)	(-0.04)	(-0.07)	(-0.08)	(-0.67)	(-0.65)	(-0.09)	(-0.35)	(-0.11)	(-0.57)	(-0.39)	(-0.87)
	R^1	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
$\tau = 0.05$	μ	-0.68	-0.26	-2.08	-3.80	-0.33	-1.7	-2.97	-3.11	0.06	-2.11	-0.53	-0.26	0.21	-0.76	-0.42	-1.42	-0.36	-0.53	1.51	0.18
		(-0.02)	(-0.38)	(0.00)	(0.00)	(-0.02)	(0.00)	(0.00)	(0.00)	(-0.92)	(0.00)	(-0.38)	(-0.32)	(-0.36)	(0.00)	(-0.09)	(0.00)	(-0.24)	(0.00)	(0.00)	(-0.56)
	ϕ	-1.75	-2.12	0.41	-1.33	-2.37	-1.4	1.02	0.31	0.37	0.89	0.18	-1.03	0.78	0.13	0.05	1.22	-0.2	2.43	0.05	0.64
		(0.00)	(0.00)	(-0.15)	(0.00)	(0.00)	(0.00)	(0.00)	(-0.35)	(-0.15)	(-0.01)	(-0.54)	(0.00)	(0)	(-0.26)	(-0.81)	(0.00)	(-0.51)	(0.00)	(-0.71)	(0.00)
	β_1	3.08	3.69	2.07	6.92	4.81	4.17	-0.04	3.2	-0.52	1.32	1.43	3.80	0.12	1.79	2.54	-0.05	1.55	-1.88	-0.04	-0.57
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(-0.94)	(0.00)	(-0.54)	(-0.04)	(-0.12)	(0.00)	(-0.65)	(0.00)	(0.00)	(-0.86)	(0.00)	(0.00)	(-0.73)	(-0.07)
	β_2	0.21	-0.25	-0.43	4.50	-0.45	-0.31	-0.63	1.53	-1.1	-0.16	-1.49	0.16	0.24	-0.43	-0.04	-1.41	0.46	0.23	1.25	-0.43
		(-0.45)	(-0.39)	(-0.24)	(0.00)	(0.00)	(-0.05)	(-0.22)	(-0.13)	(-0.09)	(-0.49)	(-0.02)	(-0.53)	(-0.3)	(-0.02)	(-0.86)	(0.00)	(-0.17)	(-0.20)	(0.00)	(-0.21)
	β_3	-1.94	-1.29	0.21	-2.59	-2.63	-1.3	0.24	-2.05	-2.69	-0.44	-1.42	-0.69	-0.79	-1.33	-1.02	-0.23	-0.8	1.46	-0.54	-0.62
		(0.00)	(0.00)	(-0.55)	(0.00)	(0)	(0.00)	(-0.69)	(-0.02)	(0)	(-0.09)	(-0.04)	(-0.02)	(0.00)	(0.00)	(-0.01)	(-0.13)	(-0.01)	(0.00)	(0.00)	(-0.05)
	R^1	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

Figure 1: Graphical illustration of GiS when the number of underlying common factors is two.

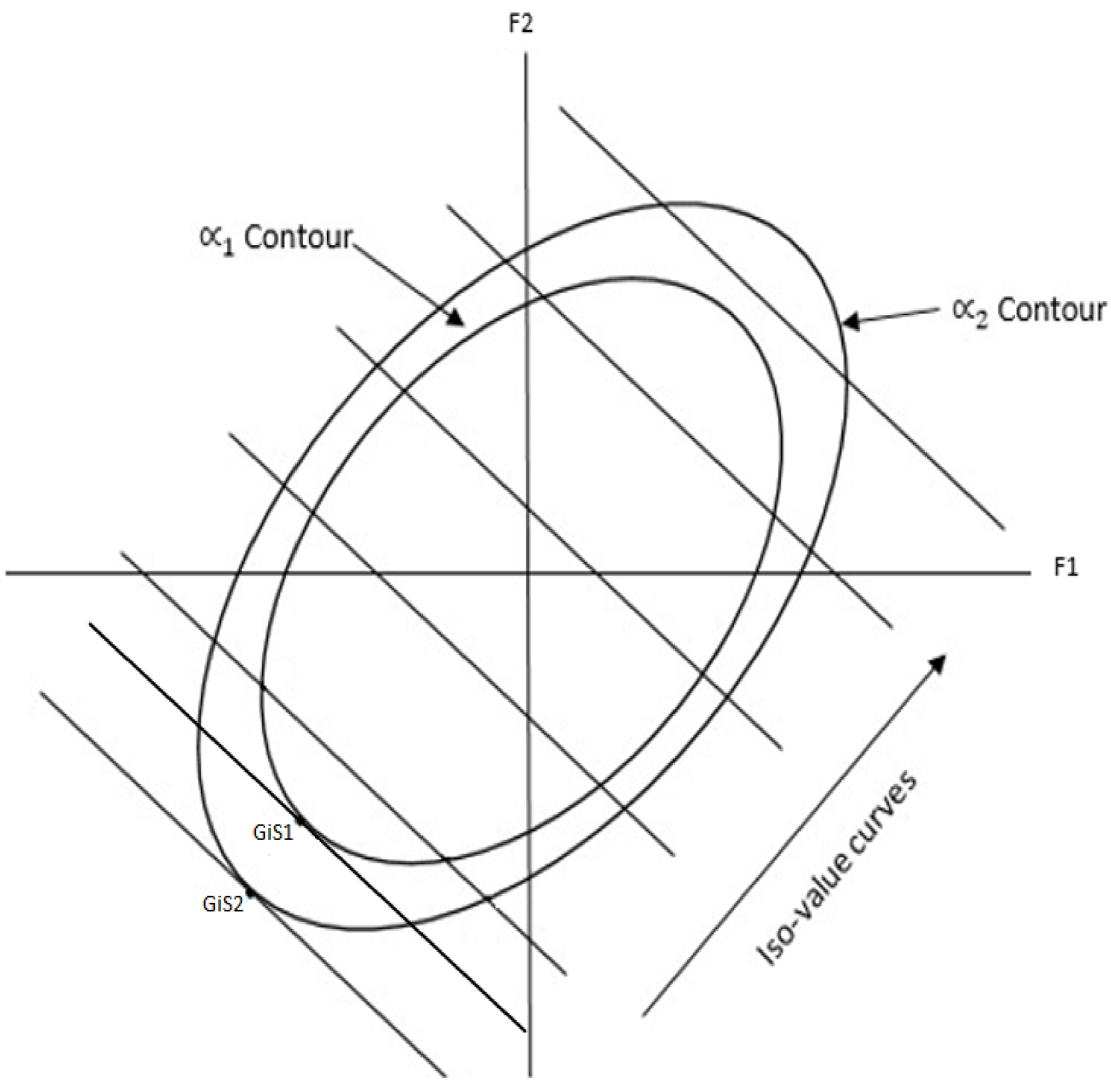


Figure 2: Top panel: First factor extracted using Principal Components from system of growths together with 95% prediction intervals (in red). Bottom panel: Estimated weights of first factor for each country together with 95% confidence intervals. The bars in red, blue, and gray correspond to industrialized, emerging, and other developing countries, respectively. The countries in 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.

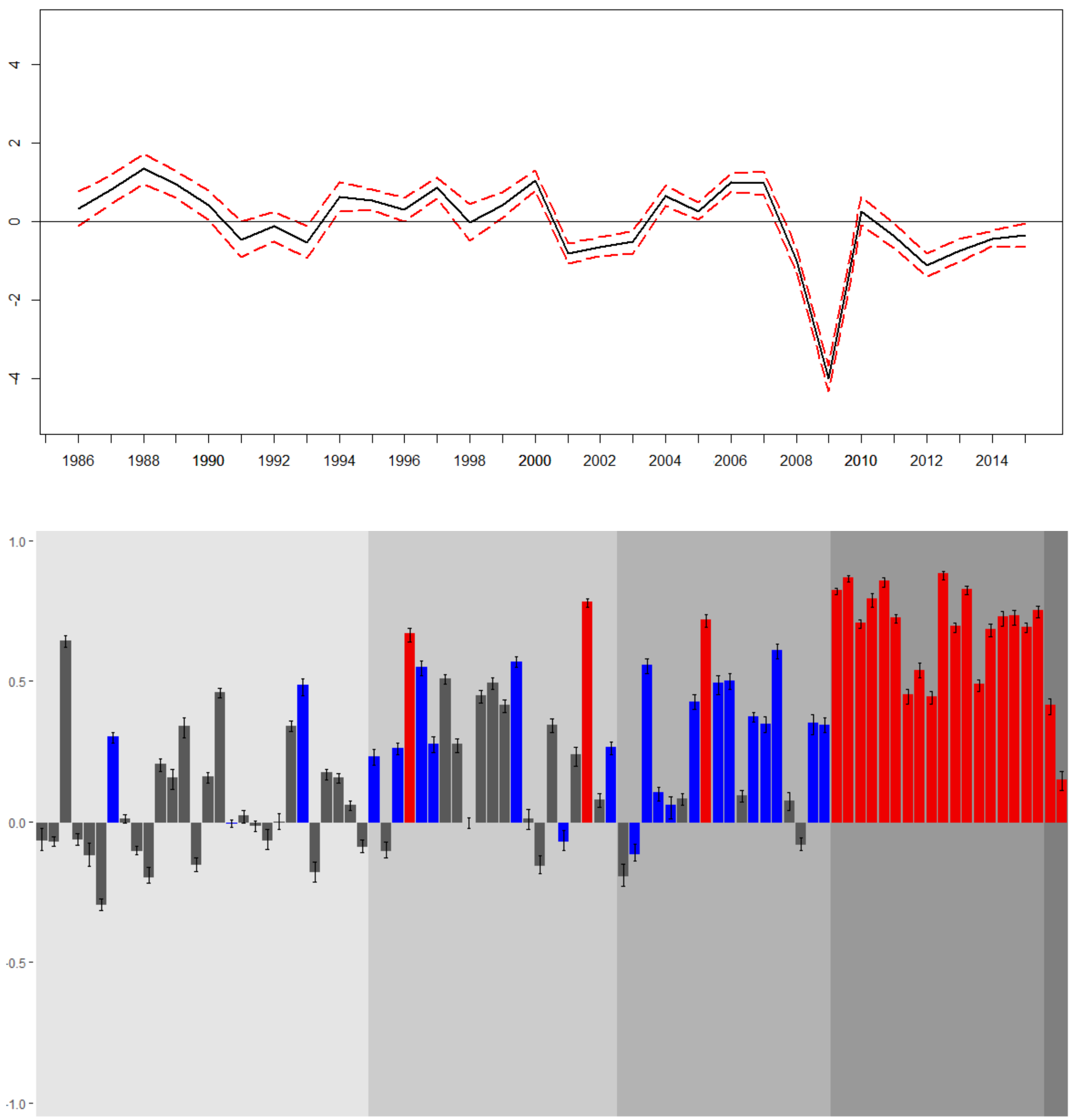
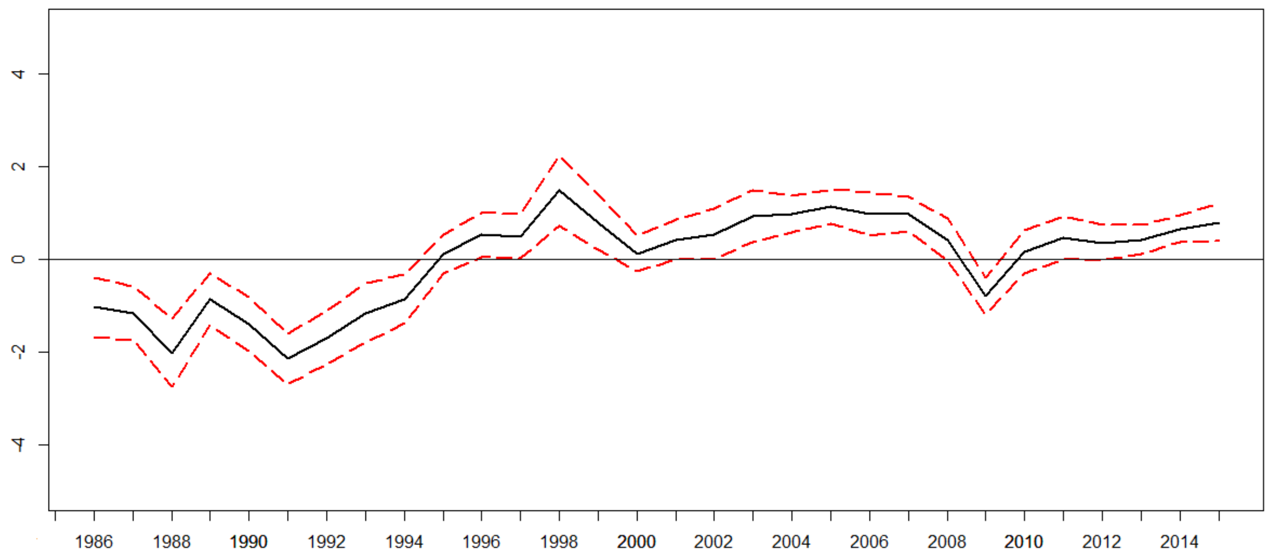


Figure 3: Top panel: Second factor extracted using Principal Components from system of growths together with 95% prediction intervals (in red). Bottom panel: Estimated weights of second factor for each country together with 95% confidence intervals. The bars in red, blue, and gray correspond to industrialized, emerging, and other developing countries, respectively. The countries in 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.



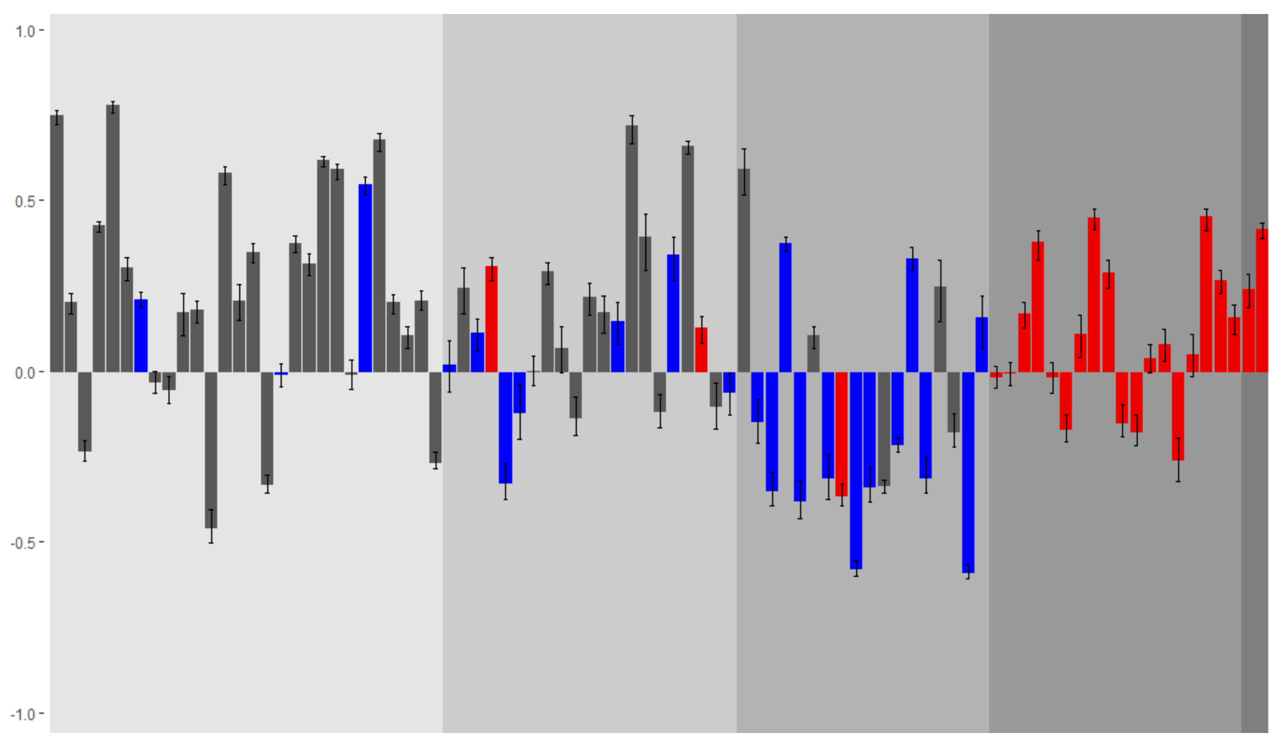
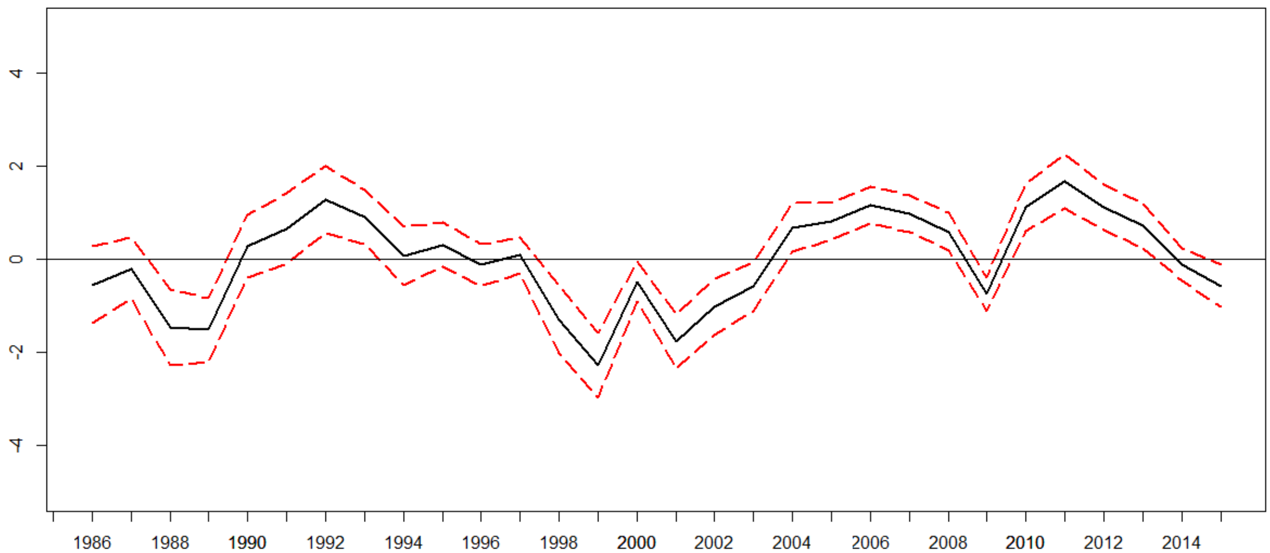


Figure 4: Top panel: Third factor extracted using Principal Components from system of growths together with 95% prediction intervals (in red). Bottom panel: Estimated weights of third factor for each country together with 95% confidence intervals. The bars in red, blue, and gray correspond to industrialized, emerging, and other developing countries, respectively. The countries in 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.



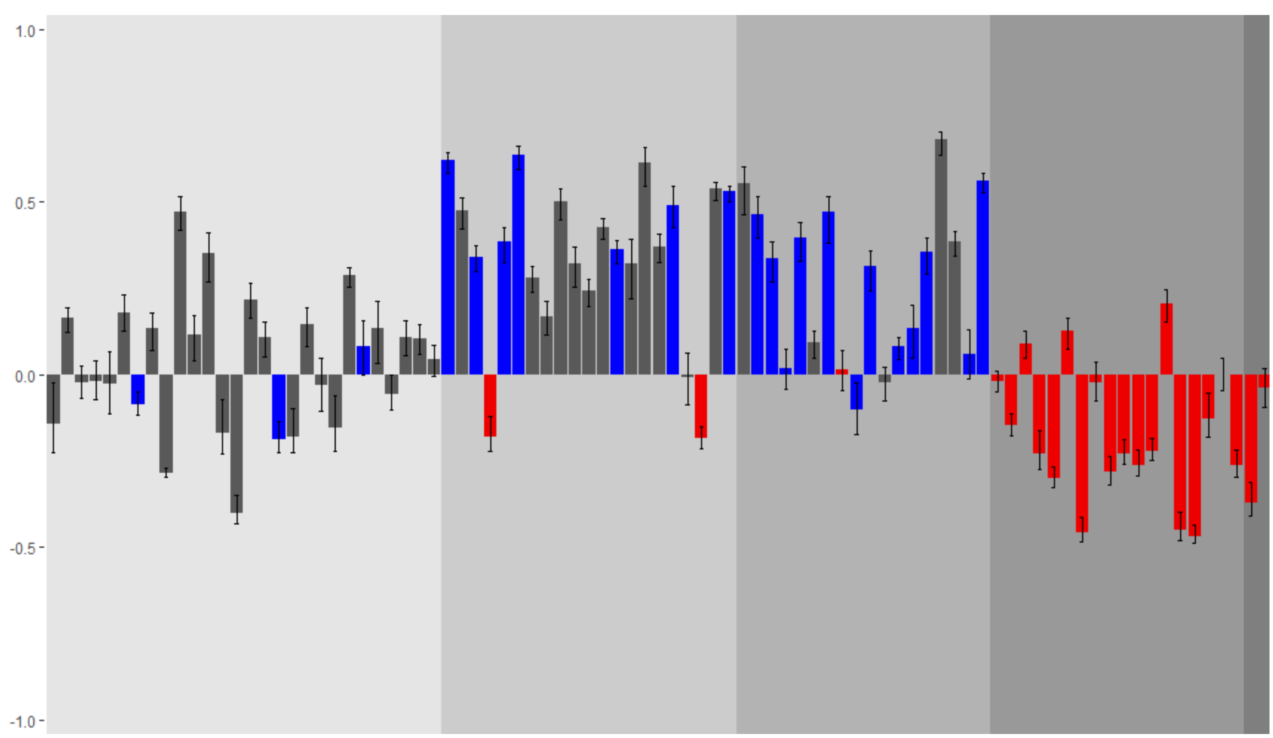


Figure 5: Resampling ellipsoids for the three factors in 1998 (blue) and 2004 (red). GiS in 1999 and 2005 for US, Germany and Greece (industrialized: first row), Brazil, China and India (emerging: second row), and Bolivia, Uganda and Nepal (developing: third row).

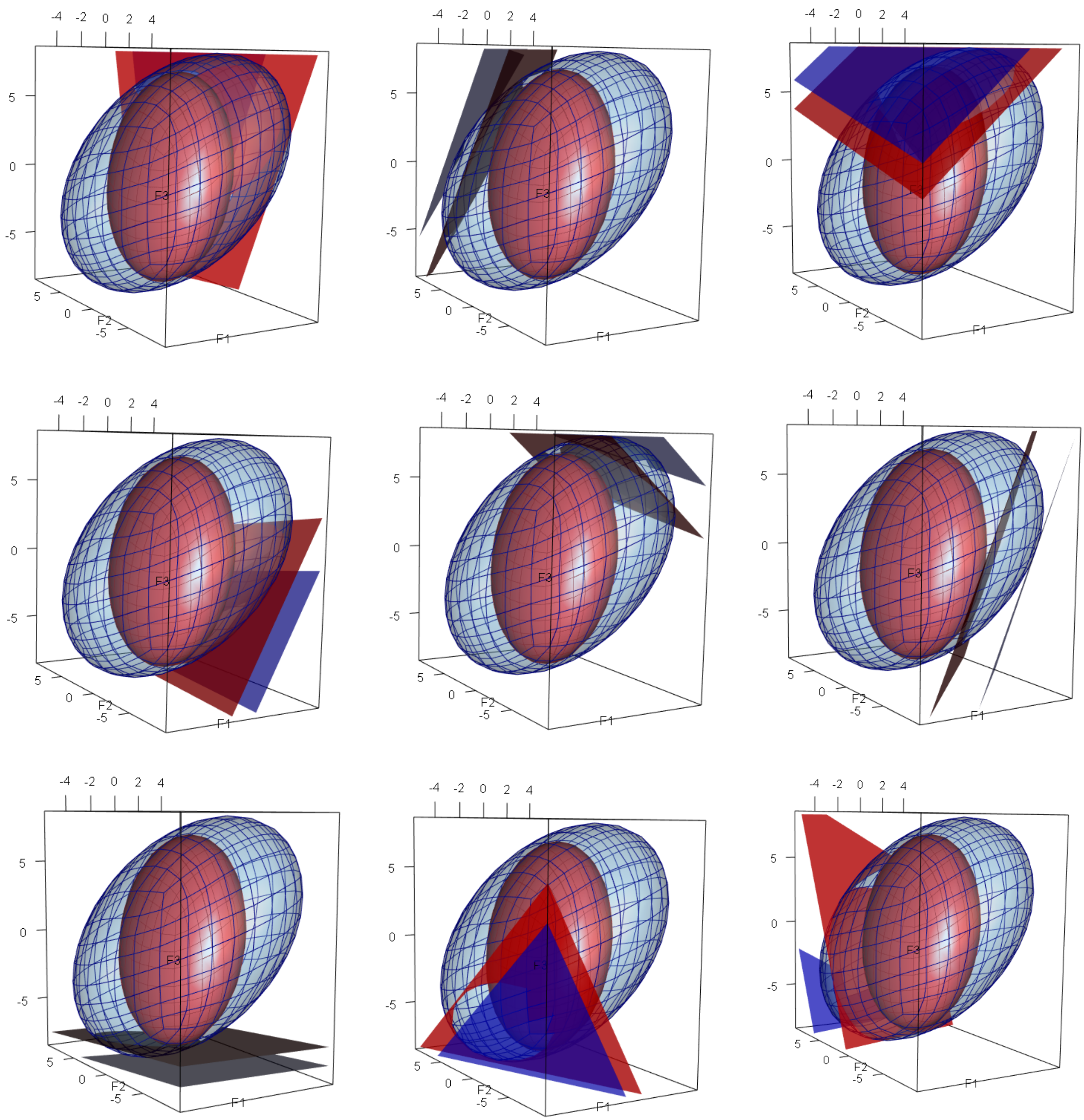


Figure 6: GiS for each industrialized (red), emerging (blue) and other developing (gray) country in Africa (top left panel), America (top right panel), Asia (bottom left panel) and Europe and Oceania (bottom right panel).

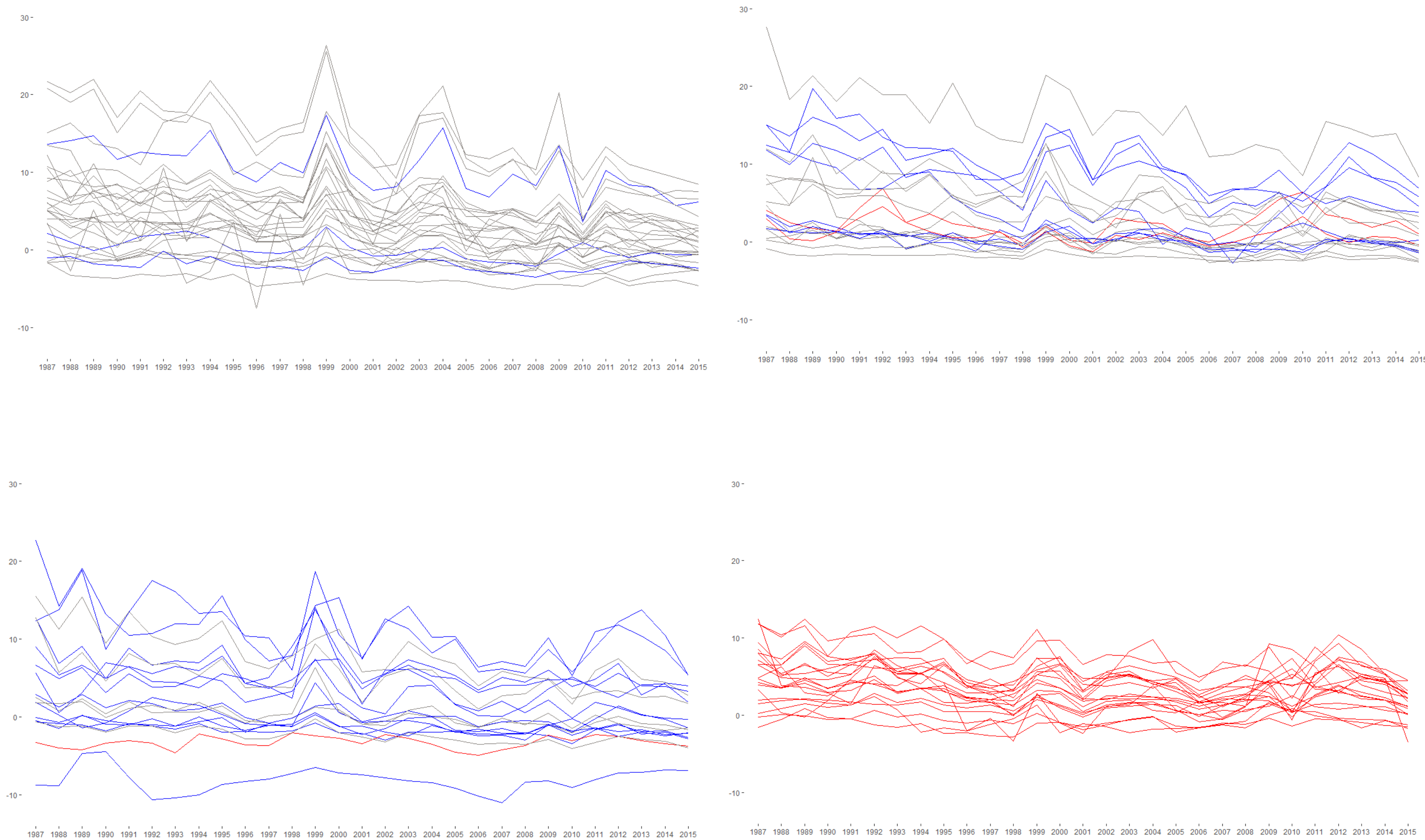


Figure 7: Average GiS (black line) and ± 2 standard deviations (red lines) among countries in Africa (top left panel), America (top right panel), Asia (bottom left panel) and Europe and Oceania (bottom right panel).

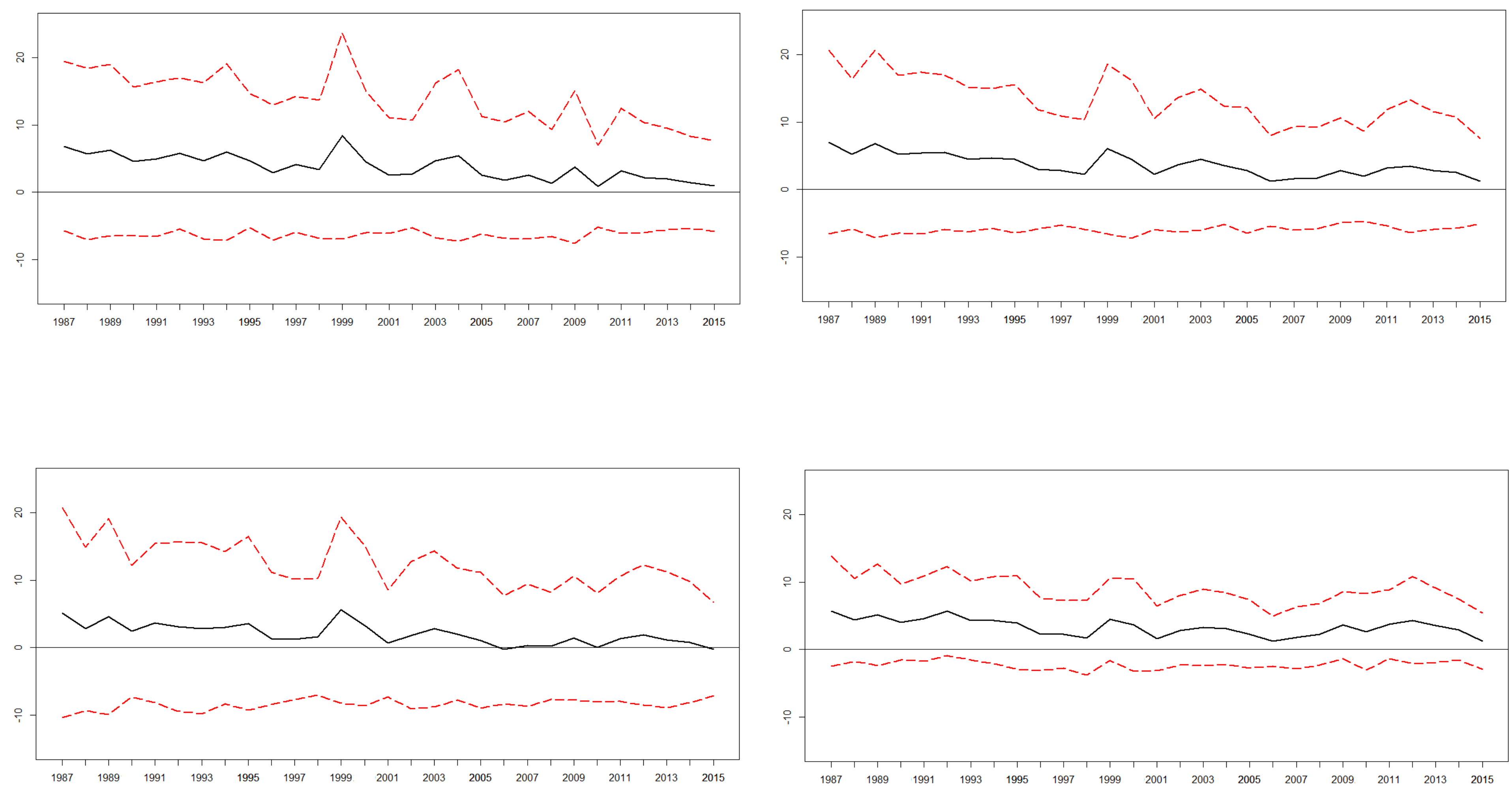


Figure 8: Average GiS (black line) and ±2 standard deviations (red lines) among other developing (top panel), emerging (middle panel) and industrialized (bottom panel) countries.

Figure 9: Resampling ellipsoids for the three factors in 1998 (blue) and 2004 (red). GiS in USA in 1999 and 2005 for the 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).

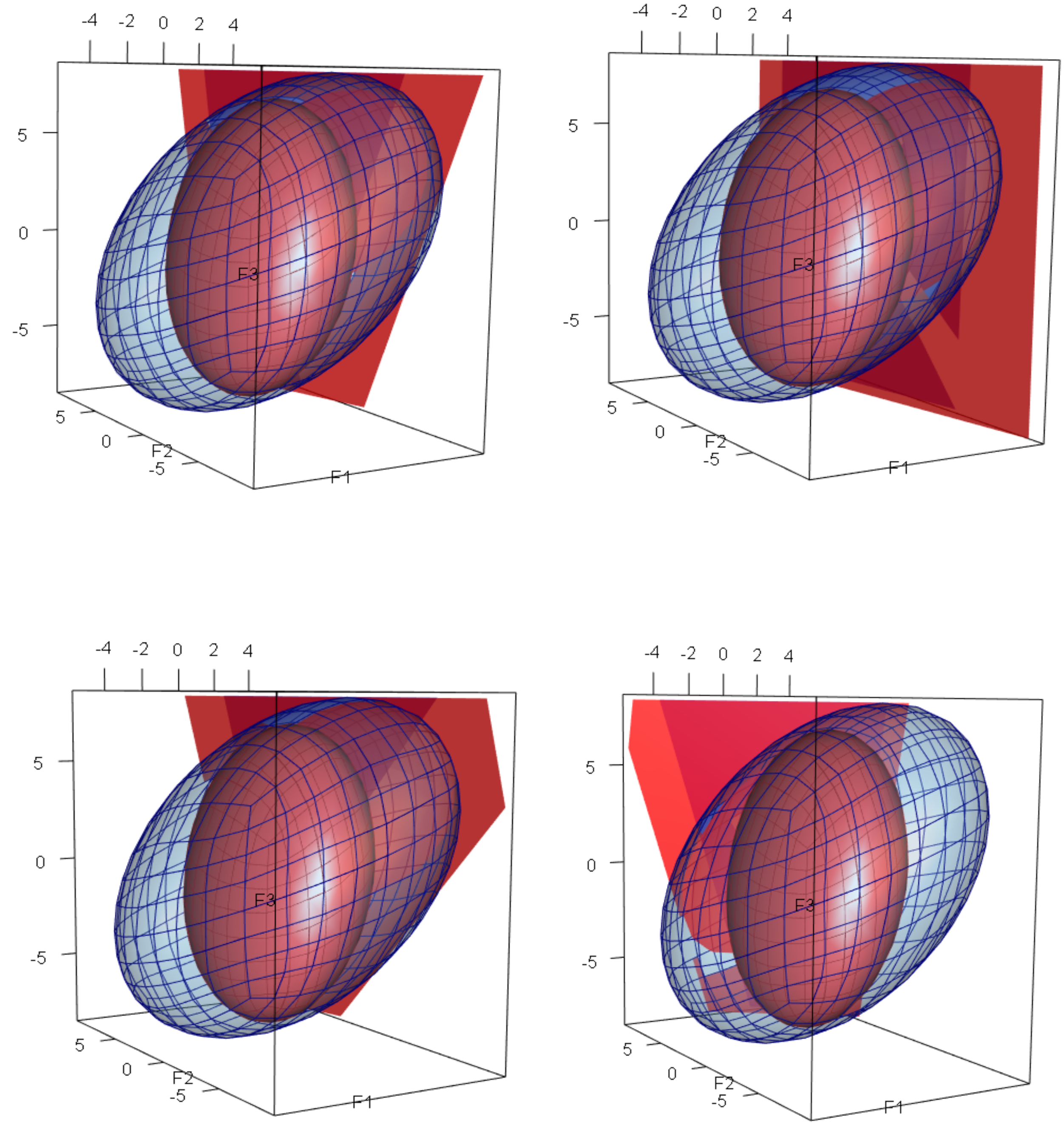


Figure 10: Resampling ellipsoids for the three factors in 1998 (blue) and 2004 (red). GiS in China in 1999 and 2005 for the predictive regression (top left panel) and quantile regressions with $\tau = 0.05$ (bottom left panel), $\tau = 0.5$ (top right panel) and $\tau = 0.95$ (bottom right panel).

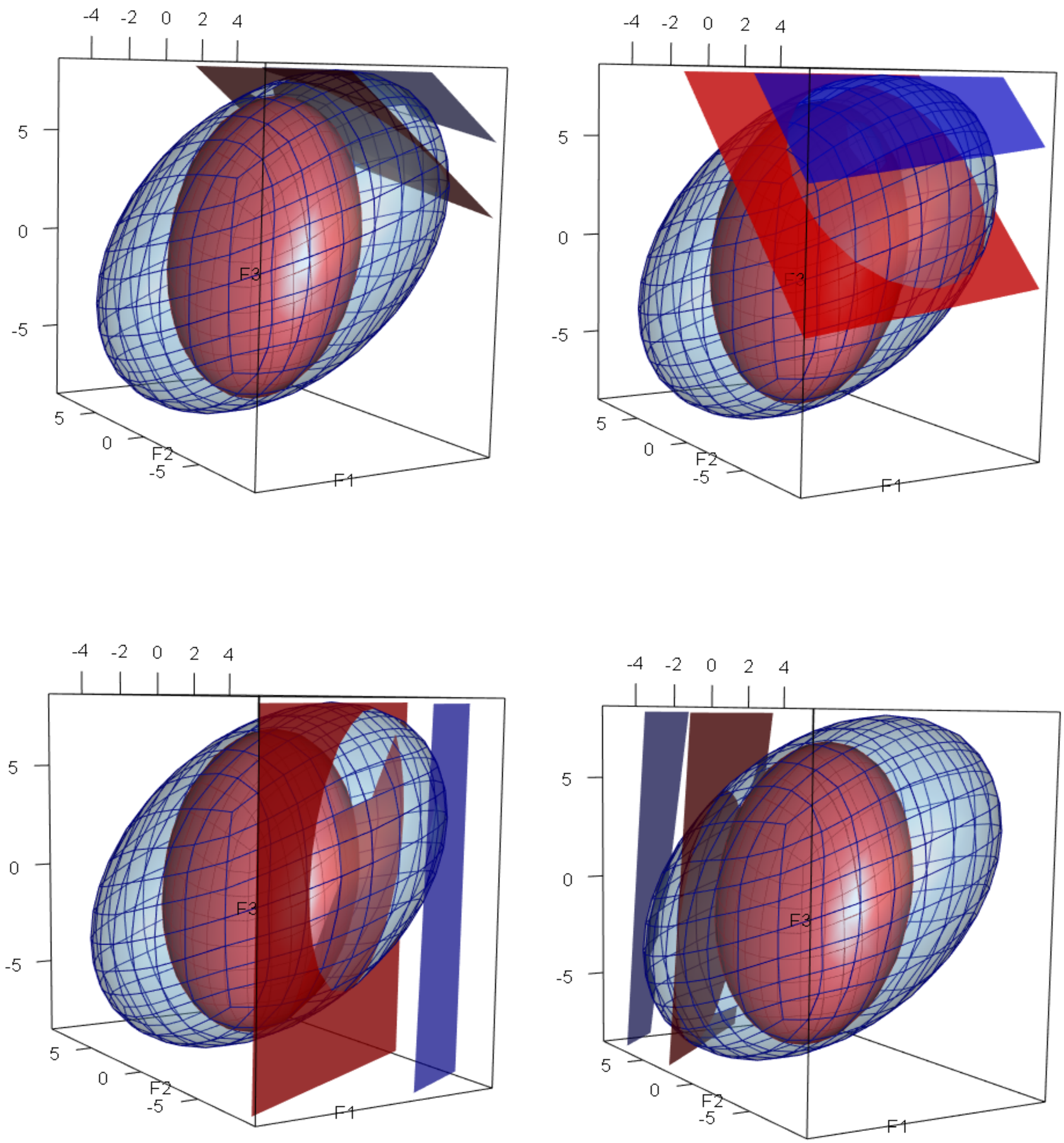


Figure 11: Resampling ellipsoids for the three factors in 1998 (blue) and 2004 (red). GiS in Uganda in 1999 and 2005 for the predictive regression (top left panel) and quantile regressions with $\tau = 0.05$ (bottom left panel), $\tau = 0.5$ (top right panel) and $\tau = 0.95$ (bottom right panel).

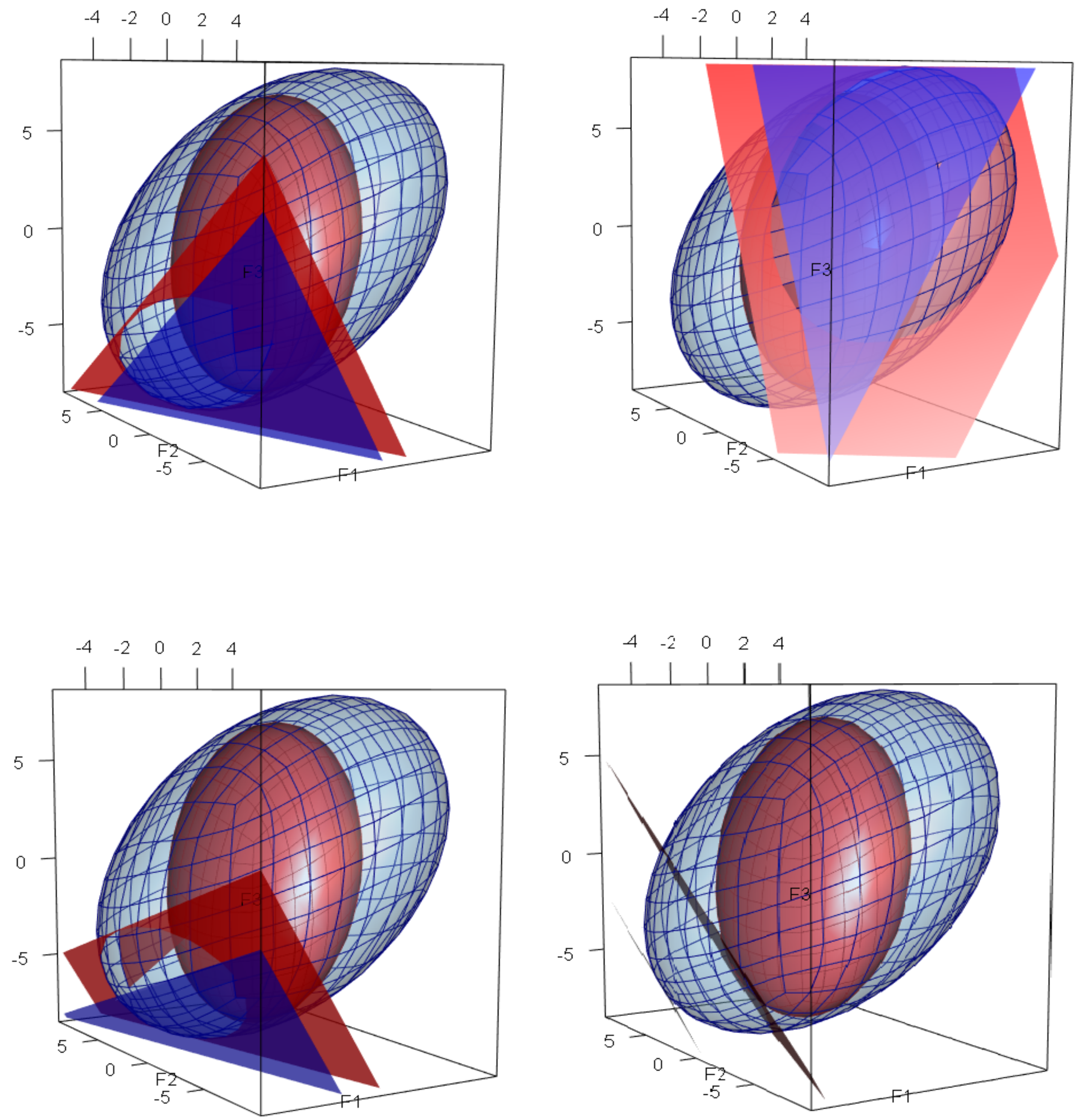


Figure 12: Average GiS (black line) and ±2 standard deviations (red lines) for $\tau = 0.05$ (first row), 0.5 (second row) and 0.95 quantiles of the growth distribution among industrialized (first column), emerging (second column) and other developing (third column) countries.