An Early Warning System for Tail Financial Risks

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Abstract

This paper formulates an Early Warning System (EWS) for tail financial risks based on real-time multi-period forecast *combinations* of Value-at-Risk (VaR) and Expected Shortfalls (ES) of portfolio returns of non-financial firms and banks. Forecast combinations include *baseline* (VaR,ES) forecasts conditional on a domestic risk factor, as well as *stress* (sVaR,sES) forecasts conditional on CoVaRs of the risk factor, thereby integrating stress testing into forecasting. Using monthly data of the G-7 economies for the period 1975:01-2018:12, The proposed EWS delivers significant out-of-sample tail financial risk forecasts and reliable vulnerability signals up to a 12-month forecasting horizon, with stress forecasts in the combination improving forecasting ability prior to periods of severe financial stress.

Keywords: Value at Risk; Expected Shortfall; Forecast combinations; Systemic Risk.
JEL Classification: C5; E3; G2.

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1 Introduction

The financial crisis of 2007-2009 has spurred significant efforts at central banks and bank regulatory agencies in designing early warning systems (EWS) for tail risks in the financial sector, where tail risks are defined as the occurrences of large financial losses with small probability. Importantly, the current implementation of key Basel bank regulations is increasingly relying on banking system-wide tail risk forecasts as embedded in stress testing exercises.

The EWS in this paper builds on the literature taking a risk management approach to the modeling and measurement of tail financial risks. An early analysis of measures of systemic risk in banking is in Lehar (2005). Current prominent statistical models aimed at capturing the dynamics of tail financial risks include the CoVaR measures of Adrian and Brunnermeier (2016), the Systemic Expected Shortfall measure of Acharya et al (2017), and the SRISK measures of Brownlees and Engle (2017). A key feature of the approach of this literature is the ex-ante definition of tail financial risk measures for which real time forecasting out-of sample is well defined. [1] Recent contributions focusing on forecasting include forecasts of aggregate financial and macroeconomic "at-risk" indicators of De Nicolo' and Lucchetta (2011, 2012, 2017), the forecasting and backtesting exercises by Brownlees et al (2018) and Banulescu et al. (2019), and the prediction of the probability of a financial crisis using SRISK measures by Engle and Ruan (2019).The contributions of this paper to this literature is its focus on real-time forecasting of measures or tail financial risks as an early warning system tool.

The proposed EWS delivers out-of-sample real-time *forecast combinations* of Value-at-Risk (VaR) and Expected Shortfall (ES) of multi-period equity returns of portfolios of non-financial firms and banks, interpreted as indicators of tail financial risks in the non-financial and banking sectors. My methodological approach follows Giacomini and White (2006) and Geweke and Amisano (2012): rather than conducting a classical horse race among competing models with the goal of determining whether a winner exists, the proposed EWS exploits the potential of several competing and likely mis-specified forecasting models to improve forecasting performance.

Three novel features characterize the proposed EWS. First, the weights assigned to each

[1] This approach contrasts with EWS defined as prediction systems of "crisis" events identified ex-post with dating based on statistics and expert assessments, which focus on the identification of predictors of crisis events

forecast in the (VaR,ES) combinations are determined by maximization of an average of a scoring function over an optimally determined evaluation window at each forecasting date. Inefficient forecasts are assigned zero weights, adopting an "elimination rule" akin to that used by Hansen, Lund and Nason (2011) to identify a "model confidence set".

Second, forecast combinations include forecasts of (VaR,ES) conditional on an observed predictor, called *baseline* forecasts, as well as forecasts conditional on tail risk measures of the predictor, called *stress* forecasts, denoted by (sVaR,sES) henceforth. These (sVaR, sES) measures are forecasting versions of the CoVaR and CoES measures introduced by Adrian and Brunnermeier (2016). The inclusion of stress forecasts in the combination gauges the value added of stress scenarios in terms of their ability to improve (VaR, ES) forecasts, integrating stress testing into forecasting.

Third, ES forecasts are used as predictors of a binary (Logit) model of the probability of the occurrence of VaR violations, defined as realizations of returns below the historical VaR. I construct a vulnerability index which takes on positive values when the model predicts a high probability of a VaR violation. The optimal *signal* threshold is determined by minimization of a linear function of forecasting errors, following standard Receiving Operating Characteriscs (ROC) analysis. This index complements the (VaR,ES) forecasts by associating a signal of vulnerability with the predicted level of declines in the market value of equity of portfolio of financial firms and banks.

I implement the EWS in real time using monthly time series of equity returns of portfolios of non-financial and financial sectors of the G-7 economies during the 1975:01-2018:12 period. Forecasts of (VaR,ES) are computed for 1-month-, 3-month-, 6 month-, and 12-month-ahead returns, obtaining forecasts of the short-end term structure of tail financial risks in both the non-financial and banking sectors. Stress test scenarios built into stress test forecasts include both domestic and external tail risk shocks, with the objective of assessing their relative importance in improving forecasting performance.

My choice of forecasting models (and methods) is deliberately parsimonious, since I wish to gauge in a transparent way the contribution of each model to the (VaR,ES) forecast combinations. However, any desired set of forecasting methods can be used. Specifically, I consider three basic models of equity returns of portfolios, where each model has an aggregate risk factor as predictor. This specification is similar to those used to assess the predictability of returns using measures of variance premia (see e.g. Bollerslev et al. (2014) and Zhou (2018)). The aggregate risk factor is a measure of the (log) volatility of stock market returns, interpreted as a measure of a "portfolio" distance-to-insolvency measure as in Atkeson, Eisfeldt, and Weill (2017). The first model is a simple linear model of equity returns under a Gaussian distribution of the innovation. The second model is the same as the first one, except that the variance of percentage change in equity values has the risk factor as predictor. The third model is a quantile model. Importantly, the candidate forecast combination also includes an equally weighted combination (EWC) of these three models. The inclusion of the EWC in the combination is motivated by the desire to assess the "forecast combination puzzle" exhibited in many studies, where EWCs have been found to dominate a variety of "optimal" weighting schemes.

As in Giacomini and White (2006), I define forecast methods as specifications of models' forecasts that vary according to the length of the estimation window and the forecast evaluation window. The weights of each method's (VaR,ES) forecast in the forecast combination maximize an average of the strictly consistent scoring function derived by Patton, Ziegel and Chen (2019) where strict consistency ensures the appropriate ordering of the forecasting performance of (VaR, ES) pairs. Tests of equal (unconditional) forecasting performance are conducted at each forecasting date and for a range of significance levels using the Diebold and Mariano (1995) test on pairwise differences of this scoring function as in Giacomini and White (2006). These tests are used to assign zero weights to forecasts found inferior to at least one competing forecast at a given significance level, called *dominated* forecasts. The consideration of the set of selected models in the combination for each significance level determines the final weights of a combination, which is selected with respect to an optimal evaluation window.

The resulting (VaR,ES) forecast combinations can still fail to pass validation tests due to model risk, since the models underlying these forecasts are likely mis-specified. To minimize model risk, the (VaR,ES) forecast combinations are further corrected by a correction factor ensuring that they both pass two backtesting tests jointly, one for VaR, and one for ES, following the procedure suggested by Boucher et al. (2014).

I obtain two main results. First, (VaR,ES) forecast combinations have significant predictive power up to the 12-month-ahead horizon, with the vulnerability index providing timely signals of increased vulnerabilities in the non-financial and banking sectors. Second, the value added of including stress forecast (sVaR,sES) in the combination is significant, as they improve forecasting performance by taking their largest weights preceding periods of financial stress, indicating that their ability to improve forecasts occurs when it is most needed.

The remainder of the paper is composed of four sections. Section 2 briefly reviews the related literature. Section 3 describes the EWS setup and the forecasting procedure. Section 4 details the empirical results. Section 5 concludes. The Appendix reports additional tables and figures referenced in the text.

2 Related literature

Forecast combinations for tail risk measures have been implemented through combinations of either density forecasts or quantile forecasts. Geweke and Amisano (2011) and Durham and Geweke (2014) focus on optimal pooled density forecasts based on the log score criterion. Diks et al (2011) and Opschoor et al (2017) study the performance of optimal weighting schemes derived from modified versions of the log score criterion, as well as from the quantile weighted probability score proposed by Gneiting and Ranjan (2011).[2] De Nicolò and Lucchetta (2017) focus on quantile forecasts evaluated according to the Gneiting and Ranjan (2011) criterion, showing the superiority of equally weighted forecast combinations relative to single model VaRs. The work closest to my paper is that by Patton, Ziegel and Chen (2019), who deliver (VaR,ES) forecasts under a model specification that directly maximizes a scoring function of (VaR,ES). Using the strictly consistent scoring function of Patton, Ziegel and Chen (2019), I construct out-of-sample forecast combinations of both VaR and ES measures in real-time

A growing literature on stress testing has recently developed focusing on the architecture, the information content, and the identification of sources of tail risks of these exercises (see e.g.

[2]Samuels and Sekkel (2017) implement a combination scheme based on a version of the model selection procedure used by Hansen, Lunde and Nason (2011) as applied to macroeconomic data rather than to measures of tail financial risk.

De Nicolò and Lucchetta (2011, 2012), Acharya et al (2014), Corbae et al. (2017), Gofman (2017)). Related practices in central banks and regulatory bodies are reviewed in BCBS (2017). However, with the exception of the work by Covas, Rump and Zakrajsek (2014) and Kupiec (2018), who explore the implications of stress test exercises for financial distress forecasts in the context of US stress testing exercises, the role of stress testing as a forecasting tool has not been explored systematically in the literature to date. The contribution of my paper in this area is the explicit integration of stress test scenarios as predictors of tail financial risks.

3 The EWS set-up

The EWS is composed of: (a) combinations of baseline and stress (VaR,ES) forecasts of equity returns of portfolios of non-financial firms and banks conditional with a risk factor as a predictor; (b) relevant vulnerability indexes signaling the probability of tail risk realizations predicted by ES forecasts. In this section I detail the choice of risk factors, the set of baseline and stress forecasts of each model, the scoring function associated with each forecast, the forecast combination strategy, and the construction of the vulnerability index.

3.1 Risk factors

Risk factors are proxy measures of the Distance to Insolvency (DI) measure derived by Atkeson, Eisfeldt, and Weill (2017) for an equity market index of each country. Based on Leland's (1994) structural model of credit risk for a single firm, Atkeson, Eisfeldt, and Weill (2017) show that $DI \leq \sigma^{-1} \leq DD$, where σ is the volatility of equity, DD is a measure of the distance to default, DI is a measure of distance to insolvency, and the above inequality is tight if creditors force firms into bankruptcy to minimize the cost of distress. Using U.S. firm level data, they show that measures of σ^{-1} for a large set of non-financial and financial firms track measures of insolvency risk derived from a wide range of structural models of firm valuation, as well as from measures derived from CDS spreads. A portfolio DI is a lower bound of the distance to insolvency of the firms in the portfolio, since its volatility is generally lower than the sum of the volatilities of its components.

Our choice of risk factors is consistent with (endogenous) volatility as a key driver of systemic risk in recent aggregate models of financial intermediation (see e.g. Brunnermeier and Sannikov, 2014, and De Nicolo', Klimenko, Pfeil, and Rochet, 2020). Measures of risk shocks obtained either by cross-sectional or time varying indicators of equity volatility have also been shown to be important sources of business cycle fluctuations (see, e.g. Christiano, Motto and Rostagno, 2014, and Brunnermeier et al., 2018).

Empirically, risk factors are measured by the (log) equity volatility (standard deviation) of portfolios equity returns constructed using daily data. As in Bandi and Perron (2008), an estimator of monthly realized variance of an equity return is given by $\sigma_t^2 = \sum_{j=1}^{d_j} r_{t-1+j/d_j}^2$, where d_j is the number of trading days in a month and r_{t-1+j/d_j}^2 is the squared continuously compounded return in day j of month t. Indexing countries by $i \in \{1, 2, .., N\}$, risk factors are defined by $V_t^i \equiv \log \sigma_t^i$.

3.2 Forecasting methods

Forecasts of (VaR, ES) pairs for a given quantile level τ are h-month-ahead projections obtained from specifications of three models, labeled Model 1, Model 2, and Model 3. As detailed below, these models will be estimated using two rolling data windows. Forecasts and estimated coefficients are denoted with a "hat".

Let $R_{t+h}^{i,j}$ denote the return of portfolio $j \in \{nf, b\}$ in country i, where nf and b denote "non-financial firms" and "banks" portfolios respectively. I consider three basic forecasting models of the (VaR,ES) of $R_{t+h}^{i,j}$, with the country risk factors V_t^i as predictors.

3.2.1 Baseline forecasts

The h-month-ahead projection of return j in country i with Model 1 is :

$$R_{t+h}^{i,j} = \alpha_h^{i,j} + \beta_h^{i,j} V_t^i + \sigma_{t+h}^{i,j} \eta_{t+h}^{i,j} \tag{1}$$

where the innovation $\eta_{t+h}^{i,j}$ is i.i.d $N(0,1)$ and $\sigma_{t+h}^{i,j}$ is the variance. The baseline forecasts of the h-month-ahead expected return and (VaR_τ, ES_τ) are:

$$E_t(\hat{R}_{t+h}^{i,j}) \equiv \hat{\alpha}_h^{i,j} + \hat{\beta}_h^{i,j} V_t^i \tag{2}$$

$$VaR_\tau(\hat{R}_{t+h}^{i,j}) = E_t(\hat{R}_{t+h}^{i,j}) + \hat{\sigma}_{t+h}^{i,j} G(\tau) \tag{3}$$

$$ES_\tau(\hat{R}_{t+h}^{i,j}) = E_t(\hat{R}_{t+h}^{i,j}) - \hat{\sigma}_{,t+h}^{i,j} H(\tau) \tag{4}$$

where $G(\tau) \equiv F^{-1}(\tau)$, $H(\tau) \equiv \frac{f(F^{-1}(\tau))}{\tau}$, and $f(.)$ and $F(.)$ are the density function and the cdf of the standardized Normal respectively.

The h-month-ahead projection of return j in country i with Model 2 is the same as in Model 2 (Equation (2)), except that the variance depends on the risk factors as in:

$$(\sigma_{t+h}^{i,j})^2 = \exp{(\phi_0^{i,j} + \phi_1^{i,j} V_t^i)} \tag{5}$$

The baseline VaR and ES forecasts of Model 2 are obtained by inserting $\sigma_{t+h}^{i,j} = \sqrt{\exp{(\phi_0^{i,j} + \phi_1^{i,j} V_t^i)}}$ in Equations (3) and (4).

Model 3 is a quantile forecasting model. As stressed by Komunjer (2013), an advantage of a quantile regression model is its independence of distributional assumptions, which may give it the potential ability to capture important time-varying asymmetries in the distribution of returns. De Nicolò and Lucchetta (2017) document that this is the case for several indicators of tail real and financial risks in the U.S.

The VaR forecast of Model 3 is the h-month-ahead quantile projection given by:

$$VaR_\tau(\hat{R}_{t+h}^{i,j}) = \hat{\alpha}_h^{i,j}(\tau) + \hat{\beta}_h^{i,j}(\tau) V_t^i \tag{6}$$

where the coefficients are estimated with quantile regressions. To estimate the conditional ES forecast, I use a version of the semi-parametric procedure implemented by Taylor (2019). The starting point of this procedure is a result by Basset, Koenker and Kordas (2004), who show that an estimate of the *unconditional* ES_τ of a time series R_t is $\hat{ES}_\tau = \hat{R} - \tau^{-1}\hat{\sigma}$, where $\hat{R}$ is the sample mean of R_t, and $\hat{\sigma}$ is the sample average of the minimized thick loss function

$\hat{\sigma}_t = (R_t - VaR_\tau(\hat{R}_t))(\tau - I(R_t \leq VaR_\tau(\hat{R}_t))$, where $VaR_\tau(\hat{R}_t)$ is the estimated quantile. The *conditional* h-month-ahead ES forecast can be written as:

$$ES_\tau(\hat{R}^{i,j}_{t+h}) = E_t R^{i,j}_{t+h} - \tau^{-1}\hat{\sigma}^{i,j}_{t+h} \tag{7}$$

where $\hat{\sigma}^{i,j}_{t+h} = (R^{i,j}_{t+h} - VaR_\tau(\hat{R}_{t+h})(\tau - I(R^{i,j}_{t+h} \leq VaR_\tau(\hat{R}^{i,j}_{t+h})$ is the forecast of the minimized thick loss function. Gourieroux and Li (2012) show that VaR and ES are connected by a link function $L(\tau)$ monotonically increasing in τ. We can then write:

$$E_t R^{i,j}_{t+h} - \tau^{-1}\hat{\sigma}^{i,j}_{t+h} = L^h_{ij}(\tau) VaR_\tau(\hat{R}^{i,j}_{t+h}) \tag{8}$$

Given a VaR forecast estimate, the ES forecast can be obtained by estimating the parameters of a specified link function. I adopt the following piece-wise linear specification:

$$L^h_{ij}(\tau) = c^h_{ij,1}(\tau) I_{(VaR_\tau(\hat{R}^{ij}_{t+h})<0)} + c^h_{ij,2}(\tau) I_{(VaR_\tau(\hat{R}^{ij}_{t+h})>0)} \tag{9}$$

The coefficients are assumed to be different depending on whether VaR values are positive or negative. This specification ensures that the ES never exceeds the VaR, as verified in all estimations described in the sequel.

Let $Z^h_{ij,t+h} \equiv R_{t+h} - \tau^{-1}\bar{\sigma}_t$. Then, the ES forecast of Model 3 is the predicted value of the following regression:

$$Z^h_{ij,t+h} = c^h_{ij,1}(\tau) I_{(VaR_\tau(\hat{R}^j_{i,t+h}<0)} + c^h_{ij,2}(\tau) I_{(VaR_\tau(\hat{R}^j_{ij,t+h}>0)} + e_{t+h} \tag{10}$$

Using Equations (8) and (9), the baseline ES forecast of Model 3 is:

$$ES_\tau(\bar{R}^{ij}_{t+h}) = [\hat{c}^h_{ij,1}(\tau) I_{VaR_\tau(\hat{R}^{ij}_{t+h})<0} + \hat{c}^h_{ij,2}(\tau) I_{VaR_\tau(\hat{R}^{ij}_{t+h}>0)}] VaR_\tau(\hat{R}^j_{ij,t+h}) \tag{11}$$

3.2.2 Stress forecasts

Stress forecasts are (VaR,ES) return forecasts conditional on CoVaRs of risk factors. These CoVaRs capture the extreme adverse realizations of risk factors typically assumed in a stress testing scenario. I construct CoVaRs of the risk factors that capture domestic and external tail risk shocks in reduced-form.

I assume the following models for: a. the VaR of the risk factor V_t^i in country i;, and, b. the VaR of the leave-one-out average of risk factors across countries, defined by $V_t^{-i} \equiv \sum_{k \neq i}^{N} \frac{V_t^k}{N-1}$, for quantile levels $\tau' \leq \tau$:

$$VaR_{\tau'}(V_t^i) = a^i(\tau') + b^i(\tau')V_{t-1}^{-i} + c^i(\tau')V_{t-1}^i \tag{12}$$

$$VaR_{\tau'}(V_t^{-i}) = a^{-i}(\tau') + b^{-i}(\tau')V_{t-1}^{-i} \tag{13}$$

By Equations (12), the VaR of a risk factor in country i is predicted by its lagged value and the lagged value of the leave-one-out average of risk factors. By Equation (13), the leave-one-out average of risk factors is predicted by its lagged value. The parameters of Equations (12) and (13) are estimated by quantile regressions.

. I consider two stress scenarios defined by the following CoVaRs:

$$co_1VaR_{\tau'}(V_t^i) = \hat{a}^i(\tau') + \hat{b}^i(\tau')V_{t-1}^{-i} + \hat{c}^i(\tau')VaR_{\tau'}(V_{t-1}^i) \tag{14}$$

$$co_2VaR_{\tau'}(V_t^i) = \hat{a}^i(\tau') + \hat{b}^i(\tau')VaR_{\tau'}(V_{t-1}^{-i}) + \hat{c}^i(\tau')V_{t-1}^i \tag{15}$$

By Equation (14), the VaR of a country risk factor is predicted conditional on its level being at its VaR in the previous period. Therefore, $co_1VaR_{\tau'}(V_t^i)$ can be viewed as capturing a domestic tail risk shock scenario. By Equation (15), the VaR of a country risk factor is predicted conditional on the level of the leave-one-out risk factor being at its VaR in the previous period. Thus, $co_2VaR_{\tau'}(V_t^i)$ can be viewed as capturing an external tail risk shock scenario.

The stress forecasts (sVaR,sES) of the returns of the non-financial and banking sectors are obtained by replacing V_t^i with $co_kVaR(V_t^i)$, for $k = 1, 2$, in all Equations (2)-(4), (6)-(9), and (10)-(11). All (sVaR,sES) forecasts are measured for the pair of quantile levels $(\tau, \tau') =$

(0.10, 0.95).

3.3 The scoring function for (VaR, ES) forecasts

Recall that a scoring function for a statistic is *strictly consistent* if there exists a score (or loss) function such that the correct prediction of this statistics is the unique minimizer of the expected score. A statistic for which a strictly consistent scoring function exists is called *elicitable*. Gneiting (2011) shows that ES is not elicitable. Fissler and Ziegel (2016) identify the family of scoring functions such that the pair (VaR,ES) is "jointly" elicitable.[3]

To evaluate the out-of-sample forecasting performance of (VaR,ES) of return R_{t+h} generated by different forecasting methods, I use the following (strictly consistent) FZ0 scoring function derived by Patton, Ziegel and Chen (2019, Proposition 1), which applies to strictly negative values of VaR and ES:

$$
\begin{aligned}
FZ0(VaR_{t+h}, ES_{t+h}) \equiv -\frac{1}{\tau ES_{t+h}} I(R_{t+h} \leq VaR_{t+h})(VaR_{t+h} - R_{t+h}) + \\
\frac{VaR_{t+h}}{ES_{t+h}} + \log(-VaR_{t+h}) - 1
\end{aligned}
\tag{16}
$$

The FZ0 statistics has negative orientation, that is, lower values indicate higher scores.

Following Giacomini and White (2006), pairwise comparisons of unconditional forecasting performance of (VaR, ES) forecasts obtained with limited memory estimators, such as those obtained with rolling windows, is carried out by applying Diebold and Mariano (1995) tests of equal forecasting performance (DM tests henceforth) using the FZ0 scoring function.

3.4 Forecast combinations

The forecasting strategy underlying the proposed EWS aims at: (a) capturing forecasting persistence; (b) exploiting the potential of stress forecasts to improve forecasting performance; and (c) excluding inferior forecasts. It is implemented in real time, replicating what a forecaster could do with the information available at each forecasting date.

This strategy is implemented in two stages. The first stage is the *method selection* stage,

[3] For a survey on elicitability and its relationship with back-testing and forecasting, see Nolde and Ziegel (2017).

which involves the construction of the forecast combination. In the second stage, the (VaR,ES) of the forecast combination obtained in the first stage is *corrected* so as to pass a VaR backtest and an ES backtest, as in Du and Escanciano (2017). This second stage can be viewed as the *model validation* stage. Model validation is embedded in the forecasting process so as to improve forecasting performance from a set of mis-specified models.

Let $(VaR_m(\hat{R}_{t+h}), ES_m(\hat{R}_{t+h}))$ be the h-period ahead forecast at t of forecasting method m, and let M be the total number of forecasting methods. Denote with $f_m(t,h)$ the $FZ0$ score associated with the h-month-ahead forecast of forecasting method m, and with $\Delta f_{m,m'}(t,h)$ the difference between the $FZ0$ scores of methods m and m'.

The comparison of performance of forecasting method m relative to m' at forecasting date t is tracked by the average of $\Delta f_{m,m',t}$ over a *rolling evaluation* window of the last w periods, given by:

$$\mu_t(m, m'|w) = \frac{1}{w}\sum_{t-w+1}^{t} \Delta f_{m,m'}(t,h) \tag{17}$$

Denote with α_j the j'th confidence level in the discrete set $A \equiv \{0.05, .., 0.95\}$, and with W a set of evaluation windows of different lenght. The h-month-ahead forecast combination of (VaR, ES) at forecasting date t is given by:

$$(VaR_\tau(\hat{R}_{t+h}), ES_\tau(\hat{R}_{T+h})) = (\sum_{m=1}^{M} w_t^m VaR_m(\hat{R}_{t+h}), \sum_{m=1}^{M} w_t^m ES_m(\hat{R}_{t+h})) \tag{18}$$

where the weights satisfy $w_t^m \geq 0$ for all models $m \in \{1, 2, ..., M\}$ and $\sum_{m=1}^{M} w_t^m = 1$. The weights of a combination depend on the confidence level and the length of an evaluation window.

3.4.1 Choosing forecast weights in the combination

The choice of forecast weights is implemented in three steps. In the first step, the inclusion of a forecast in a combination is determined by pairwise DM tests of equal forecasting performance at confidence level $\alpha_j \in A$ for any given evaluation window $w \in W$. If the forecast of method m is significantly worse than the forecast of at least one competing method m' at confidence level α_j, then the forecast m is said to be *dominated*, and is assigned zero weight. The result of this first step is the classification of dominated and non-dominated forecasts for each confidence level in A and evaluation data window in W.

In the second step, forecast combinations are computed for every confidence level in A and evaluation data window in W. The weights of each forecast at confidence level $\alpha_j \in A$ are computed as the fraction of the instances a forecast is non-dominated for all confidence levels preceding and including α_j. This second step yields weights as a function of the confidence level $\alpha_j \in A$ and evaluation window $w \in W$.

In the third and final step, the weights of the best forecast combination are obtained by selecting the confidence level α_j and the evaluation window w that minimize the average FZ0 score. This procedure is repeated at each forecasting date.

Two reasons motivate this forecast combination strategy. First, the size of a given confidence level $\alpha_j \in A$ determines the stringency of the criterion for eliminating forecasts: the set of dominated forecasts (weakly) monotonically increases with $\alpha_j \in A$, until typically only one forecast remains. Therefore, the weights assigned to each forecast for any given α_j record the fraction of instances such forecasts receive positive weights over preceding confidence levels up to α_j, that is, as the stringency of the elimination criterion becomes tighter. Second, the length of the rolling evaluation window assigns different weights to past forecasts: the shorter the window, the higher is the likelihood of capturing recent developments but at the cost of the power of the DM test given limited data. Conversely, the longer the window, the more powerful are the DM tests at the cost of more limited weighting of recent developments. Hence, the choice of the evaluation window is meant to capture these trade-off by choosing the window that minimizes the average FZ0 score. This procedure essentially determines a ranking of forecasting methods germane to the ranking of forecast combinations by quantile sorting proposed by Aiolfi and Timmermann (2006) in the context of forecast evaluation based on minimum squared forecast errors.

Formally, let $I^m(\alpha_j, w)$ denote an indicator function of forecast m taking on a value of 0 if forecast m is dominated, and 1 otherwise. The vector of weights $(w_t^{*1}, ..., w_t^{*M})$ is determined as follows:

1. For all $\alpha_j \in A$ and $w \in W$, $I^m(\alpha_j, w) = 0$ if there exists a forecast m' such that: (a)

$\mu(m, m'|w) > 0$; and, (b) the null hypothesis $\mu_(m, m'|w) = 0$ is rejected according to a DM test at a significance level $\alpha_j \in A$. $I^m(\alpha_j, w) = 1$ otherwise.

2. The weights of a forecast combination evaluated at the pair (α_j, w) are given by:

$$w_t^m(\alpha_j, w) = \frac{\sum_{h=1}^{j} I^m(\alpha_h, w)}{\sum_{m=1}^{M} \sum_{h=1}^{j} I^m(\alpha_h, w)} \tag{19}$$

3. The optimal weights are those associated with the pair (α_j, w) that minimizes the average FZ0 score defined by:

$$aFZ0(\alpha_j, w) \equiv \frac{1}{w} \sum_{i=t-w+1}^{t} FZ0(\sum_{m=1}^{M} w_i^m(\alpha_j, w) VaR^m(\hat{R}_{t+h}), \sum_{m=1}^{M} w_i^m(\alpha_j, w) ES^m(\hat{R}_{t+h})) \tag{20}$$

Table 1 illustrates how weights in the forecast combination are selected with a simple numerical example. Suppose forecasts with four different forecasting methods have been obtained (denoted with Mod.x, for x=1,2,3,4). A discrete set of confidence levels is indicated in column (1). Panels A and B report results for two evaluation windows of differing length, $w1$, and $w2$. Columns (1)-(4) report the classification of each forecast as dominated (I=0) or non-dominated (I=1) for each model according to DM tests: as the confidence level increases, the number of dominated models is (weakly) increasing. Columns (6)-(15) compute cumulative sums of indicators functions, relevant weights, and the average of the FZO score associated with each weight profile for all confidence levels and the two evaluation windows. The minimum of the FZ0 score associated with each of the two windows is marked in *red*. The chosen combination is the one corresponding to the minimum of these two FZO scores: in the example, the minimum is 0.42 corresponding to $w = w2$ and $\alpha_j = 0.75$.

3.4.2 Corrections to the forecast combinations

Validation of a tail risk forecasts is typically assessed through backtesting. Several tests are available to backtest VaR, and many tests have been recently proposed in the literature to backtest ES. As pointed out by Acerbi and Szekely (2017), however, while VaR is backtestable since it is elicitable, ES is not backtestable in isolation since it is not elicitable: in other words, elicitability is a necessary condition for backtestability. Acerbi and Szekely (2017) propose "ridge backtests" that allow to backtest (VaR,ES) forecasts jointly.[4]. As detailed momentarily, I use simple joint validation tests of (VaR,ES) forecasts.

Note that a forecast that does not pass a validation test indicates that the forecaster is exposed to *model risk*, which may be unavoidable if forecasting models are mis-specified. A strategy to minimize model risk and improve forecasts is based on *corrections* to VaR and ES forecasts based on several backtesting measures. These corrections essentially modify the original forecasts to ensure a set of backtests is passed at a given confidence level. In this application, I implement these corrections using hte procedure suggested by Boucher et al. (2014), implemented using the unconditional coverage tests formulated for VaR by Kupiec (1995), and that for ES formulated by Du and Escanciano (2017).

The corrections are implemented as follows. Let $(VaR_\tau^P(t,h)), (ES_\tau^P(t,h))$ denote the forecast combination selected at forecasting date t on the basis of the evaluation window $\bar{w}$. The null hypothesis of the Kupiec's test posits that the estimated frequency of violations of the VaR equals the probability level p of interest (in this paper, $p = 0.10$). The test statistics is a likelihood ratio test distributed asymptotically as a χ^2 with one degree of freedom. The null hypothesis of the Du and Escanciano's test is that the estimated frequency of *cumulative* violations, defined by $H(p) = \frac{1}{p}(p - u_t)I(u_t \leq p)$, where u_t is the estimated probability level corresponding to the empirical distribution of returns, equals the probability level $p/2$. The corresponding test statistics is distributed as a standardized normal. Then, the percentage corrections $cVaR, cES$ are determined such that $((1 + cVaR)VaR_\tau^P(\hat{R}_{t+h})), (1 + cES)ES_\tau^P(\hat{R}_{t+h}))$ pass both the VaR and ES backtests at a 5% confidence level.

3.5 A vulnerability index

The quantitative results of the (VaR,ES) forecast combinations are embedded in the EWS by using these forecasts to generate signals of forthcoming increases in tail risks. To this end, I use

[4]Separate backtests of VaR and ES based on the Fissler and Ziegel (2016) scoring functions have been recently implemented by Patton et al (2019) and Nolde and Ziegel (2017)

a binary model where the probability of the empirical VaR violations is predicted by lagged ES forecasts. A prediction exceeding a threshold determined by minimization of the sum of forecast errors provides a signal of future realizations of VaR violations. The vulnerability index is thus constructed based on a standard Receiver Operating Characteristic (ROC) analysis.

Formally, define the indicator function $I(R_t) = 1$ if $R_t \leq q(R_t)$, and $I(R_t) = 0$ otherwise, where the event $R_t \leq q_\tau(R_t)$ is the violation of the empirical VaR computed over all observations of a return up to the forecasting date t. The binary model of the probability of a violation estimated with the available data up to the forecasting date t is a Logistic regression given by:

$$P(I(R_t)) = Logit\big(\sum_{h=0}^{12} a_h ES^*(\hat{R}_{t-h})\big) \tag{21}$$

where the probability of a violation is predicted by 12 lags of ES forecasts.

To obtain a signal of the probability of a violation, the prediction of Equation (22) is used to identify the threshold value of $P(I(R_t))$ corresponding to the minimization of a weighted sum of the probability of issuing a signal when $R_t > q_\tau(R_t)$ (a false alarm) , and that of not issuing a signal when $R_t \leq q_\tau(R_t)$ (a missed violation). Denote the fraction of false alarms and missed tail risk realizations with P_1 and P_2 respectively. Then, the threshold $\hat{P}(I(R_t))$ is chosen to minimize the linear combination of errors $\alpha P_1 + (1-\alpha)P_2$, where $\alpha \in (0,1)$. The weight α is chosen according to the relative costs associated with false alarms and missed tail risk realizations. The predictive ability of such signal is evaluated using the area under the ROC curve (AUROC). [5]

Denoting with $P^*(I(R_t))$ and $\hat{P}(I(R_t))$ the threshold probability and the actual prediction at forecasting date t respectively, the vulnerability index is defined by:

$$VI(R_T) = \max\{0, \hat{P}(I(R_t)) - P^*(I(R_t))\} \tag{22}$$

The interpretation of this index is straightforward: a signal of a high probability of a tail risk

[5] The AUROC provides a simple test against the null hypothesis value of 0.5, which corresponds to classifying states of tail risk and no-tail risk realizations via a coin toss. The AUROC is bounded above by 1, which denotes a perfect classification. Under the assumption of asymptotic normality, a test of significant difference of the estimated AUROC value against the null of 0.5 can be performed.

realization is issued when the predicted probability of a violation is greater than the threshold, with the size of the difference capturing the severity of the deviation.

4 Tail risks in the G7 non-financial and banking sectors

I implement the EWS using monthly equity returns of indexes of non-financial firms (RNF) and banks (RB) for the G7 countries during the period 1975:1-2018:12. To illustrate some properties of the data and the mechanics of the EWS, I first present the results of a combination that includes in-sample predictions of the three models and the relevant equally weighted combination (EWC) of their predictions. Then I turn to illustrate the results obtained by constructing forecast combinations in real time and assessing the signal properties of the vulnerability index.

4.1 In-sample prediction combinations

Table 2 reports the parameters of the three models and relevant HAC p-values estimated over the entire sample. Across all models and samples, the risk factor predicts lower h-period ahead expected returns and 0.10 quantiles (models 1 and 3 respectively) and higher return volatility (model 2), although in few instances coefficients are not statistically different from zero at a 5% significance level.

Table 3 reports the optimal weights of Models 1-3 and the EWC. Note that in this case, the evaluation data window is the entire data set. The inclusion of the EWC in the combination is instrumental in assessing to what extent deviations from equal weights of each model in the prediction combination identify their effective contribution to the fit of the prediction. Across the two variables, the four horizons, and the seven countries, there is significant variation of the weights of each model and the EWC. However, every model contributes to the prediction combination as it receives a non-trivial positive weight, although the largest weights are in most cases associated with Models 2 and 3, suggesting an important role on the impact of the risk factor on return volatility (through Model 2) and the presence of asymmetries in the distribution of returns captured by the quantile model (Model 3). The EWC contributes significantly to the predictive combination as well, but the relatively large positive weights of the individual models imply that the EWC is not the best prediction combination.

Figure 1 reports mean and standard deviation of the prediction combination of ES for all variables and countries. Two results are worth noticing. First, both mean and volatility of the ES forecast vary markedly across variables, horizons and countries, suggesting significant heterogeneity in the sources of risks. Second, the ES forecast of RNF is strictly lower than the ES forecast of RB in *all* countries, indicating significantly higher exposures of the banking sectors to the risk factor relative to the non-financial sectors.

4.2 Real-time forecast combinations

I construct a forecast combination that includes the following set of forecasting methods:

1. baseline forecasts of each model and their EWC combinations obtained with 120-month and 84-month rolling estimation windows;

2. EWC forecast combinations of the two stress test specifications using a 84-month rolling estimation window.

Therefore, the forecast combination for each of the four forecasting horizons is obtained by selecting weights of 10 forecasting methods: 4 baseline forecasts for 2 estimation windows plus 2 EWC stress forecasts estimated on the shorter window. The first estimation is conducted on the data window 1975:1-1984:12, with the first 1-month ahead forecast for 1985:1. The first evaluation window starts in 1985:1 and ends in 1991:12. Thereafter, all forecasts are produced from 1992:1 on.

The weights obtained with the forecasting strategy described previously indicate the marginal contribution of each individual model specification to the forecast combination. The inclusion of the EWC combinations is useful to assess how weights diverge from the EWC. [6] The inclusion of forecasts using different estimation windows aims at capturing the potential time variation in the estimated parameters. In sum, the contribution of stress forecasts to forecasting performance is assessed by the size of their weights in the forecast combination.

[6]Note, however, that other pre-determined combinations could be considered, such as one whose weights are proportional to the relative magnitude of the FZ0 score associated with each model, if so desired.

Table 4 reports averages of mean, minima and maxima of weights across all countries (Appendix Tables A1 and A2 reports these statistics for each country). Three results stand out. First, while average weights do not appear to differ significantly across methods, there are notable variations across maxima, which suggest that some methods contribute most to the forecast combination in specific time periods. Moreover, no forecast receives positive weights over all forecasting dates, indicating that every forecast ends up being dominated at some dates. Second, average weights of baseline forecasts using the longer and the shorter rolling windows are similar, suggesting that the exclusive use of one rolling window of fixed length, often used in some contributions of the literature, is not necessarily best in a forecasting context. Third, the weights of the domestic stress scenarios (Stress 1) relative to the external stress scenario (Stress 2) are lower at shorter forecast horizons and larger at a longer horizon. This suggests a larger impact of external shocks in the short term, and a stronger impact of domestic shocks in the longer term.

Focusing on comparisons of aggregate weights of baseline and stress forecasts, the weights of the latter are sizeable and increase with the length of the horizon, reaching about a 30% average for the 12-month horizon for both RNF and RB returns. Figure set 1 illustrates the dynamics of baseline and stress aggregate weights for the US, UK and Germany (BD) for 1-month- and 12 month-ahead forecasts. Time variations of weights are significant, with stress forecast receiving larger weight at longer horizons even during periods of relatively low values of the risk factor.

Turning to the relationship of ES forecasts with indicators of real and financial stress, Figure Sets 2 and 3 depict ES forecast combinations for both RNF and RB in each country. The jagged lines mark the dates of indicators of "real distress" and "financial distress". The real distress indicator is the 3-month sum of a series that takes the values of 1 and 2 if the yearly growth of industrial production is between the 10th and 5th quantile, and lower than the 5th quantile, respectively, and 0 otherwise. The financial distress indicator is that constructed by Romer and Romer (2017) based on OECD textual coding of perceived financial stress by OECD observers. In almost all cases, the ES forecasts of RNF and RB anticipate periods of real and financial stress. Importantly, the 12-month ES forecast appears to be the ones that first anticipate stress dates: these are indeed the ES forecast combinations where stress forecasts receive the larger weights.

Do ES forecasts capture the externality-driven forces that may turn bank portfolios' tail risks into systemic risk? Brownlee and Engle (2017) proposed their SRISK measure as one capturing these externalities, based on the notion that the likelihood of a realization of systemic risk is higher when the banking system as a whole is under-capitalized. Note that the SRISK measure is built bottom up from a large set of individual bank returns. By contrast, my measures are based on bank portfolios that include a more limited sample of the banks. Yet, as shown in Figure Set 4, the ES forecasts closely track, and in some instances even anticipate, the SRISK measure. This result suggests that ES forecast combinations constructed in this paper also capture tail risk realizations arising from systemic risk.

Does the vulnerability indicator (VI) provide relatively accurate and timely signals of tail risk realizations? The answer appears affirmative. As shown in Table 5, its predictive accuracy is relatively high and stable, as measured by mean and minima and maxima of the AUROC computed at each forecasting date. For all countries and on average, the AUROC ranges between 80% and 90%. Furthermore, as shown in Figure 5, the VI for RB tracks and even anticipates in some instances the Romer and Romer financial stress index described previously.

5 Conclusion

This paper has formulated an EWS based on forecast combinations of (VaR,ES) pairs for indicators of tail financial risk in the non-financial and banking sectors that integrates stress testing scenarios into forecasting. The implementation on data for the G7 countries shows that the proposed EWS is promising in delivering timely early warning signals for tail risks up to a 12-month forecasting horizon and an assessment of their quantitative impact. Importantly, integrating stress testing into forecasting improves the EWS forecasting performance.

The EWS presented in this paper has been designed parsimoniously in terms of models and variables used to illustrate in a transparent way its underlying assumptions and the details of its implementation. However, the proposed methodology can be easily and usefully expanded in several directions due to its flexibility. For example, the EWS can be implemented using data at any level of dis-aggregation (firm, sector, country), and it can incorporate any desired set of forecasting models and methods from which to construct useful forecasts of tail financial risk measures. Some of these extensions are part of my ongoing research.

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Tables and Figures

Table 1. Forecasting Strategy Example

Indicator functions (I=0: dominated)							Cumulative sum of indicator functions				Cumulative weights				aFZ0(w)
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
alpha	Mod 1	Mod 2	Mod 3	Mod 4	sum I	cum. sum I	Mod 1	Mod 2	Mod 3	Mod 4	w1	w2	w3	w4	
							Panel A (w=w1)								
0.05	0	1	1	1	3	3	0	1	1	1	0.00	0.33	0.33	0.33	0.57
0.25	0	1	1	0	2	5	0	2	2	1	0.00	0.40	0.40	0.20	0.53
0.50	**0**	**1**	**1**	**0**	**2**	**7**	**0**	**3**	**3**	**1**	**0.00**	**0.43**	**0.43**	**0.14**	**0.48**
0.75	0	0	1	0	1	8	0	3	4	1	0.00	0.38	0.50	0.13	0.51
0.95	0	0	1	0	1	9	0	3	5	1	0.00	0.33	0.56	0.11	0.63
							Panel B (w=w2)								
0.05	1	1	1	1	4	4	1	1	1	1	0.25	0.25	0.25	0.25	0.53
0.25	0	1	1	1	3	7	1	2	2	2	0.14	0.29	0.29	0.29	0.51
0.50	0	1	1	1	3	10	1	3	3	3	0.10	0.30	0.30	0.30	0.48
0.75	**0**	**1**	**1**	**0**	**2**	**12**	**1**	**4**	**4**	**3**	**0.08**	**0.33**	**0.33**	**0.25**	**0.42**
0.95	0	0	1	0	1	13	1	4	5	3	0.08	0.31	0.38	0.23	0.56

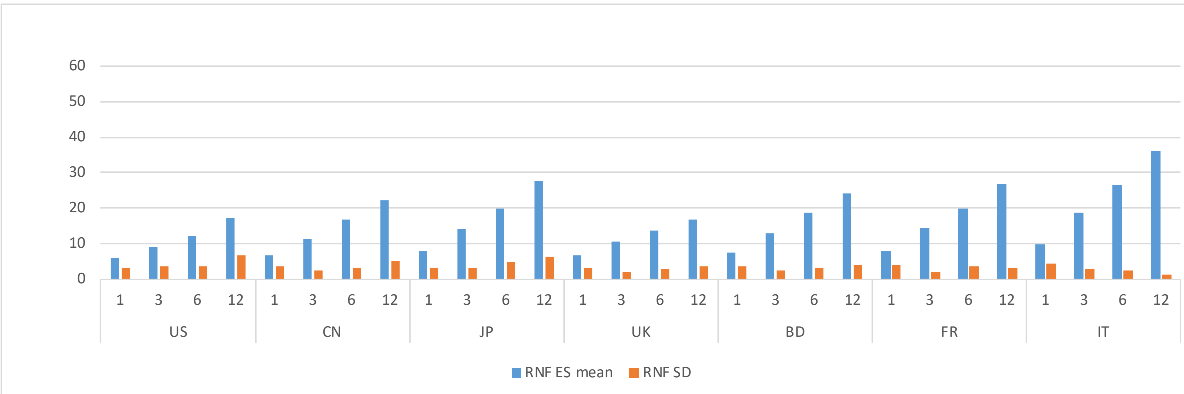
Table 2. Estimated Coefficients of Models 1-3

			Model 1		Model 2				Model 3	
		horizon h	beta(h)	p-value	beta(h)	p-value	phi(h)	p-value	beta(tau,h)	p-values
US										
	RNF	1	**-2.37**	0.00	**-0.95**	0.02	**1.83**	0.00	**-6.12**	0.00
		3	**-2.19**	0.00	**-0.78**	0.30	**1.52**	0.00	**-2.86**	0.10
		6	**-2.25**	0.01	**-1.44**	0.20	**1.43**	0.00	**-3.04**	0.00
		12	**-4.76**	0.00	**-4.45**	0.01	**1.39**	0.00	**-3.00**	0.01
	RB	1	**-3.12**	0.00	**-1.66**	0.00	**1.67**	0.00	**-8.83**	0.00
		3	**-4.66**	0.00	**-1.67**	0.11	**1.36**	0.00	**-1.29**	0.60
		6	**-5.28**	0.00	**-3.40**	0.04	**1.20**	0.00	**-3.01**	0.06
		12	**-6.15**	0.00	**-5.50**	0.03	**0.98**	0.00	**-1.83**	0.25
CN										
	RNF	1	**-2.51**	0.00	**-0.45**	0.30	**1.79**	0.00	**-5.95**	0.00
		3	**-1.99**	0.00	**-0.25**	0.78	**1.10**	0.00	**-2.67**	0.04
		6	**-2.12**	0.04	**-1.37**	0.32	**1.03**	0.00	**-1.92**	0.04
		12	**-5.29**	0.00	**-4.12**	0.03	**0.93**	0.00	**-1.22**	0.22
	RB	1	**-1.60**	0.00	**-1.07**	0.04	**1.20**	0.00	**-4.92**	0.00
		3	**-0.91**	0.15	**-0.77**	0.41	**0.84**	0.00	**0.51**	0.70
		6	**0.35**	0.71	**-1.01**	0.43	**0.80**	0.00	**-0.72**	0.47
		12	**1.07**	0.51	**-0.40**	0.83	**0.47**	0.00	**0.39**	0.73
JP										
	RNF	1	**-2.06**	0.00	**-0.53**	0.12	**1.56**	0.00	**-5.07**	0.00
		3	**-3.40**	0.00	**-2.51**	0.00	**0.90**	0.00	**-0.55**	0.70
		6	**-5.37**	0.00	**-5.02**	0.00	**0.80**	0.00	**-3.67**	0.00
		12	**-8.09**	0.00	**-7.61**	0.00	**0.63**	0.00	**-1.67**	0.12
	RB	1	**-2.73**	0.00	**-1.31**	0.01	**1.54**	0.00	**-7.81**	0.00
		3	**-5.50**	0.00	**-5.12**	0.00	**0.60**	0.00	**-0.91**	0.60
		6	**-7.84**	0.00	**-7.93**	0.00	**0.61**	0.00	**-6.02**	0.00
		12	**-13.65**	0.00	**-13.82**	0.00	**0.33**	0.02	**-5.44**	0.00
UK										
	RNF	1	**-1.03**	0.00	**-0.71**	0.10	**1.95**	0.00	**-5.55**	0.00
		3	**0.08**	0.89	**-0.72**	0.43	**1.25**	0.00	**-1.18**	0.21
		6	**0.29**	0.75	**-1.13**	0.37	**1.15**	0.00	**-2.24**	0.00
		12	**0.73**	0.58	**-1.50**	0.37	**1.19**	0.00	**-0.46**	0.60
	RB	1	**-2.56**	0.00	**-1.91**	0.00	**1.89**	0.00	**-9.43**	0.00
		3	**-3.09**	0.00	**-4.03**	0.00	**1.38**	0.00	**-0.66**	0.81
		6	**-4.43**	0.00	**-6.01**	0.00	**1.31**	0.00	**-4.17**	0.02
		12	**-5.42**	0.01	**-8.13**	0.00	**1.04**	0.00	**-1.90**	0.24
BD										
	RNF	1	**-2.67**	0.00	**-0.27**	0.50	**1.68**	0.00	**-6.13**	0.00
		3	**-2.06**	0.01	**-0.13**	0.88	**1.04**	0.00	**-1.86**	0.43
		6	**-2.31**	0.04	**-0.82**	0.54	**0.86**	0.00	**-3.34**	0.01
		12	**-4.95**	0.00	**-4.40**	0.02	**0.51**	0.00	**-2.08**	0.08
	RB	1	**-4.21**	0.00	**-0.14**	0.82	**1.88**	0.00	**-8.79**	0.00
		3	**-4.59**	0.00	**-1.47**	0.23	**1.56**	0.00	**1.66**	0.58
		6	**-5.18**	0.01	**-3.80**	0.07	**1.44**	0.00	**-4.25**	0.00
		12	**-9.12**	0.00	**-10.45**	0.00	**0.99**	0.00	**-3.13**	0.05
FR										
	RNF	1	**-3.38**	0.00	**-1.51**	0.01	**1.77**	0.00	**-8.01**	0.00
		3	**-2.65**	0.00	**-1.18**	0.35	**0.85**	0.00	**-2.41**	0.07
		6	**-4.34**	0.01	**-3.55**	0.06	**0.75**	0.00	**-2.63**	0.02
		12	**-4.74**	0.07	**-4.97**	0.07	**0.43**	0.02	**1.37**	0.24
	RB	1	**-4.31**	0.00	**-1.65**	0.01	**1.72**	0.00	**-10.12**	0.00
		3	**-3.98**	0.00	**-1.78**	0.16	**1.05**	0.00	**-1.43**	0.44
		6	**-4.95**	0.00	**-4.07**	0.05	**0.87**	0.00	**-3.55**	0.04
		12	**-4.62**	0.12	**-4.78**	0.13	**0.23**	0.15	**1.53**	0.33
IT										
	RNF	1	**-2.19**	0.00	**-1.42**	0.04	**1.87**	0.00	**-7.46**	0.00
		3	**-2.77**	0.03	**-2.37**	0.08	**0.88**	0.00	**-3.78**	0.02
		6	**-2.82**	0.12	**-2.44**	0.24	**0.40**	0.00	**-0.68**	0.67
		12	**-5.02**	0.12	**-5.73**	0.06	**-0.21**	0.24	**-2.47**	0.05
	RB	1	**-5.15**	0.40	**-8.41**	0.00	**-1.64**	0.00	**-11.02**	0.00
		3	**-10.23**	0.28	**-9.65**	0.00	**-1.74**	0.00	**-1.03**	0.60
		6	**-14.69**	0.17	**-14.97**	0.01	**-1.47**	0.00	**-6.01**	0.00
		12	**-24.33**	0.13	**-27.59**	0.00	**-1.88**	0.00	**-3.13**	0.11

Table 3. Weights of the prediction combination (1975:1-2018:12)

		Models' weights								Effective models' weights					
		RNF				RB				RNF			RB		
	h	Model 1	Model 2	Model 3	EWC	Model 1	Model 2	Model 3	EWC	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
US	1	0.00	0.33	0.33	**0.33**	0.00	0.33	0.33	**0.33**	0.11	0.44	0.44	0.11	0.44	0.44
	3	0.00	0.33	0.33	**0.33**	0.25	0.25	0.25	**0.25**	0.11	0.44	0.44	0.33	0.33	0.33
	6	0.26	0.26	0.23	**0.26**	0.31	0.31	0.06	**0.31**	0.34	0.34	0.32	0.42	0.42	0.16
	12	0.41	0.45	0.04	**0.11**	0.34	0.34	0.05	**0.26**	0.44	0.49	0.07	0.43	0.43	0.14
CN	1	0.00	0.33	0.33	**0.33**	0.25	0.25	0.25	**0.25**	0.11	0.44	0.44	0.33	0.33	0.33
	3	0.27	0.27	0.18	**0.27**	0.33	0.33	0.00	**0.33**	0.36	0.36	0.27	0.44	0.44	0.12
	6	0.33	0.33	0.01	**0.33**	0.33	0.33	0.01	**0.33**	0.44	0.44	0.12	0.44	0.44	0.12
	12	0.33	0.33	0.01	**0.33**	0.33	0.33	0.02	**0.33**	0.44	0.44	0.12	0.44	0.44	0.13
JP	1	0.00	0.33	0.33	**0.33**	0.00	0.50	0.50	**0.00**	0.11	0.44	0.44	0.00	0.50	0.50
	3	0.33	0.33	0.00	**0.33**	0.09	0.38	0.15	**0.38**	0.44	0.44	0.11	0.21	0.51	0.28
	6	0.33	0.33	0.00	**0.33**	0.33	0.34	0.00	**0.34**	0.44	0.44	0.11	0.44	0.45	0.11
	12	0.33	0.33	0.00	**0.33**	0.33	0.33	0.00	**0.33**	0.44	0.44	0.11	0.44	0.44	0.11
UK	1	0.00	0.33	0.33	**0.33**	0.00	0.33	0.33	**0.33**	0.11	0.44	0.44	0.11	0.44	0.44
	3	0.28	0.28	0.18	**0.28**	0.25	0.25	0.25	**0.25**	0.37	0.37	0.27	0.33	0.33	0.33
	6	0.22	0.35	0.07	**0.35**	0.31	0.33	0.02	**0.33**	0.34	0.47	0.19	0.42	0.44	0.14
	12	0.44	0.46	0.04	**0.07**	0.32	0.32	0.03	**0.32**	0.46	0.48	0.06	0.43	0.43	0.14
BD	1	0.00	0.33	0.33	**0.33**	0.00	0.50	0.50	**0.00**	0.11	0.44	0.44	0.00	0.50	0.50
	3	0.27	0.27	0.18	**0.27**	0.36	0.47	0.01	**0.16**	0.36	0.36	0.27	0.42	0.52	0.06
	6	0.33	0.33	0.00	**0.33**	0.32	0.34	0.00	**0.34**	0.44	0.44	0.11	0.43	0.46	0.11
	12	0.33	0.33	0.01	**0.33**	0.33	0.33	0.00	**0.33**	0.44	0.44	0.12	0.44	0.44	0.11
FR	1	0.00	0.33	0.33	**0.33**	0.00	0.33	0.33	**0.33**	0.11	0.44	0.44	0.11	0.44	0.44
	3	0.32	0.32	0.03	**0.32**	0.33	0.33	0.01	**0.33**	0.43	0.43	0.13	0.44	0.44	0.12
	6	0.33	0.33	0.01	**0.33**	0.33	0.33	0.01	**0.33**	0.44	0.44	0.12	0.44	0.44	0.12
	12	0.33	0.33	0.01	**0.33**	0.33	0.33	0.00	**0.33**	0.44	0.44	0.12	0.44	0.44	0.11
IT	1	0.00	0.33	0.33	**0.33**	0.00	0.00	1.00	**0.00**	0.11	0.44	0.44	0.00	0.00	1.00
	3	0.33	0.33	0.01	**0.33**	0.00	0.00	0.50	**0.50**	0.44	0.44	0.12	0.17	0.17	0.67
	6	0.33	0.33	0.00	**0.33**	0.00	0.00	0.50	**0.50**	0.44	0.44	0.11	0.17	0.17	0.67
	12	0.33	0.33	0.00	**0.33**	0.00	0.00	0.50	**0.50**	0.44	0.44	0.11	0.17	0.17	0.67
Average	1	*0.00*	*0.33*	*0.33*	**0.33**	*0.04*	*0.32*	*0.46*	**0.18**	*0.11*	*0.44*	*0.44*	**0.10**	**0.38**	**0.52**
	3	*0.26*	*0.31*	*0.13*	**0.31**	*0.23*	*0.29*	*0.17*	**0.31**	*0.36*	*0.41*	*0.23*	**0.33**	**0.39**	**0.27**
	6	*0.30*	*0.32*	*0.05*	**0.32**	*0.28*	*0.28*	*0.09*	**0.36**	*0.41*	*0.43*	*0.16*	**0.39**	**0.40**	**0.20**
	12	*0.36*	*0.37*	*0.02*	**0.26**	*0.28*	*0.28*	*0.09*	**0.34**	*0.44*	*0.45*	*0.10*	**0.40**	**0.40**	**0.20**

Figure 1. Mean and Standard Deviations of the ES prediction combination (1975:01-2018:12)



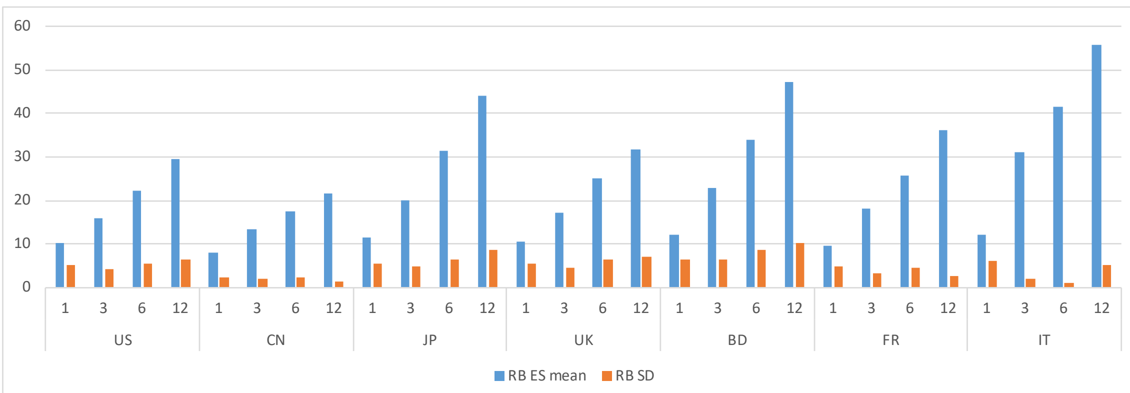


Table 4. Mean, minimum and maximum of weights of forecasting methods in the forecast combinations (1992:01-2018:12)

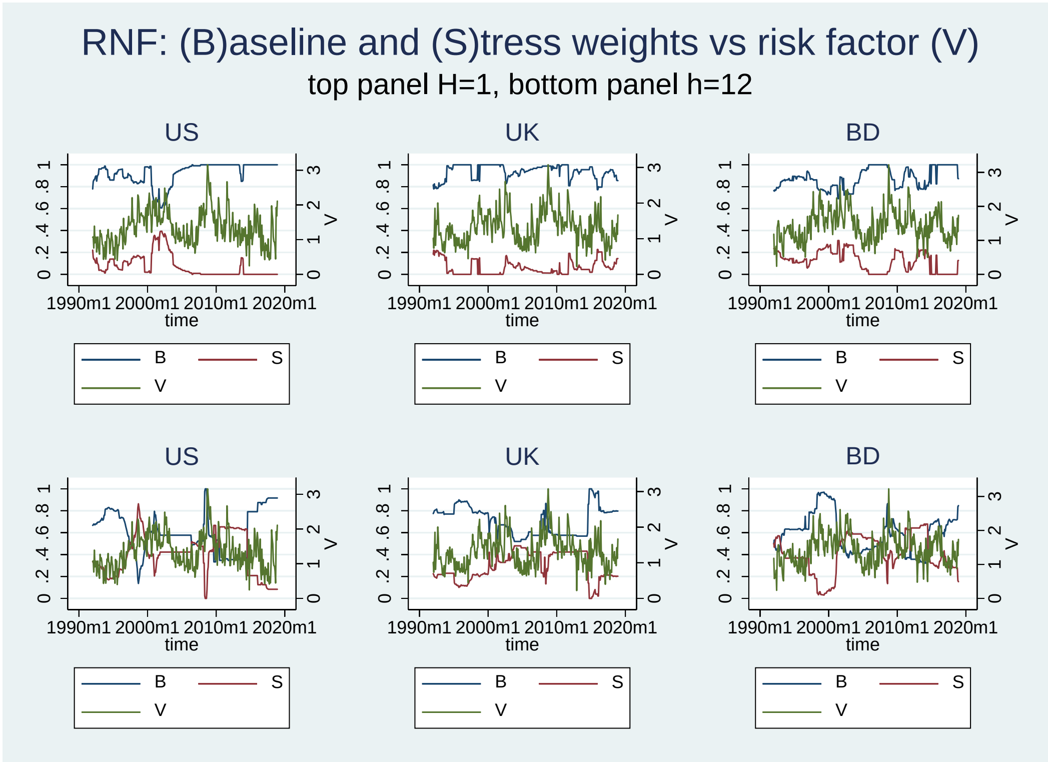
RNF

Horizon	h=1			h=3			h=6			h=12		
	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Mod.1 (w=120)	0.09	0.00	0.27	0.04	0.00	0.17	0.06	0.01	0.20	0.07	0.00	0.27
Mod.1 (w=84)	0.10	0.00	0.23	0.06	0.00	0.23	0.06	0.00	0.21	0.09	0.00	0.27
Mod.2 (w=120)	0.13	0.01	0.28	0.12	0.01	0.29	0.12	0.01	0.26	0.08	0.00	0.25
Mod.2 (w=84)	0.16	0.04	0.37	0.15	0.04	0.30	0.16	0.03	0.28	0.12	0.00	0.29
Mod.3 (w=120)	0.09	0.00	0.20	0.10	0.01	0.21	0.09	0.01	0.24	0.11	0.01	0.29
Mod.3 (w=84)	0.13	0.02	0.49	0.14	0.02	0.28	0.12	0.02	0.30	0.13	0.01	0.32
EWC (w=120)	**0.08**	**0.00**	**0.20**	**0.08**	**0.00**	**0.25**	**0.06**	**0.00**	**0.18**	**0.06**	**0.00**	**0.19**
EWC (w=84)	**0.13**	**0.01**	**0.26**	**0.10**	**0.01**	**0.22**	**0.08**	**0.02**	**0.20**	**0.05**	**0.00**	**0.18**
Stress 1 EWC (w=84)	**0.03**	**0.00**	**0.20**	**0.11**	**0.00**	**0.33**	**0.14**	**0.01**	**0.38**	**0.17**	**0.00**	**0.46**
Stress 2 EWC (w=84)	**0.06**	**0.00**	**0.38**	**0.11**	**0.01**	**0.28**	**0.11**	**0.00**	**0.27**	**0.13**	**0.01**	**0.40**
Baseline	**0.91**	**0.60**	**1.00**	**0.78**	**0.51**	**0.99**	**0.75**	**0.48**	**0.97**	**0.70**	**0.35**	**0.98**
Stress	**0.09**	**0.00**	**0.40**	**0.22**	**0.01**	**0.49**	**0.25**	**0.03**	**0.52**	**0.30**	**0.02**	**0.65**

RB

Horizon (months)	h=1			h=3			h=6			h=12		
	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Mod.1 (w=120)	0.09	0.01	0.23	0.05	0.00	0.17	0.06	0.00	0.19	0.08	0.00	0.24
Mod.1 (w=84)	0.10	0.00	0.26	0.05	0.00	0.19	0.09	0.01	0.22	0.10	0.00	0.25
Mod.2 (w=120)	0.12	0.02	0.23	0.12	0.01	0.30	0.11	0.00	0.32	0.07	0.00	0.25
Mod.2 (w=84)	0.14	0.03	0.34	0.14	0.02	0.30	0.15	0.01	0.32	0.11	0.00	0.30
Mod.3 (w=120)	0.11	0.01	0.26	0.09	0.01	0.24	0.07	0.01	0.22	0.07	0.00	0.25
Mod.3 (w=84)	0.11	0.02	0.35	0.14	0.03	0.33	0.12	0.02	0.27	0.14	0.02	0.34
EWC (w=120)	**0.11**	**0.00**	**0.20**	**0.08**	**0.00**	**0.21**	**0.05**	**0.00**	**0.18**	**0.06**	**0.00**	**0.21**
EWC (w=84)	**0.12**	**0.02**	**0.24**	**0.10**	**0.01**	**0.23**	**0.09**	**0.01**	**0.22**	**0.06**	**0.00**	**0.22**
Stress 1 EWC (w=84)	**0.03**	**0.00**	**0.16**	**0.10**	**0.00**	**0.31**	**0.16**	**0.00**	**0.36**	**0.20**	**0.02**	**0.46**
Stress 2 EWC (w=84)	**0.07**	**0.00**	**0.27**	**0.13**	**0.00**	**0.36**	**0.11**	**0.01**	**0.31**	**0.11**	**0.00**	**0.38**
Baseline	**0.90**	**0.69**	**1.00**	**0.77**	**0.38**	**0.98**	**0.73**	**0.49**	**0.95**	**0.69**	**0.34**	**0.94**
Stress	**0.10**	**0.00**	**0.31**	**0.23**	**0.02**	**0.62**	**0.27**	**0.05**	**0.51**	**0.31**	**0.06**	**0.66**

Figure Set 1


RNF: (B)aseline and (S)tress weights vs risk factor (V)
top panel H=1, bottom panel h=12
US
UK
BD
0 .2 .4 .6 .8 1
0 1 2 3
V
1990m1 2000m1 2010m1 2020m1
time
B
S
V

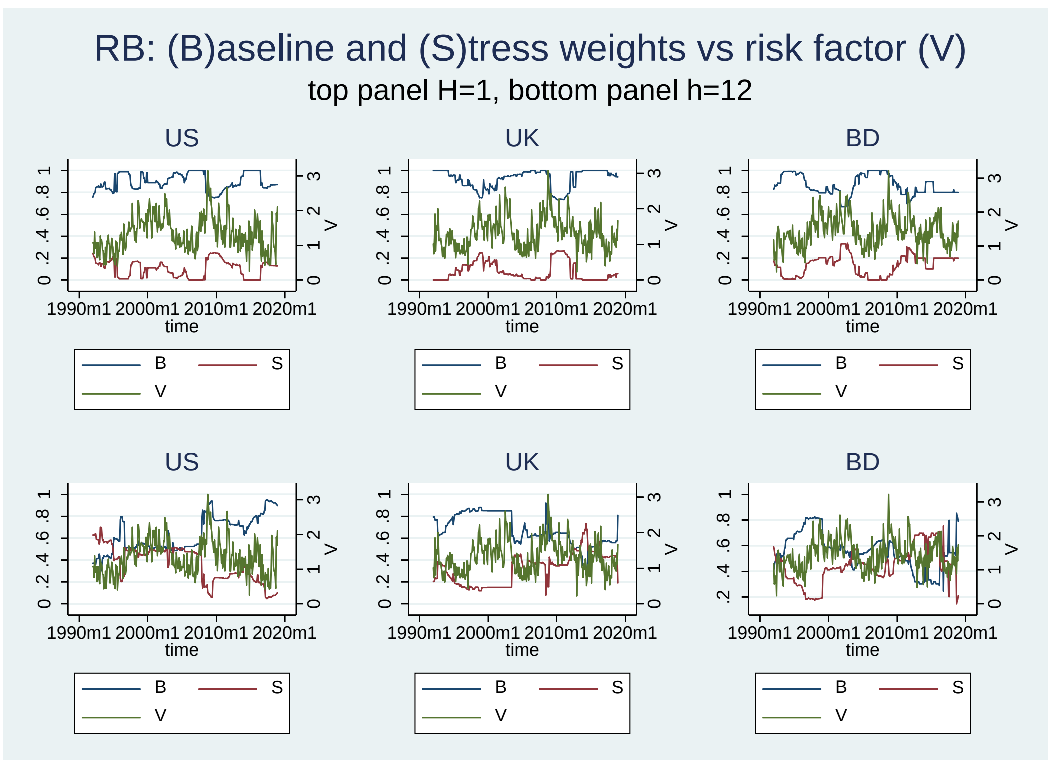
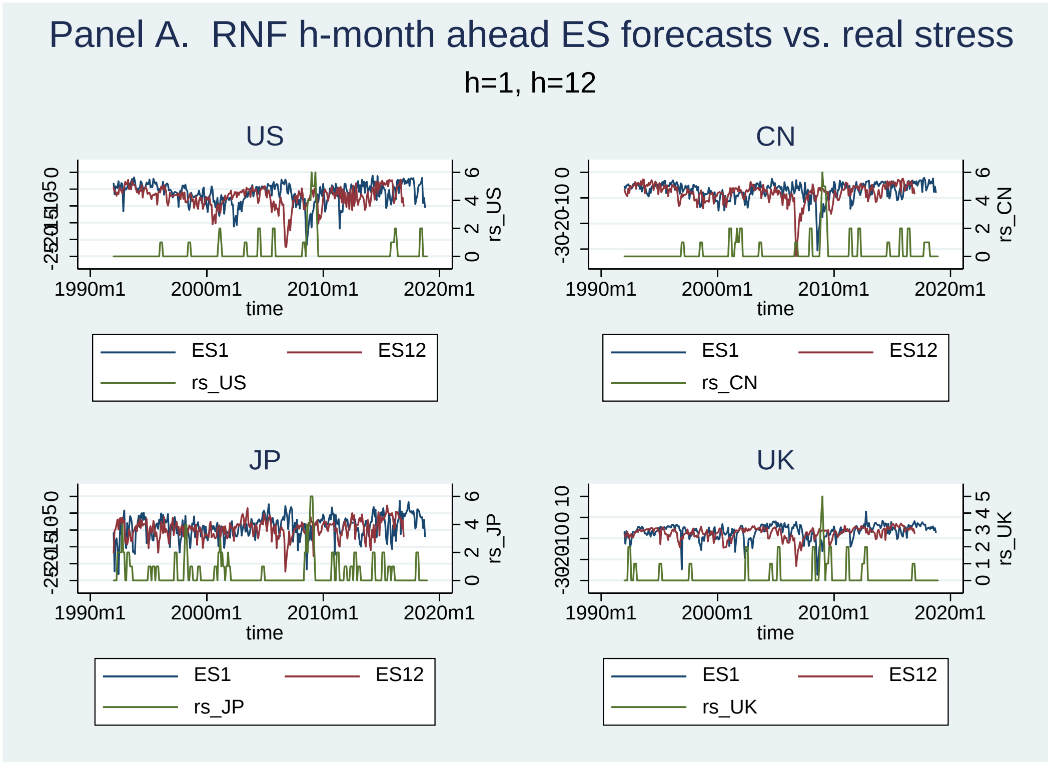

RB: (B)aseline and (S)tress weights vs risk factor (V)
top panel H=1, bottom panel h=12
US
UK
BD
0 .2 .4 .6 .8 1
.2 .4 .6 .8 1
0 1 2 3
V
1990m1 2000m1 2010m1 2020m1
time
B
S
V

Figure Set 2


Panel A. RNF h-month ahead ES forecasts vs. real stress
h=1, h=12
US
CN
JP
UK
1990m1
2000m1
2010m1
2020m1
time
ES1
ES12
rs_US
rs_CN
rs_JP
rs_UK

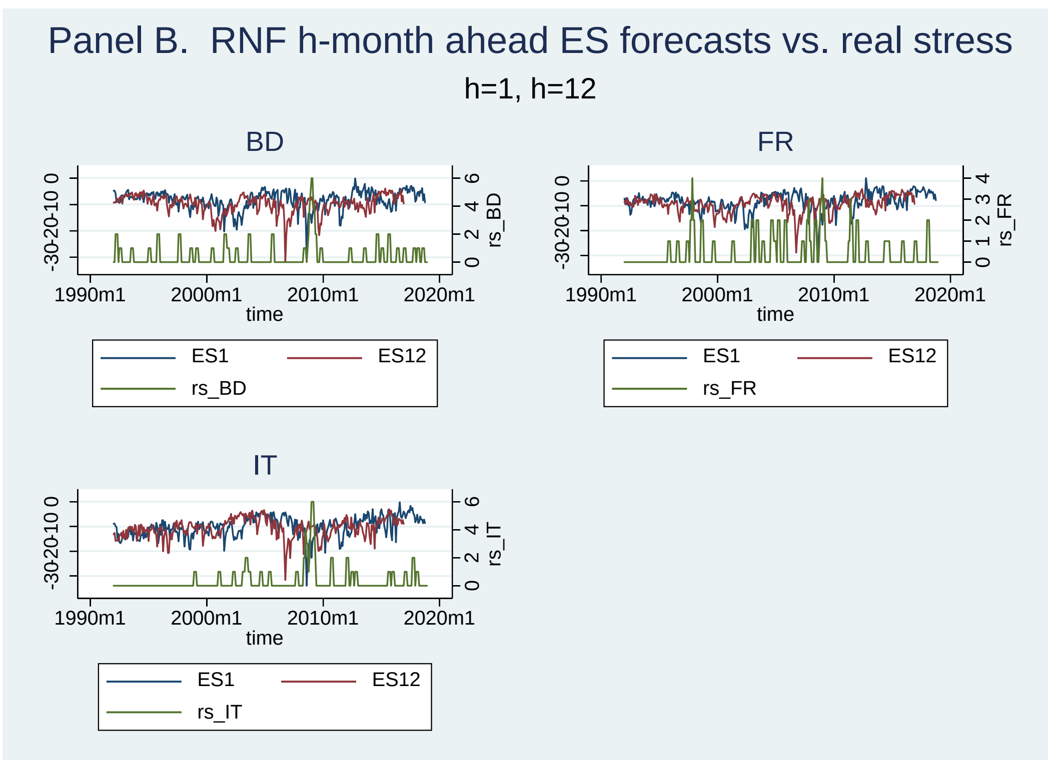
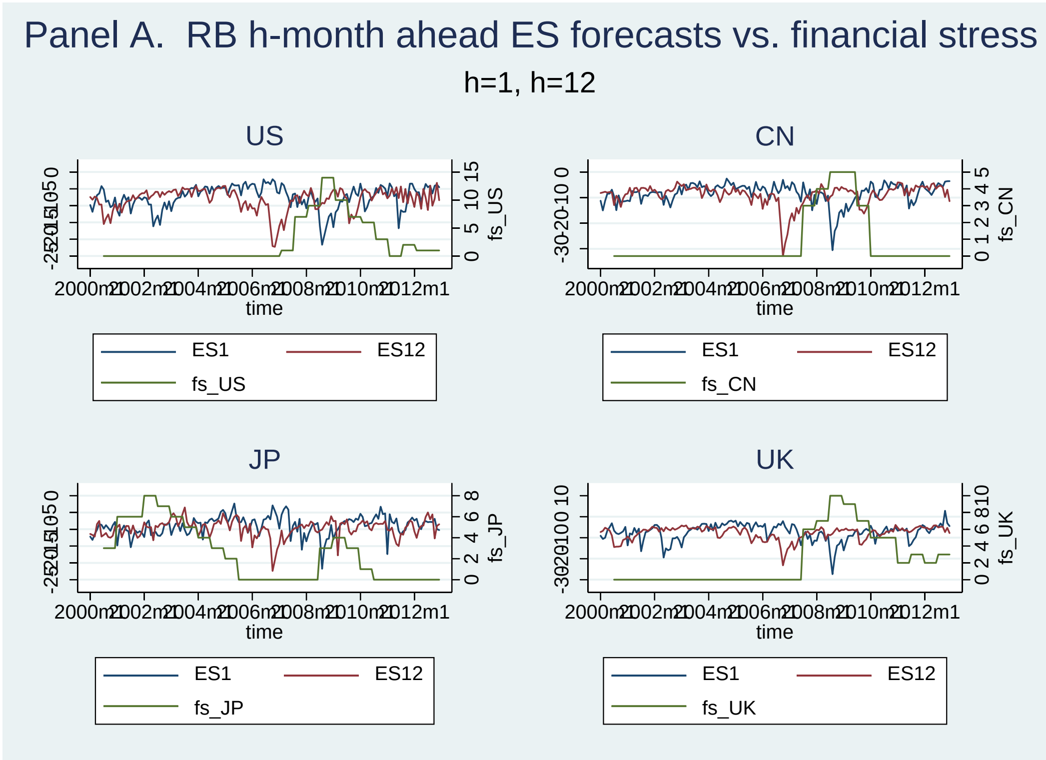

Panel B. RNF h-month ahead ES forecasts vs. real stress
h=1, h=12
BD
FR
IT
1990m1
2000m1
2010m1
2020m1
time
ES1
ES12
rs_BD
rs_FR
rs_IT

Figure Set 3


Panel A. RB h-month ahead ES forecasts vs. financial stress
h=1, h=12
US
CN
JP
UK
time
ES1
ES12
fs_US
fs_CN
fs_JP
fs_UK

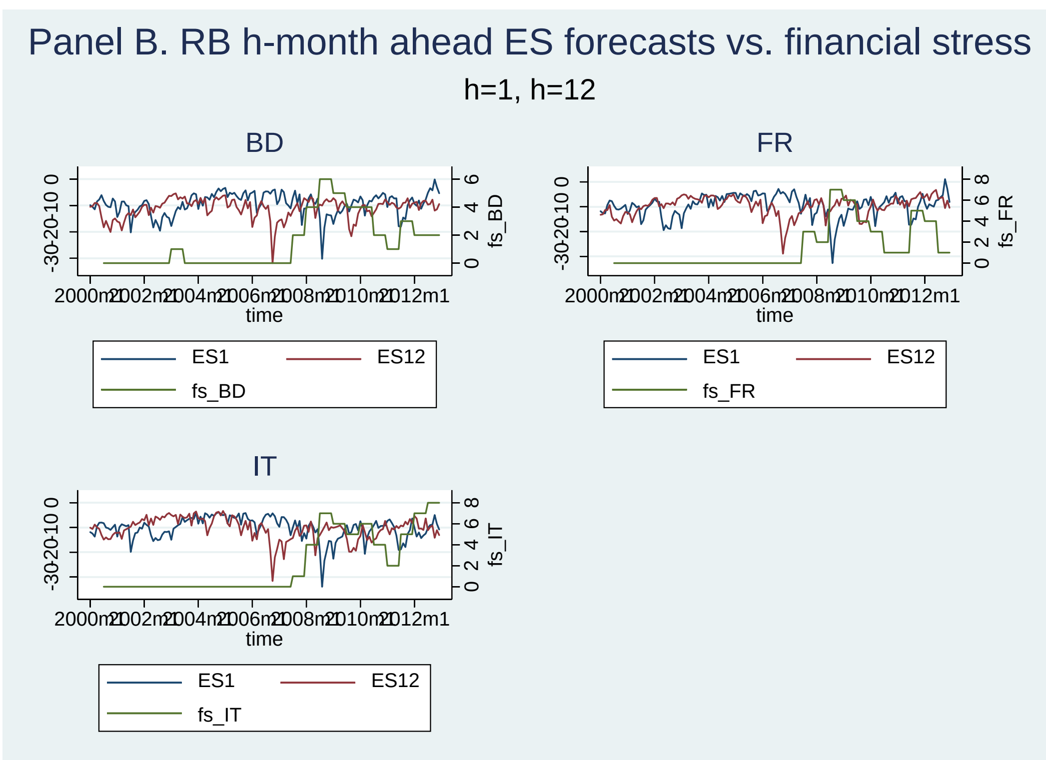
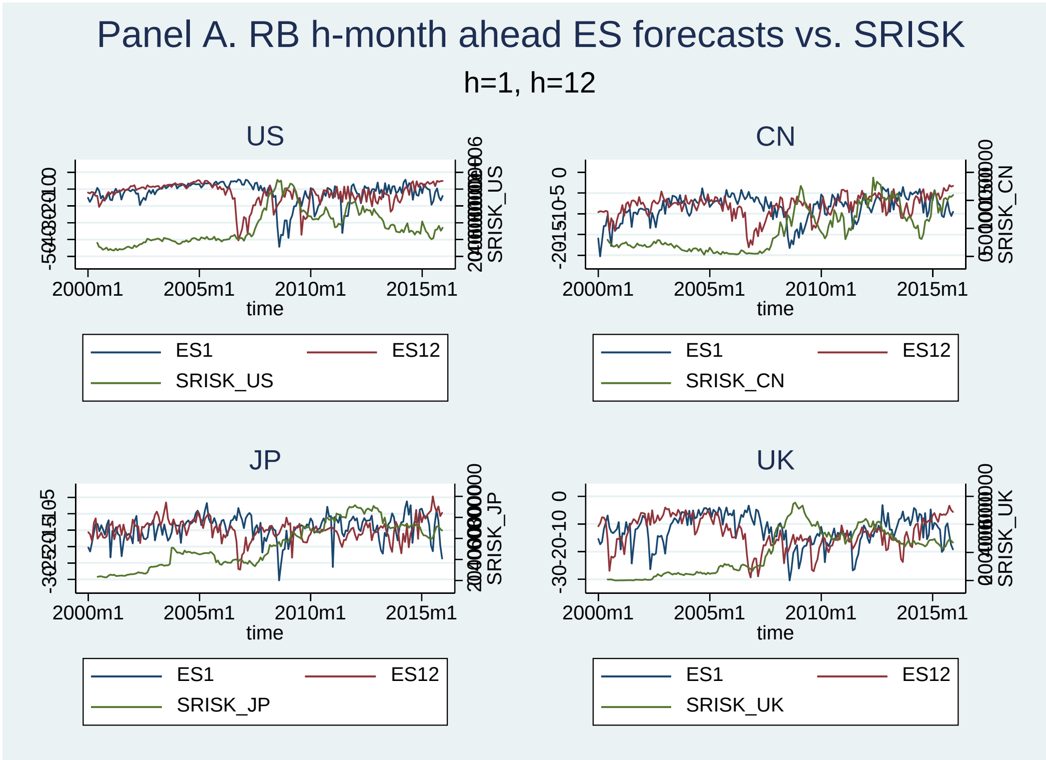

Panel B. RB h-month ahead ES forecasts vs. financial stress
h=1, h=12
BD
FR
IT
time
ES1
ES12
fs_BD
fs_FR
fs_IT

Figure Set 4


Panel A. RB h-month ahead ES forecasts vs. SRISK
h=1, h=12
US
CN
JP
UK
2000m1
2005m1
2010m1
2015m1
time
SRISK_US
SRISK_CN
SRISK_JP
SRISK_UK
ES1
ES12
SRISK_US
SRISK_CN
SRISK_JP
SRISK_UK

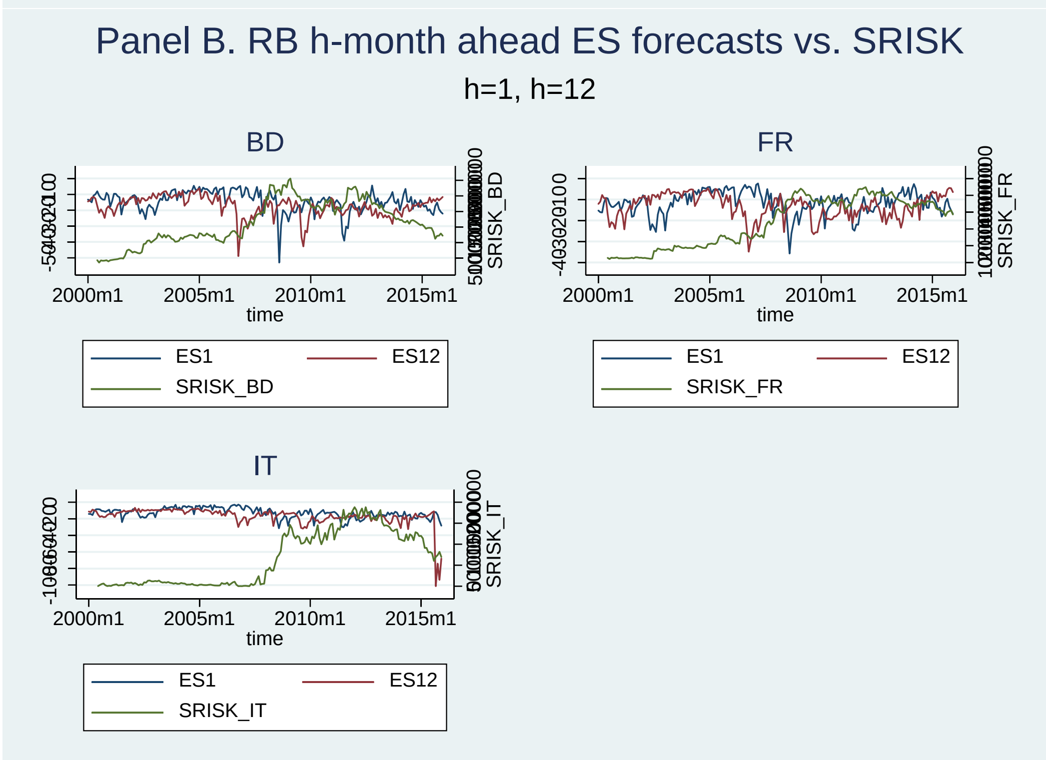
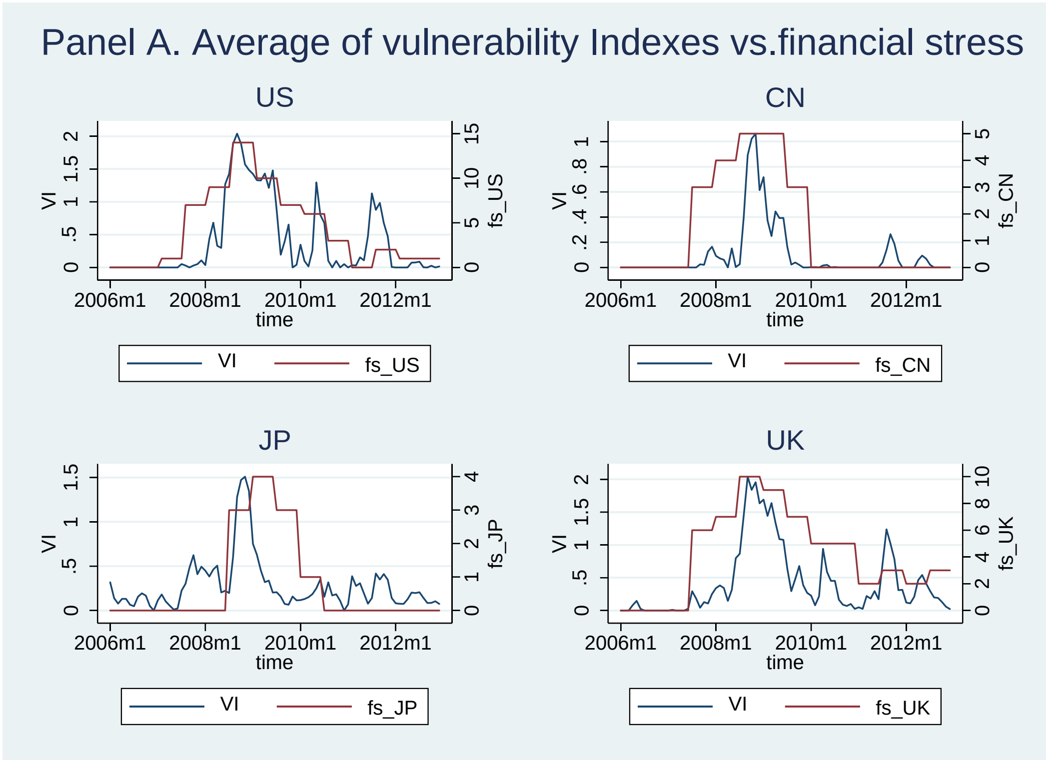
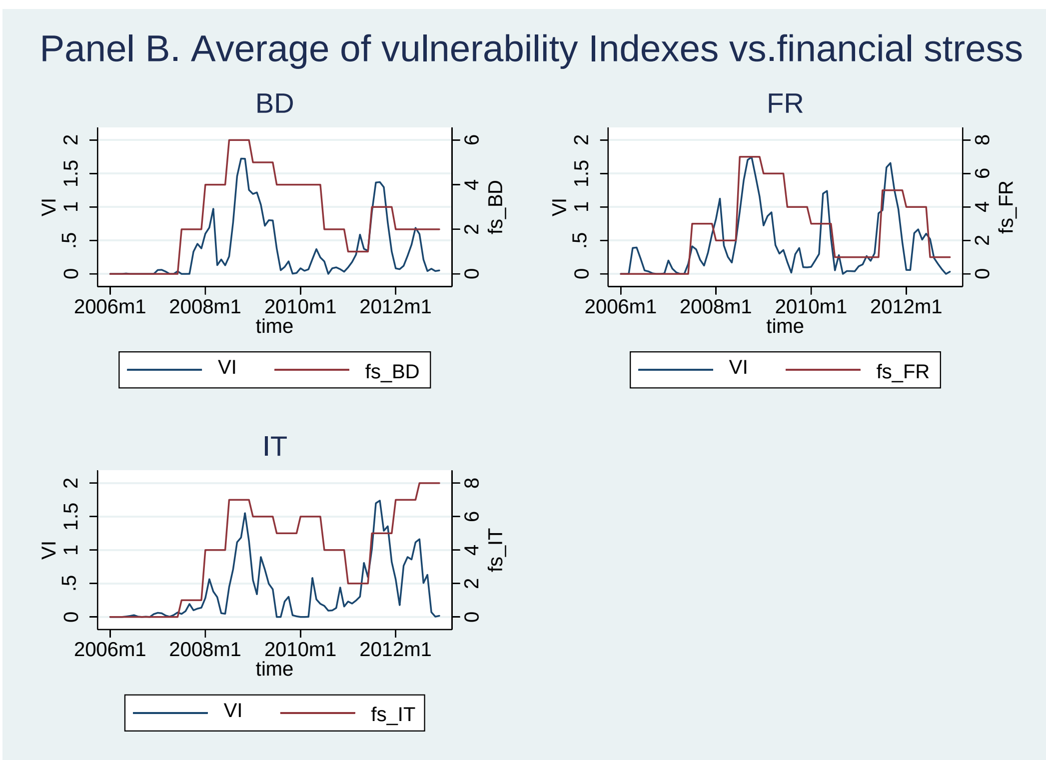

Panel B. RB h-month ahead ES forecasts vs. SRISK
h=1, h=12
BD
FR
IT
2000m1
2005m1
2010m1
2015m1
time
SRISK_BD
SRISK_FR
SRISK_IT
ES1
ES12
SRISK_BD
SRISK_FR
SRISK_IT

Table 5. Area under the ROC curve (AUROC) of the Logit model (sample: 2000:01-2018:12)

		RNF				RF		
	h (months)	**Mean**	**Min**	**Max**		**Mean**	**Min**	**Max**
US	1	0.82	0.78	0.85		0.78	0.75	0.80
	3	0.86	0.82	0.90		0.84	0.81	0.86
	6	0.86	0.81	0.89		0.85	0.81	0.87
	12	0.81	0.50	0.88		0.86	0.83	0.88
CN	1	0.83	0.79	0.85		0.80	0.76	0.84
	3	0.85	0.81	0.89		0.84	0.79	0.87
	6	0.86	0.81	0.89		0.77	0.70	0.83
	12	0.85	0.82	0.88		0.79	0.75	0.84
JP	1	0.80	0.76	0.84		0.86	0.82	0.89
	3	0.84	0.79	0.87		0.86	0.81	0.90
	6	0.77	0.70	0.83		0.85	0.80	0.89
	12	0.79	0.75	0.84		0.81	0.76	0.87
UK	1	0.86	0.82	0.89		0.82	0.78	0.84
	3	0.86	0.81	0.90		0.84	0.80	0.86
	6	0.85	0.80	0.89		0.84	0.79	0.87
	12	0.81	0.76	0.87		0.81	0.78	0.84
BD	1	0.80	0.78	0.83		0.86	0.82	0.89
	3	0.86	0.82	0.88		0.86	0.82	0.90
	6	0.85	0.81	0.87		0.84	0.81	0.88
	12	0.83	0.81	0.85		0.84	0.80	0.88
FR	1	0.86	0.82	0.89		0.79	0.76	0.83
	3	0.86	0.82	0.90		0.84	0.79	0.87
	6	0.84	0.81	0.88		0.84	0.79	0.87
	12	0.84	0.80	0.88		0.83	0.80	0.85
IT	1	0.82	0.77	0.86		0.85	0.82	0.87
	3	0.86	0.81	0.90		0.86	0.81	0.88
	6	0.84	0.80	0.88		0.85	0.82	0.88
	12	0.83	0.79	0.86		0.83	0.81	0.85
Average	**1**	**0.83**	**0.79**	**0.86**		**0.82**	**0.79**	**0.85**
	3	**0.86**	**0.81**	**0.89**		**0.85**	**0.80**	**0.88**
	6	**0.84**	**0.79**	**0.87**		**0.83**	**0.79**	**0.87**
	12	**0.82**	**0.75**	**0.87**		**0.83**	**0.79**	**0.86**

Figure Set 5


Panel A. Average of vulnerability Indexes vs.financial stress
US
CN
JP
UK
VI
fs_US
fs_CN
fs_JP
fs_UK
time
2006m1
2008m1
2010m1
2012m1


Panel B. Average of vulnerability Indexes vs.financial stress
BD
FR
IT
VI
fs_BD
fs_FR
fs_IT
time
2006m1
2008m1
2010m1
2012m1

Appendix

Table A1. RNF forecast combination weights (mean, min and max)

Horizon (months)		h=1			h=3			h=6			h=12	
	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
US												
Mod.1 (w=120)	0.08	0.00	0.18	0.03	0.00	0.13	0.02	0.00	0.24	0.05	0.00	0.22
Mod.1 (w=84)	0.10	0.00	0.21	0.03	0.00	0.28	0.05	0.00	0.25	0.08	0.00	0.37
Mod.2 (w=120)	0.13	0.02	0.22	0.09	0.00	0.31	0.14	0.04	0.25	0.06	0.00	0.22
Mod.2 (w=84)	0.18	0.07	0.36	0.19	0.00	0.37	0.17	0.00	0.29	0.11	0.00	0.28
Mod.3 (w=120)	0.11	0.00	0.23	0.09	0.00	0.24	0.12	0.02	0.24	0.08	0.00	0.27
Mod.3 (w=84)	0.07	0.02	0.24	0.20	0.07	0.38	0.16	0.05	0.38	0.14	0.02	0.46
EWC (w=120)	**0.09**	**0.00**	**0.19**	**0.07**	**0.00**	**0.35**	**0.04**	**0.00**	**0.19**	**0.05**	**0.00**	**0.23**
EWC (w=84)	**0.14**	**0.01**	**0.30**	**0.12**	**0.04**	**0.26**	**0.08**	**0.02**	**0.22**	**0.04**	**0.00**	**0.14**
Stress 1 EWC (w=84)	**0.01**	**0.00**	**0.16**	**0.06**	**0.00**	**0.21**	**0.06**	**0.00**	**0.18**	**0.24**	**0.00**	**0.86**
Stress 2 EWC (w=84)	**0.08**	**0.00**	**0.42**	**0.12**	**0.00**	**0.26**	**0.15**	**0.00**	**0.25**	**0.15**	**0.00**	**0.43**
CN												
Mod.1 (w=120)	0.10	0.00	0.32	0.05	0.00	0.18	0.08	0.01	0.24	0.04	0.00	0.21
Mod.1 (w=84)	0.11	0.00	0.21	0.06	0.00	0.20	0.08	0.00	0.29	0.11	0.00	0.26
Mod.2 (w=120)	0.12	0.02	0.22	0.12	0.00	0.30	0.11	0.00	0.32	0.10	0.00	0.22
Mod.2 (w=84)	0.13	0.00	0.32	0.15	0.04	0.28	0.17	0.05	0.30	0.15	0.00	0.27
Mod.3 (w=120)	0.07	0.00	0.17	0.08	0.00	0.19	0.09	0.01	0.28	0.08	0.00	0.25
Mod.3 (w=84)	0.13	0.01	0.53	0.16	0.03	0.32	0.13	0.03	0.38	0.13	0.01	0.28
EWC (w=120)	**0.11**	**0.00**	**0.23**	**0.07**	**0.00**	**0.20**	**0.06**	**0.00**	**0.17**	**0.04**	**0.00**	**0.17**
EWC (w=84)	**0.13**	**0.00**	**0.25**	**0.10**	**0.02**	**0.20**	**0.10**	**0.03**	**0.20**	**0.07**	**0.00**	**0.20**
Stress 1 EWC (w=84)	**0.01**	**0.00**	**0.20**	**0.09**	**0.00**	**0.28**	**0.08**	**0.00**	**0.23**	**0.18**	**0.00**	**0.39**
Stress 2 EWC (w=84)	**0.09**	**0.00**	**0.40**	**0.12**	**0.00**	**0.28**	**0.11**	**0.00**	**0.25**	**0.12**	**0.00**	**0.25**
JP												
Mod.1 (w=120)	0.11	0.00	0.29	0.04	0.00	0.19	0.02	0.00	0.17	0.06	0.00	0.17
Mod.1 (w=84)	0.08	0.00	0.20	0.05	0.00	0.24	0.03	0.00	0.14	0.09	0.00	0.23
Mod.2 (w=120)	0.13	0.00	0.40	0.14	0.00	0.32	0.17	0.00	0.41	0.13	0.00	0.26
Mod.2 (w=84)	0.18	0.07	0.43	0.09	0.00	0.19	0.13	0.00	0.27	0.15	0.02	0.39
Mod.3 (w=120)	0.06	0.00	0.17	0.10	0.00	0.17	0.08	0.00	0.20	0.19	0.04	0.41
Mod.3 (w=84)	0.20	0.09	0.67	0.09	0.00	0.20	0.10	0.00	0.23	0.07	0.00	0.24
EWC (w=120)	0.07	0.00	0.20	0.10	0.00	0.39	0.09	0.00	0.21	0.08	0.00	0.17
EWC (w=84)	0.13	0.00	0.21	0.10	0.00	0.20	0.05	0.00	0.17	0.06	0.00	0.19
Stress 1 EWC (w=84)	0.01	0.00	0.19	0.17	0.00	0.63	0.24	0.05	0.63	0.05	0.00	0.21
Stress 2 EWC (w=84)	0.03	0.00	0.22	0.12	0.00	0.22	0.07	0.00	0.24	0.12	0.03	0.32
UK												
Mod.1 (w=120)	0.07	0.00	0.33	0.04	0.00	0.17	0.06	0.00	0.15	0.08	0.00	0.24
Mod.1 (w=84)	0.09	0.00	0.20	0.05	0.00	0.22	0.05	0.00	0.24	0.14	0.00	0.33
Mod.2 (w=120)	0.16	0.00	0.34	0.16	0.01	0.28	0.11	0.01	0.20	0.06	0.00	0.25
Mod.2 (w=84)	0.18	0.00	0.40	0.18	0.09	0.31	0.16	0.01	0.30	0.15	0.01	0.32
Mod.3 (w=120)	0.08	0.00	0.21	0.11	0.00	0.21	0.11	0.02	0.25	0.08	0.00	0.25
Mod.3 (w=84)	0.15	0.01	0.41	0.13	0.00	0.25	0.09	0.00	0.23	0.10	0.04	0.30
EWC (w=120)	**0.07**	**0.00**	**0.19**	**0.09**	**0.00**	**0.25**	**0.09**	**0.00**	**0.22**	**0.05**	**0.00**	**0.16**
EWC (w=84)	**0.14**	**0.04**	**0.26**	**0.11**	**0.00**	**0.23**	**0.08**	**0.00**	**0.18**	**0.06**	**0.00**	**0.16**
Stress 1 EWC (w=84)	**0.03**	**0.00**	**0.23**	**0.07**	**0.00**	**0.26**	**0.12**	**0.00**	**0.28**	**0.11**	**0.00**	**0.32**
Stress 2 EWC (w=84)	**0.05**	**0.00**	**0.39**	**0.06**	**0.00**	**0.25**	**0.14**	**0.00**	**0.35**	**0.17**	**0.00**	**0.34**
BD												
Mod.1 (w=120)	0.08	0.00	0.20	0.03	0.00	0.17	0.02	0.00	0.14	0.03	0.00	0.21
Mod.1 (w=84)	0.10	0.00	0.23	0.03	0.00	0.16	0.07	0.00	0.16	0.05	0.00	0.23
Mod.2 (w=120)	0.14	0.01	0.29	0.14	0.02	0.28	0.03	0.00	0.23	0.05	0.00	0.38
Mod.2 (w=84)	0.16	0.06	0.29	0.14	0.06	0.24	0.19	0.03	0.31	0.13	0.00	0.28
Mod.3 (w=120)	0.09	0.00	0.18	0.13	0.02	0.23	0.03	0.00	0.25	0.11	0.00	0.34
Mod.3 (w=84)	0.11	0.03	0.29	0.12	0.00	0.23	0.21	0.05	0.33	0.17	0.01	0.33
EWC (w=120)	**0.06**	**0.00**	**0.18**	**0.10**	**0.00**	**0.23**	**0.02**	**0.00**	**0.15**	**0.03**	**0.00**	**0.20**
EWC (w=84)	**0.13**	**0.00**	**0.25**	**0.11**	**0.00**	**0.20**	**0.13**	**0.04**	**0.24**	**0.03**	**0.00**	**0.18**
Stress 1 EWC (w=84)	**0.07**	**0.00**	**0.23**	**0.09**	**0.00**	**0.22**	**0.25**	**0.01**	**0.42**	**0.23**	**0.00**	**0.56**
Stress 2 EWC (w=84)	**0.05**	**0.00**	**0.22**	**0.11**	**0.00**	**0.33**	**0.05**	**0.00**	**0.25**	**0.17**	**0.02**	**0.41**
FR												
Mod.1 (w=120)	0.08	0.00	0.20	0.01	0.00	0.14	0.10	0.03	0.19	0.10	0.00	0.49
Mod.1 (w=84)	0.11	0.00	0.23	0.12	0.01	0.30	0.05	0.00	0.19	0.09	0.00	0.25
Mod.2 (w=120)	0.12	0.00	0.25	0.08	0.00	0.20	0.11	0.00	0.24	0.07	0.00	0.16
Mod.2 (w=84)	0.17	0.09	0.35	0.17	0.07	0.27	0.17	0.04	0.27	0.07	0.00	0.22
Mod.3 (w=120)	0.09	0.00	0.18	0.07	0.01	0.21	0.09	0.00	0.20	0.07	0.00	0.18
Mod.3 (w=84)	0.12	0.00	0.36	0.19	0.04	0.32	0.10	0.00	0.27	0.15	0.00	0.33
EWC (w=120)	**0.07**	**0.00**	**0.19**	**0.03**	**0.00**	**0.15**	**0.05**	**0.00**	**0.16**	**0.07**	**0.00**	**0.18**
EWC (w=84)	**0.14**	**0.02**	**0.23**	**0.08**	**0.01**	**0.21**	**0.08**	**0.02**	**0.17**	**0.06**	**0.00**	**0.21**
Stress 1 EWC (w=84)	**0.05**	**0.00**	**0.20**	**0.12**	**0.00**	**0.21**	**0.10**	**0.00**	**0.41**	**0.16**	**0.00**	**0.33**
Stress 2 EWC (w=84)	**0.04**	**0.00**	**0.56**	**0.12**	**0.04**	**0.30**	**0.16**	**0.02**	**0.33**	**0.15**	**0.00**	**1.00**
IT												
Mod.1 (w=120)	0.10	0.00	0.34	0.10	0.00	0.21	0.13	0.00	0.29	0.15	0.02	0.33
Mod.1 (w=84)	0.09	0.00	0.32	0.06	0.00	0.20	0.06	0.00	0.21	0.03	0.00	0.25
Mod.2 (w=120)	0.10	0.00	0.23	0.12	0.00	0.33	0.13	0.00	0.19	0.11	0.01	0.24
Mod.2 (w=84)	0.11	0.00	0.45	0.13	0.02	0.47	0.11	0.05	0.25	0.08	0.00	0.26
Mod.3 (w=120)	0.12	0.00	0.26	0.09	0.02	0.23	0.10	0.03	0.25	0.14	0.00	0.32
Mod.3 (w=84)	0.14	0.00	0.90	0.06	0.00	0.25	0.08	0.00	0.27	0.12	0.00	0.31
EWC (w=120)	**0.11**	**0.00**	**0.23**	**0.08**	**0.02**	**0.16**	**0.10**	**0.00**	**0.19**	**0.11**	**0.00**	**0.23**
EWC (w=84)	**0.11**	**0.00**	**0.32**	**0.07**	**0.02**	**0.25**	**0.06**	**0.01**	**0.25**	**0.04**	**0.00**	**0.20**
Stress 1 EWC (w=84)	**0.03**	**0.00**	**0.18**	**0.17**	**0.00**	**0.48**	**0.12**	**0.00**	**0.50**	**0.20**	**0.00**	**0.56**
Stress 2 EWC (w=84)	**0.10**	**0.00**	**0.43**	**0.12**	**0.00**	**0.28**	**0.10**	**0.00**	**0.23**	**0.01**	**0.00**	**0.03**

Table A2. RB forecast combination weights (mean, min and max)

	h=1			h=3			h=6			h=12		
	Mean	**Min**	**Max**	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**
US												
Mod.1 (w=120)	0.11	0.02	0.28	0.05	0.00	0.20	0.07	0.00	0.18	0.04	0.00	0.19
Mod.1 (w=84)	0.11	0.01	0.29	0.05	0.00	0.19	0.08	0.00	0.25	0.09	0.00	0.23
Mod.2 (w=120)	0.12	0.02	0.21	0.12	0.01	0.20	0.13	0.01	0.28	0.07	0.00	0.21
Mod.2 (w=84)	0.14	0.03	0.40	0.15	0.04	0.29	0.13	0.00	0.33	0.08	0.00	0.29
Mod.3 (w=120)	0.10	0.01	0.23	0.11	0.01	0.22	0.10	0.01	0.27	0.07	0.00	0.29
Mod.3 (w=84)	0.10	0.00	0.33	0.15	0.00	0.53	0.09	0.00	0.25	0.17	0.03	0.33
EWC (w=120)	**0.11**	**0.00**	**0.18**	**0.09**	**0.01**	**0.20**	**0.09**	**0.00**	**0.24**	**0.05**	**0.00**	**0.16**
EWC (w=84)	**0.10**	**0.00**	**0.16**	**0.08**	**0.01**	**0.21**	**0.06**	**0.00**	**0.20**	**0.06**	**0.00**	**0.20**
Stress 1 EWC (w=84)	**0.03**	**0.00**	**0.16**	**0.11**	**0.00**	**0.21**	**0.13**	**0.00**	**0.33**	**0.19**	**0.03**	**0.34**
Stress 2 EWC (w=84)	**0.09**	**0.00**	**0.32**	**0.09**	**0.00**	**0.29**	**0.12**	**0.00**	**0.33**	**0.19**	**0.00**	**0.54**
CN												
Mod.1 (w=120)	0.11	0.00	0.21	0.06	0.00	0.18	0.11	0.00	0.20	0.10	0.00	0.19
Mod.1 (w=84)	0.12	0.00	0.38	0.06	0.00	0.20	0.05	0.01	0.17	0.08	0.01	0.24
Mod.2 (w=120)	0.11	0.00	0.21	0.11	0.03	0.22	0.07	0.00	0.28	0.09	0.01	0.18
Mod.2 (w=84)	0.16	0.05	0.59	0.13	0.02	0.23	0.16	0.00	0.36	0.17	0.00	0.32
Mod.3 (w=120)	0.09	0.00	0.25	0.07	0.01	0.19	0.06	0.01	0.21	0.07	0.00	0.24
Mod.3 (w=84)	0.11	0.02	0.52	0.18	0.08	0.31	0.17	0.05	0.32	0.13	0.01	0.27
EWC (w=120)	**0.09**	**0.00**	**0.17**	**0.08**	**0.01**	**0.20**	**0.07**	**0.02**	**0.20**	**0.08**	**0.00**	**0.24**
EWC (w=84)	**0.10**	**0.00**	**0.22**	**0.10**	**0.01**	**0.23**	**0.11**	**0.01**	**0.21**	**0.09**	**0.00**	**0.21**
Stress 1 EWC (w=84)	**0.02**	**0.00**	**0.17**	**0.08**	**0.00**	**0.24**	**0.10**	**0.00**	**0.22**	**0.10**	**0.00**	**0.27**
Stress 2 EWC (w=84)	**0.08**	**0.00**	**0.38**	**0.14**	**0.00**	**0.33**	**0.09**	**0.00**	**0.29**	**0.10**	**0.00**	**0.27**
JP												
Mod.1 (w=120)	0.11	0.02	0.34	0.04	0.00	0.22	0.02	0.00	0.19	0.14	0.00	0.44
Mod.1 (w=84)	0.08	0.00	0.21	0.11	0.00	0.27	0.14	0.00	0.30	0.11	0.00	0.26
Mod.2 (w=120)	0.11	0.00	0.27	0.12	0.00	0.27	0.19	0.00	0.45	0.06	0.00	0.32
Mod.2 (w=84)	0.13	0.00	0.22	0.15	0.03	0.30	0.10	0.00	0.44	0.08	0.00	0.27
Mod.3 (w=120)	0.16	0.06	0.38	0.13	0.00	0.28	0.06	0.00	0.25	0.12	0.00	0.33
Mod.3 (w=84)	0.14	0.00	0.30	0.07	0.00	0.18	0.07	0.00	0.23	0.07	0.00	0.23
EWC (w=120)	**0.12**	**0.01**	**0.23**	**0.09**	**0.00**	**0.22**	**0.09**	**0.00**	**0.25**	**0.10**	**0.00**	**0.28**
EWC (w=84)	**0.11**	**0.00**	**0.22**	**0.08**	**0.00**	**0.19**	**0.11**	**0.00**	**0.27**	**0.09**	**0.00**	**0.21**
Stress 1 EWC (w=84)	**0.02**	**0.00**	**0.12**	**0.11**	**0.00**	**0.37**	**0.14**	**0.00**	**0.57**	**0.17**	**0.00**	**0.63**
Stress 2 EWC (w=84)	**0.02**	**0.00**	**0.16**	**0.10**	**0.00**	**0.26**	**0.09**	**0.00**	**0.32**	**0.06**	**0.00**	**0.21**
UK												
Mod.1 (w=120)	0.05	0.00	0.20	0.01	0.00	0.08	0.07	0.00	0.17	0.05	0.00	0.24
Mod.1 (w=84)	0.12	0.00	0.32	0.01	0.00	0.07	0.12	0.02	0.24	0.13	0.01	0.24
Mod.2 (w=120)	0.15	0.02	0.23	0.04	0.00	0.20	0.10	0.00	0.23	0.04	0.00	0.13
Mod.2 (w=84)	0.12	0.00	0.21	0.22	0.00	0.36	0.18	0.01	0.27	0.09	0.00	0.22
Mod.3 (w=120)	0.11	0.00	0.25	0.08	0.00	0.23	0.04	0.00	0.16	0.07	0.02	0.26
Mod.3 (w=84)	0.06	0.00	0.65	0.20	0.06	0.32	0.06	0.00	0.18	0.18	0.01	0.38
EWC (w=120)	**0.14**	**0.00**	**0.26**	**0.01**	**0.00**	**0.15**	**0.02**	**0.00**	**0.13**	**0.05**	**0.00**	**0.14**
EWC (w=84)	**0.17**	**0.06**	**0.34**	**0.17**	**0.00**	**0.36**	**0.06**	**0.00**	**0.18**	**0.07**	**0.00**	**0.17**
Stress 1 EWC (w=84)	**0.01**	**0.00**	**0.15**	**0.07**	**0.00**	**0.44**	**0.19**	**0.00**	**0.36**	**0.20**	**0.04**	**0.44**
Stress 2 EWC (w=84)	**0.06**	**0.00**	**0.25**	**0.19**	**0.01**	**0.44**	**0.15**	**0.04**	**0.32**	**0.12**	**0.00**	**0.35**
BD												
Mod.1 (w=120)	0.09	0.00	0.26	0.02	0.00	0.06	0.02	0.00	0.13	0.03	0.00	0.20
Mod.1 (w=84)	0.10	0.01	0.16	0.03	0.00	0.20	0.15	0.04	0.24	0.06	0.00	0.19
Mod.2 (w=120)	0.13	0.05	0.27	0.22	0.00	0.38	0.04	0.00	0.19	0.03	0.00	0.18
Mod.2 (w=84)	0.16	0.07	0.43	0.09	0.00	0.24	0.15	0.01	0.26	0.12	0.00	0.34
Mod.3 (w=120)	0.09	0.00	0.17	0.09	0.02	0.23	0.02	0.00	0.15	0.05	0.00	0.14
Mod.3 (w=84)	0.12	0.05	0.21	0.16	0.00	0.37	0.19	0.11	0.26	0.18	0.03	0.38
EWC (w=120)	**0.09**	**0.00**	**0.18**	**0.11**	**0.00**	**0.29**	**0.02**	**0.00**	**0.13**	**0.02**	**0.00**	**0.15**
EWC (w=84)	**0.09**	**0.00**	**0.19**	**0.09**	**0.01**	**0.21**	**0.09**	**0.01**	**0.26**	**0.05**	**0.00**	**0.32**
Stress 1 EWC (w=84)	**0.06**	**0.00**	**0.17**	**0.07**	**0.00**	**0.22**	**0.23**	**0.01**	**0.41**	**0.29**	**0.00**	**0.56**
Stress 2 EWC (w=84)	**0.07**	**0.00**	**0.20**	**0.14**	**0.00**	**0.53**	**0.10**	**0.00**	**0.22**	**0.15**	**0.00**	**0.68**
FR												
Mod.1 (w=120)	0.11	0.00	0.19	0.05	0.00	0.18	0.02	0.00	0.21	0.05	0.00	0.17
Mod.1 (w=84)	0.09	0.01	0.20	0.06	0.00	0.17	0.07	0.00	0.20	0.10	0.00	0.37
Mod.2 (w=120)	0.12	0.03	0.26	0.09	0.00	0.27	0.07	0.00	0.20	0.07	0.00	0.43
Mod.2 (w=84)	0.15	0.07	0.27	0.13	0.04	0.25	0.18	0.04	0.25	0.12	0.00	0.35
Mod.3 (w=120)	0.09	0.00	0.24	0.11	0.00	0.25	0.13	0.01	0.29	0.06	0.00	0.23
Mod.3 (w=84)	0.10	0.03	0.24	0.15	0.05	0.37	0.11	0.01	0.28	0.17	0.02	0.45
EWC (w=120)	**0.11**	**0.01**	**0.20**	**0.06**	**0.00**	**0.18**	**0.02**	**0.00**	**0.18**	**0.04**	**0.00**	**0.24**
EWC (w=84)	**0.11**	**0.02**	**0.27**	**0.10**	**0.00**	**0.20**	**0.13**	**0.03**	**0.21**	**0.06**	**0.00**	**0.21**
Stress 1 EWC (w=84)	**0.05**	**0.00**	**0.16**	**0.13**	**0.00**	**0.35**	**0.14**	**0.00**	**0.27**	**0.23**	**0.00**	**0.54**
Stress 2 EWC (w=84)	**0.07**	**0.00**	**0.21**	**0.12**	**0.00**	**0.35**	**0.13**	**0.02**	**0.40**	**0.08**	**0.00**	**0.35**
IT												
Mod.1 (w=120)	0.02	0.00	0.14	0.11	0.00	0.25	0.10	0.00	0.27	0.12	0.00	0.23
Mod.1 (w=84)	0.12	0.00	0.26	0.06	0.00	0.25	0.04	0.00	0.16	0.10	0.00	0.25
Mod.2 (w=120)	0.11	0.00	0.20	0.17	0.00	0.54	0.19	0.00	0.61	0.14	0.00	0.30
Mod.2 (w=84)	0.14	0.02	0.29	0.12	0.00	0.40	0.13	0.00	0.35	0.08	0.00	0.30
Mod.3 (w=120)	0.14	0.03	0.29	0.09	0.00	0.27	0.04	0.00	0.20	0.06	0.00	0.23
Mod.3 (w=84)	0.14	0.07	0.23	0.05	0.00	0.21	0.12	0.00	0.36	0.09	0.00	0.37
EWC (w=120)	**0.09**	**0.00**	**0.20**	**0.11**	**0.00**	**0.23**	**0.03**	**0.00**	**0.17**	**0.10**	**0.00**	**0.28**
EWC (w=84)	**0.13**	**0.05**	**0.29**	**0.05**	**0.00**	**0.19**	**0.07**	**0.00**	**0.23**	**0.03**	**0.00**	**0.21**
Stress 1 EWC (w=84)	**0.01**	**0.00**	**0.15**	**0.15**	**0.01**	**0.34**	**0.19**	**0.01**	**0.39**	**0.24**	**0.04**	**0.43**
Stress 2 EWC (w=84)	**0.10**	**0.00**	**0.35**	**0.10**	**0.00**	**0.33**	**0.08**	**0.00**	**0.32**	**0.03**	**0.00**	**0.30**

Table A3. Weights of baseline and stress forecasts in the forecast combination (Mean, minimum and maximum) (sample: 1992:01-2018:12)

RNF

		Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
US	Baseline	0.91	0.57	1.00	0.82	0.64	1.00	0.79	0.63	1.00	0.61	0.14	1.00
	Stress	0.09	0.00	0.43	0.18	0.00	0.36	0.21	0.00	0.37	0.39	0.00	0.86
CN	Baseline	0.90	0.53	1.00	0.78	0.43	1.00	0.81	0.52	1.00	0.70	0.49	1.00
	Stress	0.10	0.00	0.47	0.22	0.00	0.57	0.19	0.00	0.48	0.30	0.00	0.51
JP	Baseline	0.95	0.77	1.00	0.70	0.37	1.00	0.68	0.33	0.90	0.83	0.56	0.95
	Stress	0.05	0.00	0.23	0.30	0.00	0.63	0.32	0.10	0.67	0.17	0.05	0.44
UK	Baseline	0.92	0.61	1.00	0.86	0.59	1.00	0.74	0.48	0.97	0.71	0.52	1.00
	Stress	0.08	0.00	0.39	0.14	0.00	0.41	0.26	0.03	0.52	0.29	0.00	0.48
BD	Baseline	0.88	0.69	1.00	0.79	0.56	0.98	0.71	0.53	0.96	0.59	0.32	0.97
	Stress	0.12	0.00	0.31	0.21	0.02	0.44	0.29	0.04	0.47	0.41	0.03	0.68
FR	Baseline	0.91	0.44	1.00	0.76	0.59	0.93	0.74	0.43	0.98	0.68	0.00	0.91
	Stress	0.09	0.00	0.56	0.24	0.07	0.41	0.26	0.02	0.57	0.32	0.09	1.00
IT	Baseline	0.87	0.57	1.00	0.72	0.42	1.00	0.78	0.44	1.00	0.79	0.44	1.00
	Stress	0.13	0.00	0.43	0.28	0.00	0.58	0.22	0.00	0.56	0.21	0.00	0.56
Average	**Baseline**	**0.91**	**0.60**	**1.00**	**0.78**	**0.51**	**0.99**	**0.75**	**0.48**	**0.97**	**0.70**	**0.35**	**0.98**
	Stress	**0.09**	**0.00**	**0.40**	**0.22**	**0.01**	**0.49**	**0.25**	**0.03**	**0.52**	**0.30**	**0.02**	**0.65**

RB

		Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
US	Baseline	0.89	0.66	1.00	0.80	0.61	0.99	0.75	0.34	1.00	0.62	0.30	0.95
	Stress	0.11	0.00	0.34	0.20	0.01	0.39	0.25	0.00	0.66	0.38	0.05	0.70
CN	Baseline	0.89	0.58	1.00	0.78	0.47	0.97	0.81	0.65	0.97	0.80	0.46	1.00
	Stress	0.11	0.00	0.42	0.22	0.03	0.53	0.19	0.03	0.35	0.20	0.00	0.54
JP	Baseline	0.96	0.79	1.00	0.79	0.44	0.99	0.77	0.33	1.00	0.77	0.37	0.98
	Stress	0.04	0.00	0.21	0.21	0.01	0.56	0.23	0.00	0.67	0.23	0.02	0.63
UK	Baseline	0.92	0.73	1.00	0.73	0.12	0.97	0.66	0.40	0.85	0.68	0.27	0.92
	Stress	0.08	0.00	0.27	0.27	0.03	0.88	0.34	0.15	0.60	0.32	0.08	0.73
BD	Baseline	0.86	0.66	1.00	0.80	0.31	0.98	0.68	0.54	0.92	0.56	0.24	0.85
	Stress	0.14	0.00	0.34	0.20	0.02	0.69	0.32	0.08	0.46	0.44	0.15	0.76
FR	Baseline	0.88	0.74	1.00	0.75	0.42	0.96	0.72	0.59	0.94	0.68	0.36	0.95
	Stress	0.12	0.00	0.26	0.25	0.04	0.58	0.28	0.06	0.41	0.32	0.05	0.64
IT	Baseline	0.89	0.65	1.00	0.75	0.33	0.97	0.73	0.55	0.95	0.72	0.41	0.89
	Stress	0.11	0.00	0.35	0.25	0.03	0.67	0.27	0.05	0.45	0.28	0.11	0.59
Average	**Baseline**	**0.90**	**0.69**	**1.00**	**0.77**	**0.38**	**0.98**	**0.73**	**0.49**	**0.95**	**0.69**	**0.34**	**0.94**
	Stress	**0.10**	**0.00**	**0.31**	**0.23**	**0.02**	**0.62**	**0.27**	**0.05**	**0.51**	**0.31**	**0.06**	**0.66**

Table A4. Weights of domestic and external stress forecasts in the forecast combination (Mean, minimum and maximum, 1992:01-2018:12)

RNF

		Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
US	Stress 1	0.01	0.00	0.16	0.06	0.00	0.21	0.06	0.00	0.18	0.24	0.00	0.86
	Stress 2	0.08	0.00	0.42	0.12	0.00	0.26	0.15	0.00	0.25	0.15	0.00	0.43
CN	Stress 1	0.01	0.00	0.20	0.09	0.00	0.28	0.08	0.00	0.23	0.18	0.00	0.39
	Stress 2	0.09	0.00	0.40	0.12	0.00	0.28	0.11	0.00	0.25	0.12	0.00	0.25
JP	Stress 1	0.01	0.00	0.19	0.17	0.00	0.63	0.24	0.05	0.63	0.05	0.00	0.21
	Stress 2	0.03	0.00	0.22	0.12	0.00	0.22	0.07	0.00	0.24	0.12	0.03	0.32
UK	Stress 1	0.03	0.00	0.23	0.07	0.00	0.26	0.12	0.00	0.28	0.11	0.00	0.32
	Stress 2	0.05	0.00	0.39	0.06	0.00	0.25	0.14	0.00	0.35	0.17	0.00	0.34
BD	Stress 1	0.07	0.00	0.23	0.09	0.00	0.22	0.25	0.01	0.42	0.23	0.00	0.56
	Stress 2	0.05	0.00	0.22	0.11	0.00	0.33	0.05	0.00	0.25	0.17	0.02	0.41
FR	Stress 1	0.05	0.00	0.20	0.12	0.00	0.21	0.10	0.00	0.41	0.16	0.00	0.33
	Stress 2	0.04	0.00	0.56	0.12	0.04	0.30	0.16	0.02	0.33	0.15	0.00	1.00
IT	Stress 1	0.03	0.00	0.18	0.17	0.00	0.48	0.12	0.00	0.50	0.20	0.00	0.56
	Stress 2	0.10	0.00	0.43	0.12	0.00	0.28	0.10	0.00	0.23	0.01	0.00	0.13
Average	**Stress 1**	**0.03**	**0.00**	**0.20**	**0.11**	**0.00**	**0.33**	**0.14**	**0.01**	**0.38**	**0.17**	**0.00**	**0.46**
	Stress 2	**0.06**	**0.00**	**0.38**	**0.11**	**0.01**	**0.28**	**0.11**	**0.00**	**0.27**	**0.13**	**0.01**	**0.41**

RB

		Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
US	Stress 1	0.03	0.00	0.16	0.11	0.00	0.21	0.13	0.00	0.33	0.19	0.03	0.34
	Stress 2	0.09	0.00	0.32	0.09	0.00	0.29	0.12	0.00	0.33	0.19	0.00	0.54
CN	Stress 1	0.02	0.00	0.17	0.08	0.00	0.24	0.10	0.00	0.22	0.10	0.00	0.27
	Stress 2	0.08	0.00	0.38	0.14	0.00	0.33	0.09	0.00	0.29	0.10	0.00	0.27
JP	Stress 1	0.02	0.00	0.12	0.11	0.00	0.37	0.14	0.00	0.57	0.17	0.00	0.63
	Stress 2	0.02	0.00	0.16	0.10	0.00	0.26	0.09	0.00	0.32	0.06	0.00	0.21
UK	Stress 1	0.01	0.00	0.15	0.07	0.00	0.44	0.19	0.00	0.36	0.20	0.04	0.44
	Stress 2	0.06	0.00	0.25	0.19	0.01	0.44	0.15	0.04	0.32	0.12	0.00	0.35
BD	Stress 1	0.06	0.00	0.17	0.07	0.00	0.22	0.23	0.01	0.41	0.29	0.00	0.56
	Stress 2	0.07	0.00	0.20	0.14	0.00	0.53	0.10	0.00	0.22	0.15	0.00	0.68
FR	Stress 1	0.05	0.00	0.16	0.13	0.00	0.35	0.14	0.00	0.27	0.23	0.00	0.54
	Stress 2	0.07	0.00	0.21	0.12	0.00	0.35	0.13	0.02	0.40	0.08	0.00	0.35
IT	Stress 1	0.01	0.00	0.15	0.15	0.01	0.34	0.19	0.01	0.39	0.24	0.04	0.43
	Stress 2	0.10	0.00	0.35	0.10	0.00	0.33	0.08	0.00	0.32	0.03	0.00	0.30
Average	**Stress 1**	**0.03**	**0.00**	**0.16**	**0.10**	**0.00**	**0.31**	**0.16**	**0.00**	**0.36**	**0.20**	**0.02**	**0.46**
	Stress 2	**0.07**	**0.00**	**0.27**	**0.13**	**0.00**	**0.36**	**0.11**	**0.01**	**0.31**	**0.11**	**0.00**	**0.38**