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On the efficient synthesis of short financial time series: A Dynamic Factor Model approach

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ABSTRACT

In this paper, we present a fully data-driven statistical approach to building a synthetic index based on intrinsic information of the considered ecosystem, namely the financial one. Among the several methods made available in the literature, we propose the employment of a Dynamic Factor Model approach which allows us to compare observations at hand in space and time. We contribute to the research field by offering a statistically sound methodology which goes beyond state-of-the-art techniques on dimension reduction, mainly based on Principal Component Analysis. We adopt a country-by-country fitting strategy to elicit the inner country-specific characteristics and then we combine results together by means of a Vector Autoregressive and Kalman filter approach. To this aim, we analyze a set of 17 Financial Soundness Indicators provided by the International Monetary Fund ranging from 2010 to 2020 for 116 countries that span the globe, including both strong and developing economies. Results show that our index is able to identify banking and debt crisis and the contribution of the latent variables can isolate countries that experienced crisis, representing a valid aid to policy makers and institutions in understanding countries movements, reactions and suffering periods.

1. Introduction

In many diversified application fields, there is a great demand for summary indicators able to generate useful and comprehensive information on the phenomenon under analysis. A common way to summarize information from a large set of variables is to create synthetic indexes, based on assumptions made by domain experts, which typically result in the use of synthetic measures like, for example, the weighted average. However, these measures are subjective by nature and therefore can be questionable, leading to endless debate on which one represents a robust indicator.

Several prior studies in the economics literature have proposed methods for calculating synthetic indexes. They can be mainly grouped into two classes: econometric approaches and statistical learning methods. The former comprises, among the others, the studies of Moccero et al. (2014), Opschoor et al. (2014), Mamatzakis and Tsionas (2020), Huang et al. (2021). Those papers typically employ Vector Autoregressive or GARCH models to naturally elicit the temporal evolution of the considered variables. The latter mainly deploy dimension reduction techniques, such as Principal Component Analysis or Factorial Analysis, receiving considerable recent attention (Kabundi and Mbelu, 2017; Ahamed and Mallick, 2019; Saha and Dutta, 2020; Bitetto et al., 2021, 2023). In the finance literature, many studies proposed the production of reliable synthetic indicators to be used as predictors for further empirical analysis.

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Following the recent international financial crisis, the research effort has been especially focused on measuring financial stability by applying various methods and models, which have primarily focused on specific countries accounting for the role of specific peculiarities and economic characteristics. However, unlike price stability, financial stability is more difficult to define or measure due to the interdependence and the complex interactions of different elements of the financial system among themselves and with the real economy. This complexity is further amplified by the inherent time and cross-border dimensions of such interactions. Nevertheless, composite quantitative measures of financial system stability that could signal warning conditions are especially attractive, since they enable policy-makers and financial system participants to better monitor the degree of the financial system's stability, to anticipate the sources and causes of financial system stress, and to communicate effectively the impact of such conditions.

From a theoretical perspective, an effective financial stability measure must provide adequate warnings for policy makers to react. Warnings must be able to not miss actual turmoil (type I error) but also not cause excessive false alarms (type II error) leading to inappropriate intervention. Earlier studies suggest different approaches to model development. For example, Lo Duca and Peltonen (2011) combine a logit model with a signal approach to allow for policy choices between the type I and type II errors tradeoff. They find that discrete choice models outperform stand-alone models in predicting crises. Caggiano et al. (2014) and Bussiere and Fratzscher (2006) use a multinomial logit model to address crisis duration bias that is due to time endogeneity concerns. The multinomial logit model accounts for tranquil, crisis and in-crisis conditions as three separate regimes. Dawood et al. (2017) use a dynamic-recursive forecasting model that allows for both the prediction and duration of a crisis and suggest that their approach yields more accurate forecasts of crisis periods.

More recent studies apply econometric, network-based and machine learning methods (Battiston and Martinez-Jaramillo, 2018). Constantin et al. (2018) develop an early warning model to predict financial distress along two contagion mechanisms based on bank- and country-level networks. Beutel et al. (2019) find that in recursive out-of-sample assessments the logit model outperforms various machine learning approaches. In contrast, Holopainen and Sarlin (2017) and Bluwstein et al. (2020) find that machine learning models outperform the logit model. Alessi and Detken (2018) develop a financial instability model based on the gradual build-up of excessive credit growth. Virtanen et al. (2018) argue that leveraged bubbles precede financial disruptions and they use a set of exuberance indicators to predict bubbles. Boyd et al. (2019) stress the role of timing of financial crises by distinguishing between shock and policy responses, which they use to construct a crisis-timing model.

From an empirical point of view, individual country studies mainly focus on developed ones. With respect to the US economy, Nelson and Perli (2007) produced a weekly measure of financial fragility, computed in two steps using twelve market-based financial stress measures. In the first step, they reduced the standardized inputs to three summary indicators: the level factor (variance-equal weighted average), the rate-of-change factor (rolling eight-week percentage change in the level factor) and the correlation factor (percentage of total variation in the individual stress variables explained by the first principal component over a rolling 26-week window). In the second step, they computed the financial fragility indicator as the fitted probability from a logit model with the three summary indicators as explanatory variables and a binary pre-defined crisis indicator as the dependent variable. Further, Hakkio and Keeton (2009) proposed the Kansas City Financial Stress Index (KCFSI). This index uses eleven financial variables during 1990–2007, each of which captures one or more key features of financial stress. Applying a similar methodology, Kliesen and Smith (2010) aggregated 18 weekly financial market indicators into the St. Louis Fed Financial Stress Index (STLFSI). Moreover, Oet et al. (2011) produced the Cleveland Financial Stress Index (CFSI) by integrating 11 daily financial indicators form the debt, equity, foreign exchange and credit markets. They normalized the raw indicators by transforming the series values into the corresponding CDF values. The transformed indicators were subsequently aggregated into a synthetic indicator by applying time-varying credit weights, which are proportional to the quarterly financing flows of the four markets. Lastly, Brave and Butters (2011) constructed a financial condition index (FCI) for the USA using a hundred financial indicators from early 1970s to late 2010s. They used both a PCA and a dynamic factor analysis on annual time-series data to estimate a weighted average value, which was designated as a threshold for assessing financial stability vs. instability. They validated the FCI by regressing it against macroeconomic variables and including high-frequency non-financial measures of economic activity. Elsewhere, Illing and Liu (2006) developed a daily financial stress index for the Canadian financial system and proposed an alternative approach to aggregate individual stress indicators into a synthetic stress index. The latte comprises eleven financial variables, which are aggregated using weights determined by the relative size of the market to which each indicator pertains compared to a broad measure of total credit in the economy. Yiu et al. (2010) computed a monthly financial soundness index (FSI) for Hong Kong using six financial market variables and a variance-equal weighting'' aggregation method. Arzamasov and Penikas (2014) combine sixteen IMF financial soundness indicators during 2003–2013 to measure financial stability in Israel. They applied three different methods, i.e., principal component analysis (PCA), regression and hybrid models, and concluded that the PCA method was the most effective one. Louzis and Vouldis (2011) constructed a monthly Financial Systemic Stress Index (FSSI) for Greece, by aggregating 14 stress measures based on financial market data and monthly bank balance sheet data grouped into five sub-indices using a portfolio-theoretic approach (i.e. cross-correlations) computed through a multivariate GARCH model. They applied PCA at the sub-index level and normalized the sub-indices using logistic transformation.

Financial stability indicators were also produced for less developed economies. Morales and Estrada (2010) proposed a financial stress index for the Colombian economy, using measures of financial institutions' profitability, liquidity and probability of default from January 1995 to November 2008. They used a heterogeneous group of financial institutions that included commercial banks, mortgage banks, commercial financial companies and financial cooperatives. To produce their stress index, they used different quantitative methods, such as a variance-equal weight, PCA and count data methods. Further, Koong et al. (2017) proposed a financial stability index for the Malaysian economy deploying a dynamic factor model that uses fifteen diverse financial measures, ranging from non-performing loans to crude oil price and private capital funding, etc. The authors tested the predictive power of their index against the Malaysian business cycle and used it to examine the effect of credit expansion on the stability of the Malaysian financial system during April 1997 to December 2011. Sere-Ejembi et al. (2014) constructed a banking system stability index (BSSI) for Nigeria using quarterly data during 2007–2012 and a weighted combination of the country's banking soundness index, the banking vulnerability index and the economic climate index. The BSSI index performed well in predicting the domestic financial crisis and therefore the authors proposed it as an early warning tool. Sales et al. (2012) analyzed Brazil's financial stability system using quarterly macroeconomic indicators during 1995–2011. They developed a broad financial stability indicator (BFSI) and a specific financial stability indicator (SFSI), both of which were able to predict three Brazilian financial crisis episodes. They applied a principal factor method based on unobserved factors to construct the BFSI as well as an OLS regression of three main financial market indicators to construct the SFSI. They also applied a business cycle decomposition method that used the co-movement of financial and real indicators to assess the driving role of financial vs. real factors, respectively.

A more recent wave of studies developed cross-county financial stability indicators, especially in the eurozone, using more sophisticated methods. For example, Holló et al. (2012) proposed a synthetic indicator of systemic stress (CISS) for the eurozone countries. They applied portfolio theory to compose five market-specific sub-indices based on fifteen individual financial stress measures. The CISS index considers the time-varying cross-correlations between the sub-indices as well. Applied to the Euro area, the CISS takes a systemic risk perspective, which assigns more weight on situations in which financial stress prevails simultaneously in several market segments. The authors establish critical CISS levels beyond which financial stress negatively affects real economic activity. Albulescu (2013) analyzes the role of monetary policy on financial stability. He specifically analyzed the impact of the European Central Bank's (ECB) decisions by measuring the difference between the optimal and real interest rates during 1999–2011 using quarterly data. He applied a stochastic reduced form model that uses information on inflation and the GDP growth rate to build the financial stability index. The index predicted the 2007–8 crisis and suggested an increase of the interest rate during 2010–11 as a balancing mechanism to contain inflation. Roye (2011) drew on the approach proposed by Brave and Butters (2011) to construct a financial market stress indicator (FSI) for the Euro area. The FSI comprises 23 and 22 raw financial stress factors from the banking sector, securities markets and foreign exchange conditions. Following a similar approach, Grimaldi (2010) computed a weekly financial stability index for the Eurozone based on 16 financial variables. He used only the level and the rate of change as explanatory variables in a probit regression, documenting a significant correlation coefficient. He then used a keyword-search through relevant parts of the ECB Monthly Bulletin to identify crisis events for the computation of the binary indicator. Cardarelli et al. (2011) produce a monthly financial stress index for 17 advanced economies as the simple average of twelve standardized market-based financial stress indicators using the "variance-equal weighting" aggregation method. They grouped the individual indicators into three sub-indices representing the banking, securities, and foreign exchange markets. The (European Central Bank, 2009) developed its Global Index of Financial Turbulence (GIFT) using parsimonious stress indicators for the 29 EU economies, each comprising six market-based indicators that capture stress in fixed income, equity and foreign exchange markets. The index was produced using a variance-equal weighted approach and was subsequently normalized using a logistical transformation. Lo Duca and Peltonen (2011) produced parsimonious stress FSIs for 10 advanced and 18 emerging economies by taking the arithmetic average of five raw stress indicators, each transformed on the basis of its quartiles derived from the empirical CDF. With respect to the less developed countries, Jakubik and Slacik (2013) develop a financial instability index (FII) for nine Central Eastern and South Eastern European countries using monetary, financial and foreign exchange data during 1996–2012. In order to construct the index, they clustered the variables into five groups and subsequently used the quantile distribution to identify periods of financial stability versus financial instability. Finally, they used the resulting weighted average to produce their index and fit a panel GMM regression to identify the most influential variables on the index evolution.

The development of these composite measures of financial system stability has changed over the years following a shift of concern from the micro-prudential to the macroprudential dimensions of financial stability. From the analysis of early warning indicators to monitor the state of the banking system, particularly the risk of default of individual institutions, the focus has shifted to a broader system-wide assessment of risks to the financial markets, institutions and infrastructure. More recently, the analytical focus has further concentrated on the financial system's behavioral dynamics, the potential build-up of unstable conditions and the external shocks' transmission mechanisms. A key challenge underlying these analytical developments is the need to bridge the financial data gaps and segmentation in several areas and apply a homogeneous cross-country approach to analyzing financial stability. Segmented data from different sources and individual country approaches lack generalization power, depriving policymakers and practitioners from effectively analyzing the complex interconnectedness of the global financial system (Stensrud, 2009).

Our paper responds to these challenges by using a fully data-driven statistical approach to building a synthetic index based on fundamental financial system information. While data-driven approaches have been used by prior studies, these are mostly individual country based, use information that does not capture policy considerations and often study financial vulnerabilities associated with static rather dynamic conditions and cross-market/bank interdependencies. We build our index by combining 17 financial soundness indicators[1] generated by the International Monetary Fund (IMF) during 2010–2020 for 116 countries, including both developed and developing economies. A key strength of our data is that it includes credible and objective information, which incorporates institution-wide, market-wide and policy-level considerations altogether. An additional novelty of our approach is that it uses a sophisticated analytical approach applied consistently to all countries. More specifically, we use a Dynamic Factor Model approach (hereafter DFM) which allows us to analyze comparative country performance across both space and time. Our approach differs from other studies employing a DFM approach in that we first adopt a country-by-country fitting strategy to elicit the inner country specific

[1] https://data.imf.org/?sk=51B096FA-2CD2-40C2-8D09-0699CC1764DA

characteristics and subsequently combine the results using a Vector Autoregressive and Kalman filter approach. This computation strategy is indicated by the large size and complex structure of our data (116 countries × 17 variables × 11 years) as well as the identifiability constraints. Our approach is in line with the suggestions of the BIS/IFC that financial stability analysis should use several variables both individually and in combinations taking in to account both the cross-section and time dimensions of financial system stress during both normal times and stress times (Gadanecz and Jayaram, 2008).

The paper is organized as follows: in Section 2 we present our modeling strategy, in Section 3 we briefly describe the data, in Section 4 we discuss our findings and in Section 5 we draw conclusions.

2. Methodology

We take advantage of a statistical methodology to build our proposed index following a dimensionality reduction approach based on Factor Analysis (FA). FA models the measurement of latent variables, seen through the relationships they cause in a set of X variables. The model is represented by a set of equations $X_i = b_i F_i + u_i, i = 1, \dots, p$, where X_i are the original variables, F_i are the latent factors and b_i, u_i are the parameters of the combination. Recalling that our dataset has three dimensions, *Country*, *Variable* and *Time*, we evaluate a temporal dependent version of FA called Dynamic Factor Model (DFM), modeling country/variable interactions for all the available years within the same model. Given the $p \times n$ matrix $\mathbf{X}$, the model assumes that there exist some $k \times n$ factors $\mathbf{F}$ such that their mutual interaction over time can be expressed by a $k \times k$ interaction matrix $\mathbf{A}$ and the observed variable can be expressed as a linear function of the factors themselves through a $p \times k$ loading matrix $\mathbf{C}$. The problem can be solved as a system of equations:

$$\begin{cases} \mathbf{F}_t = \mathbf{A}\mathbf{F}_{t-1} + \mathcal{N}(0, \mathbf{Q}) \\ \mathbf{X}_t = \mathbf{C}\mathbf{F}_t + \mathcal{N}(0, \mathbf{R}) \end{cases} \tag{1}$$

where $\mathcal{N}$ is the normal probability distribution and $\mathbf{Q}$ and $\mathbf{R}$ are the covariance matrix of the residuals of each equation in Eq. (1), respectively. Due to the short time series of the independent variables, this model cannot be fitted considering all countries together as the resulting system of equations Eq. (1) is under-determined. Thus, we deal with the problem as follows: first, following (Holmes et al., 2018), we fit DFM for each country, obtaining the factor matrices $\mathbf{F}^i$, the factor interactions $\mathbf{A}^i$ and the factor loadings $\mathbf{C}^i$, $i = 1, \dots, n$. Second, we fit a Vector Auto Regressive (VAR) model in order to get $\hat{\boldsymbol{A}}$ 1-year lag matrix that incorporates cross-countries interactions of $\mathbf{A}^i$. We implement the model using *R* package `sparsevar` because this calibration problem has too many parameters to estimate relative to the number of observations, thus requiring a sparse approach.

Then, we use Kalman Filter to get smoothed factors $\widehat{\mathbf{F}^i}$ using $\hat{\boldsymbol{A}}$ and $\hat{\boldsymbol{C}} = diag(\boldsymbol{C}^i)$, that is to get latent factors that incorporate cross-countries interactions. Briefly, Kalman filter re-estimates the factor matrix $\mathbf{F}$ iterating the two equations in Eq. (1) until the error between the predicted observed variables $\hat{\boldsymbol{X}}$ and the true one is minimized. We implement the model using *R* package `FKF`. We assume $\hat{\boldsymbol{C}}$ to be diagonal in order not to double-count correlations within the observed variables and because cross-country interactions are already modeled through the VAR. Moreover, the described procedure depends upon two hyper-parameters: the sparsity coefficient α of the VAR and the correlation structure of the residuals for Kalman filter.

Thus, we simulate synthetic factors $\widetilde{\mathbf{F}}$ with different combinations of number of observed variables, countries, years, latent factors $\mathbf{F}$, and we generate the corresponding $\mathbf{X}_t$ given different combination of $\mathbf{A}$, defined by α, and $\mathbf{C}$, randomly generated, using Eq. (1). Then, for each of the previous combination and correlation structure of residuals $\mathbf{Q}$, we apply the described algorithm and assess the reconstruction error on the fitted factors $\widetilde{\mathbf{F}}$ with the simulated factors $\mathbf{F}$. The optimal parameters found are $\alpha = 0.2$ and a diagonal structure. The final index, hereinafter referred to as Financial Soundness Index (FSIND), will be represented by the k-dimensional factor matrix F.

One of the goals is to select the optimal number of components k as a trade-off between the maximal explained variance and the smallest value of components k. We produce a k-dimensional continuous FSIND per country–year pair. Afterwards, we evaluate the R^2 on both the whole dataset and subsets with values trimmed for the 95th and 99th percentiles in order to check for the impact of outliers. In our context, in analogy with the classical R^2, we compute the RSS term as the squared residuals given after the reconstruction step using only the retained principal components and the TSS term as the total variance contained in the original variables. We fit the DFM model with one and two factors as well under the assumption of interactions between factors, i.e. estimated $\hat{\boldsymbol{A}}$, and no interactions, i.e. $\hat{\boldsymbol{A}} = \boldsymbol{I}$, where $\boldsymbol{I}$ is the identity matrix.

3. The data

We analyze a set of 17 Financial Soundness Indicators (FSI)[2] provided by the International Monetary Fund ranging from 2007 to 2020 for 140 countries that span the globe, including both strong and developing economies. The data consisted of 33,320 observations (5232 of which are missing) and the variables have been short-listed according to availability of data for most countries and economic relevance for the purpose. The final list of variables pertains to six main areas, as identified by IMF: for *Asset Quality* variables 1–2 cover the Sectoral distribution of loans to total loans and Nonperforming loans to total gross loans, for *Capital Adequacy* variables from 3 to 6 cover Tier 1 capital to assets, Nonperforming loans net of provisions to capital, Regulatory capital to risk-weighted assets and Common Equity Tier 1 capital to risk-weighted assets, for *Deposit Takers* variables from 7 to 10 cover Customer

[2] https://data.imf.org/?sk=51B096FA-2CD2-40C2-8D09-0699CC1764DA

Table 1
List of variables used to build the FSIND index, with sources, total number of non-missing observations and descriptive summary statistics.

Variable	Set	Obs	Mean	S.D.	Min	P25	Median	P75	Max
1 — Sectoral distribution of loans to total loans	Asset Quality	1,121	88.02	15.99	20.67	83.76	94.77	99.5	100
2 — Nonperforming loans to total gross loans		1,233	6.68	7.96	0	2.09	3.86	8.58	63.51
3 — Tier 1 capital to assets	Capital Adequacy	1,186	10.3	3.52	1.49	7.62	10.02	12.43	24.85
4 — Nonperforming loans net of provisions to capital		1,231	17.66	37.84	−51.61	3.5	8.26	18.66	413.56
5 — Regulatory capital to risk-weighted assets		1,237	17.98	4.92	−2.77	14.89	17.08	19.83	42.2
6 — Common Equity Tier 1 capital to risk-weighted assets		1,232	15.72	4.99	−1.61	12.6	14.7	17.85	40.3
7 — Customer deposits to total (non-interbank) loans	Deposit Takers	1,124	120.86	59.41	29.01	89.95	109.89	131.75	647.35
8 — Foreign-currency-denominated liabilities to total liabilities		1,008	29.51	23.8	0	9.78	23.7	47.44	100
9 — Foreign-currency-denominated loans to total loans		1,030	27.74	24.87	0	7.77	22.28	42.25	100.06
10 — Personnel expenses to non-interest expenses		1,156	43.62	12.45	−5.31	36.71	43.94	50.54	91.58
11 — Interest margin to gross income	Earnings and Profitability	1,239	58.72	17.74	−294.33	51.14	60.33	68.7	142.77
12 — Non-interest expenses to gross income		1,239	58.06	16.82	−303.46	49.1	57.06	66.5	115.79
13 — Return on assets		1,235	1.49	1.65	−25.61	0.74	1.38	2.17	10.28
14 — Return on equity		1,232	13.07	19.51	−505.64	8.17	13.68	19.73	65.4
15 — Liquid assets to short term liabilities for all DTs	Liquidity	1,175	67.6	58.52	6.25	33.84	47.19	77.26	690.37
16 — Liquid assets to total assets (liquid asset ratio) for all DTs		1,207	27.64	13.18	4.99	18.55	25.13	33.3	74.97
17 — Net open position in foreign exchange to capital	Sensitivity to Market Risk	974	9.55	32.4	−95.43	0.29	2.91	8.5	407.97

Table 2
Results for DFM methods with different number of factors and factors interactions. R^2 is reported for the full dataset and for the 99th and 95th percentiles. We also report Im–Pesaran–Shin test for stationarity on the FSIND index.

Factors interactions	Number of factors	R^2	R^2 on 99th	R^2 on 95th	Im–Pesaran–Shin test
No	1	35.7%	36.5%	39.4%	$\ll 0.01$
No	2	39.9%	42.9%	44.3%	$\ll 0.01$
Yes	1	64.1%	66.5%	69.7%	$\ll 0.01$
Yes	2	66.4%	67.7%	70.3%	$\ll 0.01$

deposits to total (non-interbank) loans, Foreign-currency-denominated liabilities to total liabilities, Foreign-currency-denominated loans to total loans and Personnel expenses to non-interest expenses, for *Earnings and Profitability* variables from 11 to 14 cover Interest margin to gross income, Non-interest expenses to gross income, Return on assets and Return on equity, for *Liquidity* variables 15–16 cover Liquid assets to short term liabilities for all Deposit Takers and Liquid assets to total assets (liquid asset ratio) for all Deposit Takers and for *Sensitivity to Market Risk* variable 17 covers Net open position in foreign exchange to capital. Table 1 and Figure A.2 in the Appendix present the summary statistics of the index's constituent variables from 1 to 17 and their pairwise correlations, respectively.

Before employing the methodology explained in Section 2, we assess the data quality and cope with issues related to the presence of missing data. In this way, we can assure that results are not biased by low levels of quality and inconsistencies.

Indeed, some countries have missing values for the 17 pairs variables/years. As a result, we restrict our analysis to 116 countries and time span of 11 years, from 2010 to 2020, selected with an incidence of missing values not exceeding 30%. In our sample, 18 countries show a percentage of missing values between 20%–29%. The final dataset consisted of 21,692, 1833 (9%) of which are missing. The way missing values are imputed can highly impact the analysis on data, as showed in Freyberger et al. (2021), where the authors prove that common practice of imputing mean of median biases the results. Therefore, we apply two alternative data imputation methods: a Matrix Completion with Low Rank SVD method (MC-SVD) (Hastie et al., 2015) and Bayesian Tensor Factorization (BTF) method (Khan and Ammad-ud-din, 2016). Briefly, MC-SVD solves the minimization problem $\frac{1}{2}\|X - AB^T\|_F^2 + \frac{\lambda}{2}(\|A\|_F^2 + \|B\|_F^2)$ for A and B where $\|\cdot\|_F$ is the Frobenius norm by setting to 0 the missing values. Once estimated, AB^T can approximate the original matrix X, including the missing values. This is applied to the 2-dimensional "slice" of countries-variables for each year. BTF acts in a similar way but using a tensorial decomposition of the 3-dimensional tensors that stacks all the annual slices together so that the imputation process involves information coming from a temporal dimension as well. Overall, we find that Bayesian Tensor Factorization performs better, as explained in Appendix B.

4. Results

In this section we discuss results obtained by the employment of the DFM approach explained in Section 2.

Table 2 reports the R^2 both on the whole dataset and on subsets with values trimmed for the 95th and 99th percentiles to check for outliers' impact. In our context, in analogy with the classical R^2, we compute the RSS term as the squared residuals given after the reconstruction step using only the selected number of factors and the TSS term as the total variance contained in

Table 3
Results based on the three different PCA. The first two principal component are provided and evaluated in terms of mean R^2 and mean R^2 trimmed the top 1st and 5th percentile.

Method	Number of PC	Mean R^2	Mean R^2 on 99th	Mean R^2 on 95th	Im–Pesaran–Shin test
RobPCA	1	$23.1 \pm 6.2\%$	$27.6 \pm 13.2\%$	$34.1 \pm 19.8\%$	$\ll 0.01$
	2	$36.7 \pm 9.1\%$	$42.5 \pm 13.9\%$	$51.1 \pm 13.2\%$	$\ll 0.01$
KernelPCA degree = 2	1	$66.4 \pm 5.2\%$	$67.6 \pm 8.1\%$	$69.2 \pm 11.5\%$	$\ll 0.01$
	2	$68.1 \pm 4.3\%$	$69.7 \pm 4.7\%$	$72.1 \pm 10.1\%$	$\ll 0.01$
KernelPCA degree = 3	1	$68.2 \pm 3.9\%$	$70.1 \pm 4.5\%$	$72.3 \pm 9.7\%$	$\ll 0.01$
	2	$69.4 \pm 5.3\%$	$71.3 \pm 8.7\%$	$73.6 \pm 6.5\%$	$\ll 0.01$

the original variables. Models with no factors' interactions have low performance, meaning that cross-countries effects are relevant in order to capture the intrinsic relationship within the data. In fact, the normalized entries of the estimated interaction matrix $\hat{\boldsymbol{A}}$ turn out to be rather large, ranging between $[-0.76, 0.75]$. Moreover, the use of two factors provides very small improvements on the performances compared to the single factor version in both model settings. Therefore, we prefer to retain only the single factor model, which explains at its minimum a R^2 of 65% and because the possibility of building up our FSIND index considering just one component eases the interpretation, the relative employment and the subsequent monitoring. Additionally, we run the Im–Pesaran–Shin test (Im et al., 2003) on the FSIND index which results into a p-value $\ll 0.01$ for all model specifications ensuring its stationarity. The stationarity is important because we can infer that the changes over time, which the index is expected to capture, can be statistically robust and not caused by any trend in the data or mean-reversion effects.

When dealing with dimensionality reduction approaches, a key role is played by loadings which interpretation in terms of relative importance and impact on each country can induce insights and speculations on the effects of the original variables.

As described in Section 2 the loadings $\mathbf{C}^i$ for the ith country are stacked into the diagonal matrix $\mathbf{C}$, whereas the cross-country interactions are introduced by the matrix $\hat{\boldsymbol{A}}$ estimated with a VAR. Our setting forces the $\mathbf{C}^i$ to be constant, so we can estimate loadings for each country-variable pair. As representative example, Fig. 1 reports the FSIND evolution over years for four countries and the corresponding loading contribution. We select two countries as example of advanced economies (Spain and Cyprus) and two for the emerging markets (Afghanistan and Chad) and compare the relative values of FSIND with respect to Banking and Debt crisis, as described in Nguyen et al. (2022). Negative values or abrupt decrease of FSIND occur in presence of crisis period. Moreover, we can see how loading contribution can differentiate between different type of crisis. Indeed, Banking crisis seem to be affected from negative contribution of variables 1 and 4, both dealing with Nonperforming loans and positive contribution of variables 5, 6, 13, and 14, dealing with Risk-weighted asset Regulatory Capital and Return on Equity/Asset. This witnesses the capability of the FSIND index to capture the dynamics and evolution of the economies thanks to the wise choice of the 17 building variables and to the correct and meaningful mix obtained through the DFM approach.

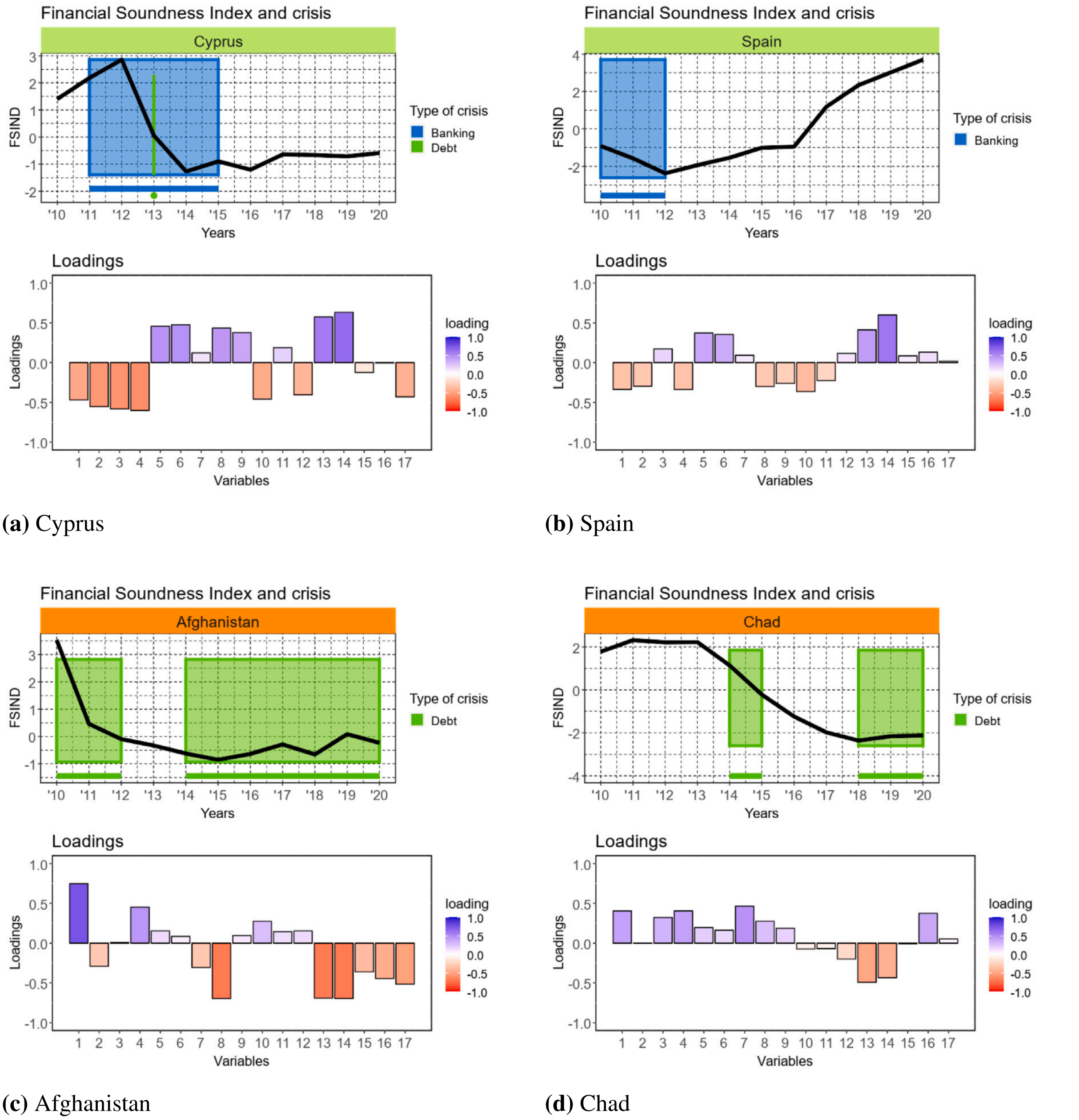
On the other side, Debt crisis seem to be characterized by positive contribution of variables 1 and 4 and a negative contribution of variables 13 and 14.

The interpretation of the FSIND index in terms of variables component should be assessed country by country, given the high heterogeneity of traits and characteristics. However, in order to compare the effect of the loadings across countries, we applied hierarchical clustering to the matrix $\mathbf{C}$ and, for ease of visualization, we used the dendrogram reordering of the variables to highlight the relative patterns in each cluster, by the means of R package `ComplexHeatmap` (Gu, 2022). Figures C.4 and C.5 in the Appendix reveal that countries that experienced Banking or Debt crisis (red ones), are mostly grouped together, showing a loadings contribution similar to the four sample countries described in Fig. 1. A more accurate inspection of the dendrograms in Figures C.4 and C.5 reveals quite clear activation patterns of groups of variables. For example, variables 7, 15 and 16 (customer deposits and liquidity) are particularly impacting on cluster 2 and partially on cluster 5. Variables 1 and 4 (related to non performing loans) are very positively related to cluster 5 and 6 and negatively to cluster 1, 2 and 3. An interpretation of the contribution of the loadings run at the cluster levels can represent a valid aid to policy makers and institutions in understanding group of countries movements, reactions and suffering periods.

For sake of robustness and comparability, we fit two alternative dimension reduction techniques which commonly represent a baseline, respectively linear and non linear: Principal Component Analysis (PCA) and Kernel Principal Analysis (KernelPCA). Such approaches do not embed naturally any temporal dynamics differently from the DFM but they represent anyhow a well established benchmark for linear (PCA) and non-linear (KernelPCA) dimensionality reduction. Briefly, Kernel PCA maps the input variables into a different space (possibly infinite-dimensional), defined by the selected non-linear kernel, where the linear PCA is performed and its rotated scores and loadings are mapped back to the input space. To overcome such issue of no proper temporal component elicitation, we fit both PCA approaches employing all the countries together year by year. In particular, for PCA we used a less sensitive to outlier algorithm, i.e. Robust PCA (Candes et al., 2009) and for KernelPCA (Schölkopf et al., 1997) we tested polynomial kernel of degree 2 and 3.

Results for both PCA approaches can be found in Table 3 where we report the average R^2 both on the whole dataset and on subsets with values trimmed for the 95th and 99th percentiles.

The reader can clearly notice that linear PCA approach performs worse in terms of Mean R^2 regardless the considered configuration, whereas KernelPCA approach shows a slight increase in performance. However, given the use of a kernel, there



(a) Cyprus **(b)** Spain **(c)** Afghanistan **(d)** Chad

Fig. 1. FSIND evolution over years for some countries and corresponding loadings contribution. Top row reports Advanced economies (in green), bottom row reports emerging/developing countries (in orange). For each country, the shaded areas represent the Banking (blue) and Debt (green) crisis (Nguyen et al., 2022). Variables' legend is reported in Table 1.

is a lack of explainability for the loadings, that cannot directly be related with the contribution of the original input variables. Moreover, we can stress how important is the proper modeling of the temporal dynamics, that lacks in both methods.

5. Final remarks

In this paper, we address an important topic relevant in many applications fields. It is common to be exposed to the management and analysis of several variables measured through time and space. In this sense, it plays a crucial role the employment of approaches to reducing the features space by creating one or more summary indexes which can be profitably used both for descriptive and predictive purposes. A common benchmark for dimension reduction is Principal Component Analysis which, despite its simplicity in the fitting process and in the interpretation, lacks of adaptability and accuracy when the available data presents strong temporal and spatial dimensions.

To overcome such limitation, we propose to employ a Dynamic Factor Model which naturally exploits any temporal dynamics and represents a valid alternative for the building up of summary indexes neither subjective nor fully experts-driven. To fully describe the potentials of the DFM, we take advantage of a financial application where it is relevant to produce an index that leverages on 17 financial indicators, able to measure the financial soundness of all the countries all over the world. We contribute to the research field, not only by proposing a new fully data driven financial soundness indicator, but also by offering a statistically sound methodology which goes beyond state-of-the-art techniques and largely outperforms baseline approaches (namely PCA). The latter, indeed, fails in properly modeling the temporal evolution of the units of interest (in the present paper the countries) and in building a summary indicator representative enough of the variability contained in the original variables.

Results show that our FSIND index can identify banking and debt crisis when in presence of negative values or abrupt decreases. Moreover, the latent variables that contribute most to the FSIND index reveal groups of countries with similar behavior and, in particular, can discriminate the countries that experienced crisis. Thus, an interpretation of the resulting clusters can represent a valid aid to policy makers and institutions in understanding group of countries movements, reactions and suffering periods.

We underline that the approach is general enough to be applied to contexts different from the present one.

The methodology can be improved in a number of ways. For example, other non linear approaches that can simultaneously evaluate the index for all countries, avoiding the two-steps approach described in this paper, could be employed and compared: neural networks autoencoders would represent a natural candidate. Further robustness checks would be useful to prove the consistency and stability of the methodology. For example, longer time series and or more granular data: from yearly based to quarterly or monthly based data. Moreover, scaling up the dimension of the analysis, by increasing the number of considered variables, can shed further light on the potentials of the DFM approach.

Lastly, it would be interesting to evaluate the performance in completely different fields like social, cultural or health related ones.

CRediT authorship contribution statement

Alessandro Bitetto: Conceived the experiment(s), Conducted the experiment(s), Analyzed the results, Reviewed the manuscript. **Paola Cerchiello:** Conceived the experiment(s), Conducted the experiment(s), Analyzed the results, Reviewed the manuscript. **Charilaos Mertzanis:** Conceived the experiment(s), Conducted the experiment(s), Analyzed the results, Reviewed the manuscript.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.frl.2023.103678.

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