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A data-driven approach to measuring financial soundness throughout the world

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A data-driven approach to measuring financial soundness throughout the world

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Abstract We use a fully data-driven approach and information provided by the IMF's financial soundness indicators to measure the soundness of a country's financial system around the world. Given the nature of the measurement problem, we apply principal component analysis (PCA) to deal with the presence of strong cross-sectional dependence in the data due to unobserved common factors. Using this comprehensive sample and various statistical methods, we produce a data-driven measure of financial soundness that provides policy makers and financial institutions with a tool that is easy to implement and update.

Keywords Financial soundness · Data-driven · Cross-country · Policy framework · Principal Component Analysis · Random Forest

JEL E32 · E42 · E61 · E02 · F02

1 Introduction

The importance of a strong financial system for sustained economic growth is well documented (Allen and Gale, 2000). A sound financial system supports economic activity by pooling and mobilizing savings for productive use, providing information on existing and potential investment opportunities, improving corporate governance and facilitating trading, diversification, and risk management. The 2007-8 financial crisis has underscored the importance of financial system resiliency in providing finance to households and business throughout the business cycle. It has also underscored the importance of limiting the types of financial and real imbalances that develop during times of prosperity. When such balances unwind, they can cause significant damage to the financial system and the economy.

Measuring financial stability is a formidable challenge (Gadanecz and Jayaram, 2008). The financial system is a complex one. It consists of many diverse actors, including banks, mutual funds, hedge funds, insurance companies, pension funds and shadow banks. All of them interact with each other and the real economy in complex ways. The 2007-8 financial

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crisis provided a clear example of this complexity and its consequences. Assessing financial stability therefore requires the consideration of the diverse macroeconomic, structural and institutional aspects of the financial system (European Central Bank, 2005). The large volume of international capital flows has made it increasingly important to strengthen the foundations of domestic financial systems in order to build up resilience to capital flow volatility and its effects on the economy. Maintaining financial resilience, strong macroeconomic performance and effective monetary policy at the national level requires sound financial institutions. Hence, central banks and governments monitor closely the health and efficiency of financial institutions and markets along with the macroeconomic and institutional developments that pose potential risks to financial stability.

The Basel Committee on Banking Supervision (2013) has stressed the need to focus on the ability of financial institutions to manage risk. The Committee identified the major shortcomings of financial institutions' ability to quickly and accurately aggregate risk exposures and identify risk concentration at the individual institution level, across business lines and between legal entities. These shortcomings affect the financial institutions' ability to quickly carry out stress testing in order to assess their exposure to risk associated with particular economic-financial scenarios. In order to achieve the efficiency, reliability and transparency required for performing large-scale risk analysis, decision-makers need a proper standardization of the data, rules for financial flow generating algorithms and sufficient computational power (Mertzanis, 2018).

Using absolute quantitative levels of risk may not adequately capture the extent of a financial institutions' or financial system's vulnerability. There is a need for implementing a "net risk" approach that combines both the quantitative and qualitative aspects of financial vulnerability based on proper information and measurement (Lo Duca and Peltonen, 2011). The net risk approach involves the quantitative evaluation of all risks faced by financial institutions and the qualitative adjustment for institutional factors. It helps to better assess whether risks are managed adequately through market discipline and internal governance in a financial institution, as well as through regulatory and supervisory frameworks in the financial system as a whole. The outcomes of these evaluations combine to produce an overall risk assessment for individual financial institutions and an overall stability assessment for the financial system as a whole.

The qualitative adjustments require the consideration of the institutional characteristics of the financial system. The nature of government intervention in the economy, the payments culture, the insolvency regime, the credit and deposit guarantees, the quality of supervision and regulation, moral hazards, corporate governance, and management quality all affect the general incentives structure of a financial system and must be taken into account in qualitative adjustments. Combining the qualitative and quantitative aspects of risk assessment is not an exact method and requires judgment. This introduces considerable complexity in the assessment process.

One way to deal with the challenges of complexity and timely execution of the financial system's risk assessment is to implement a data-driven approach to measuring financial soundness. This approach may provide a better evidence basis to support reasoning and decision. Given the complexity of the financial system, it may lead to better optimized assessments. While no data-driven algorithms exist that can lead to fully optimal assessments of financial soundness, this approach has considerable advantages, such as avoiding post-hoc rationalization, as is typical for economic narrative based methods.

In this paper, we construct a financial soundness index (FSIND) using a data-driven methodological approach and information provided by the International Monetary Fund's (IMF) Financial Soundness Indicators (FSIs). Given the nature of the measurement problem, we choose principal component analysis (PCA) to deal with the presence of strong cross-section dependence in the data due to unobserved common factors. The PCA provides a more flexible but robust approach to capturing strong common factors. Indeed, the PCA method offers a variety of statistical tools not only to assess the quality of the results but also to interpret and replicate conditional insights. This choice is in line with the methodology used in related studies (Illing and Liu, 2006, Hakkio and Keeton, 2009). We build the FSIND index by using the IMF's Financial Soundness Indicators specifically tailored to measure the strengths and weaknesses of the financial system. The FSIND index is available for 119 countries for the 2010-2017 period. We enrich the index by including information from supplementary variables that take into account geographical and cultural dimensions. We carry out extensive model validation and sensitivity analysis that makes the model robust and statistically sound. Finally, we make the index values available in both continuous and binary formats to accommodate alternative policy needs and research strategy specifications.

Our paper is related to the new wave of research on stress-testing and early warning models aimed at assessing financial stability (Alessi and Detken, 2011b, K.Rose and Spiegel, 2012, Lo Duca and Peltonen, 2013, Drehmann and Juselius, 2014). These studies use different assessment methods but they do not explicitly consider data-driven methods. Other studies use data-driven methods but they focus on either individual institutions or single countries. For example, using random forests, Alessi and Detken (2018) develop early warning models of systemic financial crises at the country level and Tanaka et al. (2016) predict failures at the level of individual banks.

Our paper contributes to the financial stability literature by creating a new financial soundness index for 119 countries that is fully data-driven, tested and validated. The data "speak" by means of an unsupervised statistical learning technique, namely the Principal Component Analysis (hereafter PCA). This technique makes neither a-priori assumptions on the relationship among the input variables nor a subjective decision on the variables to be possibly dropped. Further, the model does not need to define a target variable, thereby avoiding a further level of subjectivity. The only model assumption lays on the number of components built on the original variable space reflecting the desired level of captured variability and explainability. Moreover, the new coordinates must by construction lie on a linear space and be mutually orthogonal (i.e. independent). Independence ensures that each new principal component is describing a specific and not known in advance latent phenomenon through the linear combination of the initial variables. Our approach is methodologically related to that of Hakkio and Keeton (2009), Kliesen and Smith (2010), Brave and Butters (2011) and Louzis and Vouldis (2011), but these authors use monthly market-based data and study single counties, whilst we use aggregated bank balance-sheet and structural macro data for many countries. Finally, our analysis complements recent risk assessments based on the use of machine learning methods (Lin et al., 2012). Indeed, the authors stress that, beside the efficiency of the machine learning algorithm (often ensemble models do the job), the dataset, the selection of leading variables and the pre-processing phase in general play a key role in producing accurate assessments. We have placed special emphasis on these aspects in our analysis. We make the index values available at `https://github.com/PaperDataRepo/FSIND`.

The paper is organized as follows: in section 2 we discuss the literature on financial soundness index and relative approaches, in section 3 we present the methodology detailing the Principal Component Analysis, a more robust version employed and the validation index techniques. In section 4 we extensively discuss the data and the preprocessing phase, in section 5 results will be shown and discussed and conclusions are given in section 6.

2 Relevant literature

In carrying out financial stability assessment, it is important to evaluate how risk-taking financial institutions manage risk and how supervisors regulate the management of risk. Different financial institutions have different risk appetites. Further, the particular institutional and regulatory framework of the financial system strongly influences the level of risk-taking. This raises two challenges: the timely aggregation and measurement of financial risk and the usefulness of absolute risk levels.

The 1997 Asian financial crisis and the 2007-8 global financial crisis showed the importance of financial stability for economic activity. These crises demonstrated that certain structures of financial institutions' balance sheets could adversely affect the financial sector and lead to the origination and perpetuation of financial crises (Laeven and Valencia, 2012). These crises further demonstrated that the vulnerability of the financial institutions could exist along with robust macroeconomic conditions. As a result, the systematic and regular monitoring of both the financial institutions' balance sheets and the macroeconomic conditions emerged as key policy considerations throughout the world. These considerations have been associated with the emergence of the notion of "macro-prudential supervision". Hawkesby (2000) was the first to introduce the term referring to a set of indicators that collectively indicate the riskiness of financial institutions and its implication for financial system stability.

Guérineaua and Léon (2019) argued that the financial stability question in low-income countries has received less attention in recent years, perhaps because the 2007-8 crisis affected low-income countries less than high-income ones. The authors focused on 159 countries divided into developing and developed ones and analyzed specifically banking system instability and credit information sharing power during 2008-2014. After measuring financial stress by the non-performing loans ratio than the actual incidence of crisis (e.g. rare event), they documented a positive effect of information credit sharing on the financial stability of both developing and developed countries. Interestingly, even after controlling for credit booms, which typically adversely affect financial stability, credit information sharing still acts as a moderator of the financial crisis.

Financial institutions soundness is an important element of financial stability. The measurement and monitoring of the financial institution soundness can help the early detection of the potential buildup of systemic risk that may lead to a financial crisis. Researchers proposed several approaches to assess financial stability. The most important ones are the structured approach, the reduced-form approach, the network analysis approach and the indicators approach.

The structured approach measures financial system risk by calculating joint default risk or portfolio credit risk (Avesani et al., 2006, Huang et al., 2009, Segoviano and Goodhart, 2009). This approach uses bank balance sheet information and market price information, such as credit default swap spreads and financial security prices, and derives the marginal distribution of risk using specific copula structures to obtain the joint default probability or portfolio credit.

The reduced-form approach measures financial system risk by using a quantile regression to calculate conditional values at risk (CoVaR) (Adrian and Brunnermeier, 2016). CoVaR is defined as the change in the value at risk (VaR) of the financial system as a whole conditional on a financial institution being under distress relative to the financial system median state. Acharya et al. (2012) use the concept of systemic expected shortfall (SES) to measure the contribution of a single financial institution to financial system risk. They argue that the undercapitalization of the financial system as a whole implies undercapitalized individual financial institutions.

The network analysis approach uses information on two-way financial exposures and transactions in the balance sheets of financial institutions to establish a network of interrelatedness among them. It measures financial system risk by simulating through network models the accumulation of exposures and interactions of individual institutions. Chan-Lau et al. (2009) constructed network models to analyze the network externalities of a single bank. Billio et al. (535-559) use Granger causality tests of financial asset returns to define the edges of a network of financial institutions and show that Granger causality networks are highly dynamic and become densely interconnected prior to systemic shocks.

The financial indicator approach uses both quantitative and qualitative information from the implementation of the Financial Sector Assessment program (FSAP), administered jointly by the International Monetary Fund and the World Bank. This information arises from balance sheets and other financial sources (International Monetary Fund, 2019). Related studies have used variants of this approach. For example, Borio and Drehmann (2009) apply simultaneous extreme value theory on pairs of property prices, equity prices and credit spreads, and construct an indication of financial system risk. Alessi and Detken (2011a) use a broad range of real and financial trends in 18 OECD countries between 1970 and 2007 and constructed simple early-warning indicators. Lane (2019) followed a data-driven approach examining the implications of monetary union for macrofinancial stabilisation policies for all countries of the Euro area in the period 2003–2012, focusing on 2007–2012 for the global crisis and 2010–2012 for the area-specific crisis. Finally, Quinn et al. (2011) make a survey of main indicators of financial openness and integration used to capture the relationship of financial openness or integration with economic growth.

These approaches to financial stability assessment have been variously used to produce early warning signals, macro-stress tests and financial stability indicators (Lin et al., 2012, Alessi et al., 2011, Cavalcante et al., 2016, Quagliariello, 2009, Demyanyk and Hasan, 2009). Each approach has its advantages and limitations. Policy makers and researchers have focused on alternative statistical indicators and used various combinations to identify and describe the vulnerabilities of the financial system and achieve accurate financial stability assessments. These approaches and their metrics have evolved over time to address the transition from the micro-prudential to the macroprudential dimension of financial stability.

Most research efforts at creating specific measures of financial stability, while applying various methods and models, have mainly focused on specific countries accounting for specific peculiarities and economic characteristics. For instance, Illing and Liu (2006) developed a daily financial stress index for the Canadian financial system and proposed alternative approaches to aggregating individual stress indicators into a composite stress index. Their index comprises eleven financial market variables, which they aggregate 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. Hakkio and Keeton (2009) proposed the Kansas City Financial Stress Index (KCFSI) for the US economy. This index uses eleven financial market variables for 1990-2007, each of which captures one or more key features of financial stress. The KCFSI relates to the Canadian index (Illing and Liu, 2006) but it focuses more on the US economy and it is more interconnected than the Canadian one. Applying the same methodology, Kliesen and Smith (2010) aggregated 18 weekly financial market indicators into the St. Louis Fed's Financial Stress Index (STLFSI). Likeswise, Oet et al. (2011) produced the Cleveland Financial Stress Index (CFSI) by integrating 11 daily financial market indicators form the debt, equity, foreign exchange and banking markets. They normalized the raw indicators by transforming the series values into the corresponding

CDF values. The transformed indicators are then aggregated into the composite indicator by applying time-varying credit weights, which are proportional to the quarterly financing flows through the four markets. Morales and Estrada (2010) proposed a financial stress index for the Colombian economy, using measures of financial institutions' profitability, liquidity and probability of default. In particular, they used capital, liquidity, credit risk and return ratios monthly data (nine variables in total) from January 1995 to November 2008 for a heterogeneous bunch of financial institutions, including commercial banks, mortgage banks, commercial financial companies and financial cooperatives. The authors generated and combined information from different indicators through different quantitative methods, such as a variance-equal weight, principal component and count data methods. One of their key contributions was the development of a domestic financial stress indicator by type of institution. Holló et al. (2012) proposed the composite indicator of systemic stress (CISS). They applied portfolio theory to compose five market-specific sub-indices based on fifteen individual financial stress measures. The CISS index takes into account the time-varying cross-correlations between the sub-indices as well. Applied to the Euro area, the CISS follows 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. Koong et al. (2017) proposed a financial stability index for the Malaysian economy based on 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. They applied non-parametric tools (concordance index, OLS and GMM estimators) and concluded that the business cycle exerted a significant effect on the stability of the financial system in Malaysia but household credit did not. Arzamasov and Penikas (2014) use sixteen IMF financial soundness indicators during 2003-2013 to study financial stability in Israel. The approximate financial stability by using the economic resilience (ER) index produced by the International Institute for Management Development (IMD). The authors applied three different methods, namely principal component analysis, regression and hybrid models, and concluded that the PCA method were the most effective ones. Sere-Ejembi et al. (2014) construct a banking system stability index (BSSI) for Nigeria using a weighted combination of the banking soundness index, the banking vulnerability index and the economic climate index during 2007:Q1 to 2012:Q2. The BSSI index performed well in predicting the domestic financial crisis and the therefore the authors proposed it as an early warning tool. Jakubik and Slacik (2013) focuses on nine Central Eastern and South-eastern European countries and develops a financial instability index (FII) using monetary, financial and foreign exchange data during 1996 to 2012. In order to construct the index, they cluster variables into five groups, subsequently use the quantile distribution to identify periods of financial stability vs financial instability and finally use the resulting weighted average to designate their index. They fit a panel GMM regression to identify the most influential variables on the index evolution. Albulescu (2013) focuses on the role of monetary policy on financial stability. The authors analyzed the impact of the European Central Bank's decisions by measuring the difference between the optimal and real interest rates during 1999-2011 on a quarterly basis. They applied a stochastic reduced-form model that uses information on inflation and the GDP growth rate to build a financial stability index. They applied their index to predict the 2007-8 crisis and suggested an increase of the interest rate during 2010-11 as balancing mechanism to contain inflation. Sales et al. (2012) focuses on the Brazilian financial system and uses quarterly macroeconomic indicators during 1995:Q1 to 2011:Q4 to build the broad financial stability indicator (BFSI) and the specific financial stability indicator (SFSI), both of which are shown to predict three Brazilian financial crisis episodes. They applied a principal factor method based on unobserved factors to construct the BFSI; and an OLS regression of three main financial market indicators to construct the SFSI. They also applied a business cycle decomposition method that uses the co-movement of financial and real indicators to assess the driving role of financial vs. real factors, respectively. Brave and Butters (2011) construct a financial conditions index (FCI) for the USA using a hundred financial indicators from early 1970s to late 2010s. They use both a PCA and a dynamic factor analysis on time-series to estimate a weighted average value, which is a threshold for assessing financial stability vs. instability. They validate the FCI by regressing it against macroeconomic variables and including high-frequency non-financial measures of economic activity. Nelson and Perli (2007) of the Federal Reserve Board produced a weekly "financial fragility indicator" for the USA computed in two steps using twelve market-based financial stress measures. In the first step, the standardised inputs are first reduced 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. Following a similar approach, Grimaldi (2010) computed a similar 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, but the correlation coefficient turns significant. He then identified crisis events for the computation of the binary indicator on the basis of a keyword-search through relevant parts of the ECB Monthly Bulletin. Roye (2011) pursued an approach similar to the one by Brave and Butters (2011) to construct a "financial market stress indicator" for Germany and the euro area. The index comprises 23 and 22 raw stress factors, respectively, covering the banking sector, securities markets and foreign exchange conditions. Louzis and Vouldis (2011) constructed a monthly "Financial Systemic Stress Index" for Greece, in which they aggregated 14 individual stress measures based on financial market data and monthly bank balance sheet data into five subindices using portfolio-theoretic measures (i.e. cross-correlations) computed through a multivariate GARCH model. They applied principal component analysis at the subindex level, and the subindices were normalised using logistical transformation. All these studies, whilst interesting and often accurate, are single-country focused, lack generalization power, and therefore produce results that policymakers and practitioners cannot effectively apply to analyze the complex interconnectedness of the global financial system.

Other studies analyzed the financial stability problem in a cross-country setting. However, these studies had to deal with the considerable challenges of missing values, insignificant variables across countries (while significant at the country level) and difficulties in the assessment of control variables. For example, Holmfeldt et al. (2009) constructs a financial stress index based on the deviation of actual trends from their historical average of variables in the credit and money market for Sweden and the US from 1997 to 2007. The European Central Bank (2009) used a variance-equal weighted method to compute the Global Index of Financial Turbulence (GIFT) for 29 European economies that comprises six market-based indicators, which capture stress in fixed income, equity and foreign exchange markets. Slingenberg and de Haan (2011) assessed the financial stability of thirteen OECD countries using a simple unweighted sum of standardized IMF indicators, where positive sum values indicate financial stress. They tested the predictive power of their index using a GARCH model, which produced moderate results for most countries. Cevik et al. (2013) analyzed financial stability in four Eastern European countries and Russia. They used a PCA method to analyze aggregated indicators of riskiness of the banking sector, the securities market, the foreign exchange market, the external debt market, sovereign risk and trade finance markets. Creane et al. (2006) collected 35 indicators from a survey on 20 Middle-East and North-Africa countries from 2000 to 2003 on six main themes: non-bank financial sector development, monetary and banking sector development, regulation and supervision, financial openness and institutional environment. They constructed a Financial Developement Index summarizing the indicators by the means of a weighted average, with a subjective set of weights. Then a PCA-based set of weights was used only as a sensitivity test to reduce the reliance on qualitative judgments in selecting the most relevant weights to be assigned. Islami and Kurz-Kim (2013) used daily data of financial market indicators, such as CDS spreads, EUR/USD exchange rate volatility, 3-month and 10- year interest rates, to build a financial stability index (FSI) for all European countries. After standardizing and rescaling the time series, they produced a simple average FSI index with a daily and monthly horizon. They also used a single-equation error correction model to assess the index's predictive power relative to other benchmarks. Finally, Vermeulen et al. (2015) applied a similar approach to assess the financial stability of twenty eight OECD countries and seven stock market indices and interest rates. They further used logit models and their index to predict binary outcomes (crisis vs. no crisis) and multinomial outcomes (banking vs. currency vs. no crisis).

Overall, financial stability measures have been mostly single-country based and used less sophisticated estimation methods, often devoid of additional qualitative information. Our analysis goes further by creating a financial soundness index for both developed and developing countries that is fully model-based and data-driven, properly tested and validated, and accounts for the role of qualitative factors. In so doing, we focus on the efficiency of the machine learning algorithms, the credibility of the data source and the propriety of variable selection. We make the index values available in both continuous and binary formats to accommodate alternative policy needs and research strategy specifications.

3 Methodology

As already discussed, macroeconomic variables are often used to assess financial stability of countries. A common way to summarize information from these variables is to create synthetic indexes based on assumptions taken by financial institutions' experts and typically resulting in the usage of weighted average. However, for their inner subjective nature, such indices can be questionable and can lead to endless debate on which one should be used as a robust financial indicator and insofar as a benchmark.

In this paper we want to present a data-driven statistical approach to build a financial index based on data intrinsic information. We analyse a set of Financial Soundness Indicators (FSI) provided by International Monetary Fund ranging from 2006 to 2017 for most of worldwide countries, including both strong and developing economies. First, we assess the data quality and cope with issues related to the presence of missing data, experimenting different techniques. Then we take advantage of a statistical methodology to build the index: Principal Component Analysis (PCA). By means of PCA we create a low dimensional (1 to 2 way) continuous indicator, explaining the variance of the data at most and considering each year separately. A threshold is then appropriately set to the PCA based indicator so to assign a dichotomous label (Stable vs Unstable economy) to each country.

The aim of our analysis is to extract synthetic indicators that summarize at best the relationship among variables in a lower dimensional space. One of the most common methodology used for dimensionality reduction is Principal Component Analysis (*PCA*) .

Briefly, *PCA* aims at creating one or more new components from a larger set of observed variables, where each component is a linear combination of the Y original variables. The model is represented by the equation $C = w_1Y_1 + \ldots + w_4Y_4$, where C is the new principal component, Y_i are the original variables and w_i are the weights of the linear combination.

We recall that our dataset has three dimensions, *Country*, *Variable* and *Time*, so we decide to apply the previous dimensionality reduction technique in the following way: PCA is used to model country/variable interaction for each year.

Thus, PCA has been evaluated on each year separately, resulting in T models. For sake of stability and robustness, we also decided to evaluate and compare three different PCA techniques: regular PCA, Robust PCA and Robust Sparse PCA.

According to the definition, PCA aims at finding a new and wise linear combinations of the original data, in a way that the amount of explained variance of the data is maximised. Those combinations are mathematically constrained to be mutually orthogonal (that is independent) and are called Principal Components (PC) or loadings. Given a $n \times p$ data matrix $\mathbf{X}$, where n is the number of observations and p is the number of variables, we want to find the $k \times p$ Principal Component matrix C, with usually $k << p$ such that the projected data matrix $W = XC^T$, also called scores matrix, will have dimension $n \times k$. The problem can be seen as:

$$\begin{aligned} \underset{\mathbf{C}}{\text{minimize}} \quad & \|\mathbf{X} - \mathbf{X}\mathbf{C}\mathbf{C}^T\|_F^2 \\ \text{subject to} \quad & \mathbf{C}^T\mathbf{C} = \mathbf{I} \end{aligned}$$

where $\|\cdot\|_F$ is the Frobenius norm. We implement the model using *R* package `prcomp`.

If we want a robust estimation of the Principal Components, we can decompose the data matrix X into a low rank component L that represents the intrinsic low dimensional features and an outlier component S that captures anomalies in the data. The problem can be then solved by:

$$\begin{aligned} \underset{\mathbf{L},\mathbf{S}}{\text{minimize}} \quad & \|\mathbf{L}\|_* + \lambda\|\mathbf{S}\|_1 \\ \text{subject to} \quad & \mathbf{L} + \mathbf{S} = \mathbf{X} \end{aligned}$$

where $\|L\|_.$ is the nuclear norm and λ is a penalization term. Once fitted, $\mathbf{L}$ can be used as a proxy for $\mathbf{X}$ but cleaned up by extreme values. We implement the model as described in (Candes et al., 2009).

As a further improvement, if we want a robust estimation and a sparse representation of the Principal Components, we can add a sparsity constraint on matrix C. The problem can be then solved by:

$$\begin{aligned} \underset{\mathbf{C},\mathbf{W}}{\text{minimize}} \quad & \|\mathbf{X} - \mathbf{W}\mathbf{C}^T - \mathbf{S}\|_F^2 + \psi(\mathbf{C}) + \phi(\mathbf{W}) + \lambda\|\mathbf{S}\|_1 \\ \text{subject to} \quad & \mathbf{C}^T\mathbf{C} = \mathbf{I} \end{aligned}$$

ψ and ϕ are regularizing functions (i.e. LASSO or Elastic Net) as described in (Erichson et al., 2018).

The final index, hereinafter referred as Financial Soundness Index (FSIND), will be based upon the scores matrix W that is k-dimensional. We aim to select the number of components k as a result of a trade-off between maximal explained data variance and smallest value of k (i.e. principal components).

By construction, PCA produces a continuous output vector of size n for each of the k selected components, also known as scores vectors. Assuming that each component is a candidate Financial Soundness Index, we lay particular attention on the choice of the thresholds necessary to produce binary indices. Insofar the validation process of the thresholds that guarantees a minimal level of subjectivity, is composed of two stages. We firstly set a threshold and get the binary index, i.e. 0 or 1 labels. Then we perform a regression by means of *Random Forest* and *Gradient Boosting Machine* where the target is an economic variable (such as *GDP* or *Non Performing Loans*) and the regressors are the 2 binary indexes and finally we evaluate prediction accuracy and outliers for different thresholds. We iterate this procedure with different thresholds and select the most appropriate one according to prediction accuracy and outliers stability.

4 Dataset and Preprocessing

Our dataset consists of 17 Financial Soundness Indicators (FSI) provided by International Monetary Fund for 140 countries, spanning from 2006 to 2017. In addition, we include geographical indicators, i.e. longitude and latitude and 6 cultural indicators such as Hofstede dimensions (Hofstede, 1984), fixed through the years. A detailed list of variables is shown in Table 1.

However some countries present too many missing values, as well as, less than expected years. As a consequence, we decide to restrict our analysis on a subset of 119 countries from 2010 to 2017, selected with a *NA* incidence tolerance not exceeding 30%. The complete list of selected countries and relative percentage of *NA* is reported in A. Since the presence of many missing values can extremely impact the quality and the reliability of results, we set a protocol of missing values treatment and imputation.

As stated above, according to our protocol, missing values for the selected countries are still present, in fact 16 out of 119 countries show a percentage of *NA* between 20-29%. A complete overview of selected countries and their missing values percentage is shown in Figure 1. In order to deal with missing values and to apply further methodologies in a robust way, we test two different data imputation techniques: Matrix Completion with Low Rank SVD (MC-SVD) (Hastie et al., 2015) and Bayesian Tensor Factorization (BTF) (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 on the 2-dimensional "slice" of countries-FSI 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.

To assess imputation performances and to choose the best method, we test the algorithm in three settings. In the first (named *Original*) we consider the whole dataset made of 119 countries by 25 variables for 8 years for a total of 23800 entries. It contains 8% of missing values, thus we randomly remove some additional values representing 10%, 20% and 30% of the initial dataset. In the second (named *No missing*) we drop all entries with missing

Table 1
List of used variable.

Type	Variable	Frequency	Total Observations	Missing Values	Min	Max	Mean	Standard Deviation	Variation Coefficient
FSI	Emb Capital to assets	Yearly	952	63	1.49	24.85	10.28	3.57	0.35
	Emb Customer deposits to total non interbank loans			113	29.01	626.93	120.73	56.5	0.47
	Emb Foreign currency liabilities to total liabilities			193	0	100	30.61	24.87	0.81
	Emb Foreign currency loans to total loans			176	0	100.06	28.75	26.26	0.91
	Emb Personnel expenses to non interest expenses			93	5.29	91.58	44.17	12.04	0.27
	Interest margin to gross income			21	-294.33	142.77	59.01	18.4	0.31
	Liquid assets to short term liabilities			79	10	690.37	69.13	61.11	0.88
	Liquid assets to total assets			50	4.99	74.97	27.92	13.03	0.47
	Net open position of forex to capital			221	-95.43	407.97	9.57	36.74	3.84
	Non interest expenses to total income			21	-303.46	115.79	58.17	17.88	0.31
	Non performing loans net of capital provisions			21	-51.61	413.56	18.78	38.28	2.04
	Non performing loans to total gross loans			23	0	54.54	6.81	7.4	1.09
	Regulatory capital to risk weighted assets			19	1.75	42.2	17.67	4.83	0.27
	Regulatory tier 1 capital to risk weighted assets			24	2.18	40.3	15.43	4.86	0.31
	Return on assets			21	-25.61	10.28	1.5	1.8	1.2
	Return on equity			24	-505.64	65.4	13.22	21.93	1.66
	Sectoral distribution of loans residents			127	20.67	100	87.85	16.05	0.18
Geography	Latitude	Static	119	0	-38.42	61.92	20.44	26.93	1.32
	Longitude			0	-175.2	179.41	22.23	63.5	2.86
Hofstede	Individualism vs collectivism	Static	119	64	6	91	45.65	25.08	0.55
	Indulgence vs restraint			52	0	97	47.81	21.53	0.45
	Long term orientation vs short term normative orientation			52	4	86	45.46	21.05	0.46
	Masculinity vs femininity			64	5	88	46.16	18.55	0.4
	Power distance			64	11	104	56.65	21.47	0.38
	Uncertainty avoidance			64	8	112	68.67	23.04	0.34

values and apply the same incremental sampling procedure on the remaining subset. In the last (named *Some missing*) we drop all countries with at least 3 missing values for any year and apply again the incremental sampling procedure on the remaining subset. Furthermore, we fit the two methods, MC-SVD and BTF, on the previous 3 cases (a,b and c) with different sampling percentages and we evaluate the Mean Absolute Reconstruction Error (MARE) on the excluded observations as follows:

$$MARE = \frac{1}{M}\sum_{i}^{M}|x_{excluded} - x_{reconstructed}|$$

where M is the total number of excluded values. Moreover, we check the sensitivity to the original percentage of missing values by comparing the MARE on *No missing* and *Some missing* with the one on *Original*.

After imputing missing data, we check for stationarity of each FSI-country pair over the time span. We perform standard Augmented Dickey-Fuller and Ljung-Box test and since some non-stationarity is revealed, we integrate all time series with lag 1, in order not to sacrifice too many observations. The final dataset consists of 25 variables for 119 countries and 7 lagged years.

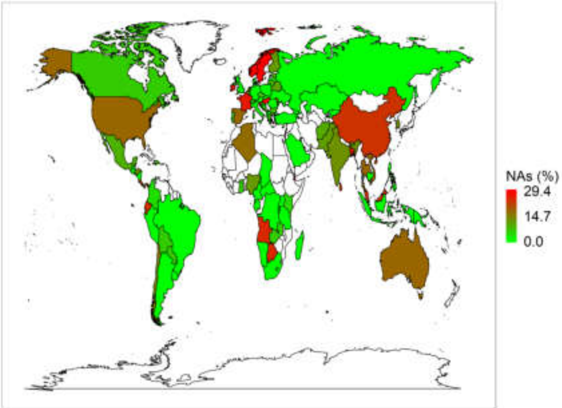


Fig. 1. Selected countries and missing values percentage

5 Data Analysis

As described in section 4, we assess the cross-validation error of the data imputation techniques and we find that Bayesian Tensor Factorization is the best technique. Details of the analysis are shown in B. We standardize the dataset for each year and then we apply the PCA method described in section 3. Results for the PCA approach can be found in Table 2. The average variance explained by loadings over all years is reported, as well as the average R^2 both on the whole dataset and on subsets with values trimmed for the $95th$ and $99th$ percentiles in order to check for outliers impact. We also decide to check only for the first two principal components so that the resulting FSIND could be visually interpretable. Robust PCA performed best. Figure 2 shows the scree plots for the loadings explained variance.

Table 2
Results from PCA. Mean is evaluated over years.

Method	Number of PC	Mean Expl. Variance	Mean R^2	Mean R^2 on 95th
PCA	1	$15.7 \pm 4\%$	$15.7 \pm 4\%$	$19.4 \pm 11.8\%$
	2	$27.9 \pm 6\%$	$27.9 \pm 6\%$	$34.3 \pm 10\%$
RobPCA	1	$40.6 \pm 3.5\%$	$94 \pm 0.9\%$	$95.7 \pm 0.9\%$
	2	$64.9 \pm 4.8\%$	$96.4 \pm 0.8\%$	$97.3 \pm 0.7\%$
RobSparPCA	1	$15.8 \pm 4\%$	$10.7 \pm 2.4\%$	$14.8 \pm 2.7\%$
	2	$28 \pm 6\%$	$20.1 \pm 3.3\%$	$28.2 \pm 2.7\%$

Being the continuous FSIND estimated, we validate the threshold to binarize it. As described in section 3, we test threshold for both dimensions ranging from -1.5 to 1.5 with a step of 0.5 (for a total of 7×7 combinations). We use as target variable for our mod-

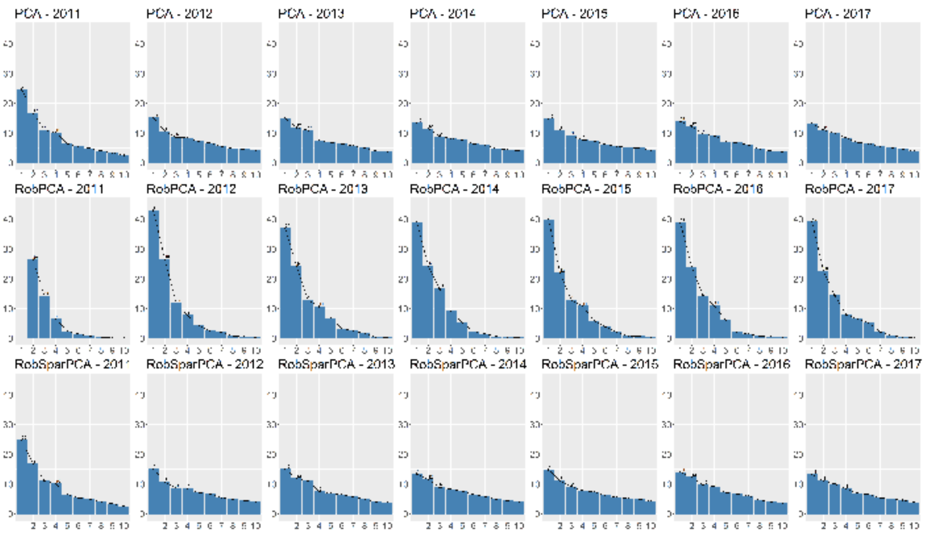


Fig. 2. Scree plot for the three PCA method

els five macroeconomic indices from World Development Indicators (WDI)[1] namely: Non-performing loans to total gross loans ratio (%), GDP per capita current, GDP per capita annual growth (%), GDP per capita PPP and Domestic credit to private sector (% of GDP).

First, we assess the outliers stability: we evaluate outliers based on extreme values of Absolute Percentage Error (APE) on prediction according to Generalized Extreme Studentized Deviate test (Rosner, 1983), then we count total number of detected outliers for each threshold and their shared percentage over all thresholds in order to check consistency. Secondly, we compare the performance of the models for each threshold according to APE in order to assess stability. As a further comparison, we also add performance of the fitted models using as regressors the initial dataset used to build the FSIND (FSI + Hofstede + Geographical details) (*original* case), the continuous FSIND (*raw index* case) and the continuous FSIND discretized according to the selected thresholds, i.e. 2 categorical variables with 8 levels each (*rank index* case).

Results for Domestic credit to private sector (% of GDP) are shown in Figure 3. Results for the remaining WDI are reported in C. As performances seem to be quite stable along with the value of thresholds, we decide to use 0 for both dimensions of FSIND.

Useful visual insights can be obtained exploring the cluster identified by the defined threshold. Some results are reported in Figure 4 where outcomes from PCA are reported for year 2014. For complete list of all years please refer to D.1.

Figure 5 shows the evolution over years of continuous FSIND for some countries. In particular Figure 5a shows that Greece and Cyprus have similar patterns as their financial systems are interdependent. In Figure 5b Saudi Arabia and Russia show similar patterns between their two indices and between each other because both countries are key oil exporters affected by similar risks and world events. Similar behavior is shown in Figure 5c because both Argentina and Chile suffer from structural deficiencies and populist politics. Also Poland, Ukraine and Russia have the same behavior because they are all

[1] `http://wdi.worldbank.org/table`

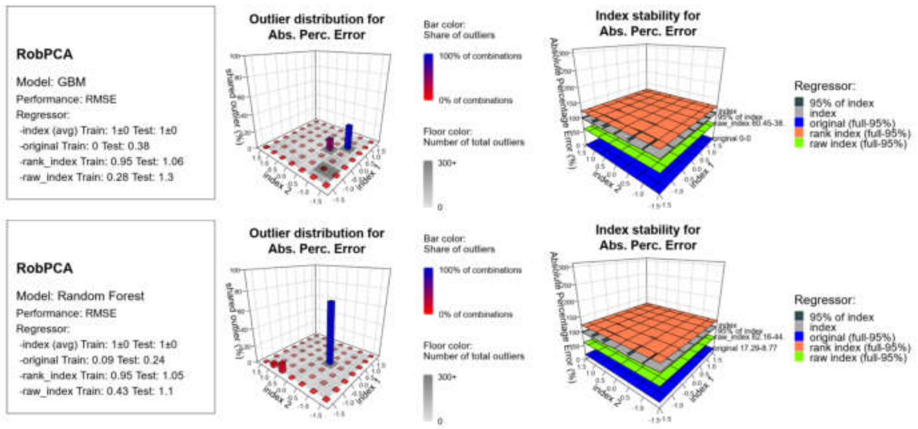


Fig. 3. Index validation for Domestic credit to private sector (% of GDP)

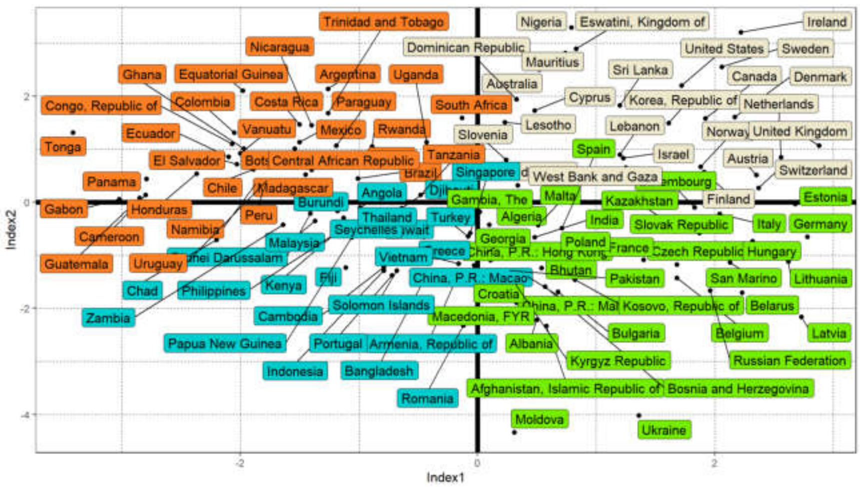
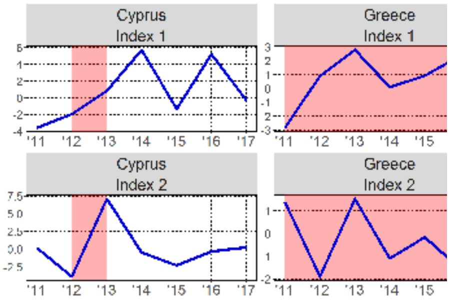
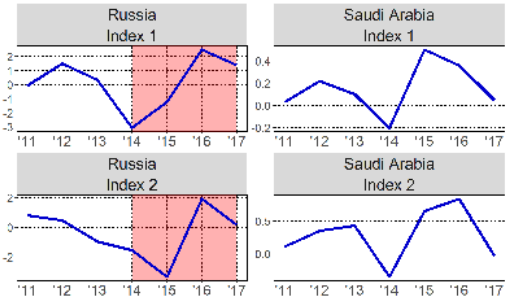


Fig. 4. Robust PCA index for 2014

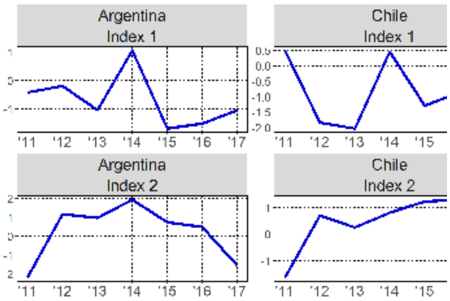
economically interdependent through the energy distribution network, common cultural origins and share similar geopolitical concerns as shown in Figure 5e. Figure 5d shows that India and China have similar patterns for index 1 and closely for index 2 as they both have to deal with similar problems of overpopulation, environmental pollution and both followed rapid credit expansion policies in recent years to accommodate the need of fast income growth and inequality reduction. For complete list of all countries please refer to D.2. Both continuous and binary FSIND for all countries can be found at `https://github.com/PaperDataRepo/FSIND`.



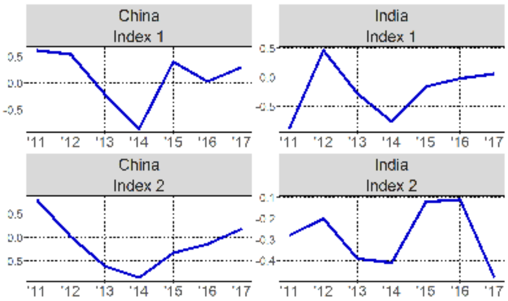
(a) Greece vs Cyprus



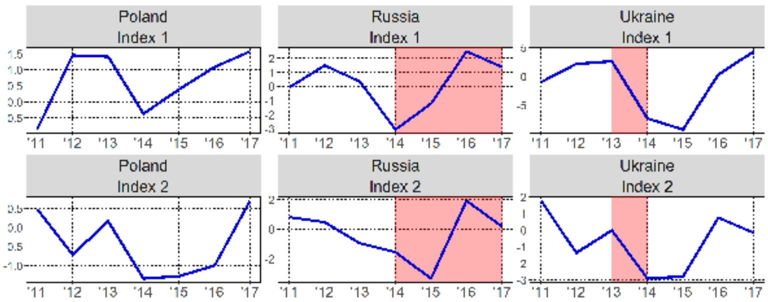
(b) Saudi Arabia vs Russia



(c) Argentina vs Chile



(d) India vs China



(e) Poland vs Ukraine vs Russia

Fig. 5. Index evolution over years for some countries. Financial crisis are shaded in red.

6 Conclusions

In this paper, we address the relevant issue of assessing financial stability considerations for 119 developed and developing countries by building up a financial soundness index using a fully model-based and data-driven approach. To construct the index, we use data of twelve financial soundness indicators from the IMF's core set for the 2010-2017 period. We supplement this data with qualitative information drawn from the Hofstede's cultural dimensions and geographical variables (i.e. latitude and longitude). We address the problem of missing data and misaligned information by applying a process of complete assessment of data quality and data imputation. Subsequently, we proceed with the application of a dimension-reduction model based on robust PCA algorithms to produce a synthetic binary FSIND index that identifies a stable vs unstable financial system in each country. Further, we produce a continuous variable version of the FSIND index. We validate the FSIND index by selecting a suitable threshold based on best performance obtained by applying alternative competing regression models. We accordingly use the FSIND index as a regressor to predict outcome variables, such as GDP growth and non-performing loans. The results show that our index construction approach summarizes and captures well the dynamics of the financial system position over time. The binary and continuous versions of our index facilitate alternative uses aiming at classification or ranking assessment of financial systems around the world.

The authors are aware of some limitation of the present work. Namely, the temporal dimension is not properly considered since each year is evaluated separately from the others. Future analysis will take advantage of native temporal models which consider and elicit the whole temporal horizon.

A List of countries

Table 3
Complete list of selected countries and relative missing values count and percentage over total number of observations.

Country	Missing values	Country	Missing values	Country	Missing values
Albania	-	Tanzania	-	Lesotho	15 (11%)
Argentina	-	Turkey	-	Pakistan	15 (11%)
Armenia	-	Uganda	-	Belgium	16 (11.8%)
Austria	-	Ukraine	-	Finland	16 (11.8%)
Brazil	-	U. K.	-	Kuwait	16 (11.8%)
Brunei	-	Uruguay	-	Nigeria	16 (11.8%)
Burundi	-	Italy	2 (1.5%)	Singapore	16 (11.8%)
Cambodia	-	Switzerland	3 (2.2%)	India	17 (12.5%)
Cameroon	-	Cyprus	4 (2.9%)	Korea Rep	17 (12.5%)
Ctr Afr Rep	-	Eswatini	4 (2.9%)	Solomon	17 (12.5%)
Chad	-	Latvia	4 (2.9%)	Honduras	18 (13.2%)
Macao	-	Seychelles	4 (2.9%)	Netherlands	18 (13.2%)
Congo	-	Colombia	5 (3.7%)	Chile	20 (14.7%)
Croatia	-	Hong Kong	6 (4.4%)	Lebanon	22 (16.2%)
Denmark	-	Fiji	6 (4.4%)	Algeria	23 (16.9%)
El Salvador	-	Kenya	6 (4.4%)	Australia	24 (17.6%)
Eq. Guinea	-	Tonga	6 (4.4%)	Moldova	24 (17.6%)
Gabon	-	Vanuatu	6 (4.4%)	Panama	24 (17.6%)
Georgia	-	Ghana	7 (5.1%)	San Marino	24 (17.6%)
Germany	-	Bolivia	8 (5.9%)	Spain	24 (17.6%)
Guatemala	-	Bosnia	8 (5.9%)	Thailand	24 (17.6%)
Indonesia	-	Canada	8 (5.9%)	United States	24 (17.6%)
Kazakhstan	-	Czech Republic	8 (5.9%)	Vietnam	24 (17.6%)
Kyrgyz Rep	-	Dominican Rep	8 (5.9%)	Sri Lanka	31 (22.8%)
Macedonia	-	Greece	8 (5.9%)	China	32 (23.5%)
Madagascar	-	Kosovo	8 (5.9%)	Costa Rica	32 (23.5%)
Malta	-	Luxembourg	8 (5.9%)	Ecuador	32 (23.5%)
Mauritius	-	Paraguay	8 (5.9%)	Malaysia	32 (23.5%)
Namibia	-	Portugal	8 (5.9%)	Angola	34 (25%)
Nicaragua	-	Trinidad Tobago	8 (5.9%)	Botswana	34 (25%)
P. N. Guinea	-	West Bank	8 (5.9%)	Gambia	34 (25%)
Peru	-	Zambia	8 (5.9%)	Bangladesh	36 (26.5%)
Philippines	-	Bulgaria	10 (7.4%)	France	36 (26.5%)
Poland	-	Lithuania	10 (7.4%)	Ireland	37 (27.2%)
Romania	-	Estonia	12 (8.8%)	Djibouti	40 (29.4%)
Russia	-	Mexico	12 (8.8%)	Hungary	40 (29.4%)
Rwanda	-	Afghanistan	13 (9.6%)	Norway	40 (29.4%)
Saudi Arabia	-	Bhutan	13 (9.6%)	Slovenia	40 (29.4%)
Slovak Rep	-	Belarus	14 (10.3%)	Sweden	40 (29.4%)
South Africa	-	Israel	14 (10.3%)		

B Missing values imputation methodology

Fig. 6. Testing missing values imputation methodologies as described in section 4

$$MARE = \frac{1}{M}\sum_{i}^{M}|x_{ablated} - x_{reconstructed}|$$

$$R = \frac{MARE}{\text{Average value of Original matrix}}$$

$$RM = \frac{max(MARE)}{\text{Average value of Original matrix}}$$

Bar whiskers are scaled value of $max(MARE)$. Comparison bars report on relative variation of MARE compared to Original set, i. e. $MARE/MARE_{\text{Orig}} - 1$

C Binary index validation

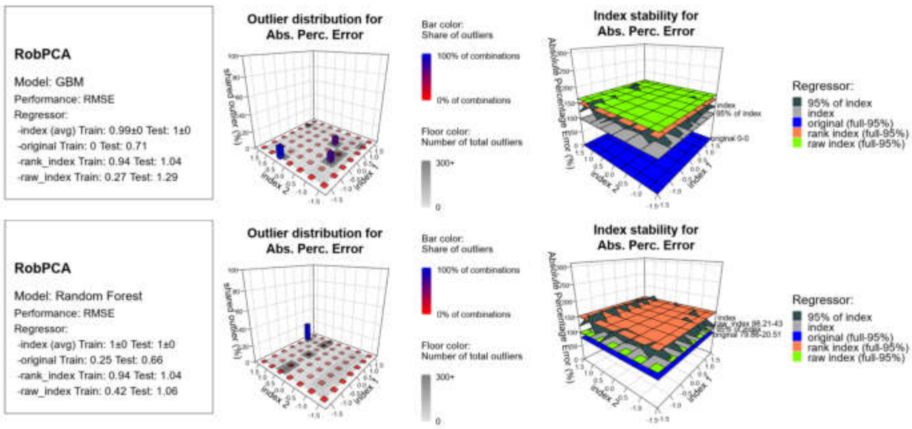


Fig. 7. Index validation for Non-performing loans to total gross loans ratio (%)

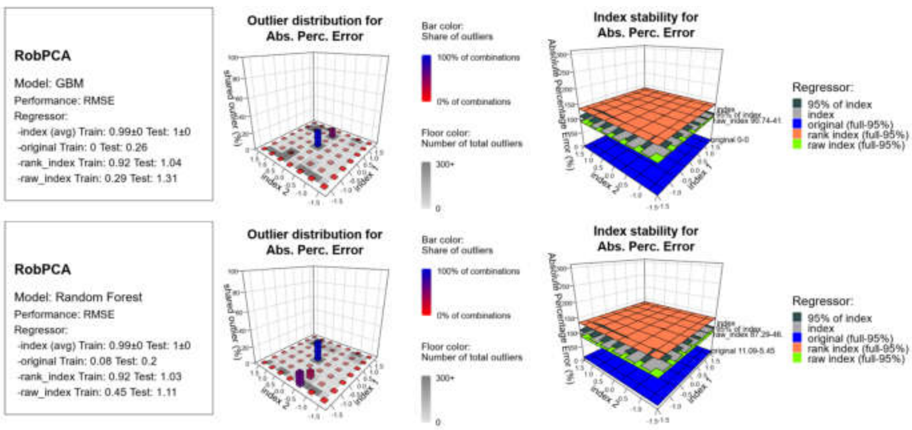


Fig. 8. Index validation for GDP per capita current

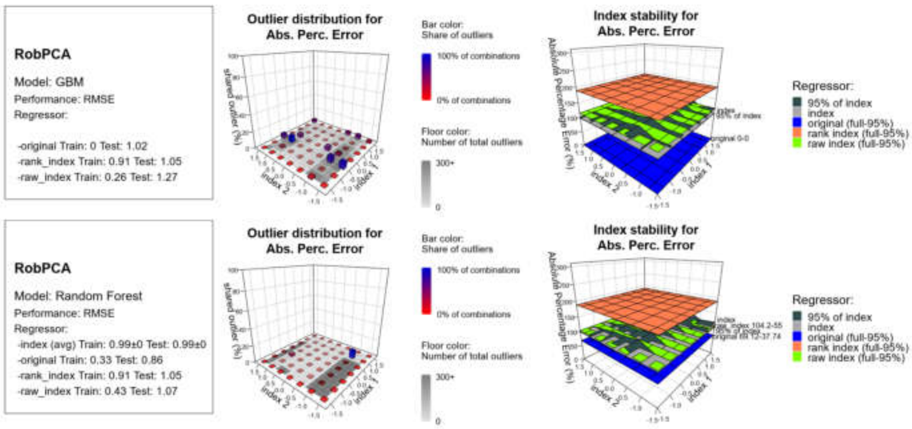


Fig. 9. Index validation for GDP per capita annual growth (%)

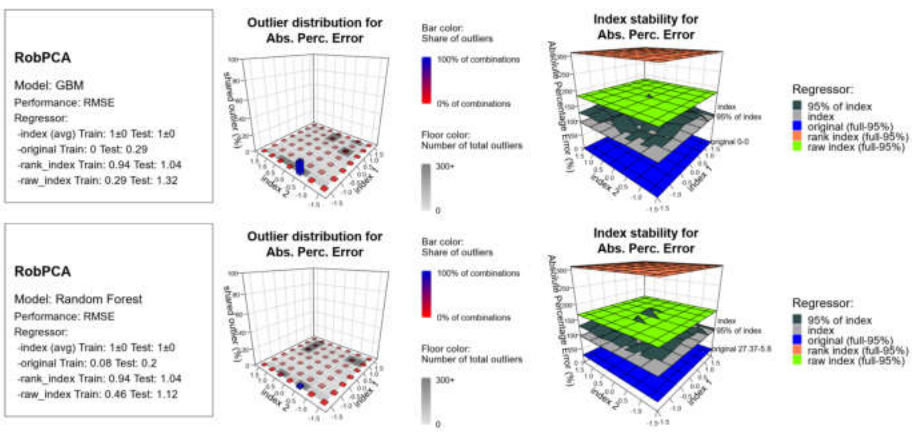


Fig. 10. Index validation for GDP per capita PPP

D Complete list of figures for all countries and years

D.1 Continuous FSIND cluster defined with threshold 0

Fig. 11. Outcome of continuous FSIND of Robust PCA for years from 2011 to 2014. Variable importance for loadings is reported on the right side.

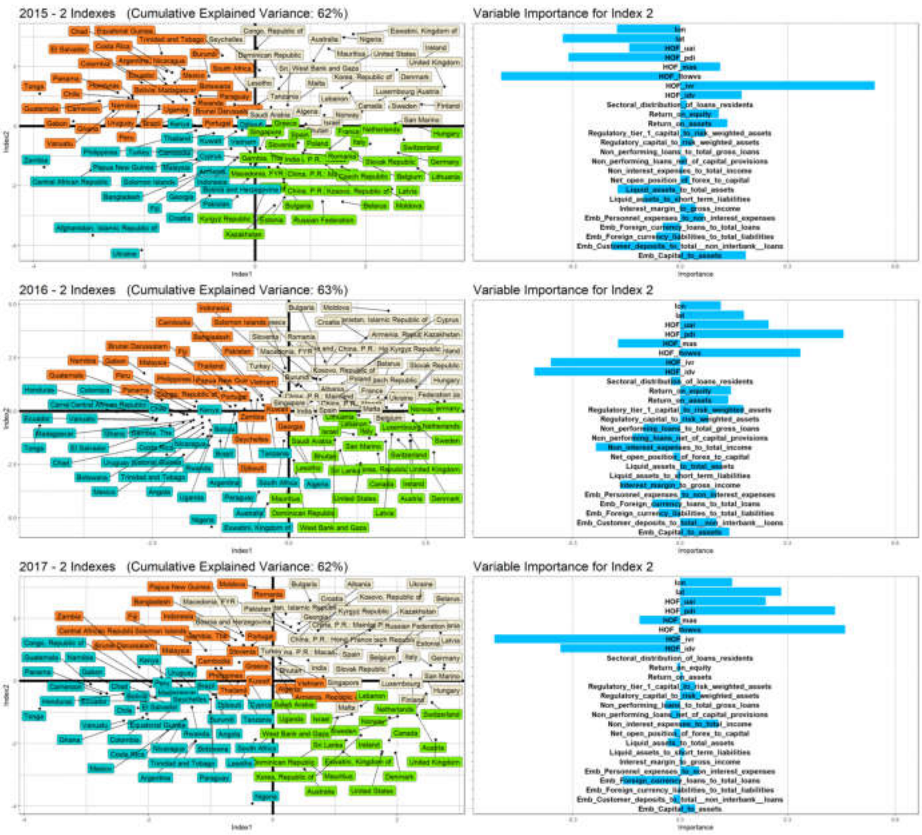


Fig. 12. Outcome of continuous FSIND of Robust PCA for years from 2015 to 2017. Variable importance for loadings is reported on the right side.

D.2 Continuous FSIND evolution over years

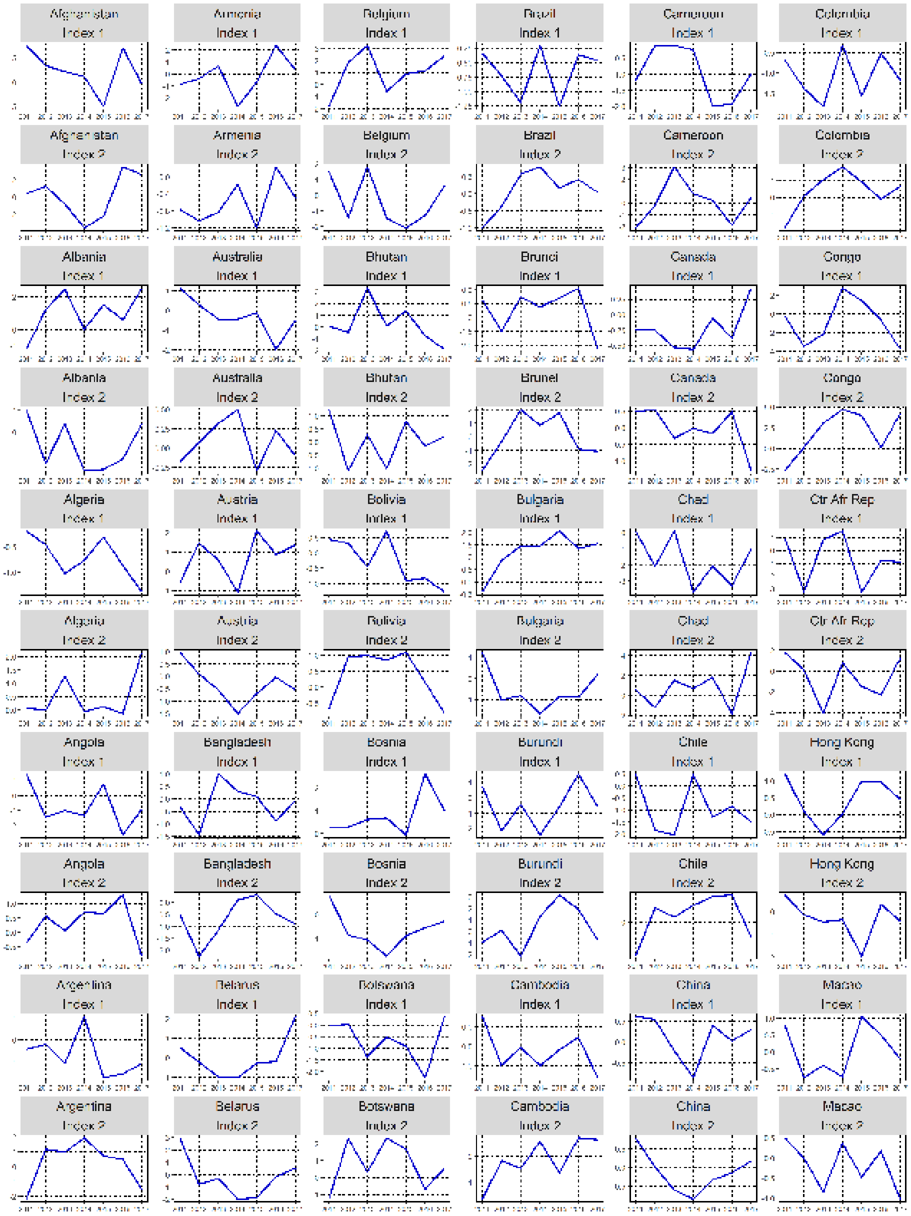


Fig. 13. Index evolution over years

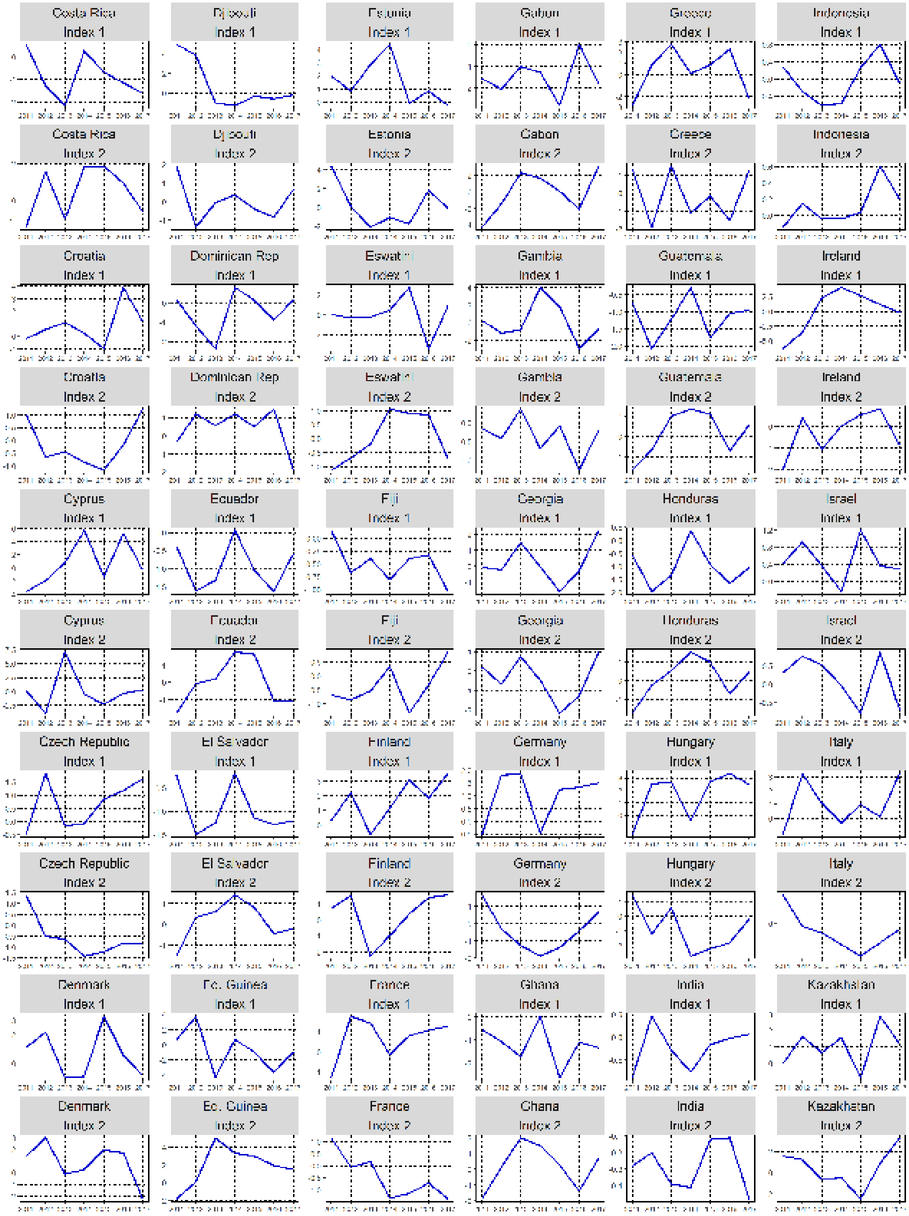


Fig. 14. Index evolution over years

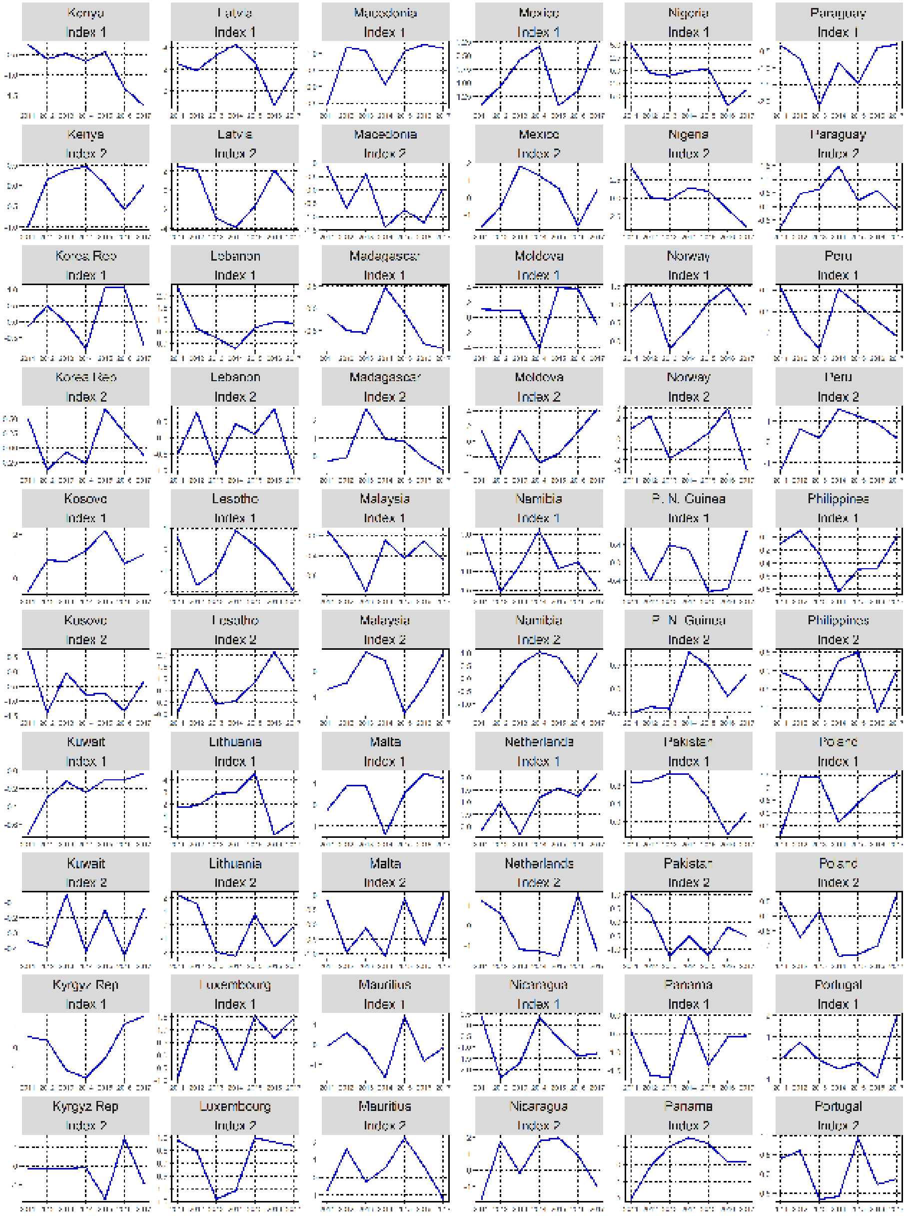


Fig. 15. Index evolution over years

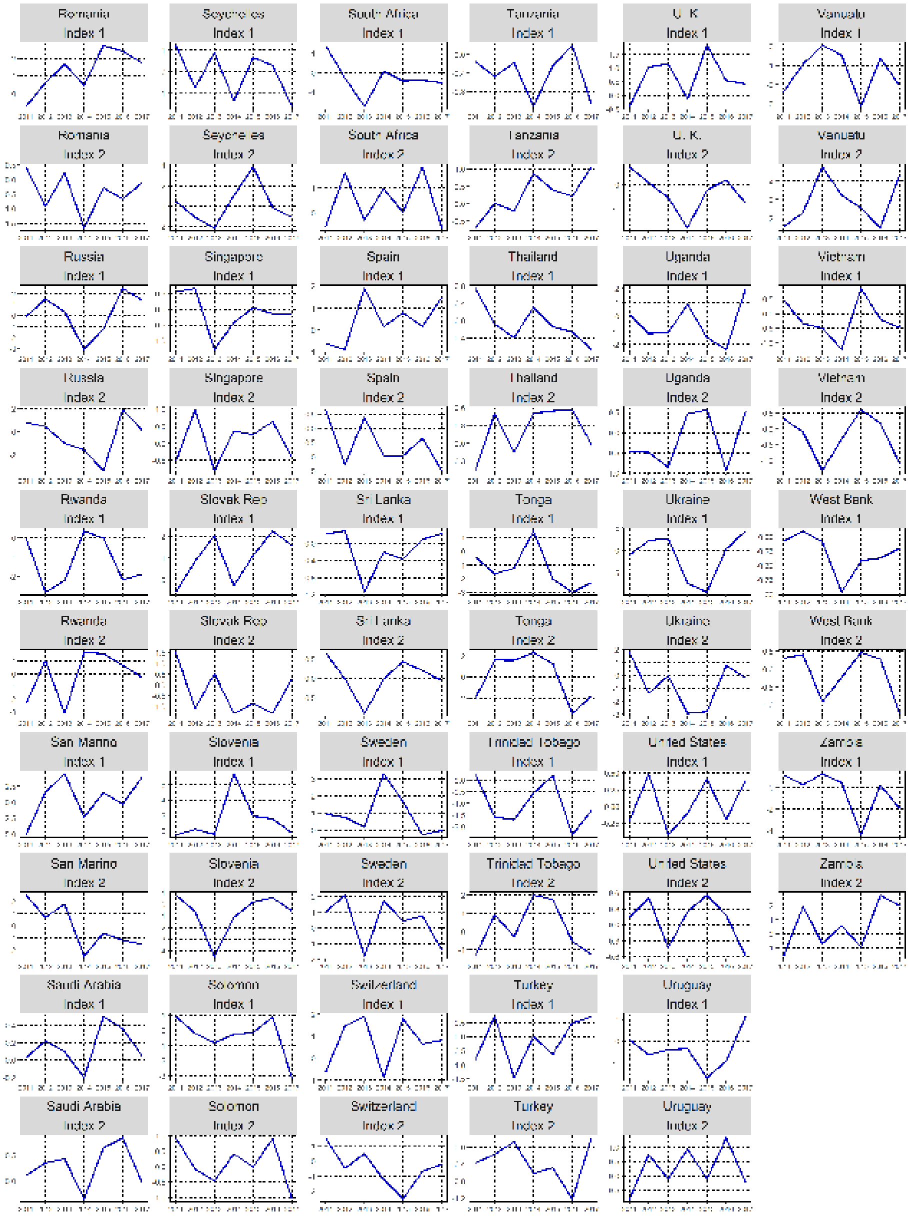


Fig. 16. Index evolution over years

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