Monitoring Financial Stability in Emerging and Frontier Markets

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Abstract

This paper outlines a methodology to build monthly financial conditions indicators (FCIs) for developing countries, including a Small Island Developing State (SIDS), least developed countries, and transitions economies as defined by the United Nations’ classification. The proposed composite index uses ragged-edge panel data as well as mixed frequency observations. FCIs are compiled using a Dynamic Factor Analysis (DFA) in order to create a synthetic index in real time (as data is released). Also the choice of variables reflects typical emerging markets considerations given to interdependency issues and include variables like capital flows and real effective exchange rates. We show, that the obtained indicators are able to capture periods of financial stress and near-miss events historically. In addition, although our FCIs are free from the business cycle, it is able to track GDP growth, in several cases with a clear leading effect. Our FCIs are therefore an interesting tool for policymakers and market participants alike since its predictive power allows them to assess financial stability in real time before financial shocks are transmitted to the real economy. Consequently, upcoming stormy macroeconomic conditions can be anticipated well ahead.


\textit{Keywords:} Financial markets, emerging and frontier markets, dynamic factor models, mixed-frequency observations, Kalman smoother, financial stress indicators, financial crisis, real-time information flow tracking, leading indicators.

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1. Introduction

Since the 2007-2008 financial crisis, the policy debate has focused on the tools and new regulations needed to avert a new global financial turmoil. Though the policy debate brought on new national and international supervising bodies, financial innovation and engineering have continued its expansion into new markets and products. Concomitantly, the combination of new prerogatives and financial innovations has increased the complexity of traditional duties of regulators and central bankers in developed countries. In addition, the global financial crisis has put on the forefront the interlinkages between shadow banking and more traditional forms of banking and their interdependence with the rest of the economy. For instance, the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 aims at ensuring macroeconomic and financial stability by curtailting the various banking activities in order to reduce interconnections and fast spreading financial contagion to all sectors of the economy. Recent political changes in the United States suggests a shift towards a regulatory framework similar to the pre-crisis one.

However, the spillover effects of financial instability on emerging and frontier markets\(^2\) have remained under scrutinized though those countries have gained in importance in recent years. As a matter of fact, financial markets in those countries have become more complex and their complexity goes well beyond the usual issues of sovereign debt sustainability traditionally associated with financial crises therein. Through the development of financial engineering and globalization, access to those markets has been made easier thanks to liquid financial products readily available to investors in developed markets, notably ETF and other money pooling schemes (often index-linked). Those products facilitate the capacity of international investors to pump relatively large amount of liquidity in and out of those markets and, at the same time, have increased market interdependence and volatility. Recent studies have shown that in the past few years, financial markets have become more prone to financial instability and volatility despite the emergence of new regulations (Filimonov et al., 2014). In some developing countries, the rise of domestic shadow banking further complicates the analysis of the national financial system. In other words, emerging and frontier markets are now subject to external as well as internal shocks whose occurrence has increased with time passing.

Divergence in financial stability, in monetary policy, cracks in the globalization process in advanced countries, and its spillover effects have highlighted the continuous struggle for macroeconomic and financial stability in emerging and developing markets. Thus, the capacity to monitor financial stability in those countries requires a complex understanding of the various forces at play, their interconnections and their impact on GDP performance. In this context, our measure and methodology for our Financial Conditions Indicators (FCIs) applied to a very heterogeneous set of developing countries is an attempt to fill in the lack of real time and reliable indicators for policy makers and market participants.

\(^2\)In this paper, emerging and frontier markets follows the United Nations classification of developing countries and transition economies. Most notably, our definition excludes the new EU member states, which are commonly defined as emerging markets by the financial industry. For more details see http://unstats.un.org/unsd/methods/m49/m49regin.htm#developed
alike. If financial instability could be anticipated ahead of time or from the early onset, market participants might have the opportunity to alter their resource allocation and policy makers could possibly alleviate the crisis fallout.

In order to measure financial stability, our FCI combines variables with mixed frequencies and different time span using Dynamic Factor Analysis (DFA) to create a synthetic index. DFA presents a number of advantages over other econometric models; in particular, it does not assume any sorts of relationship among the variables and it does not need a strong theoretical backing. By using mixed frequencies time series, we obtain a better coverage of possible sources of financial shocks and at the same time this allow us to overcome several data limitations typical of emerging countries and frontier markets, most importantly data availability. As a matter of fact, studying individual financial series in isolation or only same frequency variables may not yield the desired results as those variables may capture only a certain aspect of the economy and omit others. The resort to synthetic indicators with mixed frequencies is a logical way to overcome these limitations. Also, the choice of variables illustrates our deliberate goal to capture all sorts of interactions and interlinkages effects. We then show that our FCI correctly reacted during past financial crises in those countries. We also show that our FCI can lead GDP performance up to four quarters ahead. They are then valuable tools for policy makers because, as computed at high frequency (monthly) and in real time, policy makers can also quickly assess the effectiveness of their macroeconomic stability choices and reaction to crisis. Also in the context of debt and financial issues, international organizations and partner countries are in a better position to evaluate the effectiveness of their policy recommendations and other conditionalities.

The paper is organized as follows. Section 2 reviews the literature on financial conditions and economic indicators, given special consideration to developing countries in section 2.1 and to developed economies in section 2.2. Sections 3 introduces the model. Data and descriptive statistics are presented in Section 4. Section 5 is devoted to the estimation technique. We present our results in section 6 and we also show that the FCIs are leading determinants of the economic activity for emerging markets. Section 7 concludes.

2. Literature review of financial/economic composite indexes

There is a large body of the literature concerned with extracting signals from economic and financial time series to assess and predict the state of the real economy. For example, the term structure of interest rates has long been considered by many economists as an indicator of future inflation expectations and overall health of the economy (Bernanke, 1990). Originally in early nineties, the literature focused on extracting signals from a set of variables and on measuring deviations from the average, in particular to predict currency or banking crises. Once the deviation was above or below a certain threshold, usually associated with a relatively high probability of a crisis, it was said then that the model issued a “signal” (see for instance Edison, 2000; Bell and Pain, 2000; Reinhart and Kaminsky, 1999; Kaminsky et al., 1998). However the performance of those early econometric models, called Early Warning System (EWS), was mixed at best, because the use of a binary variable for crisis occurrences does not provide information on the intensity
of crises and near-occurrences. In addition, the research scope was too narrow focusing mostly on currency crises.

From the early models, this literature has grown remarkably since 2008 thanks to the new prerogatives assigned to financial regulators within the post-crisis regulatory framework. In this context, the use of financial composite indexes has become a popular method to assess systemic risks in the aftermath of the global financial crisis. Nonetheless, the existing indicators diverge in coverage and methodologies as the literature does not provide a unified definition of financial stress, certainly because the notion of financial stress is intangible and cannot be observed directly like investment or interest rates. The intangible nature of financial stress implies also that there are no clear-cut methodology to measure it. To take an analogy, in seismology, earthquake magnitude is often proxied for the energy released since energy is more difficult to observe. Similarly, when assessing financial stress, researchers are actually measuring the effect of financial stress, not financial stress per se, and consequently they try to capture latent conditions.

In addition, the literature traditionally distinguishes between Financial Stress Indicators (FSIs) and Financial Conditions Indicators (FCIs) and the definitions of financial stress can vary according to the authors (for a survey see Kliesen et al., 2012). For the sake of this paper, we define financial stress as a condition during a period in which financial markets are unstable because under strain and therefore vulnerable to shocks and subjects to bouts of volatility with possible spillovers in the real economy. The main difference between FSIs and FCIs, though not absolute, is that the former relies mostly on prices while the latter uses quantities, prices, and other macroeconomic aggregates. By construction FCIs tend to be rather a mapping of financial conditions onto macroeconomic conditions and to relate directly to GDP thanks to its pure macroeconomic components (Kliesen et al., 2012). In this context, though our indicators include only financial variables (prices, volatility index, interest rates...) and do not comprise macroeconomic variables like production, investment, consumption or any other GDP direct components (in this sense our index is business cycle free), we still refer to them as FCIs as they exhibit leading features over GDP performance.

The review of the literature below should start by mentioning the seminal work of Illing and Liu (2006). The authors first created a continuous daily financial stress index for Canada by adopting a system wide rather than a market specific approach, where extreme values correspond to period of financial crisis by using a panel of time series variables. From that seminal paper on, research on macrofinancial stability adopted a systemic approach as required by the new mandate entrusted to regulators after the global financial crisis. However, since large emerging countries had remained to a great extent sheltered from the fallout of the global financial crisis in 2008, research on indicators of financial systemic issues and overall macroeconomic stability crises has remained somehow muted compared to advanced countries.

In spite of that, in this section 2, we aim at providing a non exhaustive but brief overview of notable and recent work on composite indicators (FCI as well as FSI) on developed and developing countries. We start first by presenting notable work on FSI for developing countries in section 2.1 and on developed countries in section 2.2.
2.1. Existing FCI/FSI for emerging and frontier markets

The financial literature with regard to macroeconomic stability in emerging markets is relatively large. However, most of the literature is concerned with specific financial aspects (for example sovereign credit, exchange rate, or banks) or particular events (QE, tapering, Asian financial crisis, etc.). Only few recent papers attempt to create an index of systemic financial stress for those countries, in all likelihood because of data availability, and most of those indices are simplified version of existing FSI/FCI for developed countries. In addition, the econometric methodology applied to compute those indicators is often derived from a static specification, which overlooks technical issues typical of financial time series. An overview follows.

- **IMF World Economic Outlook April 2009**: The Emerging Markets Financial Stress Index (EM-FSI) presented in the IMF World Economic Outlook report of April 2009 builds on the IMF working papers versions of Balakrishnan et al. (2011) and of Cardarelli et al. (2011). The IMF EM-FSI is an adaptation to emerging markets of the Advanced Economies Financial Stress Index (AE-FSI) introduced in the World Economic Outlook of October 2008 (International Monetary Fund, 2008). Both index (AE- and EM-FSI) are built using a variance weighted average that comprises five indicators in nominal terms: an Exchange Market Pressure Index (EMPI); banking sector beta (as defined by the standard capital asset pricing model); stock market returns; stock market volatility; and sovereign debt spreads. The EM-FSI is computed for 26 countries between January 1997 and December 2008. The authors find that financial stress spread rapidly to emerging economies and with a high pass-through depending on the depth of the financial linkages.

- **Park and Mercado’s FSI**: In Park and Mercado (2014), the authors follow the methodology set by Balakrishnan et al. (2011) using as well the five indicators in nominal terms mentioned above and introducing minor differences in data sources and computations for 25 countries. Regarding the weighting method, they adopt the variance-equal weight but in addition they perform a static principal component analysis (PCA), where the first three components are simply summed up. Regarding missing values, the authors compute them by using the average of the preceding and succeeding monthly value.

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3 The methodology developed in Cardarelli et al. (2011) has been adapted by the ECB in its Financial Stability Review December 2009 and in a number of subsequent ECB working papers.

4 The EMPI developed by Eichengreen et al. (1996) is a composite index that captures currency depreciation and international reserves depletion.

5 Some of the countries included in the EM-FSI are not considered to be emerging countries by the United Nations classification, specifically Czechia, Hungary, Israel, Poland, Romania, Slovakia, and Slovenia.

6 The country coverage includes Argentina, Brazil, Chile, China, Colombia, Czechia, Egypt, Hong Kong SAR, Hungary, India, Indonesia, Israel, Rep. of Korea, Malaysia, Mexico, Peru, Philippines, Poland, Romania, Russia, South Africa, Singapore, Taiwan Province of China, Thailand and Turkey. As already noted several of those countries are neither emerging nor developing according to UN’s classification.
• Osorio et al. ’s Asia Financial Condition Index: In Osorio et al. (2011), the authors computed a quarterly FCI for 13 developed and developing countries from the Asia Pacific region between 2001 and 2011 according to data availability. They base their FCI on two methodologies: using the first one, they estimate a VAR model to derive weighted average parameters, while in the second one they employ a Dynamic Factor Model (DFM) framework from which they purge the obtained factors of their endogenous predictive component using standard econometric techniques. Finally, they compute a simple average of both approaches.

• South Africa Financial Condition Index: In Gumata et al. (2012), the authors computed a FCI for South Africa using 11 nominal indicators divided between domestic and international variables and resorting to two different methodologies: PCA and DFA. When it comes to assess the real economy, they show that their indicator outperforms the leading indicator computed by the South African Reserve Bank with an in-sample and out-of-sample forecasting exercise. Their FCI also outperforms the individual financial variables that it includes. The author therefore conclude that joint movements in financial variables effectively contain relevant information regarding the performance of GDP growth.

2.2. Existing FCI/FSI for developed markets

As explained above, the recent literature on a systemic financial indicator has derived directly from the need of developed countries to provide a measure of financial and macroeconomic stability in the aftermath of the global financial crisis. We expand the coverage to include also a well-established and tested indicator of business cycles that combines methodological aspects relevant for the construction of FCI. A brief description of notable work follows.

• KOF Barometer: Produced by ETHZ, the KOF Barometer measures the business cycle of Switzerland by relying on a database of over 400 variables. This composite leading indicator exists since 1970s and it aims at predicting how the Swiss economy should perform in the near future. The KOF Barometer benefited from a thorough revision of its methodology in 2014 (see Abberger et al., 2014). Originally, the KOF Barometer relied on six variables to which a series of filter was applied to reduce the noise-to-signal ratio. The set of variables was then extended to 25 in the 2006 revision. However, the DFA methodology adopted in 2014 eliminates the need of filtering the data and in addition allows the use of a large set of variables. Following the seminal work of Stock and Watson (2002a,b) on DFM, the method used to extract the principal component handles considerably the noise introduced by the large panel data and identifies the common variance of the variables rather than the noise and idiosyncrasies specific to some variables. Furthermore, despite a large dataset of over 400 variables, this methodology enables an automated selection

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7The countries included are Australia, China, Hong Kong SAR, India, Indonesia, Japan, Korea, Malaysia, New Zealand, Philippines, Singapore, Thailand and Taiwan Province of China.
procedure done once a year, as research has shown that pre-selected data improves the out-of-sample forecast accuracy rather than resorting to all available data (Bai and Ng, 2008).\(^8\)

- **Hatzius et al.’s FCI**: In Hatzius et al. (2010), the authors used a DFA framework to create a FCI based on 45 financial series for the United States. Their choice of variables includes prices, interest rate levels and spread, but also stock and flow variables, and national surveys of financial conditions. The stock variables capture mostly shadow banking aspects of the financial system. Regarding the methodology, the authors allow for an unbalanced panels but they purge the variability in the financial variables that can be explained by the business cycle. By doing so, the component extracted captures only exogenous shocks.

- **Chicago Federal Reserve National Financial Conditions Index (NFCI)**: This national and weekly FCI has been developed by Brave and Butters (2011) and uses third generation DFM (see section 5), as defined in the nomenclature established by Stock and Watson (2011), which combines the statistical efficiency of the state-space specification with the robustness of the principal component approach (see also section 5). The adoption of this method by the authors enables them to compute a real time indicator as individual data is released thanks to the application of the Kalman filter. Also the third generation DFM allows them to create the NFCI over the past 40 years based on 105 variables available at the weekly, monthly and quarterly frequency. Following Hatzius et al. (2010), the authors also created a purged version of their FCI (called Adjusted National Financial Condition Index or ANFCI) to study potential asymmetric response to shocks from financial and economic conditions.\(^9\)

### 3. Methodology

A number of methodologies have been developed over time to create synthetic indicators from financial time series. As mentioned above in 2, the two most popular methods are a form of weighted average and PCA. However, in addition to a balanced panel dataset, both methods impose a static specification of the synthetic indicator and therefore do not account for autocorrelations and heteroskedasticity. This is rather overly restrictive for time series analysis, in particular for developing countries subject to bouts of relatively high volatility. Moreover, the above mentioned methodologies are impractical for emerging and frontier markets often characterized by time series with missing value and ragged-edge panel data. In all logic, we consider here a DFM to build our FCI. DFM for macroeconomic forecasting has received a considerable attention in the last decade by Stock and Watson (2002a,b), Mariano and Murasawa (2003), Giannone et al. (2005, 2008), Aruoba et al. (2009) and many others (see Bai and Ng, 2008; Stock and Watson, 2011, for surveys). The main appeal of this approach is that it allows for a time-varying factor

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\(^8\)For more details see: https://www.kof.ethz.ch/en/forecasts-and-indicators/indicators/kof-economic-barometer.html

\(^9\)For more details see: https://www.chicagofed.org/publications/nfci/index
and in addition it appears particularly suited for time series analysis in economics and
finance. Recently real-time economic and financial conditions indicators have been built
based on these models. One can cite the above already mentioned KOF Barometer for
Switzerland and the NFSI of the Federal Reserve Bank of Chicago for the United States’
economy. However, to our knowledge, there exists no studies which attempt to provide
such real-time indicators for a large and diverse set of emerging and developing economies,
including LDCs and SIDS.

The aim of the present study is then to fill this gap. Hence, the model is defined as
follows:

\[ X_t = \Lambda F_t + e_t, \]

for \( t=1,\ldots,T \), where \( X_t \) is a \((n \times 1)\) observed stationary process, \( \Lambda \) is the \((n \times r)\) matrix of
factor loadings, \( F_t \) is a \( r \)-dim unobserved stationary Gaussian process with mean 0, which
represents the \( r \) common factor, i.e. the real state of the economic or financial activity
depending on the nature of the input variables, i.e. \( X_t, e_t \) is a \((n \times 1)\) dimensional stationary
process with mean 0 representing the idiosyncratic component which is assumed to be
Gaussian and uncorrelated at all leads and lags with the common factor \( F_t \). Notice that the
identification of this model requires \( r << n \). Equation (1) can be completed by specifying
a dynamic process for \( F_t \). A convenient way to parametrize the dynamic component of
the common factor is to use a finite-order stationary VAR process, which allows to write
the model into a state-space form. Consequently, a Kalman filter procedure can be used
to estimate parameters and the state vector.

4. Data and summary statistics

The dataset consists of mixed frequencies time series (monthly and quarterly) for 11
emerging and other developing countries (the five BRICS, Angola, Ecuador, Jamaica,
St. Vincent and the Grenadines, Thailand and Tanzania) over the period from 1995 M1
(the earliest) to 2017 M3 and from 1991 Q4 (the earliest) to 2017 Q1 for monthly and
quarterly data, respectively. Data were extracted from Thomson Reuters Datastream and
from the UNCTAD Financial Database. Tables 1 and 2 provide the details of our dataset
(variables, frequencies, data transformation). Our FCI includes financial indicators (real
interest rates\(^{10}\), stock and bond market indexes, commodities market prices, volatility
indexes, foreign exchange rate, etc.), which are monthly observed, as well as quarterly
macroeconomic indicators (residential real price index, debt service ratio and capital flows).
We also compute a number of variables by taking the ratio of a sector market capitalization
with respect to the broad stock market. By doing so, we are better positioned to capture
certain wealth effects, often crisis precursors, while at the same time addressing non-
stationarity issues. To avoid currency valuation effects, potentially significant given our
set of countries, all data is transformed into United States dollars and all nominal variables

\(^{10}\)Real interest rates were calculated according to Fisher hypothesis.
are deflated, except for indicators of carry trade\textsuperscript{11}, which are computed as the spread between the rates of a country’s sovereign 10 year bond and the United States 10 year Treasury Note. Notice that the real effective exchange rate, the carry trade indicator and the capital flow are crucial variables as they allow to take into account a possible direct interdependency between the countries of interest and the rest of the world. Consequently each model can be estimated for each country independently from the others.

While macroeconomic data are in general non stationary, we use deviations from different deterministic functions (a cubic trend which includes linear and quadratic trends as special cases is often sufficient to remove deterministic components). We also included dummies for possible outliers and structural breaks when it was necessary (a simple Chow test was performed for dating changes). Figure 1a, -b, and -c illustrate this upstream significant statistical treatment for some of the analyzed countries (South Africa, China and India). The results of these transformations led to stationary time-series which were used as inputs in equation (1), \textit{i.e.} the matrix of indicators $X_t$.

5. Estimation method

Many techniques have been explored to estimate dynamic factor models. As the model (1) can be written into a linear state space form, an early method (first introduced by Stock and Watson, 1989) was based on the Kalman filter procedure which uses the time-domain maximum likelihood technique. While this approach allows to deal with data irregularities (missing values, mixed-frequencies or unbalanced panels - ragged edge)\textsuperscript{12}, it is limited, for numerical and estimator convergence reasons, to matrices of small to moderate dimensions only. A second option to estimate DFM uses standard PCA. This technique can handle large data panels but unfortunately PCA is not applicable to unbalanced panels (see Stock and Watson, 2002b,a). A third generation methodology is proposed by Giannone et al. (2005, 2008), and Doz et al. (2011). It consists of a two-step estimator which combines both previous approaches: PCA and Kalman filter. The main appeal of this hybrid method resides in its ability to deal with both large-scale unbalanced panels and data irregularities. Hence, this procedure allows a great flexibility, in particular for modelling developing economies for which the information (in terms of data availability and quality) is often reduced.

Concretely, Giannone’s two-step estimator consists in applying a PCA on the balanced sample of the dataset in order to extract common factors. Loading and VAR parameters are then estimated by OLS. In the second step, factors are extracted from the whole sample using the Kalman smoother. This multi-stage methodology is particularly adapted and recommended for large scale models due to its numerical ease. Notice that the second step of Giannone's method (which exploits the state-space formulation) allows to bridge

\textsuperscript{11}According to the efficient market hypothesis, carry trade would not be a profitable strategy. However in the real world, investors exploit market imperfection to earn profits. In the case of carry trade strategies, investors base their decisions and, at the same time, capitalize on nominal interest rate differentials.

\textsuperscript{12}Unbalanced panels can be due to different publication lags, asynchronous timing of data releases or any other issue of data availability.
monthly data releases with the nowcast of quarterly information. The resulting index therefore tracks the real-time flow of information and it is therefore often called \textit{real-time measurement of economic/financial condition index} or \textit{real time economic/financial stress index}. In addition, not only the FCI hence created is able to provide a diagnostic of the overall economic conditions, but the relative contribution of each underlying variables, measured by the factor loadings, imparts indications on the analytical elements of financial and economic stability specific to a country.

We also ran the quasi-maximum likelihood estimator (QMLE) proposed by Doz et al. (2012) to take into account a possible misspecification of cross-sectional and time series correlation of the error term $e_t$ in equation (1). Also the QMLE can be more efficient when series are not Gaussian. As our set of indicators includes many financial variables (stock returns, interest rate spreads, relative stock indices, etc.) which are known to exhibit extreme values and asymmetric distributions especially at high frequency, even though these features tend to vanish at lower frequency, we run and compare the QMLE to the two-step estimator.$^{13}$

The retained r-dimension for our dynamic factor analysis is the one-factor model and the selected dynamic for our unique factor is an AR(1)$^{14}$ For the five BRICS, we selected between 12 and 14 input variables while for the six others economies, $n$ ranges between 8 and 13 (See Tables 1-2).

6. Results

The results from the DFA estimation of the loading parameters are reported in table 1 and 2. Table 3 gives the estimation periods for our 11 countries, which vary according to data availability. Starting with macro quarterly variables, we observe disparities in signs and magnitude for the factor loading estimates specific to each country, which is of course a desirable feature. Also, the dynamism embedded in the model implies that, as time passing, the loading factor estimates may switch signs and change magnitude according to new information fed in by the release of the latest data points. Though the sign switching might seem an extreme occurrence, emerging countries and frontier markets are often characterized by the high volatility of their financial markets as well as of their macroeconomic variables. For example, residential property prices loading estimates are positive in countries where property prices boom and burst have been absent in the recent past but negative elsewhere. Similarly, the sign of the loading estimates for the debt service ratio is mostly negative except in China, where the loading is relatively high and positive. This could be explained by the heavily \textit{dirigiste} approach to financial markets by Chinese policy makers where several prices and interest rates are not freely market-determined, while at the same time it highlights China’s dependence on debt to continue growing.

$^{13}$Doz et al. (2011) noticed that the two-step procedure also allows to account for both factor dynamic and idiosyncratic heteroskedasticity.

$^{14}$Since the size of the cross-section of our model being somewhat small, it does not permit us to test a large set of orders for the autoregressive process. Despite of that limitation an AR(2) dynamic was tested but was found not significant.
Generally speaking, contributions of stock markets, fixed income and commodity prices indexes are important for all analysed countries. Furthermore, we note that the volatility index is always negatively correlated with the common factor though the values of these estimates remain moderate except for South Africa.

Figures 2-a and 2-b plot the economic condition indexes obtained by the two-step procedure and QML estimation. Both estimates as very similar for all countries. These figures show that major crises and boosts are correctly captured by the indicators. For example the FCI emphasizes accurately the severity of the crisis that hit Russia in summer 1998. Subsequent stressful periods are also clearly identified, in particular the global financial crisis in 2007-2008 and 2014 instability. The FCI records also periods of economic expansion, like in the early 2000s. For Brazil, the FCI highlights the recession of 2002-2003 caused by the political climate surrounding the presidential election back then, as well as the worst of global financial crisis in September-October 2008. It also relates to the current economic difficulties, which started in 2014. Thanks to the factor loadings, we can offer a succinct explanation based on depressed commodity prices, high debt servicing and a sunken real effective exchange rate. Regarding India, the FCI highlights the economic boost of 2010 and the weaker growth performance recorded from 2012 caused by a flight of foreign capital.

By including heterogeneous information in our index such as financial stock prices, housing price indexes, commodity prices, in addition to real macroeconomic variables, we expect our index to leading features of the real economic activity for the considered countries. Indeed, the insight of these last decades is that systemic crises are often preceded by dysfunction of the banking and financial markets. As a preliminary diagnostic, Figure 3 compares the yearly evolution of GDP growth to our FCI (value in December of each year). Though our FCI does not include GDP or any of its direct component, we can observe our FCI tracks reasonably well the GDP growth path and sometimes with a clear leading effect (for example Ecuador). By using the FCI as an unique regressor to test its leading features over GDP instead of the full set of variables allows us to save degrees of freedom dramatically in the regression and to improve the reliability of the linear projections. Such a tool is particularly suitable for emerging and frontier markets for which the available information is often reduced.

Consequently, in order to investigate the leading feature of the FCI more thoroughly, we regress quarterly GDP growth upon the corresponding quarterly factor at the contemporaneous date and upon some lags (See Giannone et al., 2008). To match GDP frequency, we convert our monthly FCIs into a quarterly variable by taking the values in the last month of each quarter. We use a seemingly unrelated regression (SUR) model (Zellner, 1962) to take into account possible correlations between countries, not already captured by the capital flow, the carry trade indicator and the exchange rate variables already included in the FCI. Table 4 summarizes the results obtained by the feasible

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15The experiment could not be performed for St. Vincent and he Grenadines for which the quarterly GDP is not available.

16Furthermore, notice that for some countries these variables were not available: St. Vincent and the Grenadines, Tanzania, Jamaica and Angola (See Tables 1-2)
generalized least squares (FGLS) estimation and shows that a leading effect (for \( h=1,2,3 \) and/or 4 quarter ahead) is significant for most of the analysed countries except for China, India and Tanzania. However, for Tanzania the GDP is available only from 2008 which leaves only 32 observations for the regression (with 26 degrees of freedom). Consequently, the results for Tanzania are somewhat unreliable. Furthermore, It is important to stress that our regressions are free from any endogeneity issues since our FCI does not include the GDP or any of its components.

7. Conclusion

This paper intends to provide country-specific financial conditions indicators for developing countries and transition economies by using DFM, in order to handle data irregularities (missing values, mixed-frequencies or unbalanced panels). Our FSI includes financial indicators as real interest rates, stock and bond market indexes, commodities market prices, volatility indexes, foreign exchange rate as well as macroeconomic indicators such as residential real price index, debt service ratio and capital flows. Thanks to the time-varying specification of the factor, the model permits to pose a dynamic diagnostic regarding the source of stress in the economy. Thus, we show that our indicators are able to capture periods of financial stress and near-miss events historically. In addition, although our FCI are free from the business cycle (it does not include GDP or any of its direct component), we also show that it is able to track GDP, sometimes with a clear leading effect.

Such indicator has large implications for policy makers and market participants alike: it provides them with real time information on the state of the economy and assist them in their economic choices and resources allocation. It can also contribute to shed light on countries that might not be in the limelight of international institutions though they deserve better attention thanks to its very flexible structure. Finally, the FCI are important tool for a sound economic governance and to track in real time the effect of some policy choices, as uncertainty increases. Further work venue includes the application of this methodology to a larger set of emerging and frontier markets.

Acknowledgments

We would like to thank Stephanie Blankenburg & Richard Kozul-Wright for support on early stages, as well as Scott Brave, Prof. Didier Sornette, Dr. Klaus Abberger, Dr. Boriss Siliverstovs and Dr. Heiner Mikosch from the KOF Swiss Economic Institute for their valuable comments on the early draft. We are also very grateful to Khalil Rahman for his outstanding guidance and expertise on financial issues. Finally, we thank research assistant Esteban Arroba Del Castillo for his full engagement and Ksenia Khlopushina for managing data requests. All mistakes are ours.
Figure 1a: Illustration of the non stationarity issues. The different times series are shown before and after transformations to achieve stationarity.
Figure 1b: Illustration of the non stationarity issues. The different times series are shown before and after transformations to achieve stationarity.
Figure 1c: Illustration of the non stationarity issues. The different times series are shown before and after transformations to achieve stationarity.
Figure 2a: Comparison: Two-step Estimator and Quasi Maximum Likelihood Estimator
Figure 2b: Comparison: Two-step Estimator and Quasi Maximum Likelihood Estimator
Figure 3: FCI vs GDP
Table 1. Loading estimates of core variables

<table>
<thead>
<tr>
<th>Selected Variables</th>
<th>Freq</th>
<th>Transformation</th>
<th>Angola</th>
<th>Brazil</th>
<th>China</th>
<th>Ecuador</th>
<th>India</th>
<th>Jamaica</th>
<th>Russia</th>
<th>South Africa</th>
<th>St. Vincent</th>
<th>Tanzania</th>
<th>Thailand</th>
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<tbody>
<tr>
<td>Capital flow/GDP</td>
<td>Q</td>
<td>Level*</td>
<td>0.018</td>
<td>0.032</td>
<td>0.021</td>
<td>0.037</td>
<td>0.014</td>
<td>-0.031</td>
<td>0.065</td>
<td>0.007</td>
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<td></td>
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<tr>
<td>Debt service ratio for private non-financial sector</td>
<td>Q</td>
<td>Level*</td>
<td>-0.015</td>
<td>0.043</td>
<td>-0.030</td>
<td>-0.006</td>
<td>-0.060</td>
<td>-0.046</td>
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<tr>
<td>Residential property prices</td>
<td>Q</td>
<td>Level*</td>
<td>0.010</td>
<td>0.027</td>
<td>-0.004</td>
<td>-0.007</td>
<td>-0.038</td>
<td>-0.047</td>
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<tr>
<td>Exchange rate /USD</td>
<td>M</td>
<td>returns**</td>
<td>0.024</td>
<td></td>
<td></td>
<td></td>
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<td></td>
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<td>0.007</td>
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<tr>
<td>Real effective exchange rate index</td>
<td>M</td>
<td>returns**</td>
<td>0.246</td>
<td>-0.124</td>
<td>0.058</td>
<td>0.172</td>
<td>-0.119</td>
<td>0.084</td>
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<td>Real prime/interbank/overnight/discount rate</td>
<td>M</td>
<td>Level</td>
<td>0.009</td>
<td>-0.173</td>
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<td>-0.033</td>
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<td>Volatility index</td>
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<td>Level</td>
<td>-0.026</td>
<td>-0.011</td>
<td>-0.030</td>
<td>-0.040</td>
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<td>Financial sector index / stock exchange index</td>
<td>M</td>
<td>Level</td>
<td>-0.002</td>
<td>-0.120</td>
<td>-0.021</td>
<td>0.035</td>
<td>-0.327</td>
<td>-0.100</td>
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<tr>
<td>Real estate sector index / Stock exchange index</td>
<td>M</td>
<td>Level</td>
<td>0.047</td>
<td>-0.022</td>
<td>0.030</td>
<td>-0.003</td>
<td>0.027</td>
<td>0.371</td>
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<td>Level</td>
<td>0.345</td>
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<tr>
<td>Standard and Poor's U.S. Commodity Index</td>
<td>M</td>
<td>returns**</td>
<td>0.345</td>
<td>0.248</td>
<td>0.220</td>
<td>0.255</td>
<td>0.138</td>
<td>0.268</td>
<td>0.099</td>
<td>0.109</td>
<td>-0.010</td>
<td>0.299</td>
<td>0.518</td>
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<td>J.P. Morgan Emerging Markets Bond Index</td>
<td>M</td>
<td>returns**</td>
<td>0.061</td>
<td>0.206</td>
<td>-0.141</td>
<td>0.301</td>
<td>0.032</td>
<td>0.134</td>
<td>0.086</td>
<td>0.242</td>
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<td>J.P. Morgan Emerging Local Markets Index Plus</td>
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<td>returns**</td>
<td>0.219</td>
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<td></td>
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<td>-0.161</td>
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<tr>
<td>Stock exchange index</td>
<td>M</td>
<td>returns**</td>
<td>0.285</td>
<td>0.005</td>
<td>0.139</td>
<td>0.237</td>
<td>0.081</td>
<td>0.101</td>
<td>0.196</td>
<td>0.006</td>
<td>-0.029</td>
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<tr>
<td>Gov10Y-T-bill 3/6/12M spread</td>
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<td>Level</td>
<td>0.006</td>
<td>-0.015</td>
<td>0.149</td>
<td>0.053</td>
<td>0.195</td>
<td>0.003</td>
<td>0.060</td>
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<td>Gov10Y-US10Y spread</td>
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<td>Level</td>
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<td>-0.031</td>
<td>0.007</td>
<td>-0.081</td>
<td>-0.012</td>
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* Adjusted from possible deterministic components: linear quadratic or cubic trend, structural changes, etc.
** Returns were calculated as log(X(t)/X(t-h)), with h varies between 1 to 12 months depending on the variable of interest.
Table 2. Loading estimates of additional variables for non-BRICS countries

<table>
<thead>
<tr>
<th>Selected Variables</th>
<th>Freq</th>
<th>Transformation</th>
<th>Angola</th>
<th>Ecuador</th>
<th>Jamaica</th>
<th>St. Vincent</th>
<th>Tanzania</th>
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<tbody>
<tr>
<td>Official international reserves</td>
<td>M</td>
<td>%YOY</td>
<td>0.025</td>
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<tr>
<td>Monetary aggregate</td>
<td>M</td>
<td>%YOY</td>
<td>0.001</td>
<td>0.108</td>
<td>0.123</td>
<td>0.080</td>
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<tr>
<td>JPM EMBI GLOBAL - BLENDED SPREAD</td>
<td>M</td>
<td>returns**</td>
<td>-0.071</td>
<td>-0.143</td>
<td>-0.038</td>
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<tr>
<td>Spread lending -O/N</td>
<td>M</td>
<td>Level</td>
<td>-0.025</td>
<td></td>
<td></td>
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<tr>
<td>Barclays EM</td>
<td>M</td>
<td>returns**</td>
<td>0.060</td>
<td>0.262</td>
<td>0.207</td>
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<tr>
<td>CPI</td>
<td>M</td>
<td>%YOY</td>
<td>0.049</td>
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<tr>
<td>Use of fund credit</td>
<td>M</td>
<td>Level*</td>
<td>0.067</td>
<td>0.015</td>
<td>0.022</td>
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<tr>
<td>Domestic credit</td>
<td>M</td>
<td>%YOY</td>
<td>0.015</td>
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<tr>
<td>Credit to non-resident</td>
<td>M</td>
<td>%YOY</td>
<td>0.020</td>
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<tr>
<td>Credit to private sector</td>
<td>M</td>
<td>%YOY</td>
<td>0.021</td>
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<td>Spread lending SV-10Y USD</td>
<td>M</td>
<td>Level</td>
<td></td>
<td></td>
<td>0.125</td>
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<tr>
<td>Spread lending deposit</td>
<td>M</td>
<td>Level</td>
<td>-0.037</td>
<td>0.389</td>
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<tr>
<td>Dow Jones Sugar Commodity Index</td>
<td>M</td>
<td>returns**</td>
<td>-0.015</td>
<td></td>
<td></td>
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<tr>
<td>World price index Bananas</td>
<td>M</td>
<td>returns**</td>
<td></td>
<td></td>
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<tr>
<td>BOFA ML USD EMRG SOV Jamaica</td>
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<td>returns**</td>
<td></td>
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<td>0.146</td>
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<tr>
<td>LME-Aluminium - price</td>
<td>M</td>
<td>returns**</td>
<td></td>
<td></td>
<td>0.422</td>
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<tr>
<td>Raw Sugar-Price</td>
<td>M</td>
<td>returns**</td>
<td></td>
<td></td>
<td>0.151</td>
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<tr>
<td>Spread MoneyMarket-GVT Securities</td>
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<td>Level</td>
<td>-0.0003</td>
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<td>S&amp;P GSCI All Metals Spot Index</td>
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<td>0.422</td>
<td>0.308</td>
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</table>

* Adjusted from possible deterministic components: linear quadratic or cubic trend, structural changes, etc.

** Returns were calculated as log(X(t)/X(t-h)), with h varies between 1 to 12 months depending on the variable of interest.
<table>
<thead>
<tr>
<th>Country</th>
<th>Period of Estimation</th>
</tr>
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<tr>
<td>Angola</td>
<td>Jan 00-March 17</td>
</tr>
<tr>
<td>Brazil</td>
<td>July 95-March 17</td>
</tr>
<tr>
<td>China</td>
<td>Jan 98-March 17</td>
</tr>
<tr>
<td>Ecuador</td>
<td>Jan 96-March 17</td>
</tr>
<tr>
<td>India</td>
<td>Jan 98-March 17</td>
</tr>
<tr>
<td>Jamaica</td>
<td>Jan 96-March 17</td>
</tr>
<tr>
<td>Russia</td>
<td>Jan 96-March 17</td>
</tr>
<tr>
<td>South Africa</td>
<td>Jan 96-March 17</td>
</tr>
<tr>
<td>StVincent and the Grenadines</td>
<td>Jan 97-Feb 17</td>
</tr>
<tr>
<td>Tanzania</td>
<td>Jan 96-March 17</td>
</tr>
<tr>
<td>Thailand</td>
<td>Jan 95-March 17</td>
</tr>
<tr>
<td>Country</td>
<td>h=1</td>
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<tr>
<td>-------------------------------</td>
<td>------</td>
</tr>
<tr>
<td>Angola</td>
<td>0.028</td>
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<tr>
<td>Brazil</td>
<td>&lt;0.001</td>
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<tr>
<td>China</td>
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<tr>
<td>South Africa</td>
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<tr>
<td>St. Vincent and the Grenadines†</td>
<td>-</td>
</tr>
<tr>
<td>Thailand</td>
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<td>Russian Federation</td>
<td>0.008</td>
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<td>Ecuador</td>
<td>0.107</td>
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<td>Tanzania†</td>
<td>0.463</td>
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<tr>
<td>India</td>
<td>0.533</td>
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<tr>
<td>Jamaica</td>
<td>&lt;0.001</td>
</tr>
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</table>

* In bold: 5 and 10% significant effects
† Quarterly GDP not available for St. Vincent and the Grenadines, and available from 2008Q1 for Tanzania
9. Bibliography


