Economics Letters 216 (2022) 110528

Contents lists available at ScienceDirect

Economics Letters

journal homepage: www.elsevier.com/locate/ecolet

Financial condition indices for emerging market economies: Can Google help?☆

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ARTICLE INFO

Article history:
Received 27 September 2021
Received in revised form 12 April 2022
Accepted 15 April 2022
Available online 20 May 2022

JEL classification:
C51
E44
F30
G01
G15

Keywords:
Financial condition index
Emerging markets
Google search
Principal component analysis
VAR
Quantile regressions

ABSTRACT

We compare alternative approaches to construct financial condition indices (FCIs) for major emerging market economies (EMEs). We further test whether measures of web-search intensity for keywords related to financial tensions can complement the informative content of traditional financial variables. We find that an index constructed as a simple average of key financial variables augmented with data from google searches outperforms several alternative definitions of FCIs to explain business cycle fluctuations and capital flows episodes. These results survive when controlling for proxies of the global financial cycle, highlighting that local financial markets conditions are important for the macroeconomic performance in EMEs.

1. Introduction

The availability of tools capable of conveying insights about the state of financial markets is paramount for emerging market economies (EMEs) that are structurally vulnerable to both domestic and global shocks. Financial condition indices (FCIs) are effective tools in this regard, serving as synthetic indicators to summarize the informative content of a broad set of financial variables. Their usage has become widespread among academic researchers, policymakers, and financial institutions to study the feedback between financial markets and macroeconomic developments, monitor financial conditions and detect early warning signals of turmoil.

This paper proposes a set of FCIs specifically designed for EMEs and tests their explanatory power for real activity developments and capital flow episodes. We compute country-specific FCIs for China, India, Indonesia, South Korea (Asia region), Russia, South Africa, Turkey (EMEA), Argentina, Brazil, Colombia, Chile, and Mexico (Latin America). Additionally, we also build regional and global aggregates based on this set of countries. Besides exploiting the financial variables typically employed to build FCIs, we investigate whether web searches for keywords indicative of financial tensions, retrieved from *Google Trends,* contain additional useful information.

Literature review. The literature on FCIs is quite vast and includes both sophisticated methods as Hatzius et al. (2010) or Koop and Korobilis (2014) and simpler approaches as proposed by Matheson (2012) or Bobasu et al. (2020). We follow this second strand of literature, in line with the evidence presented in Bobasu et al. (2020) on the higher explanatory power of simpler FCIs for the macroeconomic outcomes of most countries. There is however a scarcity of academic and policy contributions explicitly focusing on EMEs, some exceptions being Gumata et al. (2012) and Kabundi and Mbelu (2021) for South Africa, Ho and Lu (2013) for Poland, Sensoy et al. (2014) for Turkey and Brandao-Marques and Ruiz (2017) for Latin American countries. We fill this gap in the literature by developing indices that are specifically designed to track financial conditions in all major EMEs, contrary to previous studies that focused on a narrow set of countries. We also contribute to the literature exploiting *Google Trends* data, a source that has already been exploited in other economic settings

☆ We thank Eric Young (editor), an anonymous referee, Pietro Catte, Fabrizio Venditti, Giovanni Veronese and participants at Bank of Italy seminars. The views expressed in the paper are those of the authors and do not involve the responsibility of the Bank of Italy.

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https://doi.org/10.1016/j.econlet.2022.110528
0165-1765/

(among others, to forecast indicators of economic activity (Choi and Varian, 2012; Carrière-Swallow and Labbé, 2013; D'Amuri and Marcucci, 2017), model the trading behavior in financial markets (Preis et al., 2013; Huang et al., 2019), develop uncertainty indices (Castelnuovo and Tran, 2017)). We employ a list of keywords that can be considered as indicative of deteriorating financial conditions in EMEs and find that Google-augmented versions of FCIs are able to offer greater insight about the interplay between financial variables and real activity.

Our approach. We adopt three different approaches to build our FCIs: *(i)* a simple average of key selected financial variables; *(ii)* the first principal component from a list of key financial variables: *(iii)* a simple average of the principal components extracted from different segments of the market, namely spreads, equity, exchange rates, and volatilities. For each of these versions, we also consider a Google-augmented FCI, and finally, an index exclusively relying on Google trends data, for a total of seven FCIs.

The seven versions of FCIs are tested through three assessment exercises. First, we use a VAR model to estimate how changes in the FCIs affect industrial production in EMEs. Second, we use quantile regression to quantify the impact of FCIs changes on the left tail distribution of industrial production growth (see Adrian et al. 2018, 2019). Third, we test the predictive power of FCIs with respect to the occurrence of critical capital flows episodes using the dataset by Forbes and Warnock (2021). Across the three exercises, we find that the FCI based on a simple average of key financial variables augmented with Google-search data outperforms the alternatives specifications of FCIs. Importantly, these results generally hold when we control for the global financial cycle, proxied either by VIX volatility index or, alternatively, by the corresponding US FCI. This is a pivotal finding and is indicative of how economic performances in EMEs remain linked to idiosyncratic developments.

2. Data

The financial variables used to build FCIs are retrieved from Refinitiv and are classified into four main categories[1]: (i) equity markets: benchmark stock market index, benchmark index of financial stocks; (ii) FX rates: spot FX rate vs USD, nominal effective FX rate; (iii) interest rates: 1Y government bond yield, 10Y government bond yield, yield curve spread (10Y-1Y government bond yield), 3M interbank rate, JPM EMBIG stripped spread; (iv) volatilities: volatility of the benchmark stock market index, 1M and 3MFX rate volatilities (vs USD).

We complement financial market variables with country-specific series retrieved from Google trends, which allows to enrich the informational content of our FCIs with data on the intensity of web searches in a given geographical area and within a determined time interval. We base our application on a list of 8 keywords that could be indicative of financial turmoil in a specific country, namely volatility, crisis, bankruptcy, debt, uncertainty, spread, financial crisis, and financial turmoil. We consider two versions of this list of keywords, the first one based on web searches in local language (*G-loc*) while the second replicates the exercise using the corresponding English term (*G-eng*). Table 5 in Appendix A presents the list of keywords for each country in the sample.

[1] Appendix A displays the full list of Refinitiv mnemonics at the country level.

3. Financial condition indices for emerging economies

Financial condition indices (FCI) are designed to summarize financial conditions into a single indicator. We base our strategy on the recent evidence in Bobasu et al. (2020) who show that more sophisticated approaches (e.g. Koop and Korobilis, 2014) do not yield significant gains compared to simpler strategies. We thus consider seven alternative FCIs that differ in the information employed and in how this information is aggregated:

1. *FCI1*: we consider a simple average of crucial financial variables for EMEs: stock prices, FX rates (spot), equity market implied volatility, EMBIG, 10Y-1Y government bond spread, interbank rate;
2. *FCI1G*: we add *G-eng* and *G-loc* to the list of the key variables that enter FCI1;
3. *FCI2*: we take the first principal component from the list of all financial variables detailed in Section 2 as the FCI;
4. *FCI2G*: we add *G-eng* and *G-loc* to the dataset that enter the computation of FCI2;
5. *FCI3*: we consider the full set of financial variables but separately extract the principal component for each category of interest, namely (i) equity, (ii) FX rates, (iii) interest rates, and (iv) volatility. Then we take their average;
6. *FCI3G*: we add a principal component from *G-eng* and *G-loc* that enters the final average.
7. *FCIG*: we consider the principal component from *G-eng* and *G-loc* by itself to be able to assess its information content more explicitly.

We employ daily data in levels and remove the quadratic trend separately for each variable. Then we standardize each variable, and build each of the FCIs as described above. Finally, we transform the daily FCIs to the monthly frequency to improve their readability and average out high-frequency movements that are not linked to macroeconomic developments.

We compute FCIs both at the country and at the aggregate geographical area (Asia, EMEA, Latin America, and the EMEs aggregate) level.[2] Fig. 1 displays the aggregate FCIs for EMEs (the plots of country-specific FCIs are available in Appendix B). Our FCIs successfully capture tensions related to broad-based episodes of turmoil such as the Global Financial Crisis and the more recent Covid-19 pandemic. However, they perform reasonably well also in the identification of country specific shocks, such as the 2002 debt crisis and the 2014–16 recession in Brazil, the 2013 tensions in India fueled by the Fed tapering announcements, the 2018 debt and currency crisis in Turkey.

4. FCI explanatory power

We perform three exercises to assess the informativeness of our FCIs. First, we run a Vector Autoregression (VAR) to estimate how changes in the FCI affect on average the industrial production (*ip*) of EMEs . Second, we use a quantile regression approach to quantify the impact of FCI changes on the left tail distribution of *ip* growth.[3] Third, we use a probit model to investigate whether FCIs are useful predictors of capital flows critical episodes. Insights from the VAR estimate are presented in Section 4.1 whereas the results from quantile regression and capital flow episodes are reported in Appendix C.

[2] The FCIs referred to the geographical areas are obtained as the GDP-weighted average of the corresponding country-level FCIs.

[3] Due to data availability limitations linked to the lack of harmonized *ip* series across countries, the sample employed in our assessment exercise ends in December 2019.

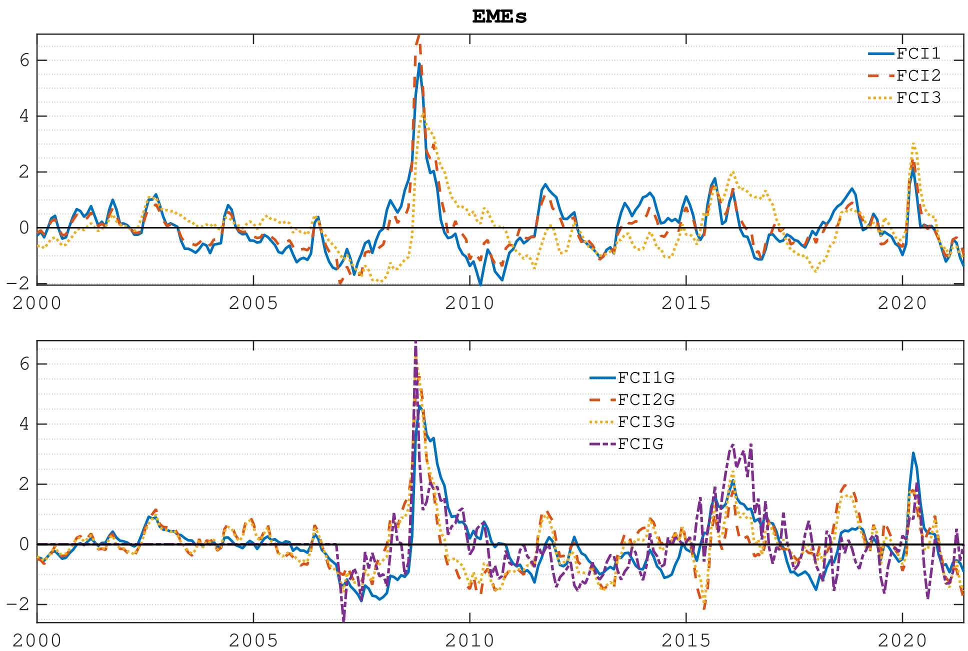

Fig. 1. FCIs-EMEs aggregate.

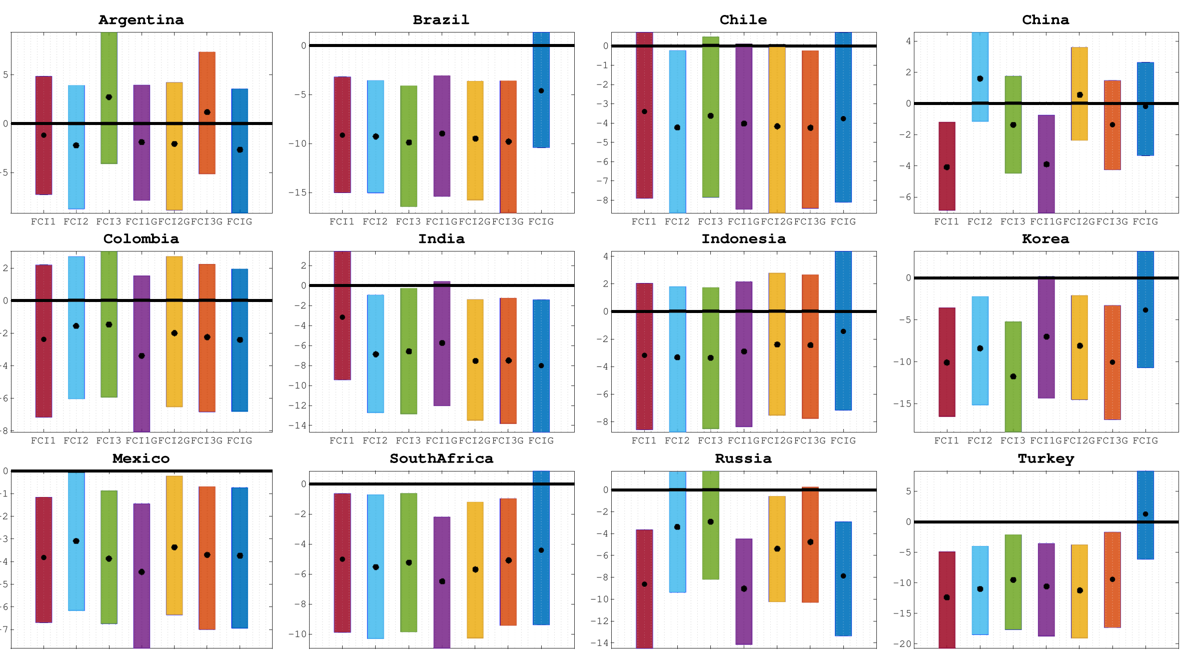

Fig. 2. FCI impact on industrial production. *Note.* The black dots indicate the median estimate, while the boxplot correspond to 90% confidence bands.

From the overall evaluation of these exercises we conclude that the most effective FCI is *FCI1G* as it exhibits the largest explanatory power for fluctuations in *ip*, both on average and for large falls, and it is a relevant predictor of capital flows episodes. This index is built as a simple average of key financial variables for EMEs and it is complemented with Google trends data on web searches related to financial tensions or crises. Importantly, these findings are robust to the inclusion of measures of global financial factors (e.g. VIX index), suggesting that the monitoring of idiosyncratic developments in EMEs is worthwhile to assess the macroeconomic and financial evolution in those countries, see Appendix C.

4.1. VAR analysis

To assess the average impact of FCI changes on *ip* at the country level, we estimate several specifications of a bivariate VAR that includes *ip* each possible version of FCIs proposed in this study;we select the optimal number of lags according to the Akaike Information Criteria in each case. The effect of FCI on *ip* is identified by considering the shock to the FCI as the residuals in the FCI equation, which corresponds to a Cholesky decomposition where FCI is ordered prior than *ip*. Our summary statistic is the cumulated one-year Impulse Response Function (IRF) of the FCI shock on *ip*.

The results in Fig. 2 indicate that FCI changes produce significant effects on economic activity in several EMEs such as Brazil, Chile, China, South Korea, Mexico, South Africa, Russia, and Turkey. The general pattern suggests that *FCI1* is the most informative version of FCI. The difference between *FCI1* and *FCI2*–*FCI3* is particular stark in China. *FCI1* have the largest impact, in general, when employed in conjunction with Google trends data (*FCI1G*), thus indicating that Google can be an important source of information to monitor financial conditions in EMEs. Interestingly, the *FCIG* (Google trends alone) significantly affect *ip* in most cases. In this perspective, the most interesting country is Russia: *FCIG* appear to be more relevant than *FCI2(G)* and *FCI3(G)*. Conversely, *FCIG* does not appear to be relevant in Turkey.

5. Conclusions

This paper identifies an index constructed as the simple average of key financial variables, augmented with Google search queries, as the best FCI in EMEs. This index outperforms several alternatives tested in this work to explain business cycle fluctuations, large negative swings in production, and capital flows episodes in EMEs. These results survive even when we control for proxies of the global financial cycle, reflecting the importance of local financial market conditions in analyzing the interplay between financial variables and real economic activity. Our index can be conveniently employed as a synthetic measure of financial markets developments both in academic research and by policymakers when studying emerging markets. Finally, this work sheds light on a promising avenue of research aimed at exploiting web searches as a complementary source of information to characterize period of financial stress in emerging markets.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.econlet.2022.110528.

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Further reading

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