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FINANCIAL CONDITION INDICES FOR EMERGING MARKET ECONOMIES: CAN GOOGLE HELP?

by Fabrizio Ferriani* and Andrea Gazzani*

Abstract

We compare different approaches to constructing 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 information 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 in explaining business cycle fluctuations and capital flows episodes. These results hold true when controlling for proxies of the global financial cycle, highlighting that local financial market conditions are important for the macroeconomic performance of EMEs

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*Bank of Italy, Directorate General for Economics, Statistics and Research – International Relations and Economics Directorate.

1 Introduction

The outbreak of the Covid-19 crisis in February-March 2020 is possibly the most vivid and recent example of how financial markets act as a barometer of the general state of the economy, even when the shock originates outside of the local economy. The availability of tools capable of conveying insights about the state of financial markets is therefore paramount for emerging market economies, which are structurally vulnerable to both domestic and global shocks. Financial condition indices (FCIs) are effective tools in this regard as they serve as synthetic indicators that summarize the informative content of a broad set of financial variables. Indeed, their usage has become widespread among academic researchers, policymakers, and financial institutions. FCIs are used to study the feedback between financial markets and macroeconomic developments, to monitor financial conditions, detect early warning signals of turmoil, and to assess the market's response to policy measures.

In this paper, we propose a set of FCIs specifically designed for emerging market economies (EMEs) and test their explanatory power for real activity developments and for capital flow episodes. We compute country-specific FCIs for China, India, Indonesia, South Korea (Asia region), Russia, South Africa, Turkey (Europe, Middle East and Africa - EMEA), Argentina, Brazil, Colombia, Chile, and Mexico (Latin America). Additionally, we also build regional and global aggregates based on this set of countries.[1] 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. Freely available alternative sources of information are particularly promising in EMEs, considering that their financial markets are often less developed and liquid than those of advanced economies (AEs) so that the use of unconventional data could be a valuable complement to capture investors' sentiment in the market.

Literature Review. The literature on FCIs is quite vast and includes both sophisticated methods as Hatzius et al. (2010); Matheson (2012); Koop and Korobilis (2014); Brave et al. (2017); Petronevich and Sahuc (2019) and simpler approaches as Guichard and Turner (2008), Ho and Lu (2013), Bobasu et al. (2020).[2] 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

[1]Countries in this list account for more than 70% of PPP-adjusted GDP of emerging and developing economies and for about 40% of PPP-adjusted world GDP based on IMF data.

[2]These latter indices are similar to those developed by Bloomberg, Citi, Goldman Sachs.

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 empirical studies in other economic settings (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, measure changes in population well-being Brodeur et al., 2021). We employ a list of keywords that can be thought 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)* is 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 relying exclusively on Google Trends data, for a total of seven FCIs.

The seven versions of FCIs are tested through three validation exercises aimed at assessing the informativeness for economic developments in EMEs. 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; Giglio et al. 2016). 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 validation exercises, we find that the measure of financial condition based on a simple average but augmented with Google-search data outperforms the remaining alternatives of FCIs. Importantly, these results generally hold when we control for the global financial cycle, proxied by the S&P500 option-implied volatility index (VIX) 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.

Outline. The rest of this paper is organized as follows. Section 2 introduces the data and details how we use Google Trend services to extract information on financial conditions in EMEs. Section 3 describes the construction of the FCIs and illustrates their dynamics over time, while Section 4 presents a set of validation exercises to assess the predictive power of our FCIs. Finally, Section 5 offers our concluding remarks.

2 Data

A first consideration in the design of FCIs regards the choice of the financial variables of interest, especially in the case of EMEs. In fact, in contrast to AEs, the availability of variables based on asset prices in sufficiently liquid financial markets or adequately long time series of data cannot be taken for granted and constraints us to employ a relatively narrow set of key financial variables. From the perspective of a cross-country analysis this choice is also aimed at enhancing the comparability of results. All financial variables used in the empirical application are retrieved from Refinitiv and can be classified into four main categories:[3]

- Equity markets: benchmark stock market index, benchmark index of financial stocks
- Exchange rates: spot exchange rate vs USD, nominal effective exchange rate
- 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.
- Volatilities: volatility of the benchmark stock market index, 1M exchange rate volatility (vs USD), 3M exchange rate volatility (vs USD)

We complement standard 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.[4] We consider two versions of this list of keywords, the first one is based on web searches in local language (*G-loc*) while the second replicates the exercise using the corresponding English term (*G-eng*). Table 5 provides an overview of the web searches for each country in the sample.[5] For each search, Google Trends provides a normalized series ranging between 0 and 100 with the highest value identifying the period with the largest number of keyword searches over a specific time period and in the geographical area of interest.

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

[4] We use "+" punctuation to include any search containing at least one of the variables included in the list. Data from Google Trends are not available before 2004, nevertheless we limit the analysis to web searches from 2007 onward as the dynamics of web queries is extremely erratic during the first years of data availability.

[5] We retrieve Google Trends data on web queries also in the case of China despite the major limitations to directly access the Google search engine from Mainland China. Indeed, according to Google Trends data, the geographical distribution of web searches in China is concentrated in wealthy provinces where investors more sensitive to financial markets conditions are more likely to reside. Our general conclusion and empirical assessment are nevertheless valid and qualitatively similar also when we exclude Google Trends data for China as shown by the validation exercises in Section 4. In the case of India, based on confrontation with local professionals, English is definitely the prevalent language of the financial sector. For this reason, but also because of the difficulty to run a nation-wide search of local terms in view of the large variety of Indian languages, we restrict the search to keywords in English; FCIs relying also on web searches in Hindi are qualitatively similar and available from the authors upon request.

3 Financial Condition indices for Emerging Economies

Financial condition indices (FCI) are designed to summarize financial conditions into a single indicator. Due to the lack of FCIs explicitly designed for EMEs, we propose and test several approaches. 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:

FCI 1: we consider a simple average of crucial financial variables for EMEs: stock prices, exchange rates (spot), equity market implied volatility, EMBI, 10-year government bond spread (to 1-year government bond yields), interbank rate.

FCI 1G: we add *G-eng* and *G-loc* to the list of the key variables that enter FCI1.

FCI 2: we take the first principal component from the list of financial variables detailed in Section 2 as the FCI.

FCI 2G: we add *G-eng* and *G-loc* to the dataset that enter the computation of FCI2.

FCI 3: we consider the full set of financial variables but separately extract the principal component for each category of interest, namely i) equity, ii) exchange rates, iii) interest rates, and iv) volatility. Then we take their average.

FCI 3G: we add a principal component from *G-eng* and *G-loc* that enters the final average.

FCI G: 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.[6] Then we standardize each variable, set missing information to 0, which corresponds to the sample average of the standardized variables, 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.[7] Figure 1 displays the aggregate FCIs for EMEs while Figures 2 to 4 present all versions of the FCIs for three representative countries (Brazil, India, and Turkey respectively; the full list of plots is 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

[6]Several papers that proposed FCIs use variables in growth rates, but this transformation retains low-frequency components that is preferable to remove. For recent econometric evidence on the effectiveness of deterministic detrending, see Canova (2020).

[7]The FCIs referred to the geographical areas are obtained as the weighted average of the corresponding country-level FCIs; weights are yearly updated and based on the relative country GDP.

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.

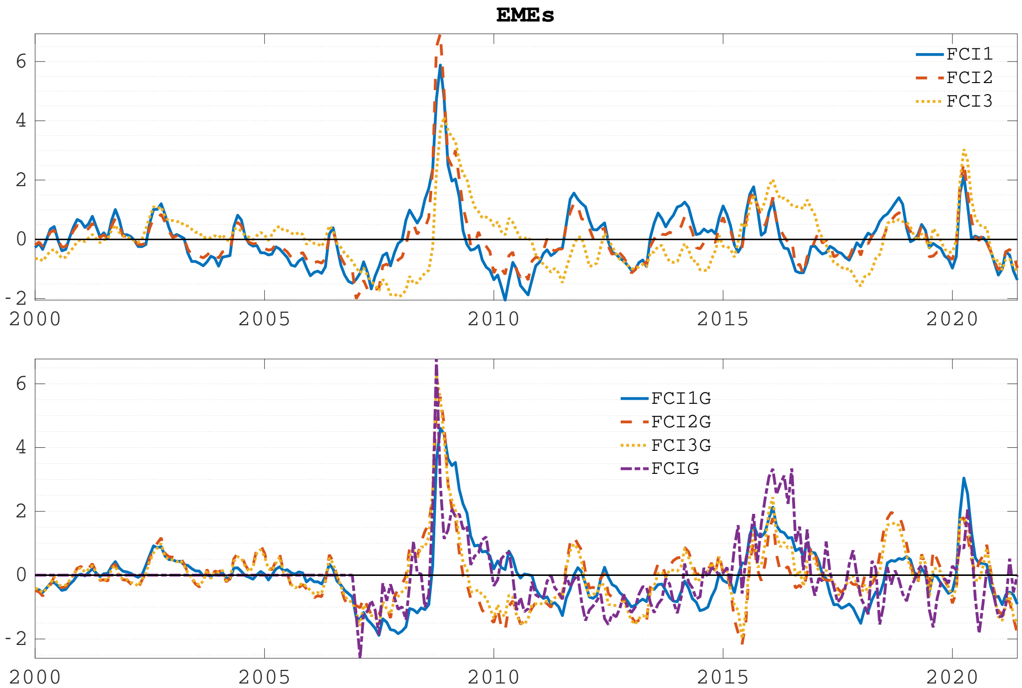

Figure 1: FCIs - EMEs aggregate

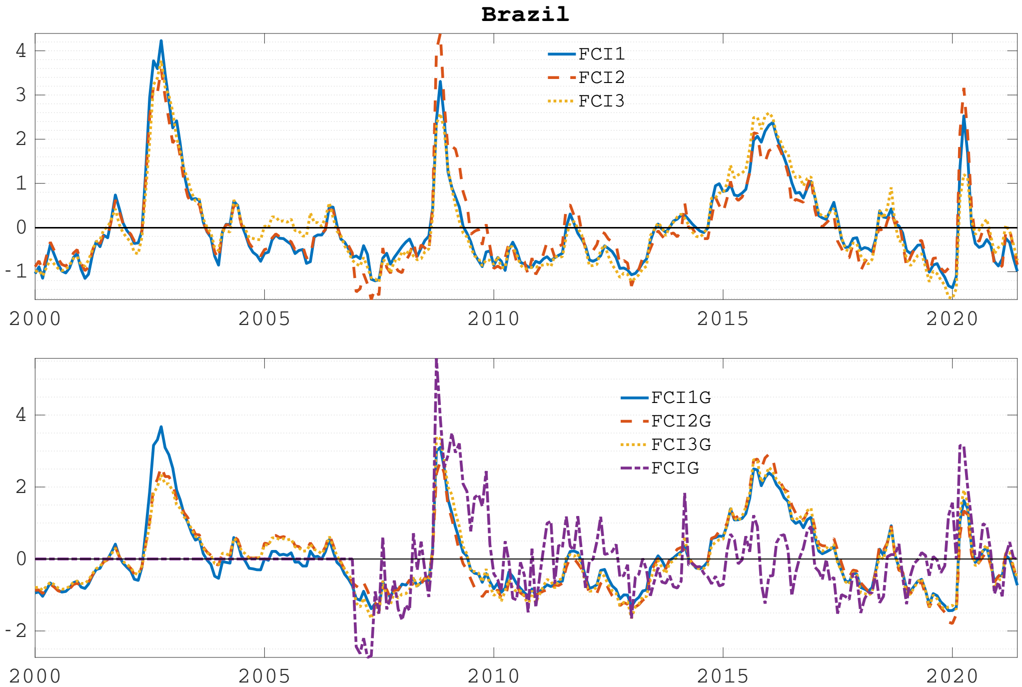

Figure 2: FCIs - Brazil

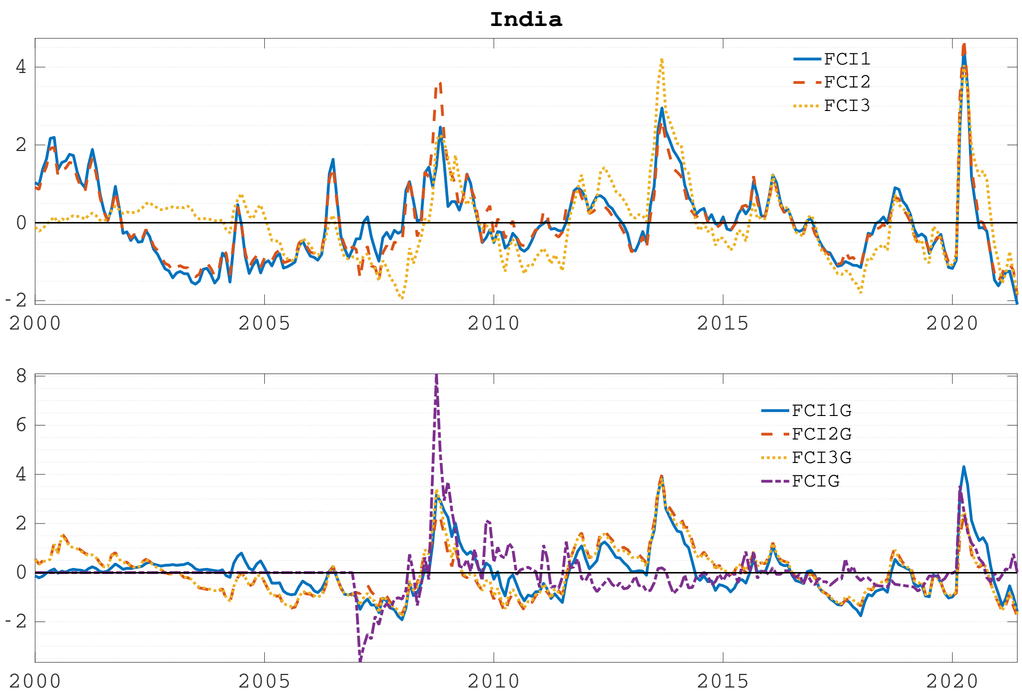

Figure 3: FCIs - India

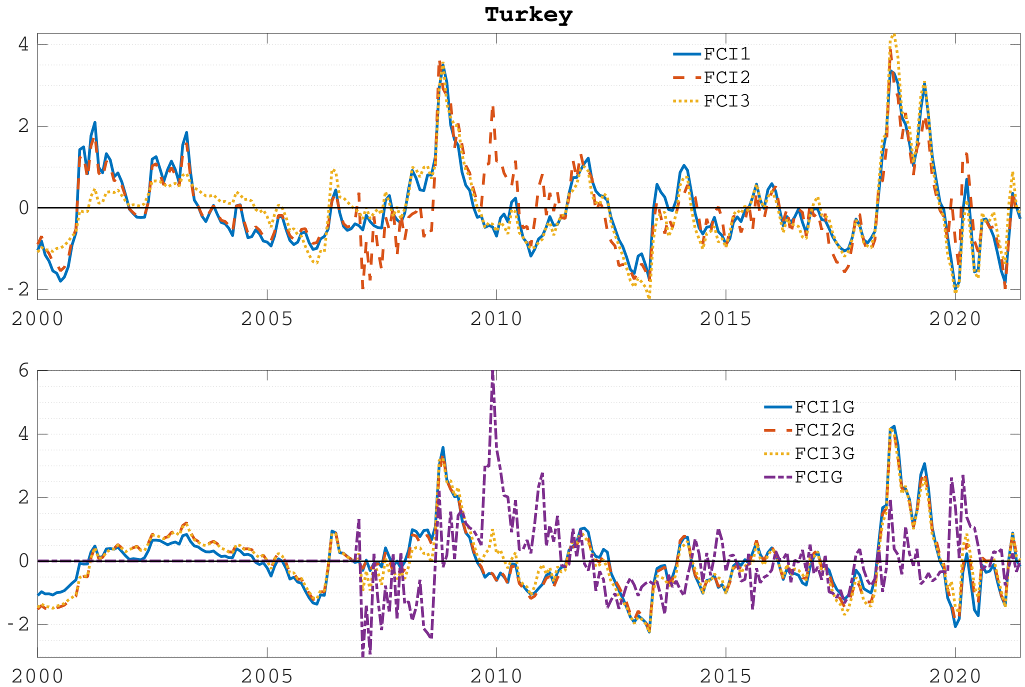

Figure 4: FCIs - Turkey

4 Validation Exercises

We perform three validation exercises to assess the informativeness of the FCIs for economic developments of emerging economies. First, we run a Vector Autoregression (VAR) exercise to estimate how changes in the FCIs affect on average the industrial production (*ip)* of EMEs. Second, we use a quantile regression approach to quantify the impact of FCIs changes on the left tail distribution of industrial production growth. Third, we exploit the dataset of Forbes and Warnock (2021) in a probit model to investigate whether FCIs are useful predictors of capital flows critical episodes. For reasons linked to unavailability of harmonized industrial production series across countries, as well as to avoid the need for more complex econometric modeling, the sample employed in our validation exercises stops in December 2019.

4.1 VAR Analysis

To assess the average impact of FCI changes on *ip*, we estimate a bivariate VAR that includes FCI and *ip* for each country and for each version of the FCIs. The number of lags is selected according to the Akaike Information Criteria (AIC) 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 (this 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 system can be represented as

$$
\begin{pmatrix} fci_t \\ ip_t \end{pmatrix} = A(L) \begin{pmatrix} fci_{t-1} \\ ip_{t-1} \end{pmatrix} + \begin{pmatrix} b_{11} & 0 \\ b_{21} & b_{22} \end{pmatrix} \begin{pmatrix} \varepsilon_t^{fci} \\ \varepsilon_t^{ip} \end{pmatrix}, \tag{1}
$$

where $A(L)$ is a lag polynomial whose order depend on the AIC criterion yielding the lags p^* with $L = 0, ..., p^*$, $B = \begin{pmatrix} b_{11} & 0 \\ b_{21} & b_{22} \end{pmatrix}$ is the impact of the shocks corresponding to a Cholesky decomposition of the variance-covariance matrix Σ of the reduced form residuals $u_t = B\varepsilon_t = B \begin{bmatrix} \varepsilon_t^{fci} & \varepsilon_t^{ip} \end{bmatrix}'$ such that $\Sigma = \mathbb{E}\left[u_t u_t'\right]$.

The results in Figure 5 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 affects *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.

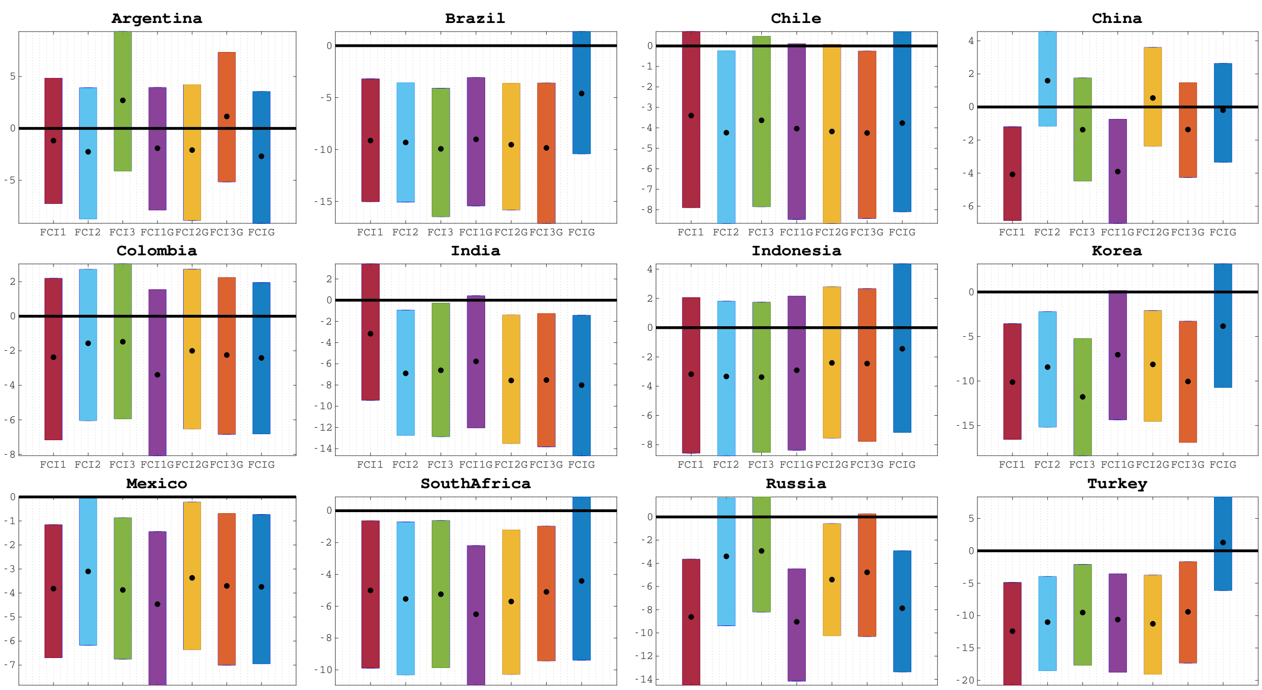

Figure 5: FCI impact on industrial production

Note. The black dots indicate the median estimate, while the boxplot correspond to 90% confidence bands.

4.2 Quantile Regression

In this Section we estimate the impact of *FCI* on the left tail distribution of *ip* growth. The coefficients estimated by the quantile regression take the form

$$\hat{\beta}_q = \underset{\beta_q}{arg\,min} \sum_{t=1}^{\prime} \left[q\mathbf{1}_{(y_t \geq x_t\beta)} |y_t - x_t\beta_q| + (1-q)\,\mathbf{1}_{(y_t < x_t\beta)} |y_t - x_t\beta_q| \right] \tag{2}$$

where $q \in (0,1)$ represents the quantile of interest, in our case the lowest 5% of *ip* growth (Δip) and $\mathbf{1}_{(.)}$ denotes the indicator function. The predicted value from this regression is given by

$$\hat{Q}_{y_t/x_t}\left(q/x_t\right) = x_t\hat{\beta}_q \tag{3}$$

In the present analysis, $y_t = \Delta ip_{t+1}$ and $x_t = fci_t$. Additionally, we control for Δip_t to account for the autocorrelation in *ip* growth.

The pattern highlighted by the linear VAR is even starker when we look at the left tail of the distribution of economic activity: *FCI1G* appears the most useful predictor of a fall in industrial production, in terms of both magnitude and statistical significance. This general conclusion stands out especially in Argentina, Brazil, Korea, Russia and Turkey, where *FCIG* alone often has predictive power for the left tail of *ip* growth distribution and thus improves both the point estimate as well as the precision of the estimation over *FCI1.*

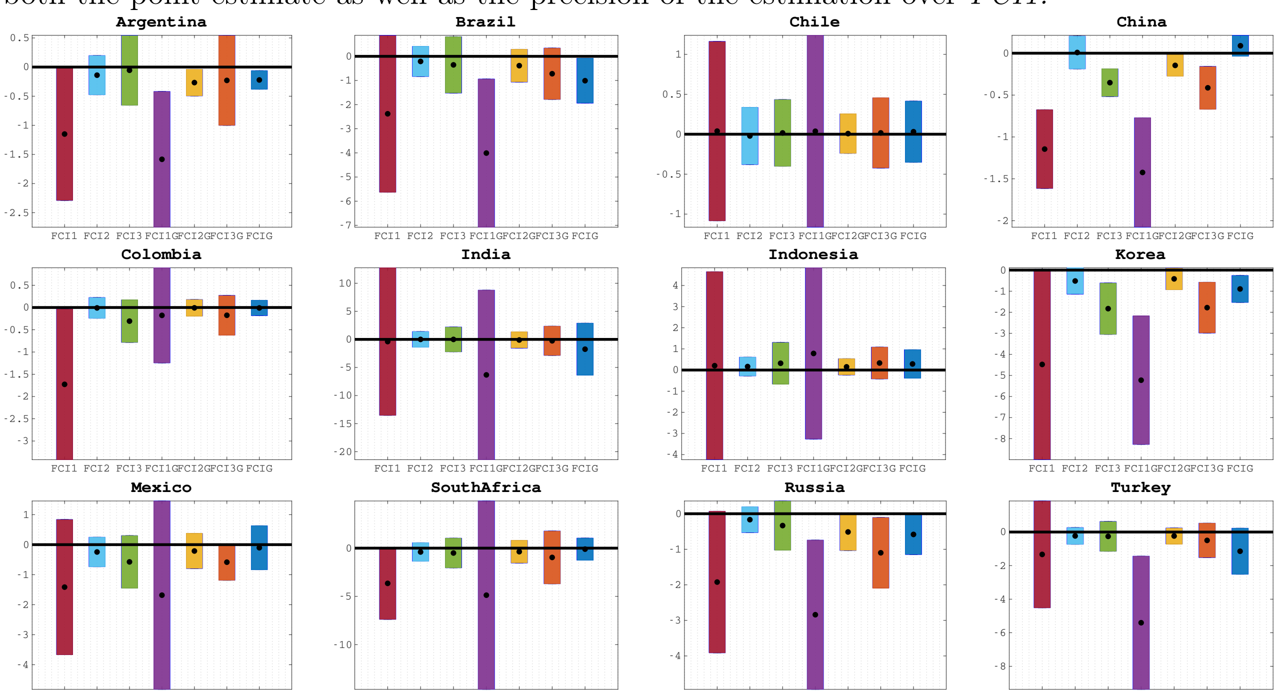

Figure 6: FCI impact on the left tail of industrial production growth distribution
Note. The black dots indicate the median estimate, while the boxplot correspond to 90% confidence bands.

4.3 Capital Flows Episodes

As a further validation exercise, we test the predictive power of FCIs in the context of capital flows, focusing in particular on portfolio flows. The motivation of this choice is twofold. First of all portfolio flows represent the most volatile component of capital flows and their dynamics is arguably the most sensitive to major fluctuations in financial markets (Eichengreen et al. 2017; Gelos et al. 2019; Ferriani 2021). Second, portfolio flows have substantially increased their importance as a consequence of the gradual shift, occurred in recent years, from bank-intermediated credit towards non-bank financing (BIS, 2021), so that they likely embody the most meaningful component of capital flows to test the validity of our FCIs. To this purpose, we rely on the database developed by Forbes and Warnock (2021) for their analysis of extreme capital flow movements. More precisely, and for each country in our sample, we restrict their database to equity and debt portfolio flows and construct dummy variables that are equal to one whenever any of the two components of portfolio flows experiences episodes of sharp movements. Consistently with their classification, we separately identify increases and decreases in capital flows by foreigners and domestics so that for each country we end up with four dummy variables to distinguish across episodes of sudden surges, stops, flights and retrenchments. We then estimate a probit model with country fixed effects and compare the predictive power of different versions of FCIs across different types of capital flows episodes. The results in terms of predictive accuracy are evaluated using ROC curve metrics and are summarized in Figure 7 where we compare the predictive accuracy of our FCIs relative to a random model (i.e. a "coin toss" exercise with accuracy equal to 0.5); as an example, the predictive accuracy of FCI1 in the case of flight episodes is 41% higher than the one of a simple random model. Figure 7 exhibits some differences in terms of predictive accuracy across alternative versions of FCIs and type of capital flows episodes, but it nevertheless points to a substantial improvement relative to the random model, with FCI1 and FCI1G moderately outperforming the remaining indices also in this exercise.

	Flight	Stop	Surge	Retrenchment	Average
FCI1	41.5%	34.0%	38.8%	36.4%	37.7%
FCI1G	39.5%	33.7%	39.6%	36.8%	37.4%
FCI2	32.1%	30.9%	39.1%	28.9%	32.7%
FCI2G	32.4%	32.9%	39.3%	29.9%	33.6%
FCI3	37.2%	29.1%	34.0%	32.2%	33.1%
FCI3G	36.5%	30.1%	35.2%	32.7%	33.6%
FCIG	26.7%	32.4%	29.9%	32.0%	30.3%

Figure 7: Capital flows episodes and predictive accuracy of FCIs

Note. The figure summarizes the predictive accuracy of FCIs across different types of capital flows episodes using ROC curves after probit estimation. Each cell reports the improvement in predictive accuracy relative to a random model (accuracy = 0.5).

4.4 Robustness and Ancillary Exercises

We run two main robustness exercises that are aimed at assessing whether the FCIs that we propose contain country-specific information, beyond global phenomena such as the global financial cycle, that are still relevant for real economic developments in EMEs. First of all we repeat the VAR and quantile regression validation exercises in Section 4 adding a global financial control. In one case, we proxy the global financial cycle through the VIX, whereas in the second case we employ US FCIs build as the original FCIs for consistency.[8] As a second robustness test, we compare our FCIs with private analysts indices by repeating the validation exercises employing the popular FCIs developed by Goldman Sachs and Citi. The exercise shows that their explanatory power for the real economy is significantly more limited as compared to our FCIs.

Controlling for the Global Financial Cycle. We report the results from the VAR that provides a more general insight on the relationship between the FCIs and economic developments in EMEs, while the results from the quantile regression approach are included in Appendix C. The exercise follows closely the original one but we control for the contemporaneous shifts in the VIX and, alternatively, in the US FCIs. The shock to the EMEs FCI is thus identified in a Cholesky decomposition where the EME FCI is ordered after the global factor, and it is then orthogonal to simultaneous change in global financial conditions. Even controlling for the US FCI, local financial conditions have still a very significant explanatory power for *ip* beyond the global financial cycle. In some cases, such as India and Colombia, results improve likely due to a sharper identification of financial tensions that are relevant for the country. When we include the VIX as control, the impact of FCIs on *ip* looses some statistical significance but it is consistently negative and we can reject a null impact for several countries (Colombia, Mexico, South Africa, Russia, and Turkey).

[8]We do not include as a robustness test the probit exercise controlling for some proxies of the global financial factor, as the inclusion of this additional regressor almost implies mechanical increase of the model predictive accuracy which is not particularly informative; the results are available from the authors upon request.

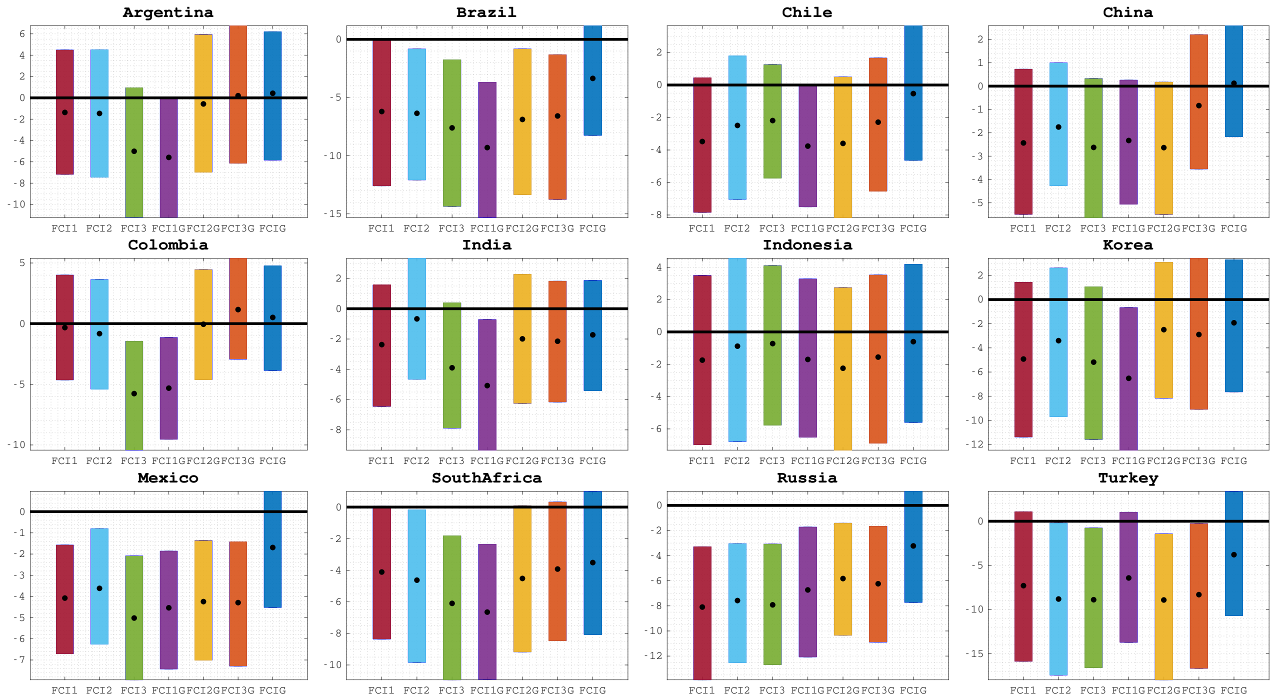

Figure 8: FCI impact on industrial production - controlling for US FCIs
Note. The black dots indicate the median estimate, while the boxplot correspond to 90% confidence bands.

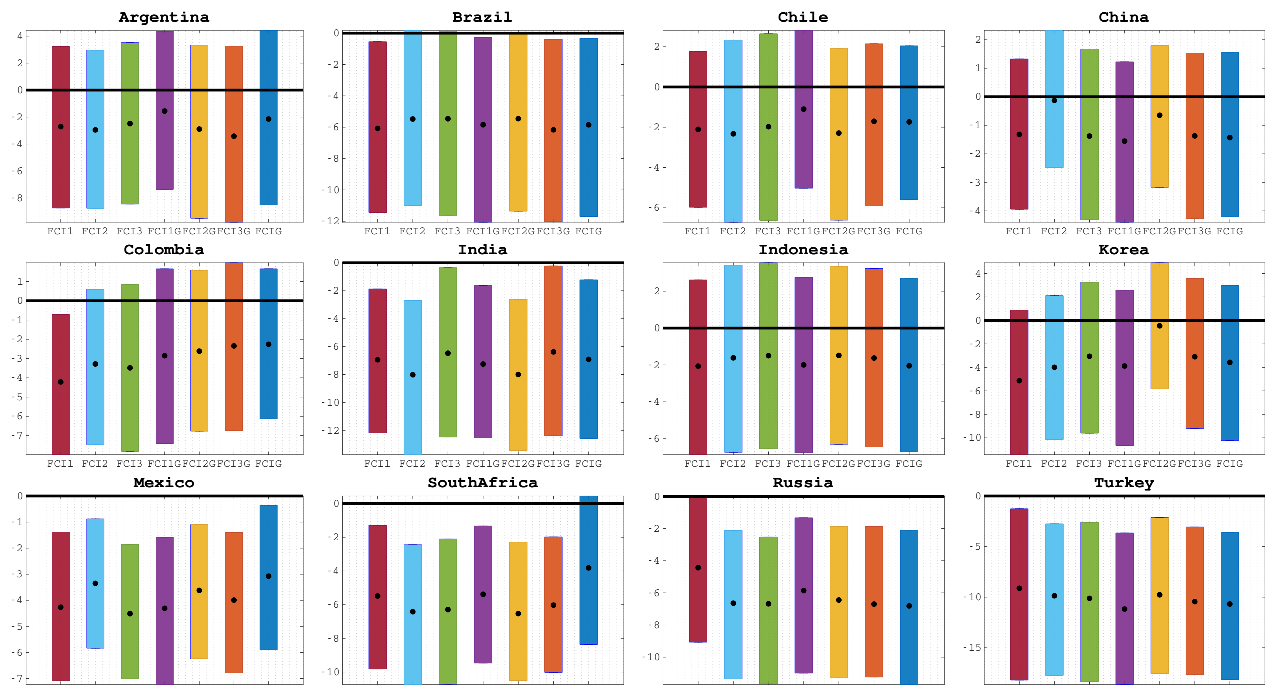

Figure 9: FCI impact on industrial production - controlling for the VIX
Note. The black dots indicate the median estimate, while the boxplot correspond to 90% confidence bands.

Comparison with popular FCIs. This subsection replicates the previous validation exercises using popular FCIs developed by the financial sector industry, namely the Goldman Sachs and the Citi FCI, see Hatzius and Stehn (2018) and Chua and Mathur (2018) respectively for methodological details. The Goldman Sachs FCI is constructed as a weighted average of a list of key financial variables and is available for most of the countries included in our sample with the exception of Argentina and Colombia, whereas the Citi FCI is based on principal component analysis and is only available for Asian countries; both series are obtained from Bloomberg.[9] Results of the VAR exercise are displayed in Figure 10 showing a statistical significant impact of popular FCIs on *ip* for less than half of the countries; importantly, our FCIs clearly outperform the financial industry indices in several cases such as Brazil, Mexico, and Russia.[10]

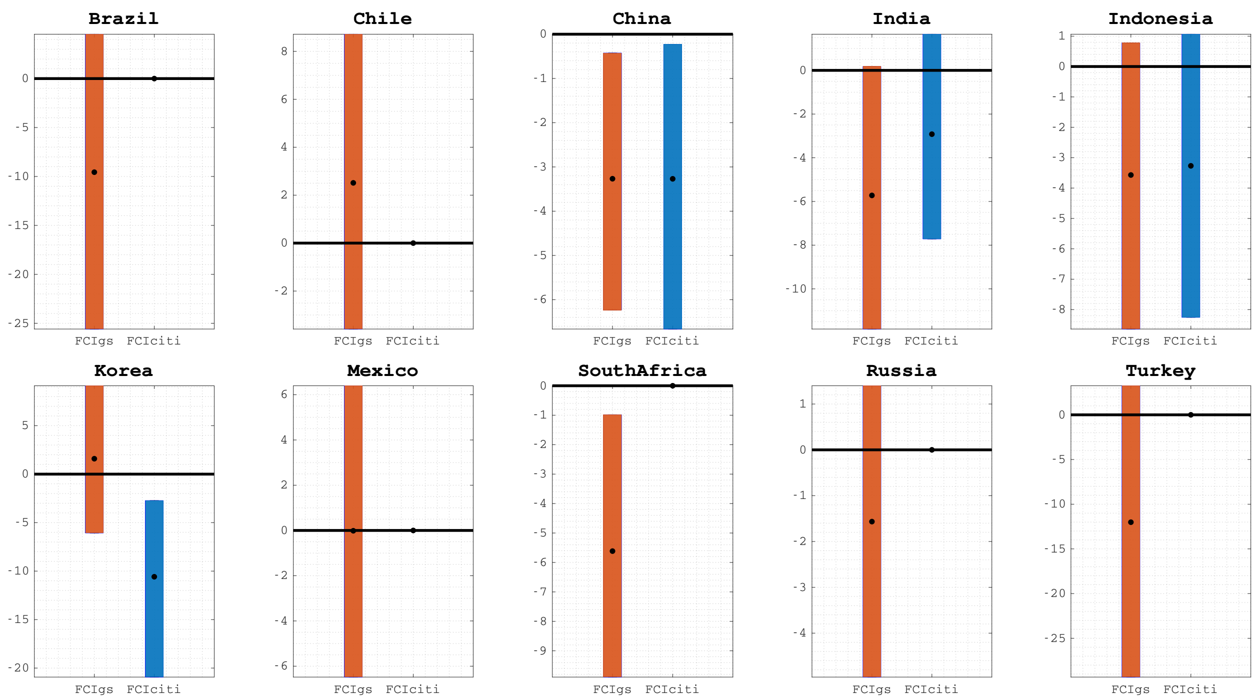

Figure 10: Industry FCI impact on industrial production

Note. The black dots indicate the median estimate, while the boxplot correspond to 90% confidence bands. Orange bars correspond to the Goldman Sachs FCI, blue bars to the Citi FCI.

4.5 Takeaway

The overall evaluation of the results from our validation exercises (including the robustness ones) shows that the most effective FCI is the version *FCI1G*. *FCI1G* has the large 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

[9]There is also an alternative version of the Citi FCI based on a weighted average approach which is not used in this robustness exercise.

[10]Similar evidence based on quantile regression is available in Appendix C.

financial variables for EMEs and it is complemented with Google Trends data on web searches related to financial tensions or crises. *FCI1G* captures country-specific financial tensions that are relevant even net of global financial factors, which allows us to conclude that monitoring idiosyncratic developments in financial conditions in EMEs is worthwhile in order to assess the macroeconomic and financial evolution in those countries.

5 Conclusions

This paper identifies an index constructed as the simple average of key financial variables, augmented with Google search queries, as the best financial condition index in emerging market economies. This index outperforms several alternatives tested in this work to explain business cycle fluctuations, large negative swings in production, and capital flows episodes in the major emerging market economies. 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 measures of financial markets developments both in academic research and by policy makers when studying emerging markets. Finally, this work sheds light on a promising avenue of research related to exploiting web searches as a complementary source of information on financial stress in emerging markets.

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Appendix

A Data

This appendix reports the list of Refinitiv mnemonics used to construct different versions of FCIs.

	Equity	Equity financials
China	CHSS300	CHSI3FN
India	ICRI500	INNSEBK
Indonesia	JAKCOMP	JAKFINC
S. Korea	KORCOMP	KORFINS
Russia	RSMICEX	MCXFINL
S. Africa	JSEOVER	JSEI1FN
Turkey	TRKISTB	TKBNKSI
Argentina	ARGMERV	X1ARFNL
Brazil	BRBOVES	BRIIFNC
Chile	IGPAGEN	SASEBNK
Colombia	BVCCAPT	FINANCB
Mexico	MXIPC35	MXI1FNS

Table 1: Equity mnemonics. The volatility is computed as the annualized standard deviation of equity benchmark returns over a two-month period.

	Spot FX rate	NEER
China	TDCNYSP	CHBINXB
India	TDINRSP	INBINXB
Indonesia	TDIDRSP	IDBINXB
S. Korea	TDKRWSP	KOBINXB
Russia	TDRUBSP	RSBINXB
S. Africa	TDZARSP	SABINXB
Turkey	TDTRYSP	TKBINXB
Argentina	TDARSSP	AGBINXB
Brazil	TDBRLSP	BRBINXB
Chile	TDCLPSP	CLBINXB
Colombia	TDCOPSP	CBBINXB
Mexico	TDMXNSP	MXBINXB

Table 2: Exchange rate mnemonics. The spot exchange rate is expressed vis-à-vis the USD. NEER stands for nominal effective exchange rate, broad index.

	1Y Interest rate	10Y Interest rate	Yield spread	3M Interb. rate	EMBIG spread
China	TRCH1YT	TRCH10T	TRCH10T-TRCH1YT	CHIB3MO	JPMGCHN
India	TRIN1YT	TRIN10T	TRIN10T-TRIN1YT	INMIR076R	JPMGINA
Indonesia	TRID1YT	TRID10T	TRID10T-TRID1YT	IDIBK3M	JPMGIND
S. Korea	TRKR1YT	TRKR10T	TRKR10T-TRKR1YT	KRIBK3M	NA
Russia	TRRS1YT	TRRS10T	TRRS10T-TRRS1YT	RSIBA90	JPMGRUS
S. Africa	TRSA1YT	TRSA10T	TRSA10T-TRSA1YT	JIBAR3M	JPMGSAF
Turkey	TRTK1YT	TRTK10T	TRTK10T-TRTK1YT	TKIBK3M	JPMGTUR
Argentina	TRAR1YT	TRAR7YT	TRAR7YT-TRAR1YT	AGIBPES	JPMGARG
Brazil	TRBR1YT	TRBR10T	TRBR10T-TRBR1YT	BRCDIIR	JPMGBRA
Chile	TRCL1YT	TRCL10T	TRCL10T-TRCL1YT	CLTAB3M	JPMGCHI
Colombia	TRCO1YT	TRCO10T	TRCO10T-TRCO1YT	CBIBOVR	JPMGCOL
Mexico	TRMX1YT	TRMX10T	TRMX10T-TRMX1YT	MXBTIIE	JPMGMEX

Table 3: Interest rate mnemonics. In the case of Argentina, due to data availability, the long term interest rate refers to the 7Y maturity instead of 10Y. The yield spread is defined as the difference between long and short term interest rates. Due to data availability the interbank rate has a 15- and 28-day maturity in the case of Argentina and Mexico respectively, while it is overnight for Brazil and Colombia. EMBIG stripped spread is not available for South Korea.

	Equity volatility	1M FX volatility	3M FX volatility
China	Vol(CHSS300)	FVCNY1M	FVCNY3M
India	Vol(ICRI500)	FVINR1M	FVINR3M
Indonesia	Vol(JAKCOMP)	FVIDR1M	FVIDR3M
S. Korea	Vol(KORCOMP)	FVKRW1M	FVKRW3M
Russia	Vol(RSMICEX)	FVRUB1M	FVRUB3M
S. Africa	Vol(JSEOVER)	FVZAR1M	FVZAR3M
Turkey	Vol(TRKISTB)	FVTRY1M	FVTRY3M
Argentina	Vol(ARGMERV)	FVARS1M	FVARS3M
Brazil	Vol(BRBOVES)	FVBRL1M	FVBRL3M
Chile	Vol(IGPAGEN)	FVCLP1M	FVCLP3M
Colombia	Vol(BVCCAPT)	FVCOP1M	FVCOP3M
Mexico	Vol(MXIPC35)	FVMXN1M	FVMXN3M

Table 4: Volatility mnemonics. Equity volatility is computed as the annualized standard deviation of the equity benchmark returns over a two-month period. 1M and 3M exchange rate volatility are obtained from option volatilities on the bilateral exchange rate between the USD and EME currencies.

China	India	Indonesia	South Korea	Russia	South Africa	Turkey
波动性	Volatility	Volatilitas	변동성	Волатильность	Volatility	Volatilite
危机	Crisis	Krisis	위기	Кризис	Crisis	Kriz
破產	Bankruptcy	Kebangkrutan	파산	Банкротство	Bankruptcy	Iflas
债务	Debt	Utang	채무	Долг	Debt	Borç
不确定性	Uncertainty	Ketidakpastian	불확실성	Неопределённость	Uncertainty	Belirsizliği
利差	Spread	Spread	스프레드	спред	Spread	Spread
金融危机	Financial crisis	Krisis finansial	금융 위기	Финансовый кризис	Financial crisis	Mali Kriz
金融动荡	Financial turmoil	Kekacauan keuangan	금융 혼란	Финансовые потрясения	Financial turmoil	Mali çalkantı

Argentina	Brazil	Chile	Colombia	Mexico	English
Volatilidad	Volatilidade	Volatilidad	Volatilidad	Volatilidad	Volatility
Crisis	Crise	Crisis	Crisis	Crisis	Crisis
Quiebra	Quebra	Quiebra	Quiebra	Quiebra	Bankruptcy
Deuda	Dívida	Deuda	Deuda	Deuda	Debt
Incertidumbre	Incerteza	Incertidumbre	Incertidumbre	Incertidumbre	Uncertainty
Spread	Spread	Spread	Spread	Spread	Spread
Crisis financiera	Crise financeira	Crisis financiera	Crisis financiera	Crisis financiera	Financial crisis
Turbulencias financieras	Turbulência financeira	Turbulencias financieras	Turbulencias financieras	Turbulencias financieras	Financial turmoil

Table 5: Google search keywords. The table reports the list of keywords in local language and in English used to obtain a web-search intensity measure of periods of financial tensions.

B Plots of FCIs

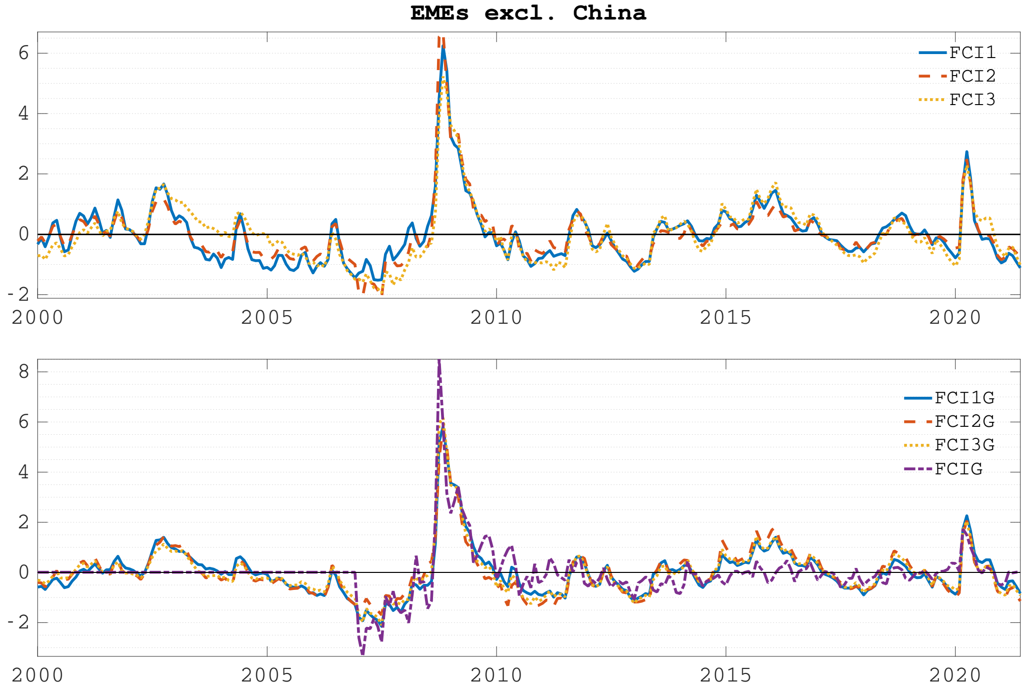

Figure 11: FCIs - EMEs excluding China

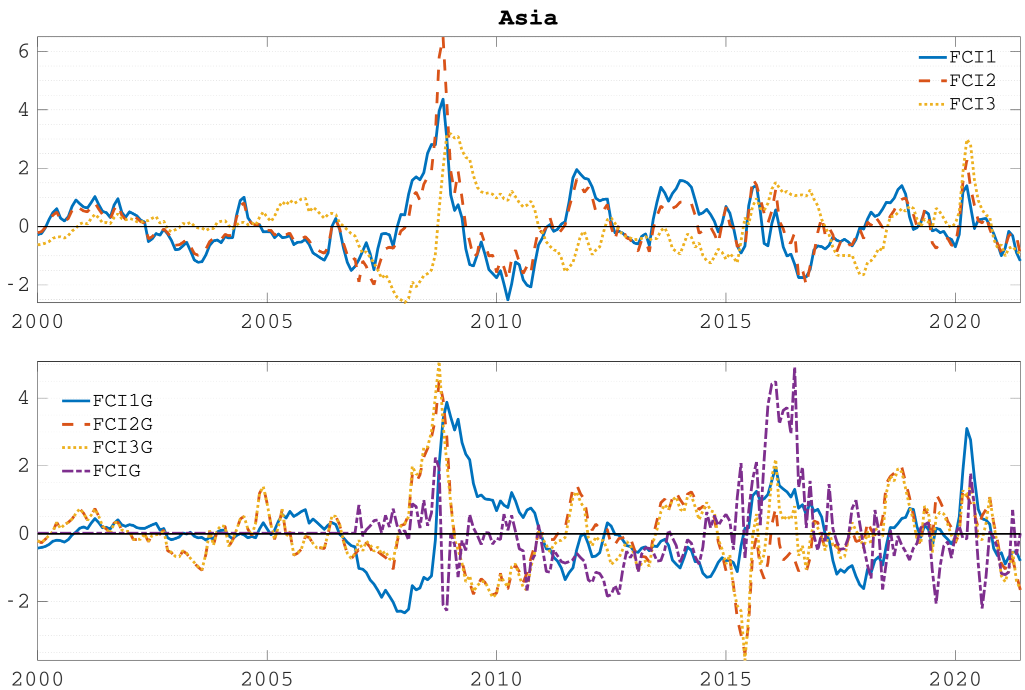

Figure 12: FCIs - Asia

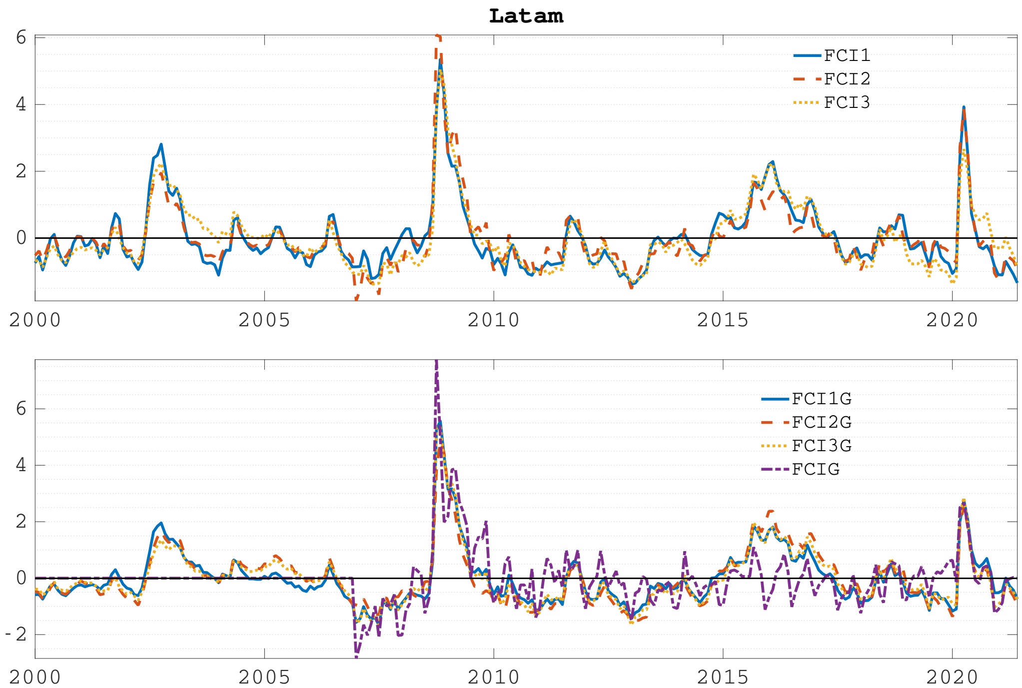

Figure 13: FCIs - LATAM

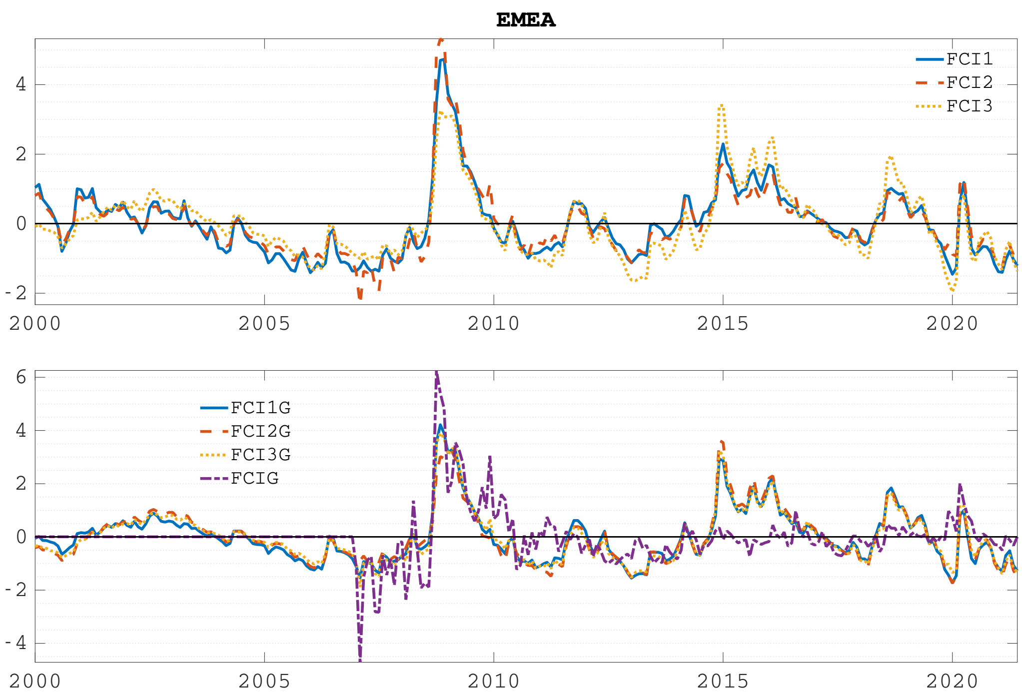

Figure 14: FCIs - EMEA

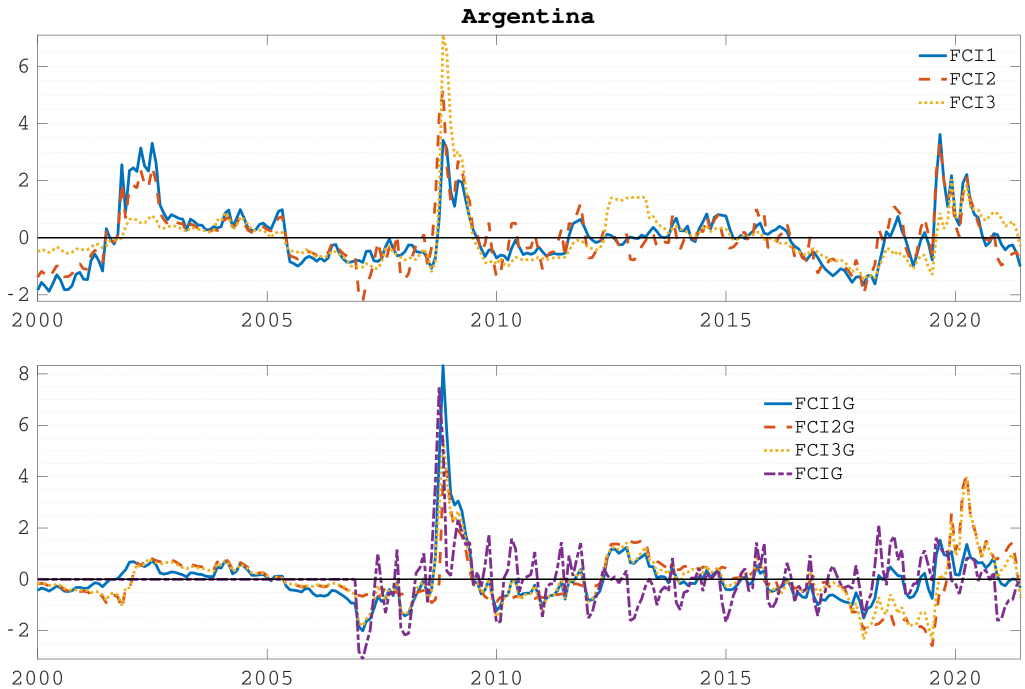

Figure 15: FCIs - Argentina

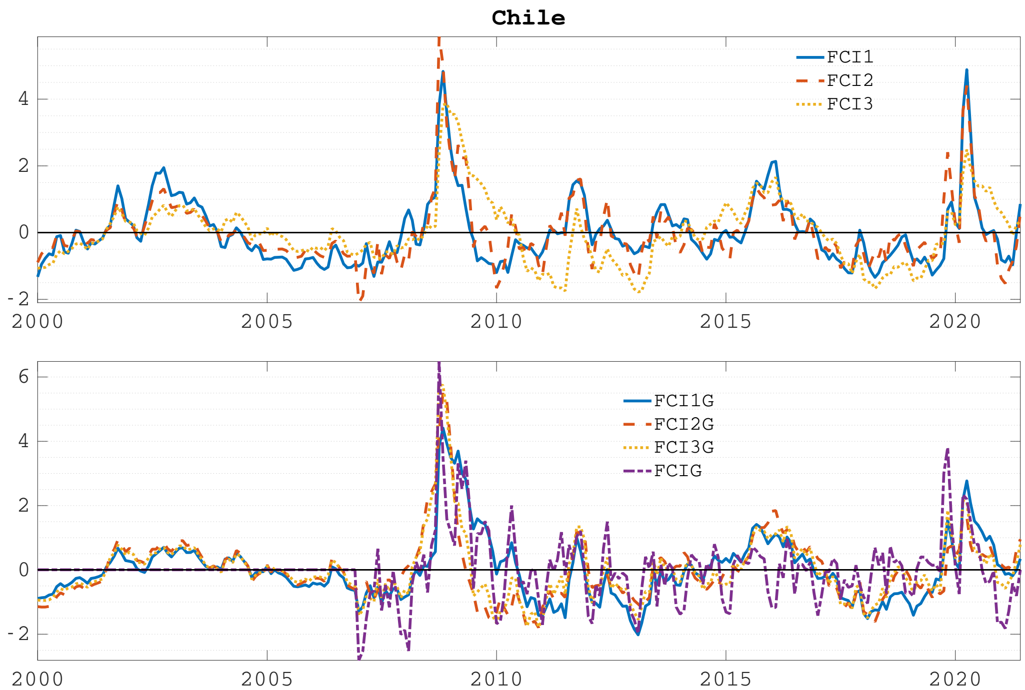

Figure 16: FCIs - Chile

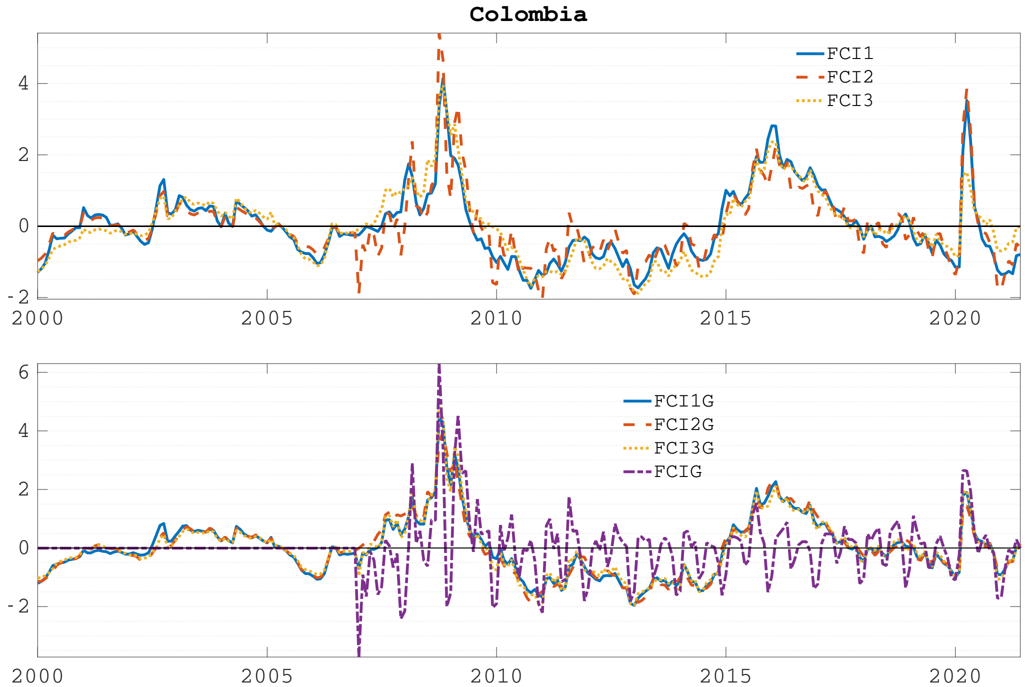

Figure 17: FCIs - Colombia

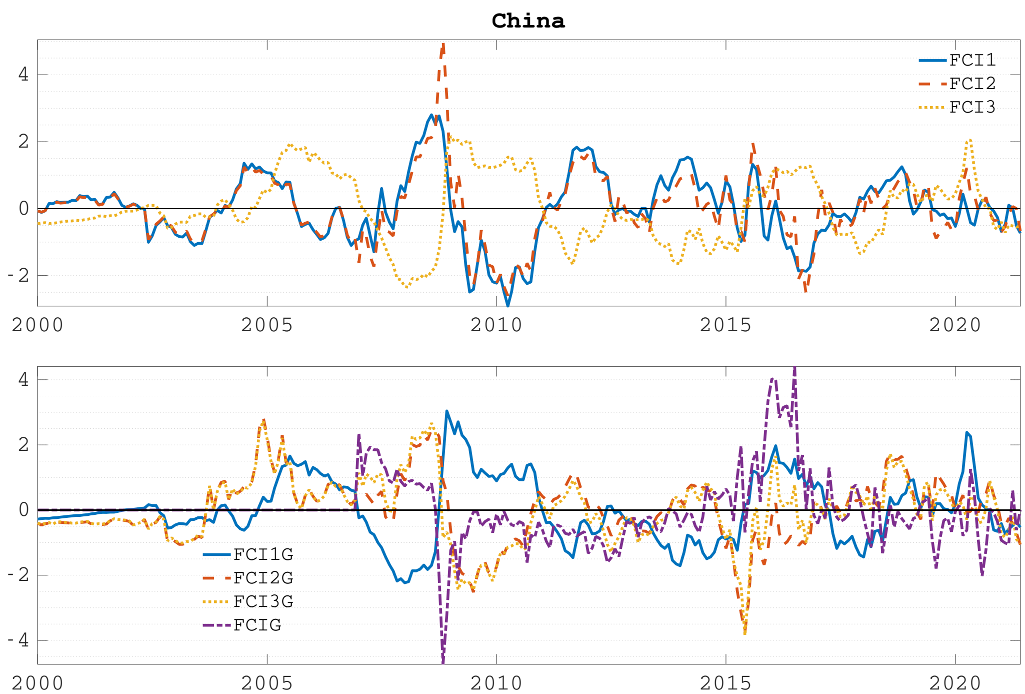

Figure 18: FCIs - China

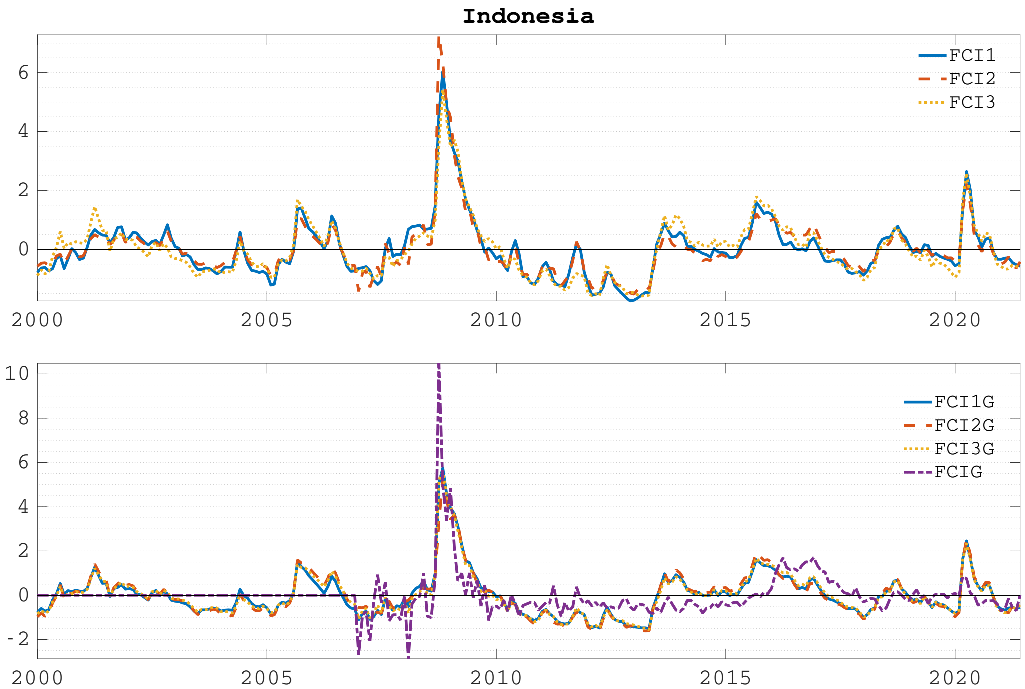

Figure 19: FCIs - Indonesia

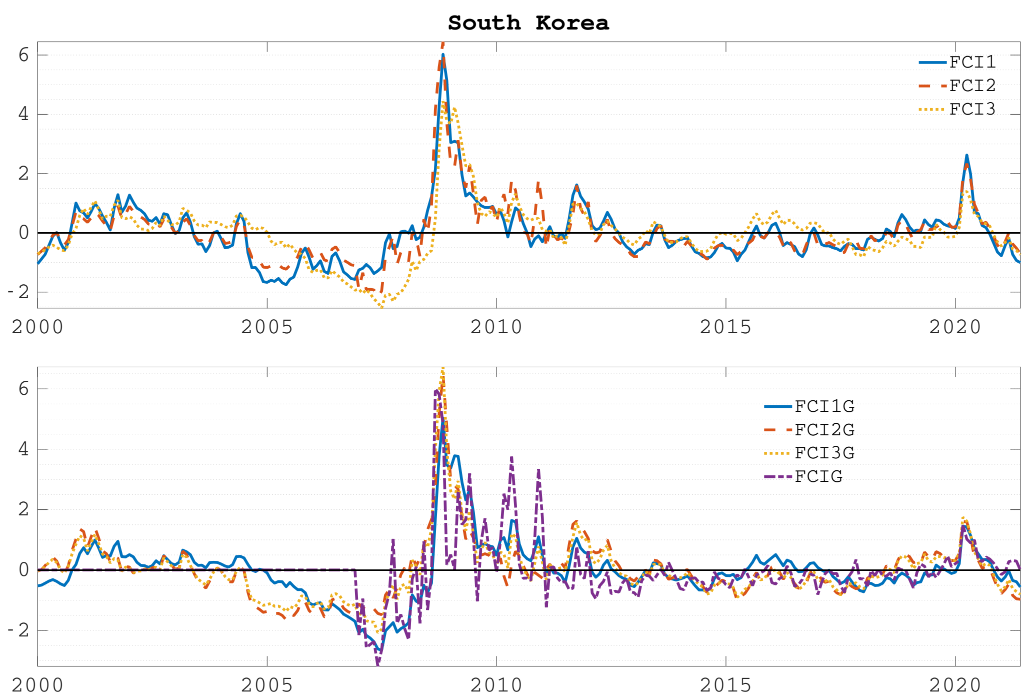

Figure 20: FCIs - South Korea

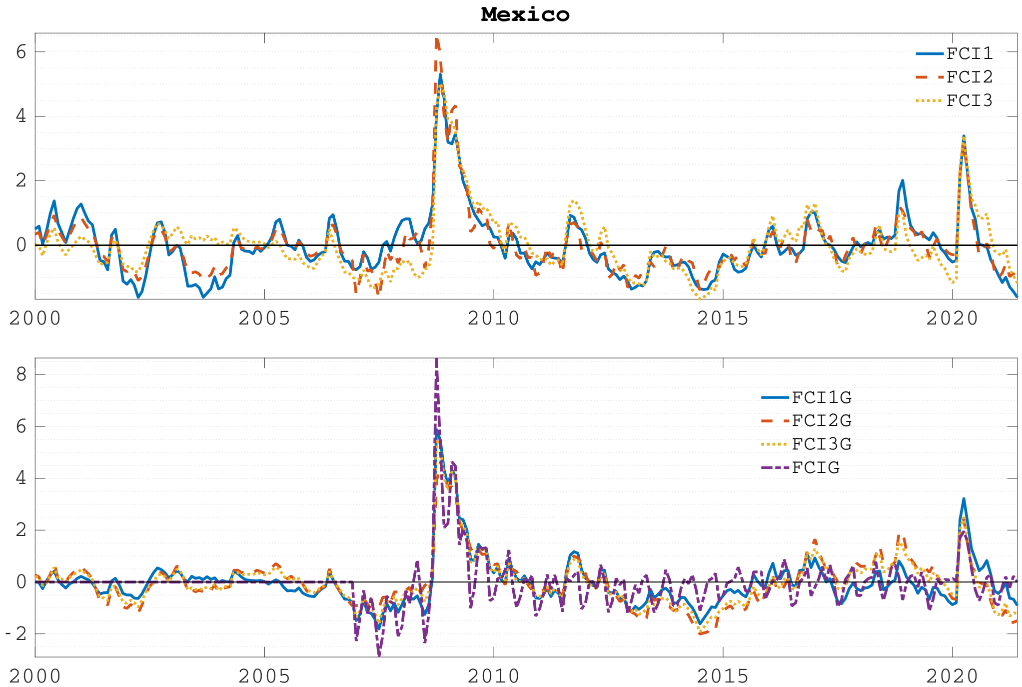

Figure 21: FCIs - Mexico

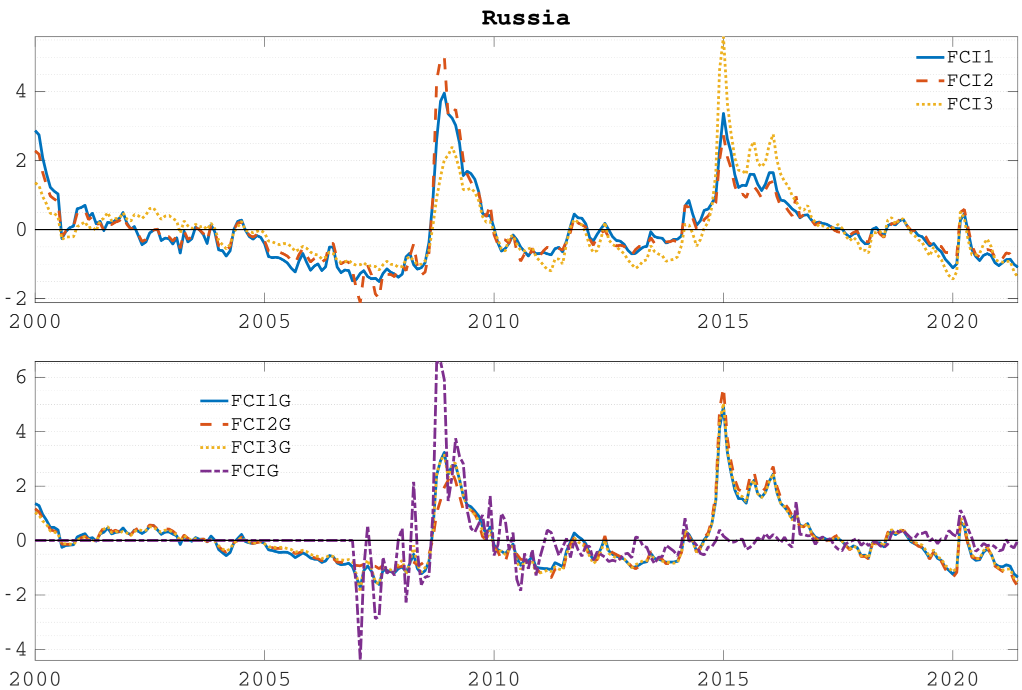

Figure 22: FCIs - Russia

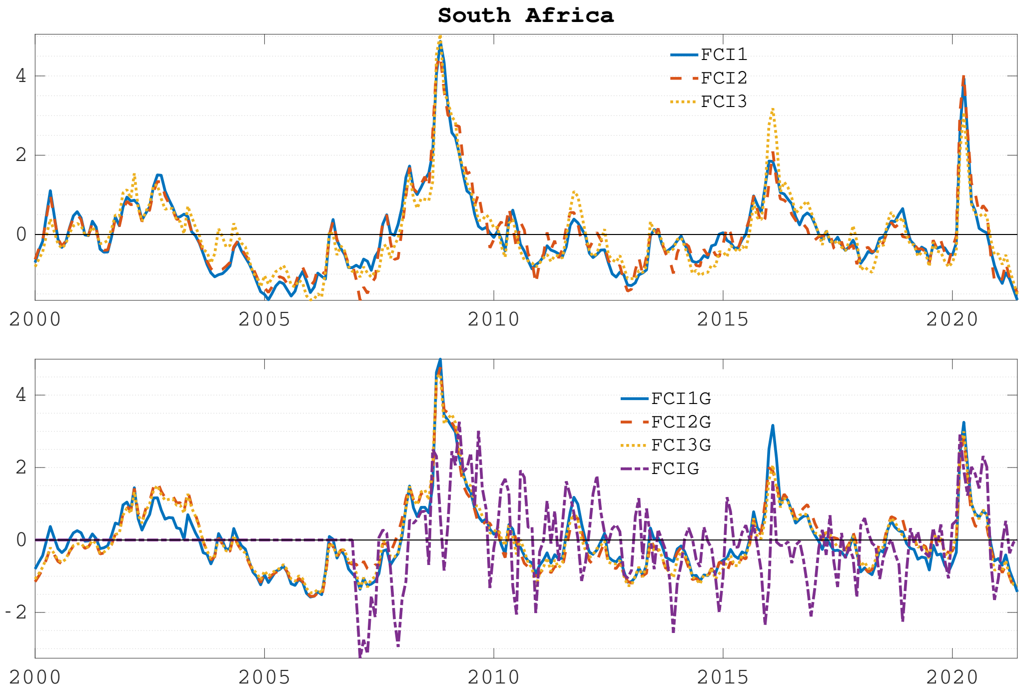

Figure 23: FCIs - South Africa

C Additional Validation Results

This Section contains the results of the validation exercises that either control for the Global Financial Cycle or substitute our FCIs with the financial industry alternatives, but are not included in the main text.

Controlling for the US FCI and for the VIX lowers but yet does not undermines altogether the statistical significance of the impact of domestic FCIs on the left tail of industrial production growth. Our quantile regression estimates reported in Figure 24 show that in the Chinese case, arguably the most important one, the results are still sizable and statistically significant, especially for our best performing measures of FCIs, *FCI1* and *FCI1G*

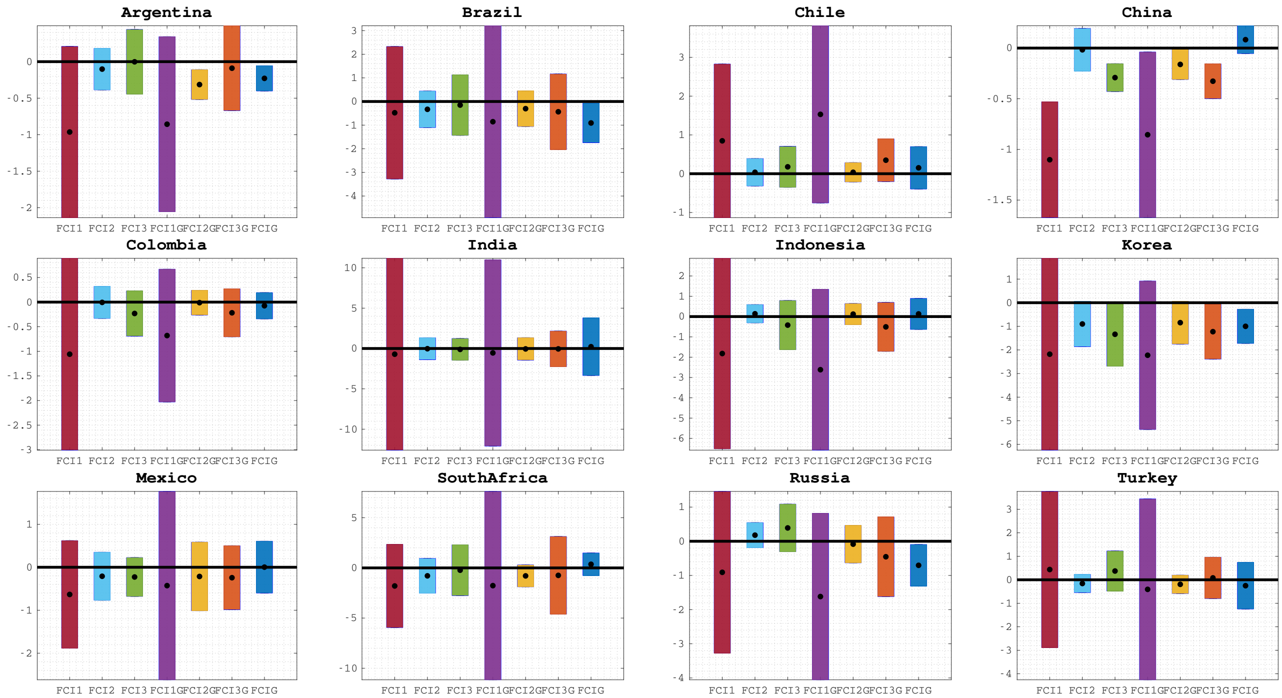

Figure 24: FCI impact on the left tail of industrial production growth - controlling for US FCIs
Note. The black dots indicate the median estimate, while the boxplot correspond to 90% confidence bands.

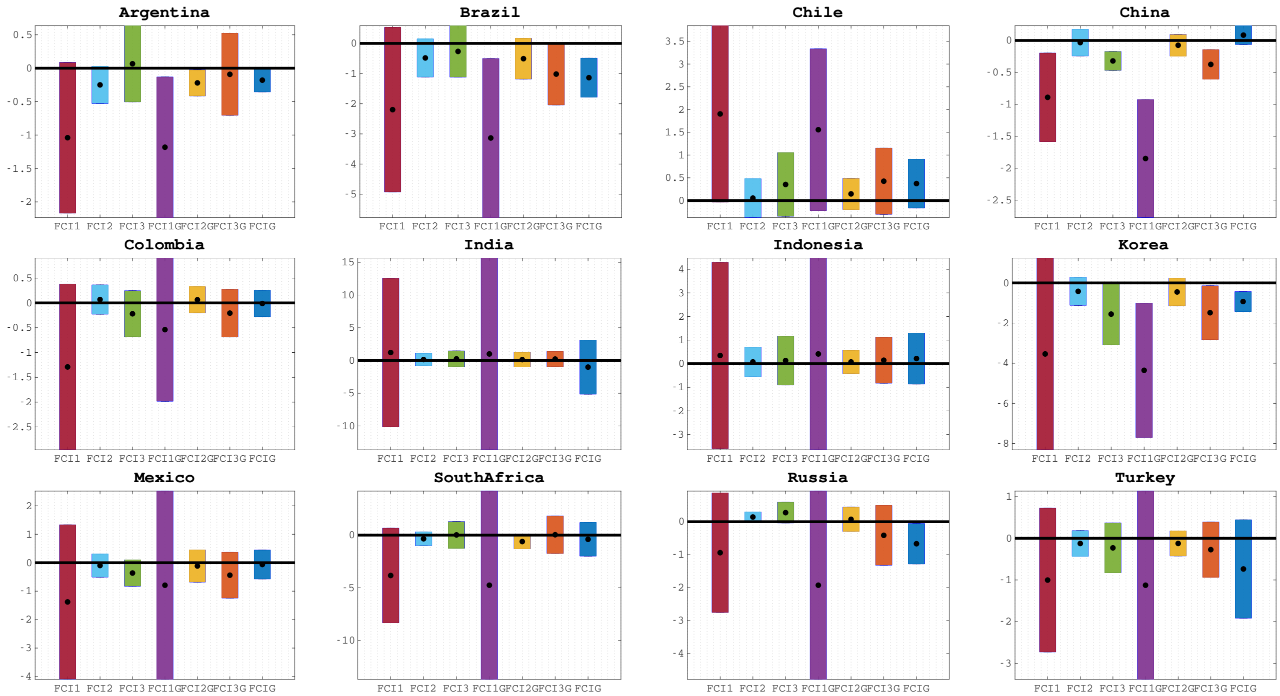

Figure 25: FCI impact on the left tail of industrial production growth distribution - controlling for the VIX

Note. The black dots indicate the median estimate, while the boxplot correspond to 90% confidence bands.

The informativeness of financial industry FCIs is further dampened when we restrict the analysis to the left tail of *ip* growth distribution, leaving Russia and partially Korea and Indonesia (with an inverted sign) as the only countries in which either Citi or Goldman Sachs FCIs presents some predictive power for lower quantiles of industrial production as displayed in Figure 26.

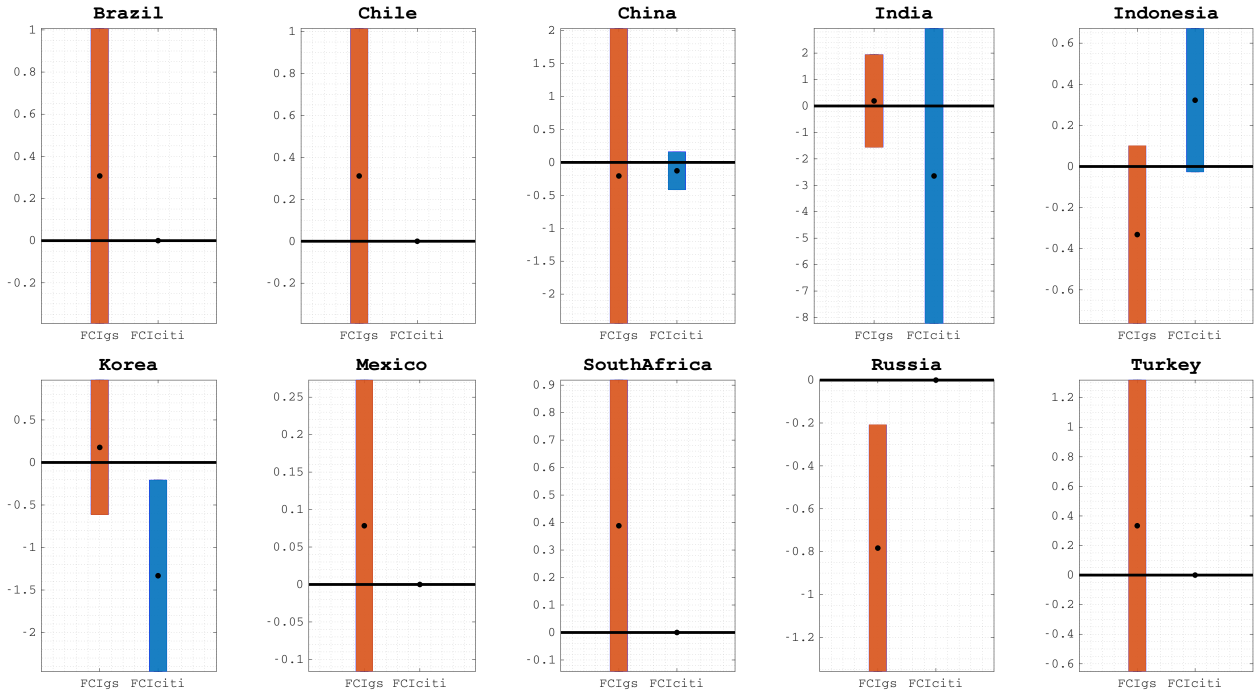

Figure 26: FCI impact on the left tail of industrial production growth
Note. The black dots indicate the median estimate, while the boxplot correspond to 90% confidence bands. Orange bars correspond to the Goldman Sachs FCI, blue bars to the Citi FCI.

Finally, Figure 27 summarizes the results of the exercise testing the predictive accuracy of financial industry FCIs with respect to capital flows episodes. The Citi FCI outperforms our measures in the case of sudden stop of capital inflows, although the comparability is somehow limited due to the different country coverage; on average our preferred indicators of FCIs nevertheless exhibit a larger improvement in terms of predictability of capital flows episodes, more evident with respect to the Goldman Sachs FCI.

	Flight	Stop	Surge	Retrenchment	Average
FCI GS	21.8%	23.5%	26.0%	21.6%	23.2%
FCI Citi	26.7%	47.5%	24.3%	30.8%	32.3%

Figure 27: Capital flows episodes and predictive accuracy of financial industry FCIs
Note. The figure summarizes the predictive accuracy of FCIs across different types of capital flows episodes using ROC curves after probit estimation. Each cell reports the improvement in predictive accuracy relative to a random model (accuracy = 0.5).