Financial Vulnerability and Risks to Growth in Emerging Markets*

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Abstract: This paper introduces a new financial vulnerability index for emerging market economies by exploiting key differences in their business cycles relative to those of advanced economies. Information on the domestic price of risk, cost of dollar hedging and market-based measures of bank vulnerability combine to generate indexes significantly more effective in capturing macro-financial vulnerability and stress compared to those based on information in trade and global factors. Our index significantly augments early warning surveillance capacity, as evidenced by out-of-sample forecasting gains around a majority of turning points in GDP growth relative to distributed lag models that are augmented with information from macro-financial indexes that are custom-built to optimize such forecasts.

Data for Financial Vulnerability Indexes available at:
http://pages.stern.nyu.edu/~sternfin/vacharya/public_html/pdfs/may-fvi.xlsx

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I. Introduction

Summary

Financial vulnerability increases risks to growth and this is reflected in the well-known association of episodes of financial sector stress and crises with longer and more severe economic downturns. Financial vulnerability, embedded in accumulation of leverage and balance-sheet mismatches of economic agents, grows during booms when financing conditions are easy, and once sufficiently elevated, greatly amplifies and prolongs the impact of shocks on the real sector.[1]

Under such circumstances, metrics that capture financial vulnerability are important therefore not only to assess risks to financial stability but also to the baseline outlook for economic growth. Information from suitably chosen financial indicators, when appropriately combined, may provide useful intelligence about future macro-financial risks. Recent work has shown that financial conditions indexes (FCIs) that aggregate information from multiple financial variables can significantly improve forecasts of tail risks to growth up to one year in advance for several major economies.[2]

Existing studies suggest that FCIs and implied tail risks-to-growth fit the data significantly better for advanced economies (AEs), including small open economies (SOEs), than for emerging economies (EMs).[3] As such, EMs have experienced tremendous growth in the depth and sophistication of their financial sectors over the last two decades as they have continued, and in some cases accelerated, their integration into the global financial system. Consequently, risks to macro-financial stability in EMs are increasingly likely to be influenced by factors similar to those in AEs over time. In particular, global risk appetite and balance-sheets of financial institutions and the private sector in EMs should hold vital clues to prospects for stability and risks to baseline growth outlooks.

Nonetheless, the precise manner in which such indicators may best be combined to yield leading information on macro-financial prospects may still be vastly different in EMs and AEs. For example, the persistence of differences in key business cycle characteristics noted by Aguiar and Gopinath (2007), between AEs (plus SOEs) and EMs would translate into significant differences in the cyclicality of balance-sheets and the domestic price of risk. Changes to the structure of the economy and to policy frameworks are also more frequent, common and significant for EMs. Therefore, neither the optimal information set, nor the optimal concatenation of its components, can be expected to be the same for EMs and AEs.

Our paper explores this issue and is the first to show that while financial vulnerability is an important early warning indicator in EMs, the precise measure of vulnerability needs to be

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[1] Simple frameworks for understanding the joint dynamics of financial vulnerability and growth risks in structural macro models are presented in Jeanne and Korinek (2010) and Bianchi (2011), drawing on the pioneering work of Mendoza (2010). Bianchi and Mendoza (2018) discuss optimal, time-consistent policy in this context. Adrian and Shin (2014) and Brunnermeier and Sannikov (2014) present eclectic models emphasizing respectively, procyclicality of lenders' balance-sheets and leverage, and asset value volatility spirals that characterize recessions around crises with a financial intermediary sector.

[2] See, for instance, Katagiri et. al. (2017) and Adrian et. al. (2018), building on De Nicolò and Lucchetta (2017) and Adrian et. al. (2019).

[3] See, for example, Adrian et. al. (2018).

developed differently compared to AEs in order to maximize relevant information content. We provide an approach to construct financial vulnerability indexes (FVIs) for EMs and use the FVIs to assess risks to growth. In doing so, we demonstrate that FVIs can be just as effective in EMs as in AEs in reflecting accumulation of macro-financial vulnerability, capturing episodes of stress and instability, as well as predicting downside risks to growth. Our construction also shows that the information indicators in the FVI and the recipe for combining them depart significantly from available indexes for AEs. Specifically, while our FVIs combine information from high-frequency domestic risk spreads and asset returns, measures of external shock transmission and the credit cycle are different compared to existing indexes for AEs. Three differences are particularly noteworthy.

First, the direct prominence of global common factors is lower for EMs. Changes in the VIX and MOVE indexes[4] reflect changes in global financial conditions and risk appetite and are known to significantly impact EMs' domestic financial conditions (IMF (2017)). However, after incorporating information from domestic price of risk indicators, we find the additional information content of global factors to be negligible. Instead, these indicators overemphasize stress around the global financial crisis (GFC), thereby decreasing the efficiency of the resulting FVIs because they inhibit information about financial vulnerability leading up to other known episodes of stress.

Second, broad cross-country evidence suggests that balance-sheet based measures of vulnerability add powerful information regarding medium-term prospects for financial and real stress, well before it is reflected in market prices.[5] In EMs where key balance-sheet vulnerabilities appear with significant lag, particularly in the financial sector, we find that market measures of institutional vulnerability and credit risk pricing are more informative than purely balance-sheet based measures from an early warning perspective. Importantly, in light of the recent literature on the predictive content of credit growth and leverage for future economic growth, we find that these measures of the credit cycle do not possess significant information content as financial vulnerability indicators for India and China.

Third, the last two decades have seen a rapid increase in EMs' integration into the global financial system, with bank-intermediated capital flows being complemented by the secular increase in portfolio flows intermediated through mutual funds. Increasing supply has been met by a corresponding increase in demand for foreign currency financing, and hence, for hedging exchange rate risk. Consistent with this observation, we find that the cost of hedging dollar exposure possesses significant information content vis-à-vis external shocks and their

[4] VIX refers to the Chicago Board Options Exchange's CBOE Volatility Index, a measure of the stock market's expectation of volatility based on the Standard and Poors 500 equity index options. MOVE refers to an index-based measure of U.S. interest rate volatility that tracks the movement in U.S. Treasury yield volatility implied by current prices of one-month over-the-counter options on 2-year, 5-year, 10-year, and 30-year Treasuries. Both measures are recognized to be important measures of global risk sentiment.

[5] See Katagiri et. al. (2017) and Adrian and Liang (2019) in the context of the literature on financial conditions/ vulnerability indexes. For the predictive content of credit for economic growth, see Shularick and Taylor (2012) and Jorda et. al. (2015) for AEs and Mian et. al. (2017) for both AEs and EMs. Krishnamurthy and Muir (2017) provide favourable evidence on the joint information content of risk spreads and credit for financial stability. Brunnermeier et. al. (2019) assess the predictive content of credit growth for economic activity in the U.S. across small and large dimensional VAR models

transmission potential.[6] On the other hand, traditionally dominant pass-through channels, including terms-of-trade and commodity prices, shown to be informative in AEs and SOEs are not so in our EM-FVIs.

In constructing FVIs, our methodological approach is to start with an encompassing set of information variables going beyond financial indicators. Shock amplification factors for EMs typically include a nexus of external and fiscal imbalances that culminate in twin deficit type episodes that, in the extreme, result in sudden stop and reversal of capital flows, domestic financial stress, financial crises, and economic slowdowns. Importantly, such amplification factors may not be fully priced in EM financial markets into risk spreads, asset values and volatility owing to lack of products for risk-sharing or the lack of depth in markets for such products. These factors could potentially limit the information content of financial variables. A good example is the lack of indicators of corporate vulnerability—credit default swap markets do not exist for trading and pricing corporate distress risk in large EMs like India and China, neither at the firm-level nor by credit quality class, and several firms—including large state-owned enterprises—may be entirely privately held.

To overcome this potential limitation, we included several external, fiscal and real amplification factors directly into our FVIs, but found them to possess negligible marginal information content. In striking contrast, appropriately chosen financial indicators do possess sufficient early warning surveillance information from both financial stability and growth risks perspectives. We view our results not as reflecting the low or decreased importance of the fiscal and external imbalance channels of shock amplification in EMs, but instead, as a possible illustration of *Goodhart's law*.[7] Fiscal and external indicators are subject to heavy management through direct and indirect policy action in EMs. For example, it is common for foreign exchange reserves as well as government debt and its yield curve to be managed as, or via, control variables, which may serve to significantly limit their information content. Another example may be the inhibition of information content in credit growth and leverage measures owing to the tight control exercised in EMs over credit through various policy instruments.[8] By contrast, market signals such as risk premia in equity markets—in spite of their limited coverage of the economy—may play a more prominent role as early warning signals because they are not (as successfully) subject to policy control action.

From a risk surveillance perspective, the performance of our FVIs should ultimately be assessed not only in terms of their ability to capture relevant stress episodes in financial and credit markets, but also, in their provision of near-to-medium term early warning signals of risk to the baseline economic outlook. Unlike most AEs and SOEs, some large EMs have not experienced economic contractions or recessions. Moreover, given the significantly greater volatility in their output, growth, consumption, and trade, most EM economic cycles are better characterized as *growth rate cycles* of accelerations and slowdowns around a (time-varying) trend GDP growth rate rather than business cycles of output expansions and

[6] Acharya and Vij (2017) and Bruno and Shin (forthcoming) discuss the implications of the significant increase in dollar funding by EM firms between 2009 and 2013.

[7] "Any observed statistical regularity will tend to collapse once pressure is placed upon it for control purposes", see Goodhart (1984).

[8] For example, in the case of India, the use of high levels of the statutory liquidity ratio (SLR) until recently and of cycle-sensitive risk weights to stimulate credit in downturns, and in case of China, the state-directed lending policy of the four largest state-owned banks.

contractions. Accounting for this important distinction, we evaluate the early warning capacity of our FVIs through a new approach, by assessing forecast gains from the information in FVIs around turning points of the growth rate cycle. An autoregressive (AR) model of economic growth with our FVI improves or provides comparable near-to-medium term out-of-sample forecasts for a majority of turning points compared to an AR model with a *turning point index* (TPI) custom-built to optimize such forecasts. In line with the existing literature, we also assess medium-term forecast performance for the GFC period tail growth realization for one leading case, albeit the paucity of tail episodes limits the robustness of tail risk forecast capacity of FVIs at this time in our view.[9]

India and China: Leading Case Studies

We organize our analysis around two leading examples of India and China, the largest EM economies. The main finding is that our methodological approach results in a fully adequate FVI for both countries that accurately captures known financial stress episodes and whose incorporation in growth risk forecast models provides significant out-of-sample gains.

We start by exploring *domestic price of risk* (DPOR) indexes—FVIs built solely on the information contained in domestic risk spreads, asset returns and market volatility. We find that these do not capture well-recognized episodes of financial stress and growth shocks outside of the unusually tight market conditions around the GFC.

For India, the DPOR index fails to capture highly stressed markets around the 2013 taper tantrum, an exogenous shock that materially impacted the price and availability of dollar funding for the corporate sector. Short in duration, the shock-induced disruption in domestic financial markets was nonetheless significant as was the increase in risks to real economic activity. Since the global common factor and the domestic price of risk tightened much more modestly in 2013 relative to the GFC in 2009, the DPOR index fails to adequately capture stress around the taper tantrum. In contrast, adding information on tightness in dollar funding for Indian firms via the increased cost of hedging dollar exposures allows to obtain a superior FVI that better reflects stress in both 2009 and 2013.

The decade after the GFC was also marked by a period of prolonged stress in Indian credit markets. This was driven by a deterioration in Indian bank credit quality starting in late 2010 followed by a dragging recognition of loan losses, especially at some public-sector banks (PSBs). DPOR indexes are ill-equipped to capture protracted levels of elevated credit market tightness. Moreover, in India's case, information on vulnerabilities in bank balance-sheet indicators was obscured for a majority of the last decade due to extensive non-performing assets (NPA) restructuring and evergreening by PSBs. Augmenting the DPOR index with market-based measures of bank vulnerability and credit pricing, the SRISK index and the prime (corporate) lending rate, help in accurately capturing macro-financial stability risk over the last two decades.[10]

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[9] Forecasts of AR models of growth tend to perform particularly well *on average* given the statistical persistence of economic growth in AEs, and for this very reason, they are likely to underperform when growth risks are realized. For EMs, greater output volatility may result in more modest average forecast gain from the AR growth models, although these are not necessarily rendered insignificant.

[10] SRISK measures the capital shortfall of a firm conditional on a severe market decline as a function of firm leverage, size and risk. Aggregate measures of SRISK can be constructed across a sample of firms by weighing

In China's case, the period since 2000 can be divided into two distinct phases. Prior to 2010, the financial sector was largely shielded from direct international connections and financial development was nascent. Financial stability challenges were primarily associated with the rise and fall of bank NPAs. Importantly, policy interventions by Chinese authorities exerted a differential impact on the information content of market indicators of bank vulnerability before and after 2010. A prominent example is the 2007 balance-sheet clean-up and recapitalization of the banking system which resulted in banks being in a much stronger position to deal with shocks associated with the GFC. As with India, policy interventions and their impact on balance-sheet indicators mean that market-based measures of bank vulnerability and credit pricing are often more informative as part of the FVI. Their inclusion is also vital because the FVI would have otherwise delivered a very different message regarding macro-financial risks during the GFC.

In the current decade, the financial sector in China grew substantially relative to GDP, was significantly liberalized, demonstrated increasing sophistication in terms of financial products intermediated and the complexity of business models deployed (by banks), and experienced growth in its interconnections with the global financial system. Simultaneously, Chinese authorities significantly enhanced banking regulation and supervision as a means to prevent a repeat of financial vulnerability seen before 2007. For constructing early warning systems, all of this enhances the information content of market-based indicators of bank vulnerability. Moreover, financial stability in China has also become materially intertwined with developments in the global economy and financial system, with external shocks and transmission becoming more important. Besides the financial sector, carry trade activity by Chinese firms took off spectacularly between 2009-14 and this increased the vulnerability of the domestic corporate sector to an increase in Renminbi-U.S.$ volatility after the unexpected, severe depreciation of the Chinese currency in 2015. Incorporating information on the cost of hedging dollar exposures or on broader measures of exchange market pressure results in a superior FVI as in the case of India. Such an FVI is particularly well suited to reflect vulnerability arising from external exposures to foreign shocks and domestic policy shocks, such as the 2013 taper tantrum, the 2015 devaluation of the Renminbi and the global trade tensions post-2017.

The rest of this paper is organized as follows. Section II situates our paper in the context of existing studies of how combinations of financial variables may be used to forecast the evolution of the macroeconomy. Section III extends the differential characterization of key EM and AE business cycle moments by Aguiar and Gopinath (2007) up to the present time for a broader set of countries. Section IV describes the approach to FVI construction, including the databases and empirical framework. Section V presents the FVIs for India and China and Section VI evaluates the potential for these indexes to improve forecasts of risk to economic growth. Section VII concludes. Technical details are relegated to the annexes.

II. Related literature

A large body of empirical work examines the value of information in asset prices for forecasts of the *baseline* growth outlook. Several asset prices have been found to be useful

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firm-specific SRISK by firm market capitalization or balance-sheet size. See Acharya et. al. (2012, 2016) and Brownlees and Engle (2017).

predictors of future GDP growth in some countries at various points in time. Short-term risk-free yields and term spreads capture the stance of monetary policy and contain useful information about future growth.[11] Corporate bond spreads (Philippon (2009)) and loan price deterioration (Saunders et al. (2020)) signal changes in the default-adjusted marginal return on business fixed investment and shocks to the profitability and creditworthiness of financial intermediaries (Gilchrist and Zakrajšek (2012)). Campbell et. al. (2001) present evidence that elevated stock-return volatility can be a useful predictor of output contraction over short horizons, albeit empirical evidence for the predictive content of stock returns is weak (Campbell (1999)).

Combining forecasts from several models with individual asset prices results in more consistent and higher-quality forecasts. This has led to construction of indexes that combine several individual indicators. These indexes are called financial conditions indexes (FCIs), since they usually reflect the ease of financing terms in the economy.[12]

We depart from this literature in two important dimensions which underpin the main contribution of our paper.

First, on index construction, our approach contains two innovations both designed to offer a methodological framework to construct FVIs for EMs that exploit the common properties of their business cycle and their increasing financial integration in the global financial system. We begin by assessing real and financial channels of external shock transmission and find the latter to be paramount in terms of information content. This reflects the increase in carry trade-based leverage of the Chinese and Indian corporate sectors and the fact that exchange market pressure rather than shocks to commodity prices and terms-of-trade is preeminent for China. Next, we turn to credit cycle indicators and find that market-based measures of bank vulnerability add more information relevant to risks to growth compared to balance-sheet based indicators such as credit growth and non-performing or restructured loans and assets.

Second, we focus on the information content of financial indicators in forecasting *risks* to GDP growth. We apply the approach of De Nicolò and Lucchetta (2017), Katagiri et. al. (2017) and Adrian et. al. (2019) to assess of gains from incorporating information in FVIs to forecast tail growth outcomes around the GFC. But our main contribution is to propose a new approach to assessing risks to growth using FVIs by running a horse race of FVI-based forecasts around turning points in the growth rate cycle against a composite leading indicator custom-built to optimize such forecasts. Our approach leads to more robust forecast evaluation, and is especially relevant to EMs since they tend to have growth rate cycles with more frequent turning points between accelerations and slowdowns compared to AEs and SOEs.

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[11] See Stock and Watson (2003) for an excellent survey of the pre-2000 literature that includes a comprehensive bibliography. See also Ang, Piazzesi and Wei (2006) for an alternative approach.

[12] This notion of financial conditions is similar to the definition proposed by Hatzius et. al. (2010). Country specific studies are plenty. In the Indian context, these include Shankar (2014), Roy et. al. (2015) and Khundrakpam et. al. (2017).

III. How Different are EM and AE Business Cycles Today?

Aguiar and Gopinath (AG henceforth) report empirical regularities of EM business cycles and where these differ significantly from AE business cycles. Specifically, they find EMs' output and growth (measured as log change in output) to be about twice as volatile as AEs' GDP and growth; EMs' consumption smoothing over the business cycle to be significantly lower in comparison to AEs' consumption smoothing; and EMs' trade balances to be more volatile than output relative to AEs' trade balances. Finally, the countercyclicality of the current account was materially larger for EMs than for AEs.[13]

Extending Aguiar's and Gopinath's (AG) sample beyond 2003 reveals several of these differences in business cycle moments have persisted through today (Table 1).

Table 1. Emerging vs. Advances Economies (Averages)

	Aguiar & Gopinath		*Extended to Present*	
	AEs	EMEs	AEs	EMEs
$\sigma(Y)$	1.34	2.74	1.36	2.73
$\sigma(\Delta Y)$	0.95	1.87	0.84	2.11
$\rho(Y)$	0.75	0.76	0.84	0.68
$\rho(\Delta Y)$	0.09	0.23	0.31	0.05
$\sigma(C)/\sigma(Y)$	0.94	1.45	0.78	1.12
$\sigma(I)/\sigma(Y)$	3.41	3.91	2.98	3.23
$\sigma(TB/Y)$	1.02	3.22	0.90	2.07
$\rho(TB/Y,Y)$	-0.17	-0.51	-0.02	-0.38
$\rho(C,Y)$	0.66	0.72	0.69	0.59
$\rho(I,Y)$	0.67	0.77	0.74	0.72

Data sources: CEIC; and authors' calculations.
Note: This table lists the average value of moments for EMEs and AEs following AG's methodology. Our sample of AEs and EMs is different from AG's: we exclude Argentina, Ecuador, Israel, Slovak Republic (EMs); Austria, Belgium, New Zealand, and Portugal (AEs), but include others not in AG's sample: Chile, India, Indonesia, Russia (EMs); France, Germany, Italy, Japan, U.K., and the U.S. (AEs).

This is despite the increasing maturity and depth of EMs' economies, their integration into global trade and financial networks and the growing sophistication of their financial markets and institutions. EM output volatility continues to be twice that in AEs. This stability in relative volatilities is also present when we look at unfiltered first differences in the output series. On the other hand, first-order autocorrelation in filtered output and unfiltered output growth is lower in EMs than in AEs over the full sampling horizon relative to AG's estimates

[13] In addition, Neumeyer and Perri (2005) found that EMs' (real, short-term) interest rates were strongly countercyclical when compared to AEs, reflecting the fact that EM exposure to international financial markets for funding real sector activity implied the need to raise policy rates in a downturn to avoid sudden stops. By contrast, most AE central banks are able to reduce rates in response to growth shocks. Given evidence of the trilemma (Obstfeld, 2015) and dilemma (Rey, 2016), we see little reason to believe that this source of disparity between cyclical properties of monetary policy in EMs and AEs has changed significantly or across-the-board.

(where the sampling horizon ends at 2003), which is likely associated with the impact of the GFC which arguably impacted AEs more severely and broadly than EMs in our sample. Consumption smoothing over the business cycle appears to have strengthened significantly for both groups of countries on average post-2003 as evidenced by the large decreases in the relative volatility of consumption to output. For example, whereas consumption was over 40 percent more volatile than GDP in EMs over 1990-2003, consumption volatility is only 12 percent higher than output volatility today. Nonetheless, relative differentials in average consumption smoothing between AEs and EMs has remained large notwithstanding the GFC is in our sampling horizon. The volatility of investment and net exports relative to output volatility over the business cycle also remains significantly higher, on average, for EMs relative to AEs. Net exports continue to covary negatively with output in EMs even as they have decoupled from output variation in AEs. The average correlation between the trade balance and GDP has fallen in both sets of countries since 2003, but continues to be significantly (more) negative for EMs.

Is sampling variation driving the results?

Since our extension is based on a comparison of average of moments in a broader cross-section of AEs and includes the larger economies in this group that was excluded by AG, we also reviewed average moments from the common sub-set of countries in our paper and AG's paper to check whether the points noted above continue to be valid. Table 2 shows that restricting the sample to a common sub-set of small open economies and EMEs leaves the results qualitatively unchanged.

Table 2. EMEs vs. SOEs (averages)

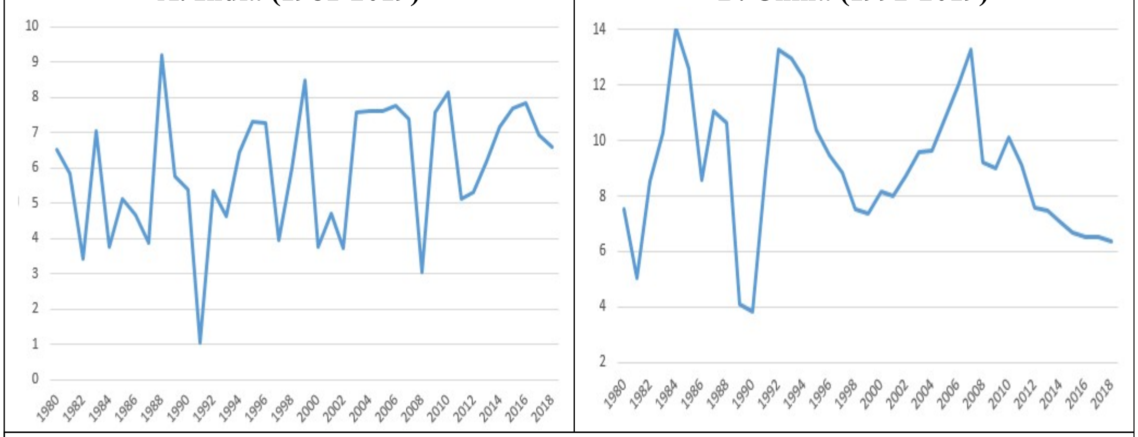
	Aguiar & Gopinath		*Extended to Present*	
	AEs	EMEs	AEs	EMEs
$\sigma(Y)$	1.40	2.92	1.39	3.20
$\sigma(\Delta Y)$	1.01	1.82	0.89	2.47
$\rho(Y)$	0.73	0.79	0.82	0.68
$\rho(\Delta Y)$	0.08	0.31	0.30	0.06
$\sigma(C)/\sigma(Y)$	0.95	1.28	0.82	1.11
$\sigma(I)/\sigma(Y)$	3.41	3.51	3.41	3.06
$\sigma(TB/Y)$	1.02	3.02	1.13	2.18
$\rho(TB/Y,Y)$	-0.21	-0.53	-0.05	-0.42
$\rho(C,Y)$	0.63	0.76	0.68	0.71
$\rho(I,Y)$	0.65	0.81	0.67	0.74

Data sources: CEIC; and authors' calculations.
Note: See Table 1. Common countries include: Brazil, Korea, Malaysia, Mexico, Peru, Philippines, South Africa, Thailand, Turkey (EMs); Australia, Canada, Denmark, Finland, Netherlands, Norway, Spain, Sweden, and Switzerland (SOEs).

Outside of a domestic financial crisis, several of the larger EMs have not experienced economic contractions or recessions over the last three decades. During the GFC, almost all AEs and SOEs experienced a severe recession while these EMs experienced either a growth slowdown or a contraction significantly less severe than their worst recession or contraction since the 1990s.[14] Given evidence of persistently greater output growth volatility in EMs, this implies that risks to their economic outlooks may be at least as well, if not better characterized, by the likelihood of acceleration or slowdown in the rate of growth, i.e., of turning points in the growth rate cycle, instead of output expansion and contraction. This is clearly seen to be the case with both China and India (Figure 1).

Figure 1. Annual Real GDP Growth in China and India (in percentage points)

A. India (1981-2019) | **B. China (1992-2019)**



Source: CEIC.

IV. Empirical Framework and Data

Vulnerability indexes—conceptual basis

Prior to providing modelling details, we discuss how the FVI is conceptualized. Information regarding amplification risk, i.e., the potential for the state of the system to exacerbate the impact of shocks on financial stability and growth, can be extracted from a variety of sources. These include the cost of transferring risks through financial markets and risks embedded in balance-sheets of economic sectors, like leverage, which render adjustment to shocks difficult, among others.

Figure 2 summarizes our conceptual mapping from various measures of amplification potential into an index. The cost of risk transfer in financial markets is called the ***domestic price of risk*** (DPOR) block, and includes term spreads, sovereign spreads, risk spreads relevant to key business sectors, and asset returns and volatility. Increasing vulnerability is reflected in rising risk spreads and asset volatility and falling asset returns. ***External risk factors*** circumscribe global financing conditions and the real channel of terms-of-trade and

[14] For example, China, India and Poland have not experienced an economic contraction; Indonesia (1997) and South Africa (2009) had a single year of output contraction; Malaysia and Thailand experienced economic contraction in two years, both during the Asian and global financial crises; and six of 12 major EMs from Asia, Europe and the Americas had GFC growth outcomes significantly better than their worst during this period.

commodities prices. They can be directly incorporated into an FVI, (the green dashed arrow), or indirectly through their impact on measures of exchange market pressure, which also incorporates domestic policy responses to external shocks. The macro-financial impact of shocks depends critically upon balance-sheet vulnerabilities which are slower moving but potentially more informative over longer horizons than DPOR and external factors.

This ***financial cycle/ balance-sheet*** block contains balance-sheet aggregates like private sector leverage, the credit-to-GDP gap, fiscal balance and government debt; macroeconomic balance-sheet risk indicators like external debt (servicing)-to-foreign exchange reserves; and key corporate and banking sector balance-sheet vulnerability indicators or market proxies of the same.

Empirical Model[15]

Dynamic Factor Models (DFM) exploit unobservable dynamic trends and filter out extra information by selecting the most relevant factors out of multiple variables. DFMs are particularly suitable for monitoring economic and financial conditions in real time. Our DFM is similar in approach to Harvey (1989) and contains the following set of equations representing a state-space model.

$$x_t = x_{t-1} + w_t;\ w_t \sim MVN(0, Q)$$

$$y_t = Zx_t + a + v_t;\ v_t \sim MVN(0, R)$$

$$x_0 \sim MVN(\Pi, \Lambda)$$

The DFM is performed using the multivariate autoregressive state-space (MARSS) package in R. The time-series of economic indicators (y) is modelled as linear combination of hidden trends x_t and factor loadings (Z) plus some offset a. The MARSS specification consists of two stochastic components: an unobservable common component, x_t and an idiosyncratic component v_t. x_t is modelled as a random walk and v_t as an autoregressive process.

By way of a concrete example, let us take the case of India and China, our two leading examples. The DPOR block consists of corporate spreads, inter-bank spreads, the term spread (China), and equity returns and return volatility. To derive the FVI corresponding to this block, we fit a model using a single-index dynamic factor. x_t is an estimate of DPOR and Z represents the loadings of the financial indicators on the common component. The identifying assumption in the above model is that the co-movements in the time series indicators arise from the single source x_t; i.e., x_t enters each indicator with different loadings, Z_i, i =1…. ,5. This is ensured by our assumption that v_{it} and x_t are mutually uncorrelated at all leads and lags for all the 5 observed financial indicators. When incorporating information from the external factors block into the DPOR index, we estimate the same model by including one or two additional variables, the local currency-US$ option implied volatility and an exchange market pressure index.[16]

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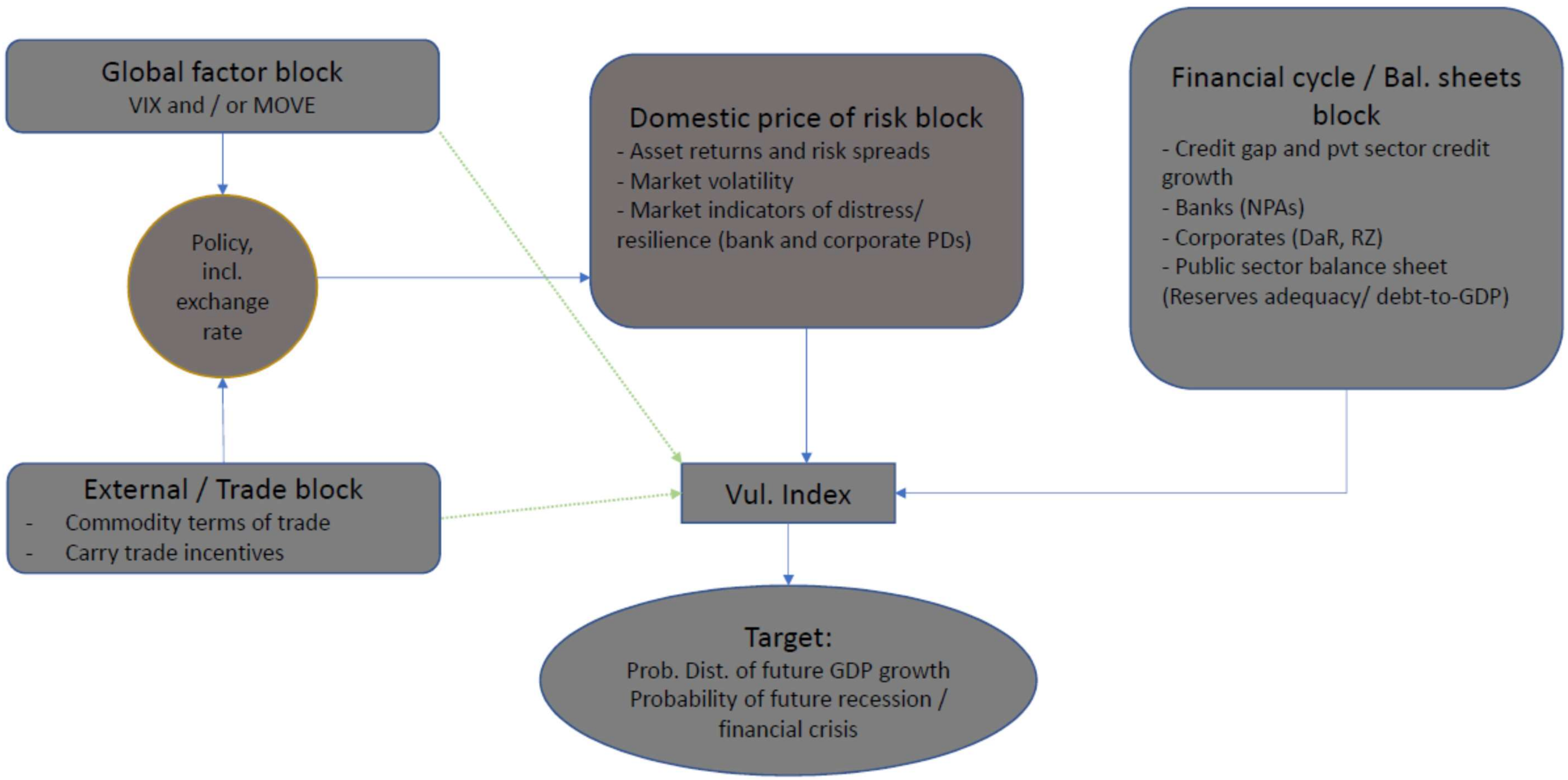
[15] Annex 1 contains further details of the empirical approach to FVI estimation.

[16] In robustness exercises, we have found that EMPI adds significant information in the case of China, but not India; hence, we report results for India wherein only the INR-US$ option volatility is added to DPOR.

Figure 2. Vulnerabilities, Shock Transmission and Risks to Growth



Finally, we integrate information from the credit cycle block to measure aggregate financial vulnerability. We included a banking sector risk index (the S-Risk measure),[17] and the price of credit (the prime lending rate) to construct this block.

In order to address data irregularities, especially those associated with non-synchronicity of the data releases, MARSS uses a Kalman filtering technique. The Kalman filter adopts the expectation maximisation algorithm, which can handle missing data (Banbura and Modugno (2014)). The algorithm is initialised by computing principal components, and model parameters are estimated by OLS regression, treating the principal components as if they were the true common factors. This is a good initialisation, given that principal components are reliable estimates of the common factors.

Data[18]

For India, the five-year AAA corporate bond spread and three-month commercial paper (over equivalent maturity domestic sovereign) spreads and three-month MIBOR-to-treasuries spread, combine data from Bloomberg, L.P. on the private sector interest rates and RBI's DBIE on sovereign rates. Data on large cap (NIFTY 50) equity returns and option implied volatility of the same, and the implied volatility of the US$-INR currency option with three-month maturity were sourced from Bloomberg. The daily prime lending rate of the largest commercial bank, the State Bank of India, a credit cycle indicator, was sourced from CEIC. For China, the five-year corporate bond (over equivalent maturity domestic sovereign) spread and the three-month SHIBOR-to-treasuries spread combined data from Bloomberg with data from CEIC; the ten-year sovereign bond over three-month treasury bill spread was calculated from CEIC data; and the Hang Seng equity return, the average of past 30 days realized volatility of Hang Seng equity return and the US$-CNY currency option volatility with maturity of three months were sourced from Bloomberg. Daily data on the loan prime rate was sourced from the People's Bank of China's database.

New York University's Volatility Lab lent us their time series estimates of S-RISK for individual commercial banks in India and China. This database constituted an unbalanced panel. We combined this data with monthly data on market capitalization of these banks from CMIE's Prowess database (India) and Bloomberg (China) to create a monthly time series of market capitalization-weighted-S-RISK for the banking sectors of India and China.

Since the FVIs are constructed at a monthly frequency, the data were transformed if available at alternate frequencies. Monthly averages of higher frequency indicators were calculated for the indicators described above. Indicators available at a lower frequency, notably real GDP growth, indicators built from firms' quarterly financial reporting (corporate sector debt-at-risk, the Rajan-Zingales external financial dependence) and the BIS house price index for India were cubic splined into monthly frequency. Z-transforms of all variables were used for FVI construction.

V. FVIs and Financial Stress Evolution in India and China

The three blocks described in the previous section are sequentially combined to measure financial vulnerability in our two leading examples of India and China. The first block

[17] See Acharya et. al. (2011) and Brownlees and Engle (2017) for the definition and construction of S-Risk.

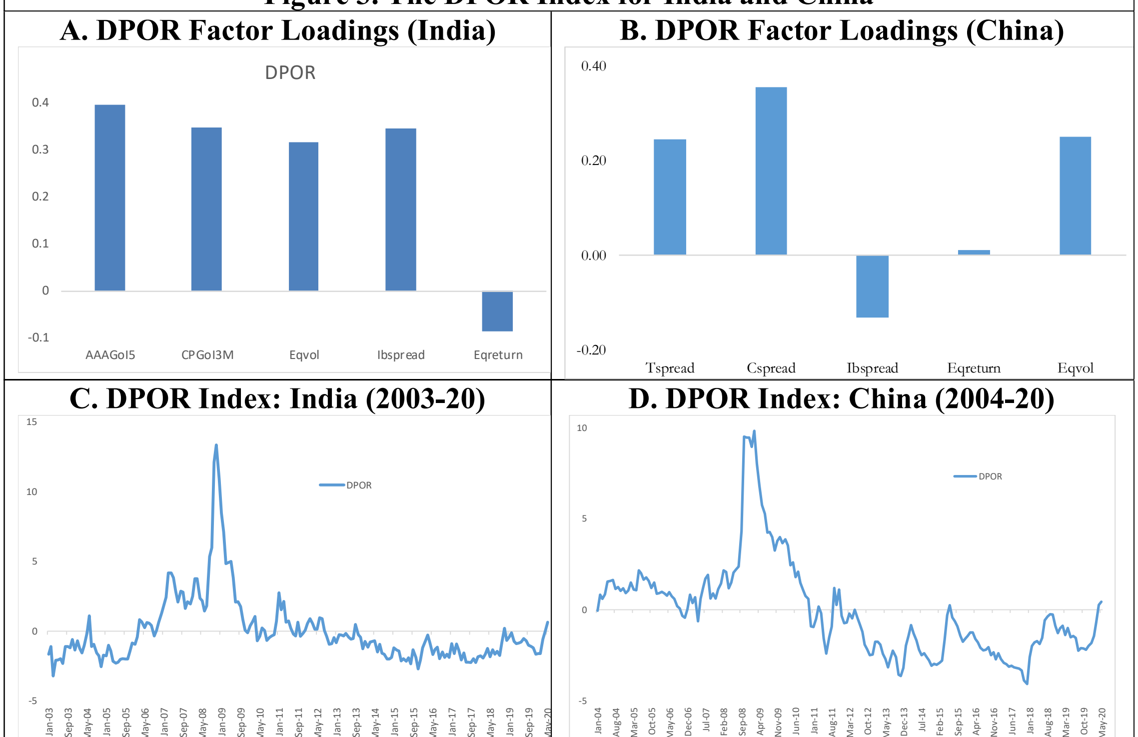
[18] See Annex 2 for further details.

consists of DPOR indicators; the second block adds external factors to the DPOR and is denoted DPOR-EXT; and then, we integrate the credit cycle block into DPOR-EXT to measure aggregate financial vulnerability, denoted by DPOR-BNK.

The DPOR Index

Common indicators used in constructing the DPOR for both countries include the interbank spread, the corporate bond spread, large cap equity returns, and equity return volatility. In addition, one country-specific indicator was added in each case given its significant information content. For India, this is the three-month commercial paper spread, a non-bank / shadow bank (NBFC) price of risk indicator, and for China, it is the term spread. Panels A and B of Figure 3 show that most risk spreads have positive loading and significance, indicating that spread widening is a key indicator of increasing financial market vulnerability.[19] Volatility in large cap equity returns is highly significant with the expected, positive loading, while equity returns are either insignificant (China) or less so with the expected, negative loading (India).

Figure 3. The DPOR Index for India and China



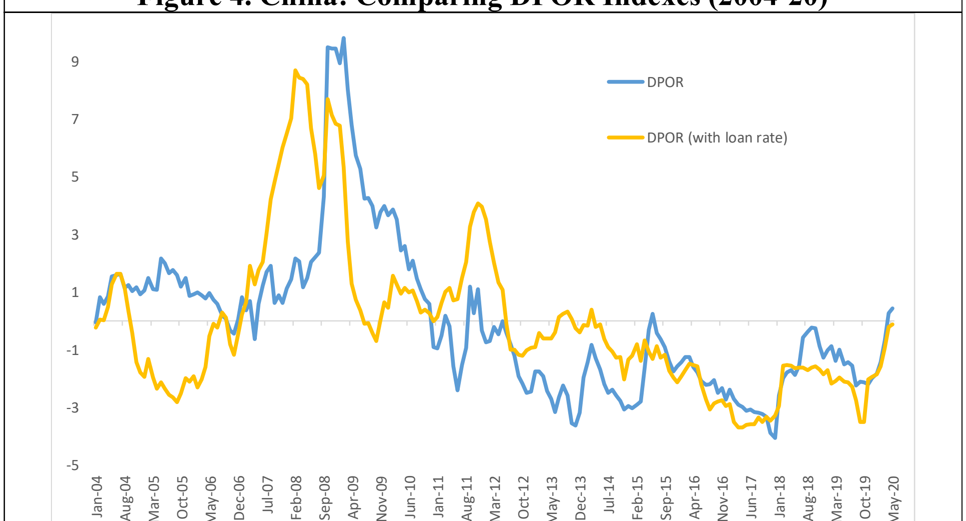
Sources: Bloomberg, L.P.; CEIC; and authors' calculations.
Notes: All indicators in Panels A and B are monthly averages of trading day values. In Panel A, AAAGoI5 = 5-year AAA corporate bond rate minus 5-year INR sovereign rate; CPGoI3M = 3 month CP rate minus 3 month INR sovereign rate; Eqvol = NIFTY 50 implied equity option volatility; Ibspread = Interbank spread; Eqreturn = NIFTY 50 monthly average equity return. In Panel B, Tspread = 10-year treasury bond rate less 3-month treasury bill rate; Cspread = 5-year corporate bond rate less 5 year Treasury bond rate; Ibspread = interbank spread; Eqreturn = Monthly average of daily Hang Seng equity return; Eqvol = average of past 30 days of realized daily volatility in equity returns on the Hang Seng index.

[19] The only exception is the interbank spread for China which has a negative loading likely because of the reduction in bank vulnerability due to a policy intervention shortly prior to the GFC.

In assessing performance of the DPOR index in capturing known macro-financial stress episodes, we note that barring the GFC, the index is unable to reflect any other episode (Panels C and D of Figure 3). For India, these include increasing stress in the banking system and the twin deficits period (2010-12); the impact of the taper tantrum (2013); RBI's 2015 banking sector asset quality review (AQR); the RBI's February 2018 circular that compelled banks to fully account for their non-performing assets; and the IL&FS bankruptcy, oil price resurgence and NBFC liquidity crisis (2018-19). For China, the DPOR index fails to capture the pre-GFC build up in banking vulnerability and associated credit market tightness eventually resolved in late-2007 through a policy intervention writing-off bad loans and recapitalizing banks. It also cannot account for the turmoil in financial markets following the unexpected Renminbi depreciation of August 2015 following the widening of the exchange rate band by Chinese authorities; the increase in trade tensions in early 2018, with a second jump in late Q2-early Q3 of that year when these tensions surged again after a temporary lull; and finally, more modestly during the 2013 taper tantrum. This is indicative of missing information in the DPOR.

In order to anticipate our approach to incorporating further relevant information, we begin by augmenting the set of indicators for China with information on money and credit market tightness (money supply, inflation and the PBOC's one-year loan prime rate). Given weakening bank health prior to the 2007 policy intervention, we would expect an increase in vulnerability to show up much earlier than the one associated with the GFC in Figure 3(D). On the other hand, since the policy intervention led to a strengthening of the banking sector, augmenting DPOR with information on money and credit market conditions should decrease the spike in the index around the Lehman bankruptcy. This is borne out in Figure 4, where the augmented index registers a sharp tightening in domestic financial conditions corresponding to credit market stress at the beginning of 2007, a short-lived loosening in H1-2008 reflecting the policy intervention and a spike around the Lehman episode that is smaller in magnitude relative to the DPOR. We take this discussion up in greater detail below when we discuss the DPOR-BNK index.

Figure 4. China: Comparing DPOR Indexes (2004-20)



Sources: Bloomberg, L.P.; and authors' calculations.

Accounting for external shock transmission

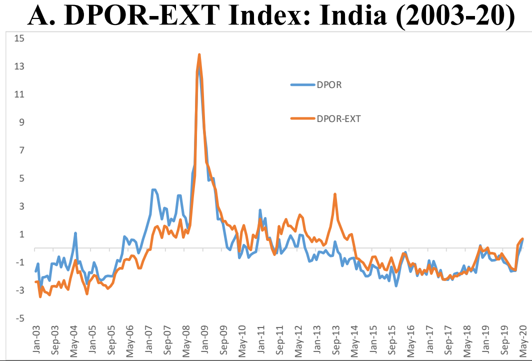
To encompass external shocks other than the GFC, we augment the DPOR with information on the cost of hedging dollar exposure reflected in the implied volatility of the option contract used by market participants. Specifically, we add the INR-US$ and CNY-US$ implied option volatility to the set of DPOR indicators to construct the DPOR-EXT index in which the loading on the currency option volatilities are significant and positive.[20]

This resulting index, DPOR-EXT indicates that increasing tightness in the global dollar market is a significant driver of stress in domestic financial markets in India particularly around the taper tantrum episode of 2013 (Figure 5A). In China's case, financial vulnerability is consistently higher after introducing the external shock transmission channel, in line with what we would expect from a country at the centre of the global trading network (Figure 5B). Importantly, the gap between DPOR-EXT and DPOR increases significantly during the 2013 taper tantrum, the 2015 devaluation, and the 2018-19 trade tensions.

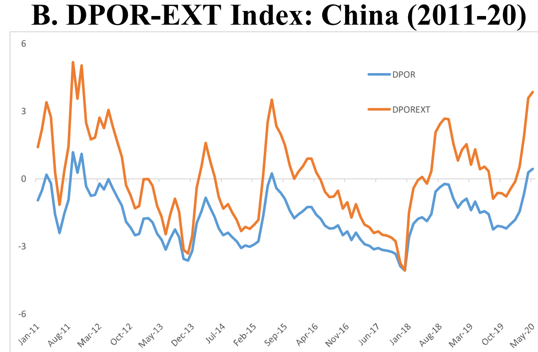
In contrast to the cost of hedging dollar exposure, direct measures of the trade channel are uninformative as are global factors like the VIX and the MOVE (except around the GFC). Since VIX and MOVE display extreme volatility at the peak of the GFC, their inclusion in the FVI tends to reduce the informativeness of the index around other stress episodes.

Figure 5. DPOR-EXT Index for India and China

A. DPOR-EXT Index: India (2003-20)



B. DPOR-EXT Index: China (2011-20)



Sources: Bloomberg, L.P.; CEIC; and authors' calculations.

Incorporating information on the credit cycle

In order to capture information on the sustained, elevated stress in the banking system and credit markets, we finally incorporate information on credit cycle indicators. The construction is sensitive to country-specific information reflecting, in particular, the nature and scale of policy interventions in the banking sector during the last two decades.

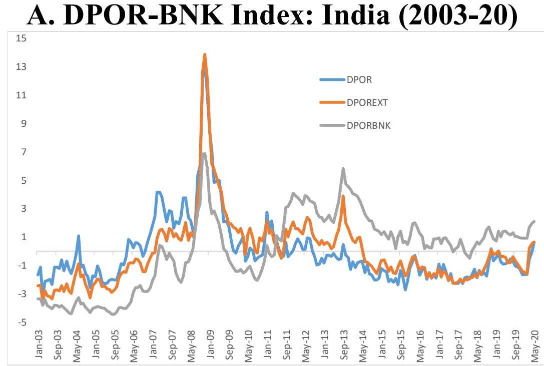
[20] In Figure 4, we report DPOR-EXT values for China starting in January 2011. This is because the currency option was not available to hedge foreign exchange risk prior to this date. Its availability and trading in the last decade is an important indicator of the distinction between 2004-10 and 2011-19 in our view. The pace of China's international financial integration was much faster after 2010, during which time, greater regulatory constraints on commercial banks also resulted in the rapid growth in shadow banking activity.

For India, we assessed the information content of several candidate variables, including (forward-looking) indicators of corporate sector and banking sector vulnerability.[21] Corporate sector indicators are insignificant contributors to variation in the FVI,[22] and loan restructuring of non-performing advances by large public-sector banks severely limits the information content of balance-sheet variables of banks. Market based measures of bank vulnerability and the cost of credit for businesses are much more informative. In order to construct an encompassing index for China, we introduce two innovations to capture country-specific characteristics. First, we regress the CNY-$ option implied volatility onto the DPOR index and use the fitted values to back-cast DPOR-EXT up to 2004.[23] Second, because of China's policy intervention in late-2007, the banking sector S-RISK is lower during the GFC in 2008-09 than during 2004-06. Hence, the S-RISK measure loads with different signs prior to, and after, 2011. In order to incorporate this change in sign, we construct DPOR-BNK separately for 2004-10 (using back-casts of DPOR-EXT) and 2011-19, and then use a levels-adjustment to the 2004-10 series to staple the two indexes together.

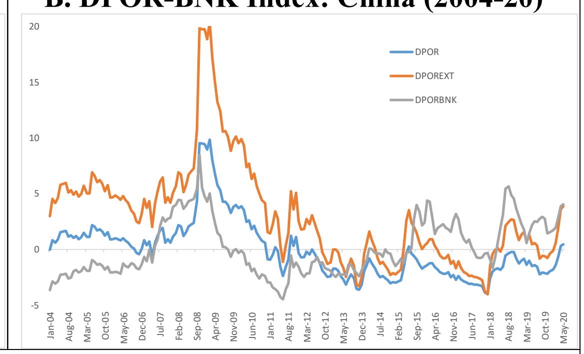
The DPOR-BNK index satisfactorily captures the evolution of financial stress and stability risks over the last two decades (Figure 6).

Figure 6. DPOR-BNK Index for India and China

A. DPOR-BNK Index: India (2003-20)



B. DPOR-BNK Index: China (2004-20)



Sources: Bloomberg, L.P.; CEIC; and authors' calculations.

In India's case, besides the GFC, it reflects growing distress in the banking sector due to the increase in NPAs during the twin deficits period (2010H2-2012H1), the taper tantrum (2013), the pressure on banks after the inception of the 2015 AQR, and the growing stress in the NBFC sector during and after the 2018 ILFS default (Figure 6B). In comparing the three indexes, the advantages of the encompassing index DPOR-BNK are evident. In comparative terms, the GFC was not a significantly greater threat to macro-financial stability and growth

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[21] Corporate sector lending, including industry and services constitutes 60 percent of the banking sector's credit exposure as of September 2018; see for example, Reserve Bank of India (2018). Hence, it constitutes a greater source of systemic risk relative to household lending.

[22] Corporate sector debt-at-risk is defined to be the share of sampled firms with interest coverage ratio less than two. These are firms that are still, typically able to service their debt, albeit whose financial viability is particularly vulnerable to earnings and funding cost shocks.

[23] In an unreported exercise, we ran a robustness check by constructing a broader exchange market pressure index that concatenated information from changes in China's foreign currency reserves and fluctuations in CNY-$ exchange rate and combined this with the DPOR and found no significant change relative to the DPOR-EXT presented in Figure 5B.

than the taper tantrum and the prolonged stress in the banking sector starting 2010 meant that the level of financial vulnerability and growth risks dissipated slowly over the last decade. In China's case, as indicated earlier (Figure 4), elevated banking sector vulnerability prior to the pre-GFC policy intervention causes DPOR-BNK to increase during 2006-2007H1, rising above DPOR. The bank recapitalization of 2007H2 put the domestic credit market and economy in a stronger position to buffer external shocks which is reflected in a stabilization of DPOR-BNK in 2008, a moderate increase during the GFC and a rapid and larger decrease in vulnerability in 2009 relative to DPOR-EXT and DPOR. Moreover, the dynamics of DPOR-BNK closely mirror those of DPOR-EXT post-2011, indicating that as carry trade by non-financial firms and shadow banks grew and financial liberalization accelerated, banking and external vulnerabilities began to move more in tandem.

Our presentation highlights the importance of continuous evaluation of the information base for EM-FVIs. Prior to 2009, the information content of the currency option volatility for international shock transmission was low (India) and its absence (China) reflected the low degree of international financial integration which cushioned the impact of external shocks. This source of shock transmission become significant after the GFC when U.S. monetary policy became extraordinarily accommodative for a long time and dollar exchange rates were very stable. This created conditions conducive for EM firms to systematically increased carry trade to benefit from interest rate differentials (India), which coincided with the opening up to external capital inflows (China).

VI. FVIs as Leading Indicators of Risks to Growth

Empirical strategy

A very general way to think about increasing economic risk is to characterize it as an unfavourable change in the probability distribution of future GDP growth. However, this approach does not lend itself easily to interpretation. For example, a risk averse population would think of an increase in the variance around an invariant baseline outlook as an unfavourable change since higher uncertainty is viewed an adverse development. But, when policy makers discuss risks to the baseline, most of the time they are expressing their concern about the evolution of downside risks.

Our findings on EMs' business cycle characteristics in section II have important implications for how to best identify risk realization episodes in order to conduct a robust evaluation of the capacity of FVIs to provide early warning intelligence in this regard. Persistently higher output and output growth volatility in EMs and the relative paucity of tail risk events compared to AEs were highlighted as two key findings. For example, during the last 4 decades, tail growth realizations in China and India are very few in number (Figure 1). The1991 balance-of-payments crisis appears as a clear case of an adverse tail event for India with the peak of the GFC being a possible, less severe, second episode.[24] In China's case, the only unambiguous tail growth episode since 1980 is the one experienced in 1988. Even at the peak of the GFC, in 2008-09, Chinese growth fell only to its 2004 level and remained

[24] While India's growth in 2008-09 was much lower than in its immediate vicinity, it was still significantly higher than in 1991.

comfortably above growth rates experienced over the decade1994-2004; hence, it is not possible to characterize the peak of the GFC as a tail growth episode for China.

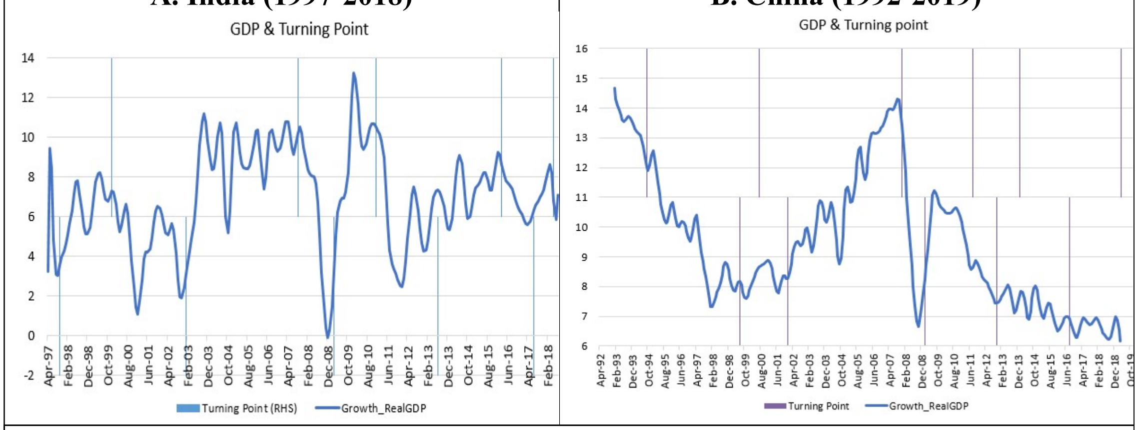
Consequently, relative performance evaluation of out-of-sample forecasts of models incorporating information in our FVIs cannot be done by relying primarily on tail growth episodes because of the paucity of such episodes. Moreover, such an approach would be inadequate in any case for countries like India and China where business cycles and growth risks appear to be better characterized as turning points between accelerations and slowdowns.

We therefore propose a new and alternative approach to assessing early warning information of FVIs for risks to growth, by assessing its forecasting capability around the turning points in the growth rate cycle. As a first step, we identify the growth rate cycle turning points (TPs). The TPs are identified using the OECD's Composite Leading Indicators (CLI) based "growth cycle" approach. OECD uses the TP detection algorithm, which is a simplified version of the original Bry and Boschan routine which parses local minima and maxima in the cycle series and applies censor rules to guarantee alternating peaks and troughs. OECD's CLI based approach identifies 10 TPs for India and 11 TPs for China (Figure 7).

To evaluate the predictive properties of the DPOR-BNK index, we run two horse races. First, we compare conditional, retrospective, real-time, out-of-sample forecasts of real GDP growth at the TPs of the growth rate cycle coming from an AR model of real GDP growth against similar forecasts coming from a model that also includes lagged values of the DPOR-BNK. The evaluation is carried out at immediate-term (i.e., one-month), near-term (i.e., one-quarter) and medium-term (one-year) forecast horizons. Subsequently, we do a similar comparison of relative forecasting accuracy of the model with DPOR-BNK versus one with an alternative index specifically constructed to optimize forecasts of TPs, called a turning point index (TPI).

Figure 7. Real GDP Growth Rate and OECD's CLI-Based Turning Points

A. India (1997-2018) | **B. China (1992-2019)**



Sources: CEIC; OECD; and authors' calculations.
Notes: 1 sets for a Peak and -1 sets for a Trough in the Turning Point

In the rest of this sub-section, we describe the construction of the TPI and compare it to DPOR-BNK. The set of indicators constituting the TPI is selected by optimizing a criterion function, with each additional indicator selected to maximize the marginal contribution to forecasting TPs. We adopt a lasso technique for variable selection from 24 (India) and 20 (China) high frequency indicators, including domestic real and fiscal variables, external sector variables, ease of domestic financing variables, a nominal block of variables, a shock transmission block of variables, and a global common factor block of variables. Seasonally adjusted annual growth rates of all real variables are included in the TPI. The criterion function is given by:

$$\sum_{i=1}^{n}\left(y_i-\beta_0-\sum_{j=1}^{p}\beta_j x_{ij}\right)^2+\lambda\sum_{j=1}^{p}\left|\beta_j\right| = RSS+\lambda\sum_{j=1}^{p}\left|\beta_j\right|,$$

where $\left|\beta_j\right|$ is the lasso penalty and the lasso coefficient β_λ^L is chosen to minimize the criterion function.[25] The lasso technique results in 16 out of 24 coefficient estimates for India and 12 of the 20 coefficient estimates for China being set to exactly zero. For India, half of the indicators in the resulting TPI are also components of the DPOR-BNK index (left panel of Figure 8). For China, a majority of indicators (barring two) in the TPI are different from those in DPOR-BNK (right panel of Figure 8). We then fit a model using a single-index dynamic factor to construct the TPI index (Figure 9). Given their composition, there is a close correspondence between the inter-temporal evolution of the DPOR-BNK and TPI indices for India but not for China.

Figure 8. TPI Composition

A. India

DPOR-BNK	TPI
Debt spreads	**Ease of financing block**
- Interbank spreads	- Blue chip index equity return
- Commercial paper spread	- Prime lending rate
- Corporate spread	- Large cap equity return
Asset returns and volatility	- Interbank spreads
- Large cap return	**Credit cycle**
- Large cap implied option volatility	- Credit growth
- US$-INR implied option volatility	**Real block**
Credit cycle indicators	- Tourist arrivals
- Banking sector S-RISK	- Auto sales
- Prime Lending Rate	- IIP (Infrastructure)

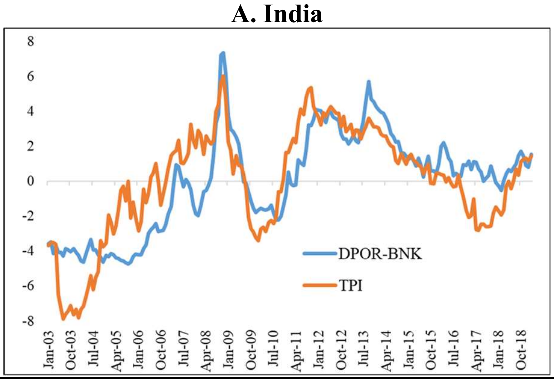
B. China

DPOR-BNK	TPI
Debt spreads	**Ease of financing block**
- Interbank spreads	- Term spread
- Corporate spread	- US$-CNY spot exchange rate
- Term	- VIX
Asset returns and volatility	**Real and fiscal block**
- Equity market return	- Fiscal revenue
- Equity return realized volatility	- Construction index
- US$-CNY option volatility	- Air passengers
Credit cycle indicators	**External block**
- Banking sector S-RISK	- Crude oil imports
- Lending Rate	- Real exchange rate

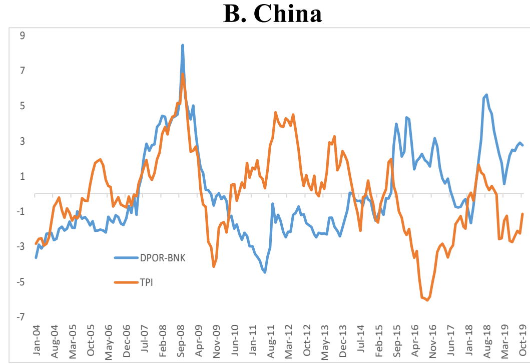
Sources: Bloomberg Finance, L.P.; CEIC; OECD; and authors' calculations.

Figure 9. Comparing DPOR-BNK and TPI Indexes

A. India



B. China



Sources: Bloomberg Finance, L.P.; CEIC; OECD; and authors' calculations.

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[25] As a result, models generated from the lasso are generally much easier to interpret than those produced by the ridge regression.

Results

Our approach to evaluating relative performance of out-of-sample forecasts of growth rate cycle TPs conditioned on information in the DPOR-BNK index is to compare the root mean square error (RMSE) of forecasts of the competing models. The forecasts are retrospective, real-time, out-of-sample, i.e., the models are trained on a slice of the historical data prior to the TP of interest and then we evaluate monthly forecasts from the trained models over a twelve-month window centred on that TP. We implement this procedure on 5 of the 10 identified TPs for India and 6 of the 11 identified TPs for China given data constraints.

Forecasts from the AR growth model are less accurate around a majority of TPs relative to conditional forecasts of the AR model augmented with information in the DPOR-BNK index at monthly and quarterly forecast horizons for both India and China (Table 3). No systematic, significant further forecast gains are evident for India from incorporating information on the real variables in the TPI as compared to the information in the DPOR-BNK. Relative forecast accuracy of the model with TPI is higher than the model with DPOR-BNK at some TPs and lower at others at short-horizons of one-to-three months, but at a policy relevant horizon of one-year, the model with DPOR-BNK registers forecast gains for 80 percent of the TPs in our sample (Table 4A). Our results for China are broadly similar (Table 4B). Replacing DPOR-BNK with TPI does not register systematic significant gains at a one-year horizon and the model with TPI underperforms the model with DPOR-BNK at shorter horizons of one-to-three months.

Table 3. Turning Point Forecasts: AR model vs. AR + DPOR-BNK model

A. India

Forecast Horizon	Turning Point	Training Set	Test Set	RMSE	
				AR	AR+DPOR
1 month	Dec. 2010	Apr 2004 - May 2010	Jun 2010 - Jun 2011	0.790	0.690
1 month	Jul. 2013	Apr 2004 - Dec 2012	Jan 2013 - Jan 2014	0.250	0.460
1 month	Mar. 2016	Apr 2004 - Aug 2015	Sep 2015 - Sep 2016	0.270	0.340
1 month	Jul. 2017	Apr 2004 - Dec 2016	Jan 2017 - Jan 2018	0.330	0.310
1 month	May 2018	Apr 2004 - Oct 2017	Nov 2017 - Nov 2018	0.210	0.200
1 quarter	Dec. 2010	Apr 2004 - May 2010	Jun 2010 - Jun 2011	1.700	1.440
1 quarter	Jul. 2013	Apr 2004 - Dec 2012	Jan 2013 - Jan 2014	0.590	1.010
1 quarter	Mar. 2016	Apr 2004 - Aug 2015	Sep 2015 - Sep 2016	0.750	0.880
1 quarter	Jul. 2017	Apr 2004 - Dec 2016	Jan 2017 - Jan 2018	0.860	0.700
1 quarter	May 2018	Apr 2004 - Oct 2017	Nov 2017 - Nov 2018	0.590	0.540

B. China

Forecast Horizon	Turning Point	Training Set	Test Set	RMSE	
				AR	AR+DPOR
1 month	Feb. 2009	May 2004 - Jul 2008	Aug 2008 - Aug 2009	0.538	0.495
1 month	Aug. 2011	May 2004 - Jan 2011	Feb 2011 - Feb 2012	0.238	0.303
1 month	Nov. 2012	May 2004 - Apr 2012	May 2012 - May 2013	0.103	0.096
1 month	Jan. 2014	May 2004 - Jun 2013	Jul 2013 - Jul 2014	0.211	0.232
1 month	Aug. 2016	May 2004 - Jan 2016	Feb 2016 - Feb 2017	0.121	0.093
1 month	Apr. 2019	May 2004 - May 2018	Jun 2018 - Jun 2019	0.191	0.171
1 quarter	Feb. 2009	May 2004 - Jul 2008	Aug 2008 - Aug 2009	1.697	1.596
1 quarter	Aug. 2011	May 2004 - Jan 2011	Feb 2011 - Feb 2012	0.750	0.849
1 quarter	Nov. 2012	May 2004 - Apr 2012	May 2012 - May 2013	0.518	0.475
1 quarter	Jan. 2014	May 2004 - Jun 2013	Jul 2013 - Jul 2014	0.513	0.469
1 quarter	Aug. 2016	May 2004 - Jan 2016	Feb 2016 - Feb 2017	0.421	0.455
1 quarter	Apr. 2019	May 2004 - May 2018	Jun 2018 - Jun 2019	0.444	0.410

Sources: Bloomberg Finance L.P.; CEIC; MOSPI; and authors' calculations.
Notes: Green cells denote lower forecast RMSE among competing models.

Table 4. Turning Point Forecasts: AR + DPOR-BNK model vs. AR+TPI model

A. India

Forecast Horizon	Turning Point	Training Set	Test Set	Relative RMSE
1 month	Dec. 2010	Apr 2004 - May 2010	Jun 2010 - Jun 2011	0.870
1 month	Jul. 2013	Apr 2004 - Dec 2012	Jan 2013 - Jan 2014	1.700
1 month	Mar. 2016	Apr 2004 - Aug 2015	Sep 2015 - Sep 2016	1.310
1 month	Jul. 2017	Apr 2004 - Dec 2016	Jan 2017 - Jan 2018	0.820
1 month	May 2018	Apr 2004 - Oct 2017	Nov 2017 - Nov 2018	1.180
1 quarter	Dec. 2010	Apr 2004 - May 2010	Jun 2010 - Jun 2011	0.890
1 quarter	Jul. 2013	Apr 2004 - Dec 2012	Jan 2013 - Jan 2014	1.600
1 quarter	Mar. 2016	Apr 2004 - Aug 2015	Sep 2015 - Sep 2016	1.420
1 quarter	Jul. 2017	Apr 2004 - Dec 2016	Jan 2017 - Jan 2018	0.620
1 quarter	May 2018	Apr 2004 - Oct 2017	Nov 2017 - Nov 2018	1.100
1 year	Dec. 2010	Apr 2004 - May 2010	Jun 2010 - Jun 2011	1.070
1 year	Jul. 2013	Apr 2004 - Dec 2012	Jan 2013 - Jan 2014	0.970
1 year	Mar. 2016	Apr 2004 - Aug 2015	Sep 2015 - Sep 2016	1.000
1 year	Jul. 2017	Apr 2004 - Dec 2016	Jan 2017 - Jan 2018	0.870
1 year	May 2018	Apr 2004 - Oct 2017	Nov 2017 - Nov 2018	0.990

B. China

Forecast Horizon	Turning Point	Training Set	Test Set	Relative RMSE
1 month	Feb. 2009	May 2004 - Jul 2008	Aug 2008 - Aug 2009	1.490
1 month	Aug. 2011	May 2004 - Jan 2011	Feb 2011 - Feb 2012	0.924
1 month	Nov. 2012	May 2004 - Apr 2012	May 2012 - May 2013	0.372
1 month	Jan. 2014	May 2004 - Jun 2013	Jul 2013 - Jul 2014	0.782
1 month	Aug. 2016	May 2004 - Jan 2016	Feb 2016 - Feb 2017	0.934
1 month	Apr. 2019	May 2004 - May 2018	Jun 2018 - Jun 2019	1.048
1 quarter	Feb. 2009	May 2004 - Jul 2008	Aug 2008 - Aug 2009	1.066
1 quarter	Aug. 2011	May 2004 - Jan 2011	Feb 2011 - Feb 2012	0.990
1 quarter	Nov. 2012	May 2004 - Apr 2012	May 2012 - May 2013	0.573
1 quarter	Jan. 2014	May 2004 - Jun 2013	Jul 2013 - Jul 2014	0.911
1 quarter	Aug. 2016	May 2004 - Jan 2016	Feb 2016 - Feb 2017	0.904
1 quarter	Apr. 2019	May 2004 - May 2018	Jun 2018 - Jun 2019	0.951
1 year	Feb. 2009	May 2004 - Jul 2008	Aug 2008 - Aug 2009	0.989
1 year	Aug. 2011	May 2004 - Jan 2011	Feb 2011 - Feb 2012	1.108
1 year	Nov. 2012	May 2004 - Apr 2012	May 2012 - May 2013	1.067
1 year	Jan. 2014	May 2004 - Jun 2013	Jul 2013 - Jul 2014	0.906
1 year	Aug. 2016	May 2004 - Jan 2016	Feb 2016 - Feb 2017	0.834
1 year	Apr. 2019	May 2004 - May 2018	Jun 2018 - Jun 2019	1.192

Sources: Bloomberg Finance L.P.; CEIC; MOSPI; and authors' calculations.
Notes: 1/ Relative RMSE = RMSE (AR+DPOR-BNK) / RMSE (AR + TPI). Green cells denote lower RMSE for AR + DPOR-BNK model.

Forecasting Tail Episodes

While we have argued against relying on forecasts in advance of tail growth episodes as a means of evaluating the early warning capacity of FVIs, we provide an assessment of the relative forecast performance of FVIs for India around the GFC given the pre-eminence of this approach in the literature.[26]

Recent papers assessing the potential of FVIs as leading indicators of risks to growth have emphasized the gain in information these indexes provide in terms of advance warning regarding evolving tail risks by exploiting the fact that an estimated (linear) relationship between these indexes and future growth changes depending on which part of the statistical distribution of future growth is emphasized in estimating the model. Formally, by regressing quantiles of future real GDP growth on an autoregressive term and the FVI to derive a measure of *growth-at-risk*; i.e., the estimated q^{th}-quantile of future economic growth conditional on information contained in current and recent growth outcomes and current financial stress as embodied in the FVI:[27]

$$y_{t+h} = \beta_{f,q}^{h} FVI_t + \beta_{y,q}^{h} y_t + \varepsilon_{t,q}^{h}$$

where y_t is the seasonally adjusted, annualized rate of growth in quarterly GDP in month t; FVI_t is the value of the DPOR-BNK index in month t, with q denoting that the regression equation corresponds to the q^{th}-quantile. Out-of-sample conditional forecasts of lower quantiles of real GDP growth derived from the model above for a horizon of up to 24-months are compared to conditional forecasts of the same quantiles of real GDP growth from an autoregressive growth model:

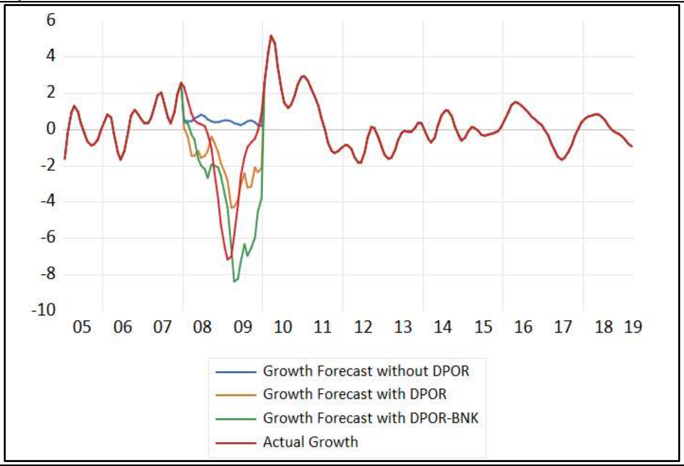
$$y_{t+h,q} = \gamma_{y,q}^{h} y_t + u_{t,q}^{h}$$

Comparing two-year ahead out-of-sample forecasts of annual real GDP growth at the peak of the GFC (2009Q1) from the autoregressive model to the model incorporating information from the FVIs indicates strong tail risk prediction properties for our FVIs. Rolling 24-months ahead forecasts from the autoregressive model project a path of growth that modestly and stably outpaces trend rate of growth over 2008-09. In contrast, comparable forecasts from the model with FVIs predicts growth rate falling to more than 2 percent below trend by mid-2008 and a further steep fall to between 4 percent (when including DPOR) to 8 percent (when using DPOR-BNK) below trend for the peak of the GFC. Strikingly, the actual economic performance is mirrored most accurately by the out-of-sample forecasts coming from the model including the DPOR-BNK index (Figure 10).

[26] As noted earlier in this section, we do not consider the GFC to have triggered a tail growth episode for China and, hence, only cover India in this section. Assessing our FVIs' forecast performance for India's balance-of-payments crisis (1991) and China's tail growth event (1988) was precluded by unavailability of data necessary to construct our FVIs, in turn, reflecting financial market underdevelopment in the two countries at that time.

[27] See Katagiri et. al. (2017) and Adrian et. al. (2019) for the rationale for using quantile regression-based forecasts of tail growth outcomes and Komunjer (2013) for more general properties of quantile prediction.

Figure 10. Forecasts of Risks-to-Growth around the GFC
(2-year ahead real GDP forecast with and without FVIs)



Sources: Bloomberg Finance, L.P.; CEIC; OECD; and authors' calculations.

VII. Conclusions

The main contribution of our paper is to offer a common approach and methodology to construct financial vulnerability indexes for EMs that exploit the common properties of their business cycle and similarities in their increasing financial interconnectedness with the rest of the world. In doing so, we open up a new area of research by showing that while financial conditions are important early warning indicators in both EMs and AEs, they need to be developed differently for EMs in order to extract maximum information relevant to macro-financial risk surveillance. Our FVIs accurately captures episodes of macro-financial stress arising from disparate domestic and international shocks and transmission channels and improves prediction of growth slowdowns over the last two decades in India and China, the two largest EM economies in the world. Our principle findings, *viz.*, that the domestic price of risk in EMs adequately captures information on domestic and global risk factors and transmission channels, but that market-based measures of bank vulnerability and the cost of hedging dollar exposures are more informative than balance-sheet vulnerabilities and trade shocks, can be expected to hold in a wider set of EMs and is worthy of further investigation.

Another important contribution is to offer a new approach to assessing risks to growth using FVIs. In addition to out-of-sample forecast evaluation of FVIs against rare, tail-risk, recessionary episodes like the GFC, we ran a horse race of relative out-of-sample forecast performance of FVIs around turning points in the growth rate cycle against a coincident leading indicator custom-built to perform well. Not only does this lead in our view to a more satisfactory forecast evaluation, but equally importantly, it expands the set of episodes against which performance evaluation may be performed. This is especially relevant to EMs given that they tend to have growth rate cycles with frequent turning points between accelerations and slowdowns instead of contractions and expansions typical to AEs and SOEs.

One of the surprising takeaways from our analysis is that fiscal and external measures of shock amplification neither contribute significantly to the FVI when incorporated nor do they systematically and significantly increase the early warning capacity of amplification indexes for business cycle turning points in EMs. As we note in the introduction, we interpret this result to reflect *Goodhart's law*; i.e., the heavy management of the evolution of key measures of external and fiscal vulnerability and of the aggregate credit cycle by policy control variables reduces their early warning potential. By contrast, market signals, either not (or only unsuccessfully) subject to such controls appear to be more informative. It is possible that the pre-eminence and stability of policy control of key macroeconomic measures of fiscal and external imbalance over the sampling horizon for our leading case studies preclude non-financial variables from having significant early warning capability in the time series domain. This constraint could possibly dissipate in a broader cross-sectional study of EMs where such measures might capture important cross-country variation in initial conditions, their use for control purposes notwithstanding. This is a question we intend to turn to in future work extending this paper's analysis.

Practical implementation of forecasting of risks to growth based on financial vulnerability will inevitably require continuous calibration of these types of models. As local financial markets develop and deepen as well as the institutional structure of credit intermediation changes, the nature and materiality of shock transmission channels will evolve. New financial indicators may therefore acquire greater importance and will need to be incorporated dynamically in order to ensure robustness against a loss of information content.

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Annex 1. Estimating FVIs

A. Seemingly Unrelated Time Series Equation (SUTSE)

- A time-series analogue of the seemingly unrelated regression equation (SURE) model was first introduced by **Zellner (1963)**
- A system of seemingly unrelated time series equation-SUTSE model is the multivariate random walk plus noise process;

$$y_t = \mu_t + \varepsilon_t;\ t = 1, \cdots, T \quad (1)$$
$$\mu_t = \mu_{t-1} + \eta_t \quad (2)$$

where μ is a $N \times 1$ vector of local level component and ε_t and η_t are $N \times 1$ vector of multivariate white noise with zero mean and covariance matrices Σ_ε and Σ_η

- As in univariate model, ε_t and η_t are assumed to be uncorrelated with each other in all time periods. The N series are linked via off-diagonal elements in Σ_ε and Σ_η. Each of these matrices contains $\frac{N(N+1)}{2}$ parameters.

B. Dynamic Factor Analysis (DFA)

- In classical factor analysis, a model is setup in which it is assumed that each of N variables is a linear combination of $K(<N)$ common factor plus a random disturbance term, see **Geweke and Singleton (1981) and Sims (1981)**
- Our discussion here will be limited only to DFA within a framework obtained from SUTSE model. A common factor model for the trend components would be represented as follows;

$$y_t = \Theta\mu_t + \mu_0 + \varepsilon_t \quad (3)$$
$$\mu_t = \mu_{t-1} + \beta + \eta_t \quad (4)$$

where μ_t is a $K \times 1$ vector of common trends, Θ is a $N \times K$ matrix of factor loadings and $0 \le K \le N$, The covariance matrices Σ_ε and Σ_η are $N \times N$ and $K \times K$ respectively.

C. Identification in DFA

- For any non-singular $K \times K$ matrix H, the matrix of factor loadings and the trend components could be redefined as;

$$\mu_t^+ = H\mu_t \quad \text{and} \quad \Theta^+ = \Theta H^{-1}$$

- Therefore, the common factor model for the trend component could be represented as;

$$y_t = \Theta^+ \mu_t^+ + \mu_0 + \varepsilon_t \quad (5)$$
$$\mu_t^+ = \mu_{t-1}^+ + \beta^+ + \eta_t^+ \quad (6)$$
$$\text{where } \eta_t^+ = H\eta_t, \beta^+ = H\beta, and$$
$$Var\ (\eta_t^+) = H\Sigma_\eta H^{'}$$

- In order for the model to be identifiable, restrictions must be placed on Σ_η and Θ. In a classical factor analysis, the covariance matrix of the common factor is taken to be an identity matrix. According to **Harvey (1989)**, this is not sufficient to make the model identifiable since if H is an orthogonal matrix, (5) and (6) would still satisfy all the restrictions of (3) and (4) because $Var(\eta_t^+) = HH^{'} = I$
- Some restrictions are needed on Θ and one way of imposing them is to require that the $ij-th$ element of Θ, $\Theta_{ij} = 0$, for $j > i, i = 1, \cdots, K-1$. Alternatively, Σ_η can be set equal to a diagonal matrix while $\Theta_{ij} = 0$ for $j > i$ and $\Theta_{ii} = 1$ for $i = 1, \cdots, K$.

D. Writing out a DFA in Multivariate Autoregressive State-Space (MARSS) form

- Following **Holmes et al. (2014)**, MARSS can be written as a "state process" and an "observation process" as follows. The DFA in the MARSS package has a structure that is identical to the DFA framework obtained from SUTSE model.
- Observation (y) are modelled as linear combination of hidden trends (x) and factor loadings (Z) plus some offsets a

$$x_t = x_{t-1} + w_t \text{ where } w_t \sim MVN(0, Q)$$
$$y_t = Zx_t + a + v_t \text{ where } v_t \sim MVN(0, R)$$
$$x_0 \sim MVN(\Pi, \Lambda)$$

- It is important to write the DFA model in MARSS form. Let's say there is a data set with six observed time series, i.e., n=6.
- And it requires to fit a model with three hidden trend, m=3.
- Writing the DFA model in MARSS matrix form (ignoring the error structure and initial conditions for now).

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}_t = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}_{t-1} + \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} w_1 \\ w_2 \\ w_3 \end{bmatrix}_t$$

- Notice the process error of the hidden trend, $w_t \sim MVN(0, Q)$ can be written as follows;

$$\begin{bmatrix} w_1 \\ w_2 \\ w_3 \end{bmatrix}_t = MVN(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} q_{11} & q_{12} & q_{13} \\ q_{21} & q_{22} & q_{23} \\ q_{31} & q_{32} & q_{33} \end{bmatrix})$$

- The matrix form representation of the equation between (y), hidden trend (x) and factor loading (Z) is as follows;

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ y_5 \\ y_6 \end{bmatrix}_t = \begin{bmatrix} z_{11} & z_{12} & z_{13} \\ z_{21} & z_{22} & z_{23} \\ z_{31} & z_{32} & z_{33} \\ z_{41} & z_{42} & z_{43} \\ z_{51} & z_{52} & z_{53} \\ z_{61} & z_{62} & z_{63} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}_t + \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \\ a_6 \end{bmatrix} + \begin{bmatrix} v_1 \\ v_2 \\ v_3 \\ v_4 \\ v_5 \\ v_6 \end{bmatrix}_t$$

- The observation error can be written as $v_t \sim MVN(0, R)$

$$\begin{bmatrix} v_1 \\ v_2 \\ v_3 \\ v_4 \\ v_5 \\ v_6 \end{bmatrix}_t \sim MVN(\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} r_{11} & r_{12} & r_{13} & r_{14} & r_{15} & r_{16} \\ r_{21} & r_{22} & r_{23} & r_{24} & r_{25} & r_{26} \\ r_{31} & r_{32} & r_{33} & r_{34} & r_{35} & r_{36} \\ r_{41} & r_{42} & r_{43} & r_{44} & r_{45} & r_{46} \\ r_{51} & r_{52} & r_{53} & r_{54} & r_{55} & r_{56} \\ r_{61} & r_{62} & r_{63} & r_{64} & r_{65} & r_{66} \end{bmatrix})$$

E. Identification in Multivariate Autoregressive State-Space (MARSS)

- This is exactly similar to what we have already specified while discussing about the identification in DFA. Following **Harvey (1989)**, identification in MARSS specification would require the following changes.
  - If Z, a, Q are not constrained, then the DFA model is unidentifiable.
  - In the first $m-1$ rows of Z, the $z-value$ in the $j-th$ column and the $i-th$ row set to zero, if $j > i$
  - a is constrained so that first m values are set to zero
  - Q is set equal to the identity matrix (I_m)
- Using these revised constraints, DFA will look as follows;

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}_t = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}_{t-1} + \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} w_1 \\ w_2 \\ w_3 \end{bmatrix}_t,$$

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ y_5 \\ y_6 \end{bmatrix}_t = \begin{bmatrix} z_{11} & 0 & 0 \\ z_{21} & z_{22} & 0 \\ z_{31} & z_{32} & z_{33} \\ z_{41} & z_{42} & z_{43} \\ z_{51} & z_{52} & z_{53} \\ z_{61} & z_{62} & z_{63} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}_t + \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} v_1 \\ v_2 \\ v_3 \\ v_4 \\ v_5 \\ v_6 \end{bmatrix}_t,$$

$$\begin{bmatrix} w_1 \\ w_2 \\ w_3 \end{bmatrix}_t = MVN\left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}\right),$$

$$\begin{bmatrix} v_1 \\ v_2 \\ v_3 \\ v_4 \\ v_5 \\ v_6 \end{bmatrix}_t \sim MVN\left(\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} r_{11} & r_{12} & r_{13} & r_{14} & r_{15} & r_{16} \\ r_{21} & r_{22} & r_{23} & r_{24} & r_{25} & r_{26} \\ r_{31} & r_{32} & r_{33} & r_{34} & r_{35} & r_{36} \\ r_{41} & r_{42} & r_{43} & r_{44} & r_{45} & r_{46} \\ r_{51} & r_{52} & r_{53} & r_{54} & r_{55} & r_{56} \\ r_{61} & r_{62} & r_{63} & r_{64} & r_{65} & r_{66} \end{bmatrix}\right)$$

- To complete the model, it is required to set the initial condition of the state. Following **Zuur et al. (2003)**, initial state vector (x_0) is set to have zero mean and diagonal variance-covariance matrix with large variance.

$$x_0 \sim MVN\left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 5 & 0 & 0 \\ 0 & 5 & 0 \\ 0 & 0 & 5 \end{bmatrix}\right)$$

We assured parameter convergence by using sufficiently many iterations.

- This model was run to convergence setting maxit (maximum number of iteration) at 5000. First, it looks like the model did an adequate job of capturing some of the high frequency variation (i.e., seasonality) in the time series. Second, some of the time series had much better overall fit than others.
- All financial indicators are Z-score transformed before running the DFA. The Z-score transformation standardizes the high frequency indicators as the deviations are now reflected around the mean.

It appears that, as anticipated, the dynamic evolution of the indexes is independent of method of concatenation of information in the individual indicators.

F. The Expectation Maximization (EM) Algorithm

- We observe five data challenges in India, which are also faced by other EMEs. These are data challenges are particularly relevant in time series analysis.
    - Big data revisions: According to **Sapre and Sengupta (2017)**, the average revision of GDP estimates in India is + 0.5 percentage points.

- Mixed frequencies data publication: The index on mining in India, for example, is published monthly, whereas the foreign exchange (FOREX) assets data is published bi-weekly and the National Stock Exchange (NSE) data daily.
- Small sample size: The CSO has recently replaced the earlier 2004-05 base year with 2011-12, and updated the National Account Statistics (NAS) methodology to align with more recent international guidelines. Using the data that has been revised in line with the updated methodology, we now have a shorter time series.
- Non-synchronous data releases: Hard data releases in India are non-synchronous. For example, monthly production of coal and crude oil is typically released on the last working day of the month, monthly production of commercial vehicles during the middle of the month, and railway freight traffic of major commodities during the first 10 days of the month.
- Varying data lags: For example, data on monthly production of steel and fertilizer for the month of December is released in the month of January of the following year. However, data on the mining and quarrying index for the month of November is released in the month of January of the following year with a lag of more than a month. Together, all of these will result in a large number of short, non-stationary time series with missing values.

- As observed by **Zuur et al. (2003)**, the EM algorithm provides a way to obtain maximum likelihood estimates of the hyper-parameters based on the incomplete data in $y_1, \cdots, y_T$. **Holmes et al. (2014)** points out that EM algorithm provides robust estimation for datasets replete with missing values and for high-dimensional models with various constraints. EM algorithm in MARSS specification is briefly discussed below;

- Starting with an initial set of hyper-parameters, which is denoted as $\hat{\Theta}_1$, an updated parameter set $\hat{\Theta}_2$ is obtained by finding the $\hat{\Theta}_2$ that maximizes the expected value of the likelihood over the distribution of the states (X) conditioned on $\hat{\Theta}_1$. Mathematically, each iteration of an EM algorithm does this maximization.

$$\hat{\Theta}_2 = \arg \max_{\Theta} E_{X|\hat{\Theta}_1} [\log(\Theta \mid Y = y_1^T, X]$$

- Then using $\hat{\Theta}_2$, the distribution of (X) conditioned on $\hat{\Theta}_2$ is computed. Then that distribution along with $\hat{\Theta}_2$ in place of $\hat{\Theta}_1$ is used to produce an updated parameter $\hat{\Theta}_3$.

This is repeated until the expected log-likelihood stops increasing or increases less than some set tolerance level.

Zuur et al. (2003) found that with the Harvey's second constraint (i.e., a is constrained so that first m values are set to zero, see identification in MARSS), the EM algorithm is not particularly robust and takes time to converge. Instead, Zuur et al. (2003) found that EM algorithm behaves better if you constrain each of the time series in x to have a mean of zero across $t=1$ to T. Therefore, Zuur et al. replaced the estimates of hidden state, x_t^T, coming out of the Kalman smoother with $x_t^T - \overline{x}$ for $t=1$ to T ; where $\overline{x}$ is mean of x_t across t. With this approach, you estimate all of the a elements, which represents average level of y_t relative to $Z(x_t - \overline{x})$. However, it was found out that demeaning x_t^T in this way can cause EM algorithm to have errors (decline in log-likelihood). Instead, demeaning data is followed by fixing all elements of a to zero is a better strategy.

Annex 2. Indicators Considered for FVI Construction

Table A.2.1. India: Indicators Considered for FVI Construction

Indicator	Description	DataFrequency	Source
Financial Variables			
Term Spreads	Difference between 10 year government bond and 91 days T-Bill yields	Daily data averaged to monthly	RBI DBIE
Interbank Spreads	Difference between MIBOR 3 month and 91 days T-Bill yields	Daily data averaged to monthly	RBI DBIE
Sovereign Spreads	Difference between 10 year Indian government bond and generic 10 year US government bond yields	Daily data averaged to monthly	RBI DBIE; Bloomberg
CorporateSpread_CEMBI10year	JPM CEMBI Broad India Blended Yield minus 10 year government bond yield	Daily data averaged to monthly	Bloomberg; RBI DBIE
CorporateSpread_AAAGoI5	5 year AAA spread over 5 year government bond yield	Daily data averaged to monthly	Bloomberg
CorporateSpread_AAGoI5	5 year AA spread over 5 year government bond yield	Daily data averaged to monthly	Bloomberg
CorporateSpread_BBBAAA5	5 year AAA spread over 5 year BBB spread	Daily data averaged to monthly	Bloomberg
CorporateSpread_BBBAA5	5 year BBB spread over 5 year AA spread	Daily data averaged to monthly	Bloomberg
CorporateSpread_CPGoI3M	Spread of 3 month corporate bond yield to 91 days T-Bill	Daily data averaged to monthly	Bloomberg; RBI DBIE
Equity Returns (Local Currency)	Log difference of the equity indices	Daily data averaged to monthly	Bloomberg
Equity Returns: NIFTY 500 Index	Market cap weighted index of 500 companies	Daily data averaged to monthly	Bloomberg
Equity Returns: NSE Large Midcap 250	250 Large and mid cap Index	Daily data averaged to monthly	Bloomberg
Equity Returns: Nifty50 Large	50 large cap companies index	Daily data averaged to monthly	Bloomberg
Equity Returns: Nifty Smallcap 50	50 small cap market cao companies index	Daily data averaged to monthly	Bloomberg
Equity Returns: Small cap100	100 small cap companies index	Daily data averaged to monthly	Bloomberg
Equity Returns: NSE Midcap Liquid 15	15 most liquid midcap companies index	Daily data averaged to monthly	Bloomberg
Equity Returns: Midcap 50	free-float market capitalization weighted index to capture midcap segment movement	Daily data averaged to monthly	Bloomberg
Equity Returns: Market minus Large Cap	Market minus Large Cap	Daily data averaged to monthly	Bloomberg
Equity Returns: Market minus Large and Medium Cap	Market minus Large and Medium Cap	Daily data averaged to monthly	Bloomberg
Equity Returns: Large cap minus Medium Cap	Large cap minus Medium Cap	Daily data averaged to monthly	Bloomberg
Equity Returns: Large cap minus Small cap	Large cap minus Small cap	Daily data averaged to monthly	Bloomberg
Equity Return Volatility I	Exponential weighted moving average of equity returns	Daily data averaged to monthly	Bloomberg
Equity Return Volatility II	average volatility of all NSE market trading and of large cap top 50 listed companies	Daily data averaged to monthly	Bloomberg
Trading Volume (equities)	Moving average of BSE total volume over 12 months, leaving previous month	Daily data averaged to monthly	Bloomberg
Market Capitalization (equities)	Moving average of total BSE Market Capitalization of last 12 months, leaving previous month	Daily data averaged to monthly	Bloomberg
House Price Index	Log difference of the house price index	Quarterly data splined to monthly	BIS
Change in Financial Sector Share	Log difference of the market capitalization of the financial sector to total market capitalization	Daily data averaged to monthly	Bloomberg
Change in Long-Term Real Interest Rate	Change in long term real interest rate (in percent) which is calculated as difference between 10 year government bond yield and inflation		RBI DBIE; Labour Bureau India
MIBOR Overnight	Overnight Mumbai Interbank Offer Rate as short rate	Daily data averaged to monthly	RBI DBIE
MIBOR 14-day	14 days Mumbai Interbank Offer Rate as short rate	Daily data averaged to monthly	RBI DBIE
MIBOR 1-month	1 month Mumbai Interbank Offer Rate as short rate	Daily data averaged to monthly	RBI DBIE
MIBOR 3-month	3 month Mumbai Interbank Offer Rate as short rate	Daily data averaged to monthly	RBI DBIE
WACR	Weighted average call rate as short term rate	Daily data averaged to monthly	RBI DBIE
Bank Rate	short term rate	Daily data averaged to monthly	CEIC
Repo Rate	short term rate	Daily data averaged to monthly	CEIC
Reverse Repo Rate	short term rate	Daily data averaged to monthly	CEIC
Marginal Standing Facility Rate	short term rate	Daily data averaged to monthly	CEIC
Cash Reserve Ratio		Daily data averaged to monthly	CEIC
Statutory Liquidity Ratio		Daily data averaged to monthly	CEIC

Indicator	Description	DataFrequency	Source
Financial Aggregates & Credit Cycle Variables			
Credit Growth	Domestic credit by banks to all sectors	monthly	CEIC
Credit Growth YoY	YoY change in domestic credit	monthly	CEIC
Credit GDP Gap	Difference of Credit to GDP ratio and its long term trend	Quarterly data splined to monthly	CEIC
Credit GDP Ratio	Ratio of domestic credit to GDP	Quarterly data splined to monthly	CEIC
Rajan-Zingales: External Finance Dependence	Ratio of difference of capital expenditure and net cash flow to capital expenditure	Annual padded to monthly fequency	Calculation based on Prowess data
Debt-at-Risk lower (ICR)	Interest expenses to PBDIT ratio less than 1.5	Quarterly data splined to monthly	Prowess
Debt-at-Risk upper (ICR)	Interest expenses to PBDIT ratio less than 2	Quarterly data splined to monthly	Prowess
S-Risk of Banking Sector	Calculated by combining current equity market value, outstanding debt and long run marginal expected shortfall	monthly	NYU V-LAB
Prime Lending Rate	Prime Lending Rate of the State Bank of India	Daily data averaged to monthly	CEIC
Banking sector default probability	Expected default frequency of the banking sector	monthly	Calculation based on Prowess data
Banking sector asset quality	Non performing assets ratio to total loans of public and private sector banks	Quarterly data splined to monthly	Bloomberg
External Shocks and Transmission Channel Variables			
Oil Spot price	WTI Oil Spot Prices	monthly	FRED
Change in spot price of Oil	Change in Oil Prices MoM	monthly	FRED
Carry Trade Index	Ratio of difference between 91days T-Bill and 3month US government bond yield to implied volatility of 3month USDINR options	monthly	Calculation based on Bloomberg data
Short rates Carry Trade Index	Ratio of difference between Repo rate and Fed rate upper bound to implied volatility of 3month USDINR options	monthly	Calculation based on Bloomberg data
REER Misalignment	Difference of Real effective exchange rate from 5 year moving averaged REER	monthly	CEIC
VIX	Chicago Board Options Exchange Market Volatility Index	Daily data averaged to monthly	Bloomberg
MOVE	Merrill Lynch Option Volatility Estimate Index	Daily data averaged to monthly	Bloomberg
Exchange Rate Movements	Change in monthly USDINR Currency	Daily data averaged to monthly	Bloomberg
USDINR implied volatility	Implied volatility of US$-INR 3 month option contract	Daily data averaged to monthly	Bloomberg
Non Financial Variables			
Real GDP	GDP at constant price 2011-12 series	Quarterly data splined to monthly	MoSPI
Real GDP Growth	percent change in monthly splined real GDP	monthly	MoSPI
Inflation	Percent annual change in CPI(IW)	monthly	Labour Bureau
Primary Deficit to GDP	Ratio of government primary deficit to monthly splined nominal GDP	monthly	CEIC; MOSPI
Government Debt Outstanding to GDP	Ratio of Outstanding Government Debt to monthly splined nominal GDP	monthly	CEIC; MOSPI
Change in PrimaryDeficit	Percent rate of change of government primary deficit	monthly	CEIC
Change in Outstanding Govt Debt	Percent rate of change of Outstanding Government Debt	monthly	CEIC
Short Term Debt to Forex	Ratio of Short-term External Debt to Foreign Exchange Reserves	monthly	CEIC
Short Term Debt to Total External Debt	Ratio of short term External Debt and total External Debt	monthly	CEIC
External Debt to GDP	Ratio of total External Debt to monthly splined Nominal GDP	monthly	CEIC
External Debt to GDP sans NRI debt	Ratio of difference between total External Debt and External Debt of NRIs to monthly splined Nominal GDP	monthly	CEIC
External Debt to GDP sans Assistance	Ratio of difference between total External Debt and External Assistance INR Debt to monthly splined Nominal GDP	monthly	CEIC
Reserve Adequacy	Ratio of Foreign reserves to sum of semiannual Import and annual short term debt	monthly	CEIC
Annual Import Coverage Ratio	Ratio of annual change in cummulative imports to Foreign reserves	monthly	CEIC
Semiannual Import Coverage Ratio	Ratio of semiannual change in cummulative reserves to foreign reserves	monthly	CEIC

Notes: Grey shaded indicators are those included in the FVIs presented below; others were considered but excluded given insignificant loading in the index; Bloomberg = Bloomberg Finance, L.P.; FRED = U.S. Federal Reserve Bank of St. Louis Database; MOSPI = Indian Ministry of Statistics and Programme Implementation

Table A.2.2. China: Indicators Included in the Financial Vulnerability Indexes

Indicator	Description	Data Frequency	Source
Financial variables			
Term spread	Difference between 10 year government bond and 91-day T-Bill yields	Daily data averaged to monthly	Thomson Reuters, OECD
InterbankSpread	Difference between 3 month interbank lending rate and 91-day T-Bill yield	Daily data averaged to monthly	Thomson Reuters, OECD
CorporateSpread	Difference between 3 month CEMBI yield (China) and 91-day T-Bill yield	Daily data averaged to monthly	Bloomberg, L.P., OECD
Equity Index Returns	Hang Seng index (HSCEI) return	Daily data averaged to monthly	Bloomberg, L.P.
Equity Index Volatility (30 days)	Standard deviation of last 30 days' HSCEI equity returns	Daily data averaged to monthly	Bloomberg, L.P.
Equity Index Volatility (90 days)	Standard deviation of last 90 days' HSCEI equity returns	Daily data averaged to monthly	Bloomberg, L.P.
External shocks and transmission			
USD-CNY Option Implied Volatility	Implied volatility of U.S.$-CNY option contract	Daily data averaged to monthly	Bloomberg, L.P.
Credit cycle indicators			
Banking sector S-RISK Index	Market capitalization weighted average of S-RISK of Chinese banks	Weekly data averaged to monthly	NYU Volatility Risk Institute
Lending Rate 1 Year	PBOC benchmark lending rate (Jan 2004-July 2019); Loan prime rate (Aug 2019-May 2020)	Monthly	Bloomberg, L.P., Thomson Reuters
Other indicators			
CPI Inflation	Annual inflation based on CPI	Monthly	FRED
RGDP Growth 1/	Real GDP growth rate (annualized)	Quarterly data splined to monthly	FRED

Note: 1/ Indicator is not used in FVI construction, but in the turning points analysis.