Emerging Market Cycles: Twin-Balance Sheet Deficits and Macro-Financial Linkages

Soumya Bhadury * Bhanu Pratap † Jay S. Surti ‡

December 2024

Abstract

This paper empirically investigates the impact of fiscal and external balance conditions on the dynamic interaction of financial conditions and vulnerabilities and macroeconomic performance across 18 major emerging market and developing economies between 2000 and 2020. Using a state-space, multivariate autoregressive model, we identify two opposing forces – a growth-inhibiting and a growth-enhancing effect – that characterize macro-financial dynamics in emerging market and developing economies. Exogenous shocks that trigger an easing of domestic financial conditions in such countries tend to accelerate near-term GDP growth, a growth enhancing channel. In turn, an acceleration of economic growth tends to rapidly (re)-tighten financial conditions in emerging market and developing economies that lead to adverse future growth outcomes, a growth inhibiting channel. The prevalence of both channels at high frequencies is statistically significant for almost half of the countries in our sample and is seen to be associated with fiscal and external imbalances that correspond to a twin-deficits problem.

Keywords: Macro-finance; Emerging Markets; Twin-deficit; Financial conditions; State-space model; Kalman filter.
JEL Classification: C53, E32, E44.

*Corresponding Author. Reserve Bank of India. Email: soumyasbhadury@rbi.org.in
†Reserve Bank of India. Email: bhanupratap@rbi.org.in
‡International Monetary Fund. Email: JSurti@imf.org.
The views expressed in this paper are those of the authors and should not be attributed to the organizations to which they belong. The authors gratefully acknowledge research assistance from Sruti Tiwari. We also thank an anonymous reviewer for helpful suggestions and feedback on the paper.

1 Introduction

Rapid economic expansions are often accompanied by easy financial conditions and buoyant asset valuations that facilitate borrowing to finance economic growth. These credit and asset price booms can breed balance-sheet vulnerabilities in the household, corporate, financial, and public sectors in the form of excessive leverage and asset-liability mismatches. If these imbalances become sufficiently high, they can serve to amplify the macro-financial impact of shocks, notably through a rapid tightening of financial conditions and deleveraging that can yield significant growth slowdowns, including recessions.[1] A growing body of literature, focused almost exclusively on advanced economies (AEs), has produced empirical evidence to support such an interaction between economic and financial cycles at both the domestic and global levels. For example, this is supported by findings of significant informational content in credit aggregates and balance-sheet leverage indicators for future economic activity (Schularick and Taylor, 2012; Jordà *et al.*, 2013; IMF, 2017; Krishnamurthy and Muir, 2017; Adrian *et al.*, 2022). However, empirical support is far more tentative regarding the existence of such interaction between financial cycles and economic cycles in emerging market and developing economies (EMDEs).

In this paper, we empirically explore whether and how business and financial cycles interact with each other in EMDEs. Our sample of countries collectively accounts for almost 34 per cent of the world's gross domestic product (GDP) in nominal terms and 46 per cent in purchasing-power-parity (PPP) terms. We use quarterly, country-level, macro-financial data from 2000 to 2020 for our analysis. This period is marked by significant intertemporal variation in macro-financial conditions, including periods of financial stress, economic crises, credit booms and busts, and growth accelerations and slowdowns, both globally and locally in many of our sampled EMEs. In particular, we specify a multivariate, state-space model to evaluate the joint dynamics of business and financial cycles in 18 major EMDEs. Our empirical model is inspired by the *predator-prey* class of models often used in ecological studies on population dynamics.[2] Applied to the macro-finance domain, our model helps us in pinning down the bi-directional relationship between the real economy and the financial system as it also explicitly captures the dynamic interaction through feedback-loops (Blanchard, 2018; Claessens and Kose, 2018).

Additionally, we construct financial condition indices (FCIs) for these 18 EMDEs, com-

[1] Theoretical studies that analyze this interplay between macroeconomic cycles and financial stability include Mendoza (2002, 2010), Jeanne and Korinek (2010), Bianchi (2011), Brunnermeier and Sannikov (2014), Gorton and Ordonez (2014) and Bianchi and Mendoza (2018), among others.

[2] Refer to Paine (1980); Frost *et al.* (1995); Ives (1995); Tilman (1996); Ives *et al.* (1999, 2003); Hampton *et al.* (2013).

prehensively integrating information across a range of price-of-risk variables (spreads and changes in asset valuations and volatility); global trade and financial indicators (foreign exchange market pressure and terms-of-trade variables); and aggregates (leverage, credit growth and credit-to-GDP gap variables)[3]. This involves synthesizing information contained in contemporaneous and near-term forward-looking indicators of stress in domestic financial conditions; global and regional indicators of trade and capital flows related risk factors; and aggregate indicators that provide complementary signals on macro-financial vulnerability (Krishnamurthy and Li, 2020).

Furthermore, the last few decades have been witness to an increased level of trade and financial integration of EMDEs with the rest of the world (Obstfeld and Taylor, 2004; Bekaert *et al.*, 2011). While a high degree of financial integration is associated with a faster adjustment of asset prices to economic news which reduces mispricing and promotes better resource allocation, it can also facilitate the cross-market and cross-border transmission of shocks. The global financial cycle literature provides insights into the simultaneous movement of gross capital flows, credit growth, leverage, and risky asset prices (Obstfeld, 2015; Rey, 2016; Miranda-Agrippino and Rey, 2022). This phenomenon demonstrates commonalities among financial intermediaries globally, wherein increased leverage and credit expansion tend to occur concurrently across different geographical regions, including EMDEs (Claessens *et al.*, 2012; Shin, 2014). Given this context, we also analyze the global dimensions of macro-financial linkages in EMDEs by accounting for global financial cycle in our model.

Our results indicate that the relationship between domestic financial conditions and the real economy in EMDEs is driven by two opposing forces which we call *growth-enhancing effect* and a *growth-inhibiting effect*. In most of the EMDEs that we study, a loosening of financial conditions stimulates economic growth in the near-term, but a positive innovation in growth tends to tighten financial conditions in the immediate future, which in turn, leads to adverse growth outcomes (see Figure 1). In almost half of the EMDEs, both the first (growth-enhancing) effect and the second (growth-inhibiting) effect are statistically significant. The macro-financial dynamics implied by our findings are that while exogenous shocks that loosen financial conditions tend to stimulate growth in EMDEs, these virtuous dynamics tend to peter out quickly, since the pick-up in GDP growth quickly re-tightens financial conditions which then retard growth momentum.

In the literature exploring the interaction of growth and financial conditions in advanced economies, it is a common finding that the growth enhancing effect is statistically signif-

[3]See Barajas *et al.* (2021) and Arrigoni *et al.* (2022) for recent work on constructing financial conditions indexes.

icant and widely prevalent. However, the build-up of balance-sheet vulnerabilities in key sectors of the economy takes several quarters. In contrast, our findings for EMDEs show that, the growth-inhibiting effect unfolds faster, over a one-quarter ahead horizon. Our baseline results indicate that a one standard deviation (sd) loosening in the aggregate EMDE FCI leads to a $0.27sd$ increase in annual median GDP growth across EMDEs the next quarter, equivalent to an increase of 46 basis points (bps) in EMDE-median GDP growth. In turn, a one sd increase in EMDE-median GDP growth leads to a $0.35sd$ or $20bps$ tightening in EMDE financial conditions the next quarter. Hence, while an easing of financial conditions triggers a temporary acceleration of growth in EMEs, this acceleration can quickly sputter out due to a subsequent re-tightening of financial conditions.

What drives these dynamics in EMDEs? The existing literature studying the interaction of financial cycles and economic cycles embeds some important assumptions regarding the state of financial development and the depth of domestic credit and financial markets (Claessens and Köse, 2013; Sufi and Taylor, 2022). Specifically, that domestic credit supply responds flexibly to positive growth innovations, facilitating the easing of financial conditions for the prolonged period of time that is necessary for both sustained economic growth as well as the accumulation of balance-sheet vulnerabilities. Such degree of elasticity in domestic credit supply is indeed present in advanced economies. In EMDEs, however, financial markets may lack adequate depth and be subject to significantly greater informational and infrastructural frictions. Importantly, in some EMDEs, the growth-elasticity of credit supply to the private sector may be significantly inhibited by crowding out due to high levels of fiscal and external imbalances. For such EMDEs, it is more likely that while an easing of domestic financial conditions can trigger a growth acceleration, this induced higher economic momentum can sputter out quickly due to a tightening of aggregate credit constraints.

Similarly, in many prominent EMDEs, fiscal deficits are notably high, ranking among the highest within the G-20 nations. Some of these economies also face significant current account deficits often exacerbated by high energy import bills. Such imbalances necessitate substantial external financing to maintain domestic consumption. These twin deficits—*fiscal* and *current account*—render EMDEs vulnerable to financial crises, including *sudden stops*.[4] Several studies have explored the theoretical and empirical aspects behind such episodes from an open-economy perspective (Joyce and Nabar, 2009; Ko-

[4] *Sudden Stops* are often described as financial crises marked by large and sudden current-account reversals. Often preceded by rapid economic growth, large current-account deficits, credit booms, and highly overvalued asset prices, sudden stops have occurred in both developed and developing economies. Such episodes tend to result in deep and prolonged recessions, large fall in asset prices, and sharp depreciation of real exchange rates.

rinek and Mendoza, 2014; Eichengreen and Gupta, 2016).[5] Moreover, higher growth stimulates demand for private credit, which often competes with government borrowing due to elevated debt levels and external imbalances, resulting in a rapid tightening of financial conditions. The *crowding-out* nature of government borrowing programmes has also been extensively documented in the literature, with rising empirical evidence in its favour (Blanchard and Perotti, 2002; Blanchard, 2003; Furceri and Sousa, 2011; Afonso and Sousa, 2012; Agnello *et al.*, 2013).[6]

Applying a two-way sample split methodology, we compare the subsamples of countries which have large fiscal and capital account deficits to countries that show significant growth-enhancing and/or inhibiting effects. The results indicate that EMDEs facing *twin-deficit* problems are much more likely to demonstrate both growth-enhancing and growth-inhibiting effects that may undermine their macro-financial stability reflected in greater volatility of economic growth. Lending support to both the *sudden stop* and *crowding-out* literature, this suggests that high debt levels and external imbalances can exacerbate macro-financial instability and influence growth outcomes in these economies. Moreover, as Aguiar and Gopinath (2007) and Cerra and Saxena (2008) have highlighted, EMDEs show proclivity for highly volatile business cycle dynamics and often tend to suffer from permanent output losses due to financial crises. In line with these studies, our results show that macroeconomic vulnerabilities at the country-level may give rise to such bi-directional interaction between the financial system and real economy in EMDEs.

Our paper makes three key contributions to the extant literature on macro-financial dynamics overall. First, we propose a dynamic, multivariate model to analyze the complex two-way interactions between real and financial cycles in an economy. Furthermore, we incorporate global financial conditions as an exogenous covariate in our empirical model to account for its potential amplification role in the interaction between economic and financial cycles in the domestic economy. This allows us to make an integrated assessment of macro-financial linkages in an economy. Notably, while we employ our proposed model in an EMDE context, it can be flexibly extended to other country-specific or cross-country contexts. Second, we construct country-specific FCI to measure domestic financial conditions for each country in our EMDE sample. We also show that our preferred measure of domestic financial conditions tends to outperform other alternate FCIs

[5] Recent work includes Akıncı and Chahrour (2018); Bianchi and Mendoza (2020); Davis *et al.* (2023).

[6] *Crowding out* occurs when financial resources are diverted into government debt instruments, significantly limiting credit availability for the private sector, thereby inhibiting investments into economic development. This effect is exacerbated in less developed financial systems due to limited funding sources and greater reliance on the banking sector. Some recent studies include Funashima and Ohtsuka (2019), Liaqat (2019) and Park and Meng (2024), amongst others.

in predicting country-level GDP growth on average. This underlines the importance of accounting for informational content embedded in both financial stress and financial vulnerability indicators as done in this paper. Finally, our results on the prevalence of both growth-enhancing and growth-inhibiting effects provides a fresh perspective on the interaction between economic and financial cycles from a broader cross-country aspect. The relatively faster unfolding of balance sheet vulnerabilities and the potential role of twin deficits, together highlight the distinct mechanisms at work in influencing macro-financial dynamics in emerging economies. The remaining parts of the paper are structured as follows. In Section 2, we discuss our methodology beginning with a conceptual overview of our analytical framework followed by laying down the details of the state-space multivariate autoregressive (MAR) model employed in our paper. We explain our data, including the construction of country-level financial conditions indices, in Section 3. Thereafter, in Section 4, we discuss the main findings of our analysis derived from both the aggregate emerging economy (EM) level as well as at the individual country-level. The paper is concluded in Section 5.

2 Methodology

We begin our discussion by providing a concise conceptual overview of our analytical framework in this section. Next, we present the main empirical framework used in the paper. As we explain later in this section, our choice of empirical model is motivated by the plausible bi-directional, dynamic interaction due to feedback between financial conditions and output growth in EMDEs. More importantly, the empirical model is also designed to capture possible *feedback loops* that govern the dynamic interaction between the financial system and the overall economy over time. Thus, our empirical framework allows us to uncover newer insights and possible mechanisms that are at play in the finance-growth interplay in emerging economies.

2.1 Conceptual Framework

From an analytical standpoint, we aim to capture the dynamic interactions between financial conditions and growth as well as understand how balance-sheet vulnerabilities in certain economic sectors of EMDEs can impact the nature and persistence of macro-financial transmission of exogenous shocks in these countries.

Consider a positive exogenous shock, say, a reduction in US monetary policy rates, which eases financial conditions globally, including domestically in our sample of EMDEs. This would lead to increased lending and risk-taking in the economy that boost economic activity and growth in the near-term. This is the growth-enhancing effect or phase of the macro-financial cyclical interaction.

Rapid and sustained credit expansion during such periods of loose financial conditions would lead to a building up of balance-sheet vulnerabilities in the economy that eventually can serve to amplify the growth and financial stability impact of adverse exogenous shock down the road, like a US monetary policy tightening. This could significantly increase the overall risk sentiment in the economy with financial markets and banks less willing to extend credit to households and businesses, firms cutting back on investments and the ensuing job losses triggering a growth slowdown. This is the growth-inhibiting effect or phase of the macro-financial cyclical interaction. Figure 1 presents a summary of our framework that captures the macro-financial interactions in an emerging market setting characterized by two distinct forces - the growth-enhancing effect and the growth-inhibiting effect.

The length of time over which the growth-enhancing phase operates in EMDEs may depend on two factors. First, domestic financial markets and savings intermediation capacity is shallower in these countries relative to AEs, and this may bind more tightly the elasticities of supply of credit and market liquidity available to meet higher credit demand responding to the positive growth impulse provided by easing financial conditions. Second, incumbent balance-sheet vulnerabilities in key sectors of the economy, such as high existing sovereign indebtedness and large current account deficits requiring financing through significant overseas borrowing may absorb the limited quantity of additional cheaper financing released by the easing of financial conditions. This can crowd-out growth friendly investments by the private sector. Empirically, these factors raise the possibility that the growth-enhancing effect may be shorter in EMDEs and that it may yield to growth-inhibiting dynamics relatively quickly in those EMDEs which have high fiscal or current account deficits or both.

During periods of high economic growth, the growth-enhancing effect is characterized by an increase in credit demand. Empirical evidence suggests that credit booms generally start during or after periods of buoyant economic growth (Dell'Ariccia *et al.*, 2012; Dell'Ariccia and Marquez, 2013). For instance, Dell'Ariccia *et al.* (2012) find that lagged GDP growth is positively associated with the probability of a credit boom. In the three years preceding a boom, the average real GDP growth rate reaches 5.1 per cent, compared to 3.4 per cent during a tranquil three-year period. When balance-sheet vulnerabilities grow beyond a critical level during a credit boom, the macro-financial impact of adverse exogenous shocks can be amplified thereby triggering the initiation of the growth-inhibiting effect. During such a period, inflationary pressures may also start to build up as higher demand for goods and services outstrips supply. To combat inflation, central banks frequently tighten monetary policy by raising interest rates, which increases the cost of borrowing, and further contributes to the tightening of financial conditions.

The rich, existing literature has emphasized a number of factors and channels as potentially important across both AEs and EMDEs in propelling the growth of balance-sheet and financial market vulnerabilities that can in combination or by themselves contribute to the end of the growth-enhancing effect and initiation of the growth-inhibiting effect.

One factor is asset price inflation. When the economy grows rapidly, asset prices, such as real estate or equity valuations, can get inflated. This rapid rise in asset prices has the potential to create a wealth effect, making households and firms more inclined to spend, invest and hire. However, when asset prices become inflated and disconnected from their underlying fundamentals, risks and financial imbalances arise. If a negative shock hits the economy, it can lead to tighter financial conditions overnight. Both advanced economies and emerging markets have seen exorbitant surges in asset prices followed by long periods of financial instability. See Evanoff *et al.* (2012) and Scherbina (2013) for detailed reviews on asset price bubbles.

A second factor is that pro-cyclical nature of lending and risk-taking by financial intermediaries can also impact the macro-financial linkages in an economy. *Herd behaviour* by financial institutions may also be responsible (Rajan, 1994), wherein banks tend to mimic each other's lending practices driven by short-term concerns, such as earnings and reputation. Such decisions are often marked by an overconfidence in being able to outperform peers even if the credit cycle experiences a downturn. As a result, such banks loosen their credit standards to make loans available more freely and for longer durations. Relaxing their credit covenants encourages pro-cyclical behaviour. Financial institutions also suffer from *cognitive* biases. For instance, financial institutions may experience *disaster myopia* or the tendency to underestimate the likelihood of extremely unlikely but high-cost, tail-risk events (Guttentag and Herring, 1984). Because of such cognitive biases, financial institutions tend to process information in a way that supports their preconceived notions about the state of the economy. The pro-cyclicality of loan growth and risk-taking is further exacerbated, according to the *institutional memory* hypothesis, which states that banks have a short memory when it comes to past credit booms. Managers' focus on short-term profits causes them to take more risks when the credit market is booming, contributing to the principal-agent problem between shareholders and managers (Williamson, 1963; Saunders *et al.*, 1990).

A third aspect is external factors that may also have an impact on the interaction between growth and financial conditions in EMDEs. Capital inflows into emerging economies tend to ease credit constraints for corporations and households as it increases the funds available to banks operating in the local economy (Claessens *et al.*, 2010a,b). Thus, capital inflows ease local financial conditions and support economic growth. However, in such economies, fluctuations in capital flows can generate significant volatility in domestic economy. In the event of a substantial, and often unexpected decline in international net capital flows – sudden stop – domestic financial conditions can undergo rapid tightening which may trigger a crisis (Joyce and Nabar, 2009; Korinek and Mendoza, 2014; Akıncı and Chahrour, 2018; Bianchi and Mendoza, 2018; Davis *et al.*, 2023). Such crises are usually accompanied by a significant increase in credit risk spreads (interest rate differentials), negative asset returns, high volatility often resulting in deep and prolonged recessions. The impact of such crisis episodes is amplified in countries with high current account deficits (Eichengreen and Gupta, 2016).

Finally, domestic fiscal imbalances also tend to influence macro-financial interactions in emerging economies. Theoretically, on the one hand, an increase in government spending can *crowd-in* the private sector by inducing an increase in the expected rate of return on capital that triggers a rise in investments (Aiyagari *et al.*, 1992; Christiano and Eichenbaum, 1992; Baxter and King, 1993). On the other hand, higher government spending if financed by debt, can *crowd-out* private sector by causing an increase in interest rates leading to lower investments (Blanchard and Perotti, 2002; Blanchard, 2003). Most empirical evidence now favours the *crowding-out* effect of government spending programmes (Furceri and Sousa, 2011; Afonso and Sousa, 2012; Funashima and Ohtsuka, 2019; Liaqat, 2019; Park and Meng, 2024). We now turn our attention to the empirical model used in this paper.

2.2 Econometric Model

As discussed in the previous section, there are various complexities involved in analyzing the macro-financial landscape in emerging economies. The relationship between growth and financial conditions not only showcases a bi-directional relationship but also evolves overtime by incorporating feedback loops. The selected model should, therefore, be able to capture this dynamic interaction between financial conditions and growth. To this end, we specify a multivariate autoregressive (MAR) model that is inspired by models of population dynamics – *predator-prey* models – rooted in ecological studies (Paine, 1980; Frost *et al.*, 1995; Ives, 1995; Tilman, 1996; Ives *et al.*, 1999, 2003; Hampton *et al.*, 2013). Our baseline empirical model is specified by Equation 1 and Equation 2 given below:

$$y_t = Zx_t + a + v_t;\ v_t \ \epsilon \ MVN(0, R) \tag{1}$$

$$x_t = Bx_t + u + w_t;\ w_t \ \epsilon \ MVN(0, Q) \tag{2}$$

Under the state-space representation, Equation 1 is the observation equation where v_t represents the observation error and R denotes the covariance structure of the observation error. y_t is an $n \times 1$ matrix of input variables, Z is an $n \times m$ matrix of factor loadings and a is an $n \times 1$ matrix with offset terms. Therefore, note that observed time-series data on financial conditions and output growth are represented by y_t in our case. Equation 2 represents the process equation with w_t denoting the process error and Q as the covariance structure of process error. The model has a stochastic equilibrium – it fluctuates around a mean given by $(I - B)^{-1} \cdot u$. Typically, we have one time series per species and that translates to $m = n$. Equation 2 in our specification is similar to what Ives *et al.* (2003) have written in their process equation and the state-space representation is scale-invariant, where u is the scaling term.

In the state-space model specified above, the process equation captures the dynamic interaction between financial conditions and growth over time. A matrix form representation of the process model for the finance-growth dynamics is provided in Equation 3 below:

$$\begin{bmatrix} x_f \\ x_g \end{bmatrix}_t = \begin{bmatrix} b_{ff} & b_{gf} \\ b_{fg} & b_{gg} \end{bmatrix} \begin{bmatrix} x_f \\ x_g \end{bmatrix}_{t-1} + \begin{bmatrix} u_f \\ u_g \end{bmatrix} + \begin{bmatrix} w_f \\ w_g \end{bmatrix}_t \tag{3}$$

$$\begin{bmatrix} w_f \\ w_g \end{bmatrix} \epsilon \ MVN(0, \begin{bmatrix} q_f & 0 \\ 0 & q_g \end{bmatrix}) \tag{4}$$

B is the interaction matrix in the process model that is to be estimated where B_{ij} is the effect of variable i on variable j. In this case, f denotes *financial conditions* and g corresponds to *output growth* in the economy. The self-interaction strengths (density-dependence) are shown by the diagonal elements while cross-interactions are represented by the off-diagonal terms of the B matrix. Thus, b_{ff} is the effect of financial conditions on itself (density-dependence), b_{fg} is the effect of a financial conditions on growth (*growth-inhibiting effect*), similarly, b_{gf} is the effect of growth on financial condition (*growth-enhancing effect*) and finally b_{gg} is the effect of output growth on itself.

According to Rey (2016) and Miranda-Agrippino and Rey (2022), the global financial cycle (GFC) also significantly influences capital flows, credit expansion, leverage, and asset prices, especially in emerging economies. Therefore, as a final step, we augment our MAR model by adding a covariate in the process equation of the model. The state-space model with covariates can be represented as follows:

$$y_t = Zx_t + u + w_t;\ \ w_t \ \epsilon \ MVN(0, Q) \tag{5}$$

$$x_t = Bx_t + Cc_t + w_t;\ \ w_t \ \epsilon \ MVN(0, Q) \tag{6}$$

$$\begin{bmatrix} x_f \\ x_g \end{bmatrix}_t = B \begin{bmatrix} x_f \\ x_g \end{bmatrix}_{t-1} + \begin{bmatrix} C_{ff} \\ C_{fg} \end{bmatrix} [GFC] + \begin{bmatrix} w_f \\ w_g \end{bmatrix}_t \tag{7}$$

C_{ff} and C_{fg} terms capture the effects of amplifying effects of GFC on the *finance-growth* interaction in the model. The above model is estimated using the maximum likelihood (ML) technique.

3 Data

This section provides an overview of the data, including the country and time sample utilized for our analysis. In particular, we discuss the construction of the financial conditions index (FCI) for various EMEs covered in our study. We begin this section by briefly laying down the concept behind the measurement of financial conditions. This is followed by detailing the data sample and variables used. We then discuss the dynamic factor model (DFM) framework used for constructing FCI at the economy-level and aggregate EMDE-level. Thereafter, we present and analyze the aggregate emerging market and developing economies' financial conditions index (EM-FCI) to conclude the section.

3.1 Data and Sample

Our sample of EMDEs include Argentina, Brazil, Chile, China, Colombia, Czech Republic, India, Indonesia, South Korea, Malaysia, Mexico, Philippines, Poland, Russia, Slovakia, South Africa, Thailand and Turkey.[7] We construct a quarterly, cross-

[7]These economies are commonly included in prominent equity and debt indices for emerging markets, such as those provided by J.P. Morgan, Morgan Stanley Capital International, and Bloomberg. Moreover, they are also keenly tracked by international organizations, such as the IMF and World Bank. Nigeria was excluded due to its classification as a low-income country during the sample period, and Qatar was excluded based on its population size.

country dataset consisting of various macro-financial indicators using data sourced from Bloomberg LLP, NYU V-lab, Bank for International Settlements (BIS), and International Monetary Fund's International Financial Statistics (IMF-IFS). The quarterly dataset spans the 2000:Q1 - 2019:Q4 period. Our empirical model uses year-on-year growth in real GDP (%) as a measure of output growth. We construct country-specific FCI to capture domestic financial conditions for our sample of EMDEs. Data on global financial cycle is taken from Miranda-Agrippino and Rey (2022). The concept and construction of country-specific FCI is detailed below.

3.2 Financial conditions Index

3.2.1 Concept

Measuring the prevailing financial conditions in an economy can enable a deeper understanding of the health of its financial system. In a shock-free environment, financial risks tend to accumulate gradually, more often, providing minimal signals of such buildup. In such a case, financial vulnerabilities can silently spread within the financial system escaping routine surveillance. However, in the event of an adverse shock impacting the economy, such vulnerabilities amplify the consequent financial stress arising out of the shock. Therefore, financial *stress* and *vulnerabilities* are crucial for understanding how the health of the financial system as well as the economy evolves over time. Importantly, the negative effects of future shocks can be reduced and financial system resilience can be maximized by effectively combining information on stress and vulnerabilities to provide a comprehensive, forward-looking measure of financial conditions in an economy.

Following Krishnamurthy and Muir (2017), we categorize financial indicators into two types: fast-moving stress indicators (for e.g., asset prices) that generally signal an impending shock and slow-moving vulnerability indicators (for e.g., debt-to-GDP ratio) reflecting the gradual buildup of risk in the system. Taken together, these indicators capture the evolving dynamics of financial conditions. Since stress and vulnerabilities can arise from any sector of the economy, it is also useful to analyze sector-specific indicators as a block. Thus, we divide our indicators into various sectoral blocks *viz.,* the *banking*, *fiscal, real Sector* and the *external trade and finance* block. These blocks may directly or indirectly impact financial conditions in the economy. Figure 2 summarizes our conceptual mapping of a financial conditions index impacted by various measures of financial stress and vulnerabilities emanating from different sectors of the economy.

Indicators that measure financial stress provide insights into the impact of the shock as reflected by the system. One such measure is *domestic price of risk (DPOR)* which includes interest rate spreads relevant for key business and government sectors as well as returns and volatility across different asset classes. An increase in financial stress is often reflected in rising rate spreads, falling asset returns and higher volatility. Similarly, external risk factors circumscribing global financing conditions, terms-of-trade and commodity prices can also impact domestic financial conditions. External indicators, such as an increase in implied options price volatility on the domestic currency (against US dollar) and exchange rate market pressure signal tighter domestic financial conditions. Finally, macroeconomic indicators that capture economy activity, real estate prices etc., also provide important signals related to the overall stress in the financial system. On the other hand, the level and duration of adverse impact from shocks to the financial system can be determined by the balance sheet vulnerabilities of key stakeholders, such as financial institutions and sovereign government. Such indicators encompassing aggregate balance sheet metrics, like private sector leverage, credit-to-GDP gap, fiscal balance, and government debt, tend to exhibit gradual but potentially more informative signals about the health of the financial system over a longer time horizon.

3.2.2 Input variables

To capture stock market performance, we use the variable *EqReturn* which represents the returns of large-cap companies in each country. Furthermore, the Bloomberg-sourced *EqVol30* variable, measuring the average 30-day volatility of large-cap listed companies, underlines equity market stability. Similarly, systemic risk, *SriskUT,* represents the market capitalization weighted-average systemic risk for the banking sector. Obtained from NYU's V-Lab, it aids in assessing the overall stability and vulnerability of the banking system in the emerging economies under consideration.[8] Reflecting the corporate sector prime lending rate, *PLR* provides information on the interest rate environment and credit cycle across countries. Reflecting market sentiments and expectations, *OptionVol3m* is measured as the implied volatility of USD to emerging markets currencies.

Term Spread measured as the difference in yields between long-term government bonds and short-term treasury bills provides insights into monetary policy stance and information about future growth. Similarly, *Corporate Spread,* measured as the difference between CEMBI corporate bond yields and short-term treasury bill yields, sheds light on the corporate bond market's credit risk premium. *Interbank Spread*, taken as the difference between the 3-month interbank lending rate and the short-term treasury bill yield proxies for interbank liquidity and financial market stability.

Taking credit conditions into account, the variable *Credit* represents outstanding credit

[8]See Acharya *et al.* (2017); Brownlees and Engle (2017).

to private non-financial sector allowing us to assess credit growth and financial intermediation in each country. Exchange market pressure index or *EMPI*, captures total pressure on the exchange rate that has been *resisted* through forex intervention or *relieved* through exchange rate movements (Girton and Roper, 1977; Eichengreen *et al.*, 1996; Levy-Yeyati and Sturzenegger, 2005). We also include key fiscal indicators in our analysis. The variable *Debt-to-GDP*, measured by taking gross government debt as a percentage of domestic GDP, represents long-term viability of public finances. Similarly, *Primary Balance* reflecting the government's fiscal position (excluding interest payments) aids in assessing the short-term fiscal stance of the sovereign.[9] Finally, variables related to the real estate market and economic activity are also included in this study. *Real-estate prices,* which includes both residential and commercial property prices, represents the trends and dynamics of a country's real estate sector. Finally, we use *Industrial Production*, sourced from the IMF database, as an indicator of economic activity in the economy. Details on the number of countries, variables used and data sources for constructing the country-wise financial conditions are summarised in Table 2.

3.2.3 Index construction

We now turn to the DFM framework that is used to combine various stress and vulnerability indicators into a single, composite measure of financial conditions at the country-level. Following the important contribution of Giannone *et al.* (2008), we assume that each observable variable $z_{i,t}$ in our dataset can be divided into two orthogonal components: an unobserved *common* component $f_{r,t}$, which represents a linear combination of a few common factors, and an *idiosyncratic* component $\varepsilon_{i,t}$, that is unique to each observed time-series. The common component follows an autoregressive process of order 1 *i.e.,* an AR(1) process. Thus, the empirical model can be represented in a matrix-form using Equation 8 and Equation 9 as follows:

$$Z_t = \Gamma \ F_t + \xi_t \tag{8}$$

$$F_t = A \ F_{t-1} + B\upsilon_t \tag{9}$$

[9] Fiscal balance, also referred to as net lending (+) or net borrowing (-) of general government, is calculated as total government revenues minus total government expenditures. The primary balance excludes interest payments from expenditure, thereby reflecting the difference between the amount of revenue a government collects and the amount it spends on providing public goods and services. A country has a primary deficit if it is spending more on public goods and services than it collects in taxes. The primary balance is thus a critical indicator of the short-term sustainability of a government's finances. We consider primary balance as a share of domestic GDP.

where Z_t is a vector of stationary observed variables driven by a vector of unobserved dynamic factor F_t in a linear combination determined by the loading vector Γ. Series-specific idiosyncratic component is captured by vector ξ_t while υ_t represents shocks to the dynamic common component. The above model is estimated for each country in our data sample to construct a country-specific FCI. Details on the DFM method and its estimation using the Kalman filter approach are discussed in Appendix A.

Subsequently, an aggregate EMDE-level FCI (EMFCI) is computed using the median-value of the country-level FCIs. Figure 3 examines the median and the 5^{th} - 95^{th} quantiles derived from the cross-country FCI values. The solid line representing the *median*-EMFCI offers a central measure of financial conditions across all EMDEs considered in our sample. This underlines the overall financial health and stability of these economies. On the other hand, the dashed lines around the median illustrate the *lower* and *upper* bounds of the cross-country financial conditions. This enables us to assess the dispersion and tail risks associated with domestic financial conditions in our EMDE sample. Periods of heightened financial stress and potential systemic vulnerabilities, such as the Great Financial Crisis of 2008-09, Eurozone debt crisis of 2011-12, currency devaluation in China during 2015-16 and the recent Covid-19 pandemic period, are well captured by our measure of financial conditions in EMEs. As a robustness exercise, we compare our constructed measure of FCI against alternate specifications in terms of its ability to predict GDP growth in an out-of-sample forecasting framework (see Appendix B). The results indicate that our preferred measure of FCI – encompassing both financial stress and vulnerabilities – generally outperforms other alternate FCIs at the country-level thereby underlining its suitability for our study.

4 Results and Discussion

The presentation of the main findings from our analysis of the dynamic interplay between financial conditions and growth in EMDEs is divided into three parts. Throughout this section, our main focus remains on the interaction matrix B and its elements denoted by B_{ij}.

In the first part, we discuss the results derived from our state-space MAR model in both, the benchmark model that does not explicitly account for the impact of global financial conditions and the augmented model with inclusion of this exogenous covariate. Since this is achieved by aggregating country-level indicators to the EMDE-level grouping, we show that these results are robust to different aggregation methods. We also analyze the finance-growth relationship across different growth quantiles that allows us to assess the strength and direction of this relationship during both tranquil times and tail-risk events.

The second part of this section focuses on country-level analysis wherein we estimate our model separately for each country in our sample. This exercise throws light on the presence of growth-enhancing and growth-inhibiting effects, helping us determine which of these effects is present and statistically significant across different countries.

Finally, in the third part, we investigate whether the presence of certain economic features or imbalances predisposes a given emerging market economy to one or both of these effects. This analysis helps us delve deeper into the possible mechanisms that drive the macro-financial relationship in EMDEs.

4.1 Regional Analysis

The coefficients for the estimated interaction matrix of the state-space MAR model with and without covariates are shown in Table 3. As mentioned earlier, we carry out this exercise at the aggregate EMDE-level by using the median value of the country-level FCIs and median GDP growth for all EMDEs in our sample represented by EMFCI and EMGDP, respectively. Shown in panel 1, Table 3), our baseline estimates indicate that a one standard deviation (sd) easing in EMFCI leads to a $0.27sd$ increase in EMGDP growth the next quarter, equivalent to a 46 basis points (bps) increase in GDP growth. This underlines the *growth-enhancing* channel at work. On the other hand, a one sd increase in EMGDP growth leads to a $0.35sd$ increase in EMFCI the next quarter, equivalent to a 20bps tightening of EMFCI, which is the *growth-inhibiting* effect in operation.

As shown in panels (2)-(3), the estimated coefficients are similar *albeit* marginally lower when we account for the role of the global financial cycle in our model. Note that model diagnostics, reported alongside the estimated coefficients, indicate a better fit in case of the model with this covariate. Nevertheless, our results, both with and without the global financial conditions covariate are statistically significant.

These results provide evidence for the presence of both *growth-enhancing* and *growth-inhibiting* phases in the macro-financial landscape of EMDEs. The implied dynamic interaction of an exogenous shock that eases EMDE financial conditions in a given quarter is a short-lived, positive spurt in EMDE economic growth, which for the median EMDE, quickly sputters out as the increase in EMGDP would in turn re-tighten EMFCI the next quarter.

To account for the fact that our data sample contains economies of significantly different sizes and complexity, we further examine whether our baseline results are robust to alternate measures of *average* EMDE GDP growth. We accomplish this by replacing the median GDP growth by a simple average measure and two weighted average measures based on weights derived from the World Bank (WB) and the IMF. The results are shown in Table 4. Overall, the results were found to be qualitatively similar to those from our benchmark specification except that the coefficients in case of the weighted average measure with WB weights were less precisely estimated (see panel 3, Table 4).

Finally, we also assess whether the *growth-enhancing* and *growth-inhibiting* effects were more (or less) prominent across different parts of the output growth distribution. To do so, we compute different quantiles of GDP growth at the EM-level and estimate our model seperately for each growth quantile. The results are shown in Table 5. As our results indicate, the estimated magnitude and significance of both B_{gf} and B_{fg} are stable in the bottom half of the growth distribution. However, both coefficients become smaller as we move towards the right-tail of the distribution with B_{fg} being statistically insignificant in the two top quantiles of the distribution. This indicates that the strength of both *growth-enhancing* and *growth-inhibiting* effects often varies across the growth distribution. Whether this is due to strong growth performance being associated systematically with greater prevalence of healthier fiscal and balance-of-payments indicators is an interesting question left for future work.

4.2 Country-level Analysis

The results and interpretation discussed above are based on an implicit assumption that business cycles and financial cycles are highly synchronized across our sample of emerging economies. However, given the evident heterogeneity in our country sample, it is of interest to assess the robustness of these aggregate results against the estimated joint dynamics of growth and financial conditions at the country-level. While replacing the median-annual GDP growth (EMGDP) with the simple (or weighted) average growth or growth quantiles provides some confidence, a granular analysis based on the country-level application of our empirical model is warranted to further understand how the finance-growth interaction evolves in different country settings.

Table 6 reports a summary of results based on the estimated joint dynamics of domestic financial conditions and domestic output growth over 2000-2020 for each country in our sample of EMDEs. For 15 of the total 18 EMDEs, an easing of domestic financial conditions is associated with an expansion in annual GDP growth the next quarter, wherein this association was found to be statistically significant in 11 economies. On the other hand, in 14 countries, an increase in real GDP growth is associated with a tightening of financial conditions over the next quarter with the relation being statistically significant in 8 countries. Interestingly, shocks to global financial conditions appear to influence near-term growth prospects in these countries more systematically than their domestic financial conditions. The direction of association between global financial conditions and domestic financial conditions and growth were along expected lines in majority of our sample countries i.e., a tightening in global financial conditions is associated with tighter domestic financial conditions and lower real GDP growth in the near future. Overall, these results suggest that the estimated dynamics of FCI and GDP growth as seen in the benchmark model also hold true at the domestic level for a majority of countries in our sample.

4.3 Macro-imbalances and Finance-Growth Interdependence

In the final part of our analysis, we delve deeper into the potential mechanisms that may be determining the macro-financial interaction at a country-level. Thus, it is of interest to leverage our country-level analysis to ask whether certain economic features or imbalances are associated with the existence and strength of the growth-inhibiting effect and a growth-enhancing effect. The first channel, which involves positive growth impact induced by easing of financial conditions, is dominant across EMDEs, displaying the correct sign in 15 out of 18 countries, excluding China, Russia, and Thailand. Conversely, the second channel, characterized by growth spurts leading financial tightening, exhibits a mixed picture, with approximately 60 percent of countries in our sample reporting it. Since this latter, growth-inhibiting effect is significant in around half of our country sample, our focus is on identifying differences in macroeconomic indicators associated with growth-driven effects within a country context.

To facilitate such an assessment, we focus on two types of aggregate macroeconomic balances − fiscal balance and current account balance − deemed important from an EMDE perspective. In many prominent EMDEs, fiscal deficits are notably high, ranking among the highest within the G-20 nations. Some of these economies also face significant current account deficits often exacerbated by high energy import bills. Such imbalances necessitate substantial external financing to maintain domestic consumption. These "twin deficits"—fiscal and current account—render EMDEs vulnerable to "sudden stops". Factors such as deteriorating government or corporate balance sheets, inflation spikes, monetary tightening in advanced economies, and global risk aversion can trigger foreign investment withdrawals from EMDEs, undermining their macro-financial stability.

Therefore, our general approach is to split the sample according to whether a country's fiscal and current account performance are both stronger than the median EM over the sampling horizon (see Figure 6). This subsample of above-median performers – Group B – contains four countries namely, China, Indonesia, Russia, and South Korea. On an average, this set of countries consistently exhibits lower levels of sovereign debt coupled with current account surpluses compared to Group A (7 countries) which run consistent twin deficits as a group.[10] Upon splitting the countries into these two groups and analyzing them separately, the Group A bloc of below median fiscal and trade performing EMDEs consistently shows the growth-inhibiting effect with both correct sign and statistically significant coefficient values. Conversely, the Group B bloc of above median performing EMDEs fails to demonstrate the growth-inhibiting effect. The presence of a twin deficit in Group A countries makes them particularly susceptible to both effects—growth-inhibiting and growth-enhancing.

While the discussion above focused on using the fiscal and current account balances to split the countries into two groups, we examine this issue from the perspective of finance-growth relation in a given country. In other words, we examine our sample of countries on the basis of significant presence of two key effects at the country-level: (i) growth-inhibiting effect, and (ii) growth-enhancing effect. Specifically, Group A comprises countries experiencing both effects, while Group B exhibits only the growth-enhancing effect. Comparing Group A and Group B reveals that Group A countries, on average, possess higher sovereign debt levels and weaker current account balances than Group B countries (see Figure 7). This further confirms that Group A countries are particularly vulnerable to macro-financial imbalances due to the twin-deficit challenges. The key takeaway from this two-way split analysis is that higher growth creates a demand for private credit, which starts competing with government demand for funds due to an already high level of sovereign debt and external imbalances, leading to a rapid tightening of financial conditions which consequently – lowers future GDP growth in emerging economies with twin deficit.

5 Conclusion

In summary, our research makes significant contributions to the literature in several ways. We employ a state-space MAR model to capture the nuanced macro-financial interactions in EMDEs characterized by diverse business cycle properties. Unlike conventional time-series approaches, the MAR model disentangles both the growth-inhibiting and growth-enhancing effects, offering a more comprehensive understanding of how financial

[10] Brazil, Colombia, India, Mexico, Slovakia, Turkey, Poland.

conditions impact economic performance. Applying a two-way sample split methodology, we find evidence of the growth-inhibiting effect in EMDEs characterized by high government debt and large current account deficits. The results from this analysis suggest that emerging markets facing *twin-deficit* problems – are much more likely to demonstrate both effects undermining their macro-financial stability.

Two key model innovations help us ascertain the desired results. First, it is important to control global economic conditions while looking at the dynamic interaction between the financial system and the real economy in EMDEs. The global financial cycle (GFC) demonstrates commonalities among financial intermediaries globally, wherein increased leverage and credit expansion tend to occur concurrently across different geographical regions, including EMDEs. Our model incorporates this phenomenon by adding exogenous variables to the model that influence the finance-growth interaction within the economy. These variables have the potential to amplify the dynamics of the finance-growth relationship, shedding light on the complexities of the interactions between financial conditions and economic growth. Second, the comprehensive incorporation of information into the estimation of local financial conditions within EMDEs becomes crucial for accurately capturing the dynamics of the system. This involves not only assessing contemporaneous risk spreads and asset price volatility but also integrating information that indicates vulnerability in the system. The distinctive features of business cycles in emerging markets, such as high consumption volatility relative to income volatility and susceptibility to dramatic sudden stops in capital inflows, distinguish them from advanced economies.

Looking forward, our study highlights the need for continued research to deepen our understanding of how global interconnectedness and domestic macroeconomic conditions shape economic trajectories in EMDEs. As these economies increasingly integrate into the global economy through trade and financial channels, the ability to anticipate and manage financial cycles becomes crucial for such countries. Future research could explore additional factors influencing macro-financial dynamics such as demography, technology, and climate change to provide a deeper understanding of resilience and growth prospects of emerging economies.

References

Acharya VV, Pedersen LH, Philippon T, Richardson M (2017). "Measuring systemic risk." *The review of financial studies*, **30**(1), 2–47.

Adrian T, Grinberg F, Liang N, Malik S, Yu J (2022). "The term structure of growth-at-risk." *American Economic Journal: Macroeconomics*, **14**(3), 283–323.

Afonso A, Sousa RM (2012). "The macroeconomic effects of fiscal policy." *Applied Economics*, **44**(34), 4439–4454.

Agnello L, Furceri D, Sousa RM (2013). "How best to measure discretionary fiscal policy? Assessing its impact on private spending." *Economic Modelling*, **34**, 15–24.

Aguiar M, Gopinath G (2007). "Emerging market business cycles: The cycle is the trend." *Journal of political Economy*, **115**(1), 69–102.

Aiyagari SR, Christiano LJ, Eichenbaum M (1992). "The output, employment, and interest rate effects of government consumption." *Journal of Monetary Economics*, **30**(1), 73–86.

Akıncı Ö, Chahrour R (2018). "Good news is bad news: Leverage cycles and sudden stops." *Journal of International Economics*, **114**, 362–375.

Arrigoni S, Bobasu A, Venditti F (2022). "Measuring financial conditions using equal weights combination." *IMF Economic Review*, **70**(4), 668.

Barajas A, Choi WG, Gan KZ, Guérin P, Mann S, Wang M, Xu Y (2021). "Loose financial conditions, rising leverage, and risks to macro-financial stability." *IMF Working Paper 2021/222*, International Monetary Fund.

Baxter M, King RG (1993). "Fiscal policy in general equilibrium." *The American Economic Review*, pp. 315–334.

Bekaert G, Harvey CR, Lundblad CT, Siegel S (2011). "What segments equity markets?" *The Review of Financial Studies*, **24**(12), 3841–3890.

Bianchi J (2011). "Overborrowing and systemic externalities in the business cycle." *American Economic Review*, **101**(7), 3400–3426.

Bianchi J, Mendoza EG (2018). "Optimal time-consistent macroprudential policy." *Journal of Political Economy*, **126**(2), 588–634.

Bianchi J, Mendoza EG (2020). "A fisherian approach to financial crises: Lessons from the sudden stops literature." *Review of Economic Dynamics*, **37**, S254–S283.

Blanchard O (2003). *Macroeconomics*. Prentice Hall, 3rd edition.

Blanchard O (2018). "Distortions in macroeconomics." *NBER Macroeconomics Annual*, **32**(1), 547–554.

Blanchard O, Perotti R (2002). "An empirical characterization of the dynamic effects of changes in government spending and taxes on output." *the Quarterly Journal of economics*, **117**(4), 1329–1368.

Brownlees C, Engle RF (2017). "SRISK: A conditional capital shortfall measure of systemic risk." *The Review of Financial Studies*, **30**(1), 48–79.

Brunnermeier MK, Sannikov Y (2014). "A macroeconomic model with a financial sector." *American Economic Review*, **104**(2), 379–421.

Cerra V, Saxena SC (2008). "Growth dynamics: the myth of economic recovery." *American Economic Review*, **98**(1), 439–457.

Christiano LJ, Eichenbaum M (1992). "Current real-business-cycle theories and aggregate labor-market fluctuations." *The American Economic Review*, pp. 430–450.

Claessens S, Dell'Ariccia G, Igan D, Laeven L (2010a). "Cross-country experiences and policy implications from the global financial crisis." *Economic policy*, **25**(62), 267–293.

Claessens S, Köse MA (2013). "FINANCIAL CRISES: REVIEW AND EVIDENCE." *Central Bank Review*, **13**(3).

Claessens S, Kose MA (2018). "Frontiers of macrofinancial linkages." *BIS Paper*, (95).

Claessens S, Kose MA, Terrones ME (2010b). "The global financial crisis: How similar? How different? How costly?" *Journal of Asian Economics*, **21**(3), 247–264.

Claessens S, Kose MA, Terrones ME (2012). "How do business and financial cycles interact?" *Journal of International economics*, **87**(1), 178–190.

Davis JS, Devereux MB, Yu C (2023). "Sudden stops and optimal foreign exchange intervention." *Journal of International Economics*, **141**, 103728.

Dell'Ariccia G, Igan D, Laeven L, Tong H, Bakker B, Vandenbussche J (2012). "Policies for macrofinancial stability: How to deal with credit booms." *IMF Staff discussion note*, **12**(06).

Dell'Ariccia G, Marquez R (2013). "Interest rates and the bank risk-taking channel." *Annu. Rev. Financ. Econ.*, **5**(1), 123–141.

Doz C, Giannone D, Reichlin L (2011). "A two-step estimator for large approximate dynamic factor models based on Kalman filtering." *Journal of Econometrics*, **164**(1), 188–205.

Eichengreen B, Gupta P (2016). "Managing sudden stops." *World Bank Policy Research Working Paper*, (7639).

Eichengreen B, Rose A, Wyplosz C (1996). "Contagious Currency Crises: First Tests." *The Scandinavian Journal of Economics*, pp. 463–484.

Evanoff DD, Kaufman GG, Malliaris AG (2012). *New perspectives on asset price bubbles*. Oxford University Press.

Forni M, Hallin M, Lippi M, Reichlin L (2000). "The generalized dynamic-factor model: Identification and estimation." *Review of Economics and statistics*, **82**(4), 540–554.

Frost TM, Carpenter SR, Ives AR, Kratz TK (1995). "Species compensation and complementarity in ecosystem function." In "Linking species & ecosystems," pp. 224–239. Springer.

Funashima Y, Ohtsuka Y (2019). "Spatial crowding-out and crowding-in effects of government spending on the private sector in Japan." *Regional Science and Urban Economics*, **75**, 35–48.

Furceri D, Sousa RM (2011). "The impact of government spending on the private sector: Crowding-out versus crowding-in effects." *Kyklos*, **64**(4), 516–533.

Giannone D, Reichlin L, Small D (2008). "Nowcasting: The real-time informational content of macroeconomic data." *Journal of monetary economics*, **55**(4), 665–676.

Girton L, Roper D (1977). "A monetary model of exchange market pressure applied to the postwar Canadian experience." *The American economic review*, **67**(4), 537–548.

Gorton G, Ordonez G (2014). "Collateral crises." *American Economic Review*, **104**(2), 343–378.

Guttentag J, Herring R (1984). "Credit rationing and financial disorder." *The Journal of Finance*, **39**(5), 1359–1382.

Hampton SE, Holmes EE, Scheef LP, Scheuerell MD, Katz SL, Pendleton DE, Ward EJ (2013). "Quantifying effects of abiotic and biotic drivers on community dynamics with multivariate autoregressive (MAR) models." *Ecology*, **94**(12), 2663–2669.

IMF (2017). "The Growing Importance of Financial Spillovers from Emerging Markets." *Global Financial Stability Report*, **2017**(2).

Ives AR (1995). "Measuring resilience in stochastic systems." *Ecological Monographs*, **65**(2), 217–233.

Ives AR, Carpenter SR, Dennis B (1999). "Community interaction webs and zooplankton responses to planktivory manipulations." *Ecology*, **80**(4), 1405–1421.

Ives AR, Dennis B, Cottingham KL, Carpenter SR (2003). "Estimating community stability and ecological interactions from time-series data." *Ecological monographs*, **73**(2), 301–330.

Jeanne O, Korinek A (2010). "Excessive volatility in capital flows: A pigouvian taxation approach." *American Economic Review*, **100**(2), 403–407.

Jordà Ò, Schularick M, Taylor AM (2013). "When credit bites back." *Journal of money, credit and banking*, **45**(s2), 3–28.

Joyce JP, Nabar M (2009). "Sudden stops, banking crises and investment collapses in emerging markets." *Journal of Development Economics*, **90**(2), 314–322.

Korinek A, Mendoza EG (2014). "From sudden stops to fisherian deflation: Quantitative theory and policy." *Annu. Rev. Econ.*, **6**(1), 299–332.

Krishnamurthy A, Li W (2020). "Dissecting mechanisms of financial crises: Intermediation and sentiment." *Technical report*, National Bureau of Economic Research Cambridge.

Krishnamurthy A, Muir T (2017). "How credit cycles across a financial crisis." *Technical report*, National Bureau of Economic Research.

Levy-Yeyati E, Sturzenegger F (2005). "Classifying exchange rate regimes: Deeds vs. words." *European economic review*, **49**(6), 1603–1635.

Liaqat Z (2019). "Does government debt crowd out capital formation? A dynamic approach using panel VAR." *Economics letters*, **178**, 86–90.

Mendoza EG (2002). "Credit, prices, and crashes: Business cycles with a sudden stop." In "Preventing currency crises in emerging markets," pp. 335–392. University of Chicago Press.

Mendoza EG (2010). "Sudden stops, financial crises, and leverage." *American Economic Review*, **100**(5), 1941–1966.

Miranda-Agrippino S, Rey H (2022). "The global financial cycle." In "Handbook of international economics," volume 6, pp. 1–43. Elsevier.

Obstfeld M (2015). "Trilemmas and Tradeoffs: Living with Financial Globalization." *Chapter 2, Global Liquidity, Spillovers to Emerging Markets and Policy Responses, edited by C. Raddatz, D. Saravia, and J. Ventura, vol. 20 of Central Banking, Analysis and Economic Policies Book Series*, **20**, 13–78.

Obstfeld M, Taylor AM (2004). *Global capital markets: integration, crisis, and growth.* Cambridge university press.

Paine RT (1980). "Food webs: linkage, interaction strength and community infrastructure." *Journal of animal ecology*, **49**(3), 667–685.

Park JK, Meng X (2024). "Crowding out or crowding in? Reevaluating the effect of government spending on private economic activities." *International Review of Economics & Finance*, **89**, 102–117.

Rajan RG (1994). "Why bank credit policies fluctuate: A theory and some evidence." *the Quarterly Journal of economics*, **109**(2), 399–441.

Rey H (2016). "International channels of transmission of monetary policy and the Mundellian trilemma." *IMF Economic Review*, **64**(1), 6–35.

Saunders A, Strock E, Travlos NG (1990). "Ownership structure, deregulation, and bank risk taking." *the Journal of Finance*, **45**(2), 643–654.

Scherbina MA (2013). *Asset price bubbles: A selective survey.* International Monetary Fund.

Schularick M, Taylor AM (2012). "Credit booms gone bust: monetary policy, leverage cycles, and financial crises, 1870–2008." *American Economic Review*, **102**(2), 1029–1061.

Shin HS (2014). "The second phase of global liquidity and its impact on emerging economies." In "Volatile Capital Flows in Korea: Current Policies and Future Responses," pp. 247–257. Springer.

Sufi A, Taylor AM (2022). "Financial crises: A survey." *Handbook of international economics*, **6**, 291–340.

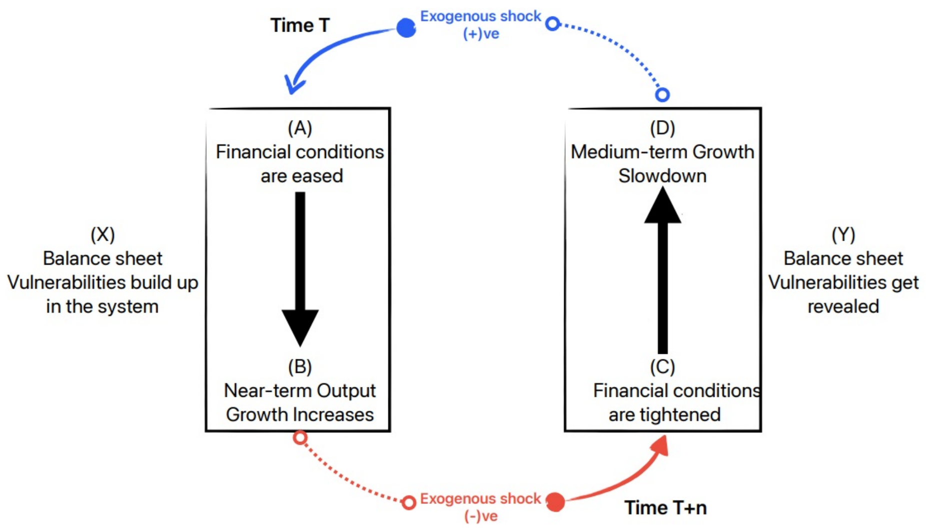
Tilman D (1996). "Biodiversity: population versus ecosystem stability." *Ecology*, **77**(2), 350–363.

Williamson OE (1963). "Managerial discretion and business behavior." *The American Economic Review*, **53**(5), 1032–1057.

6 Tables and Figures

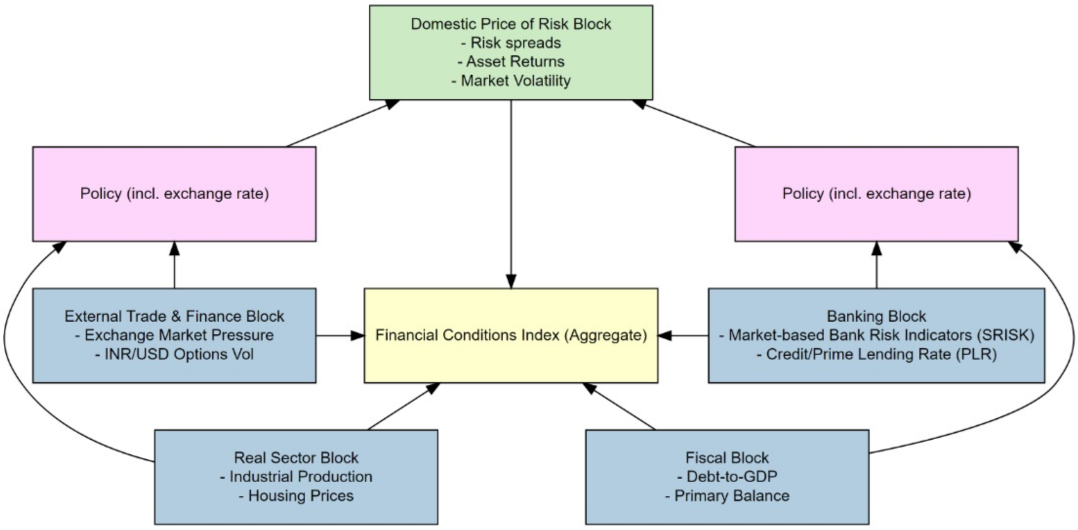
6.1 Figures

Figure 1 Macro-financial Interactions in Emerging Markets - Analytical Framework



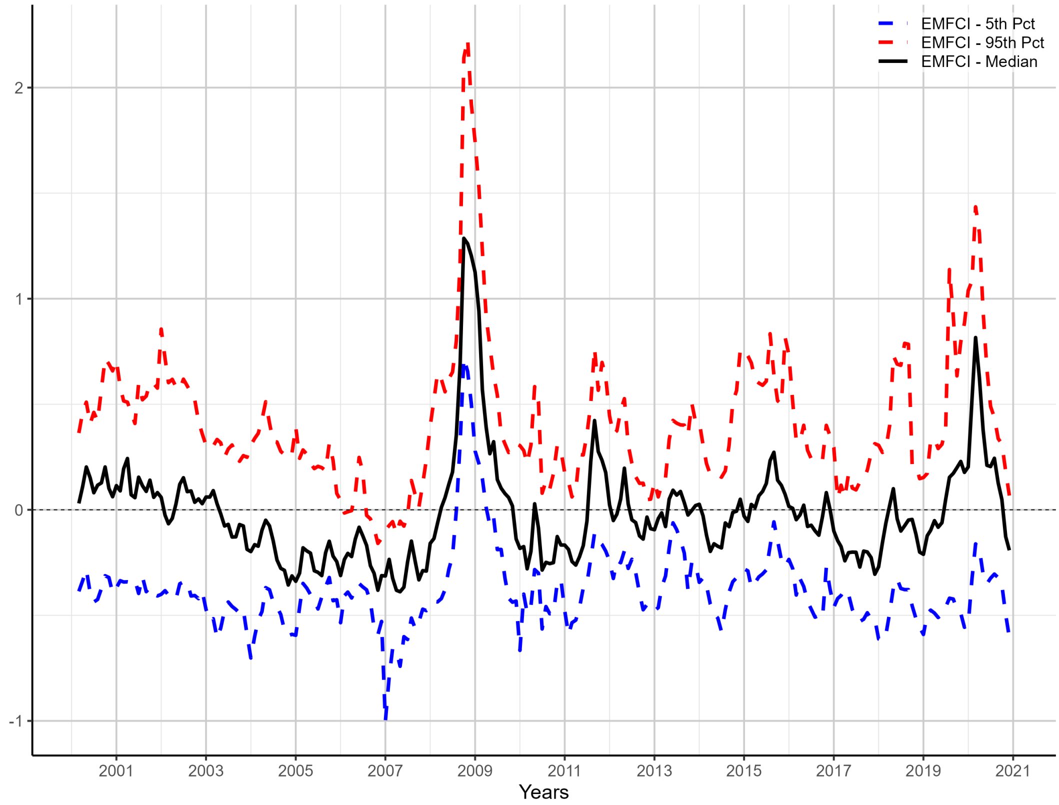
Note: The above flowchart depicts the analytical framework used for analyzing macro-financial interactions in emerging economies. Within this framework, interactions between local financial conditions and economic growth are driven by two opposing forces with *growth-enhancing* effect $[A \rightarrow (X) \rightarrow B]$ and *growth-inhibiting* effect $[C \rightarrow (Y) \rightarrow D]$ as shown in the flowchart.

Figure 2 Financial Conditions Index: Framework and Estimation



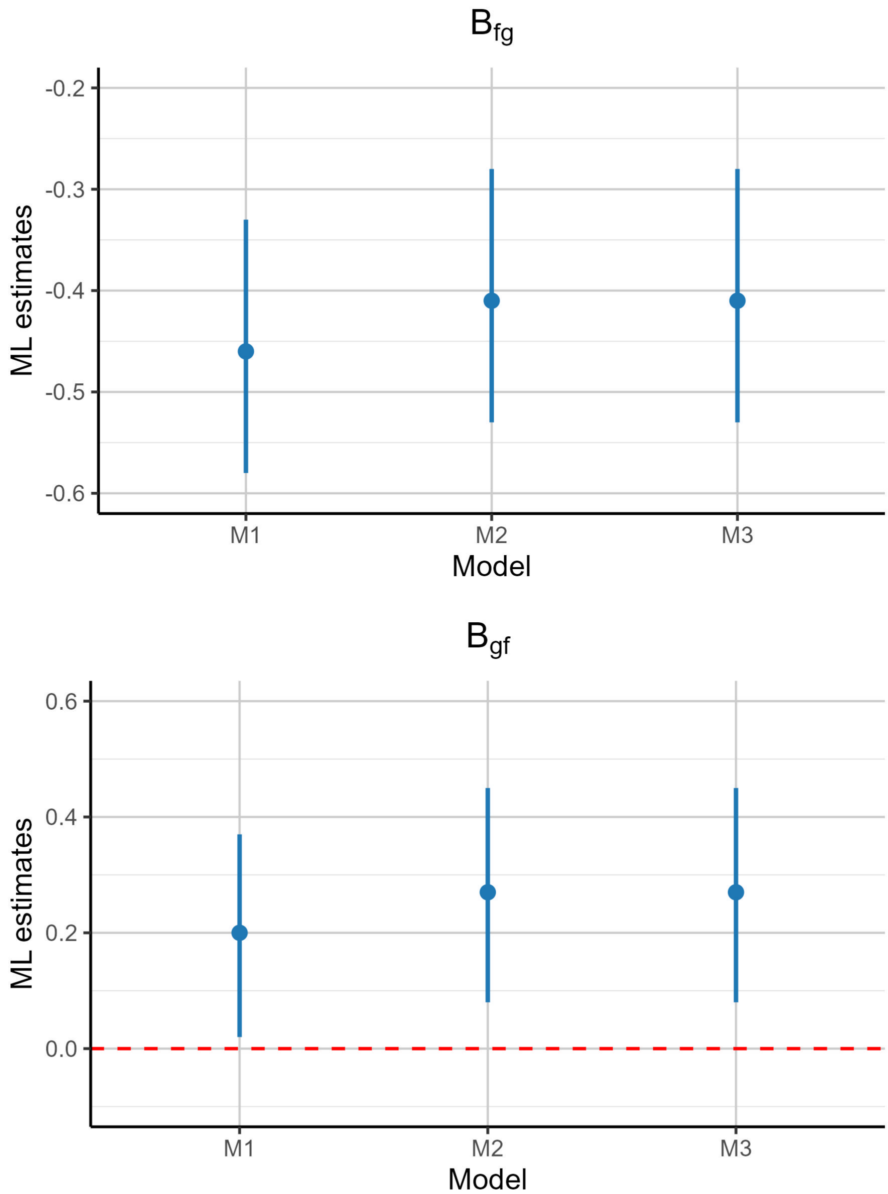
Note: The above diagram provides a broad overview of our conceptual framework for estimating a financial conditions index from an emerging market perspective. At the core of this framework lies the aggregate financial conditions which encompasses both fast-moving stress indicators (e.g., risk spreads, asset price returns) and indicators that reflect the gradual accumulation of vulnerabilities in the system (e.g., S-risk, Debt-to-GDP). Additionally, sector-specific indicators are clubbed under sectoral blocks which may directly or indirectly impact financial conditions in the economy. These indicators enable the capture of the evolving dynamics of financial conditions.

Figure 3 Financial Conditions Index (FCI) for Emerging Economies



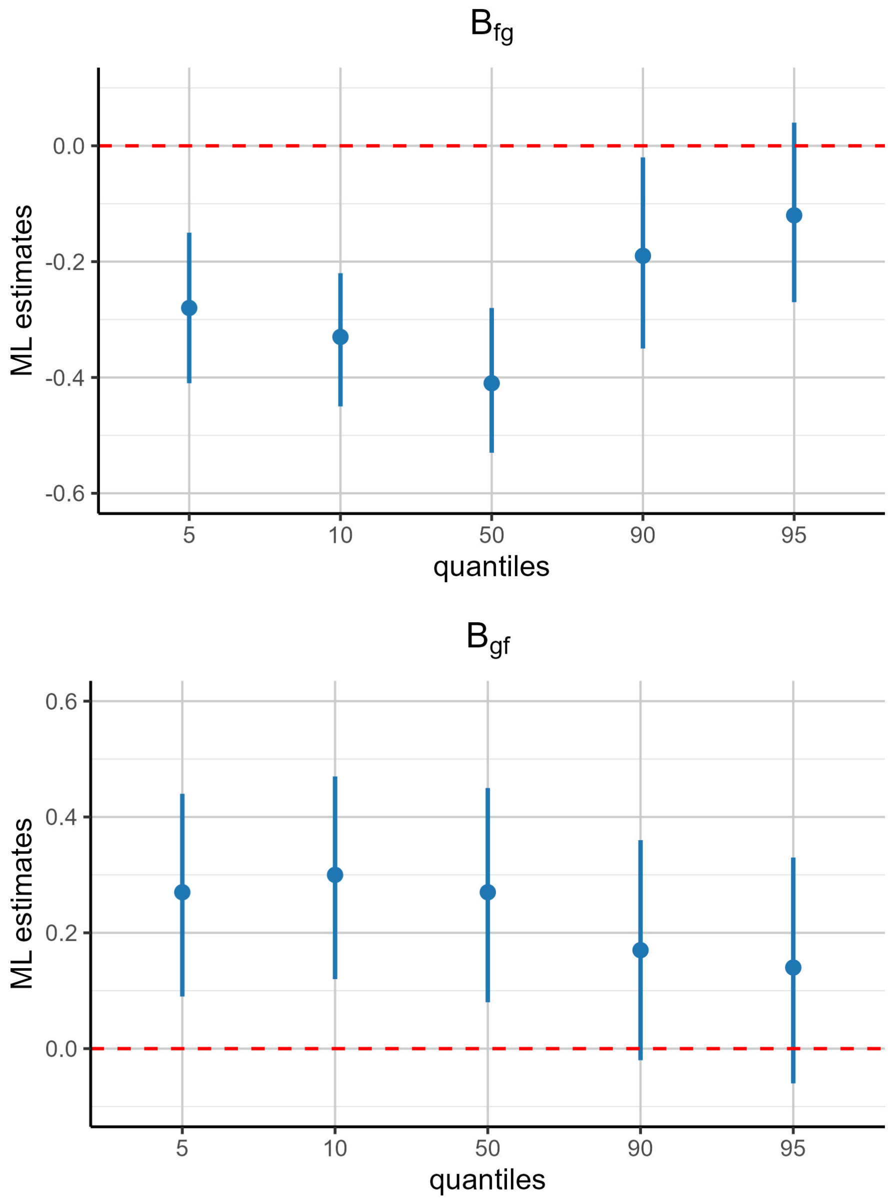
Note: The above plot shows the estimated aggregate FCI for emerging market economies for the period 2000-2021. The country-wise FCIs are estimated using the DFM approach given by equations (8) and (9). An aggregate EM-level FCI (EMFCI) is constructed by taking the median-value of country-wise FCIs shown by the solid black line. The dashed blue and red lines depict the 5^{th} and 95^{th} percentile values for the country-wise FCIs, respectively.
Source: Authors' calculations.

Figure 4 Coefficient Estimates: Baseline and Augmented



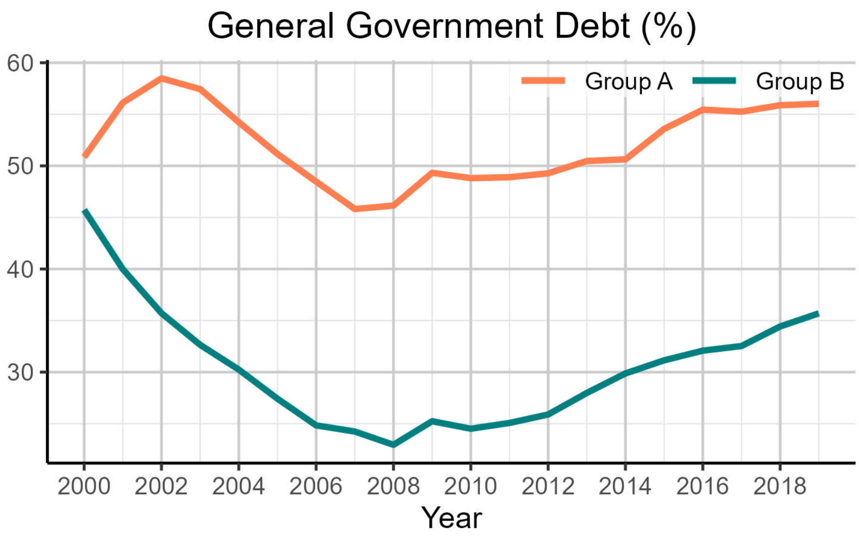
Note: The above figure shows the maximum-likelihood (ML) estimates for the interaction matrix **B** of the MAR model described in equations (5)-(7). The model is estimated for the benchmark model specification with and without exogenous covariates as discussed in section 4.1. The blue dot represents the point estimate for a given growth quantile while the bar represents the lower/upper 95 per cent confidence interval (CI). Detailed results are provided in Table 2.
Source: Authors' calculations.

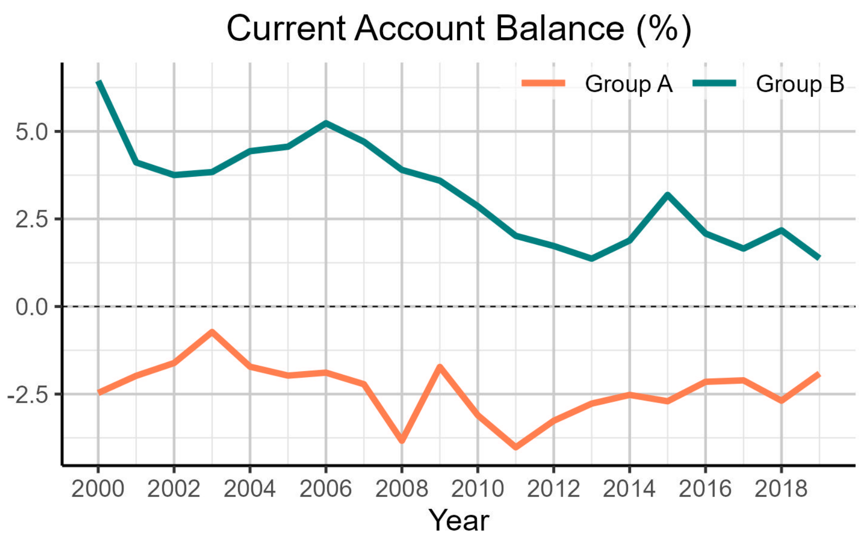
Figure 5 Coefficient Estimates: EM growth quantiles



Note: The above figure shows the maximum-likelihood (ML) estimates for the interaction matrix **B** of the MAR model described in equations (5)-(7). The model is estimated for different quantiles of GDP growth in EMEs as discussed in section 4.1. The blue dot represents the point estimate for a given growth quantile while the bar represents the lower/upper 95 per cent confidence interval (CI). Detailed results are provided in Table 3.
Source: Authors' calculations.

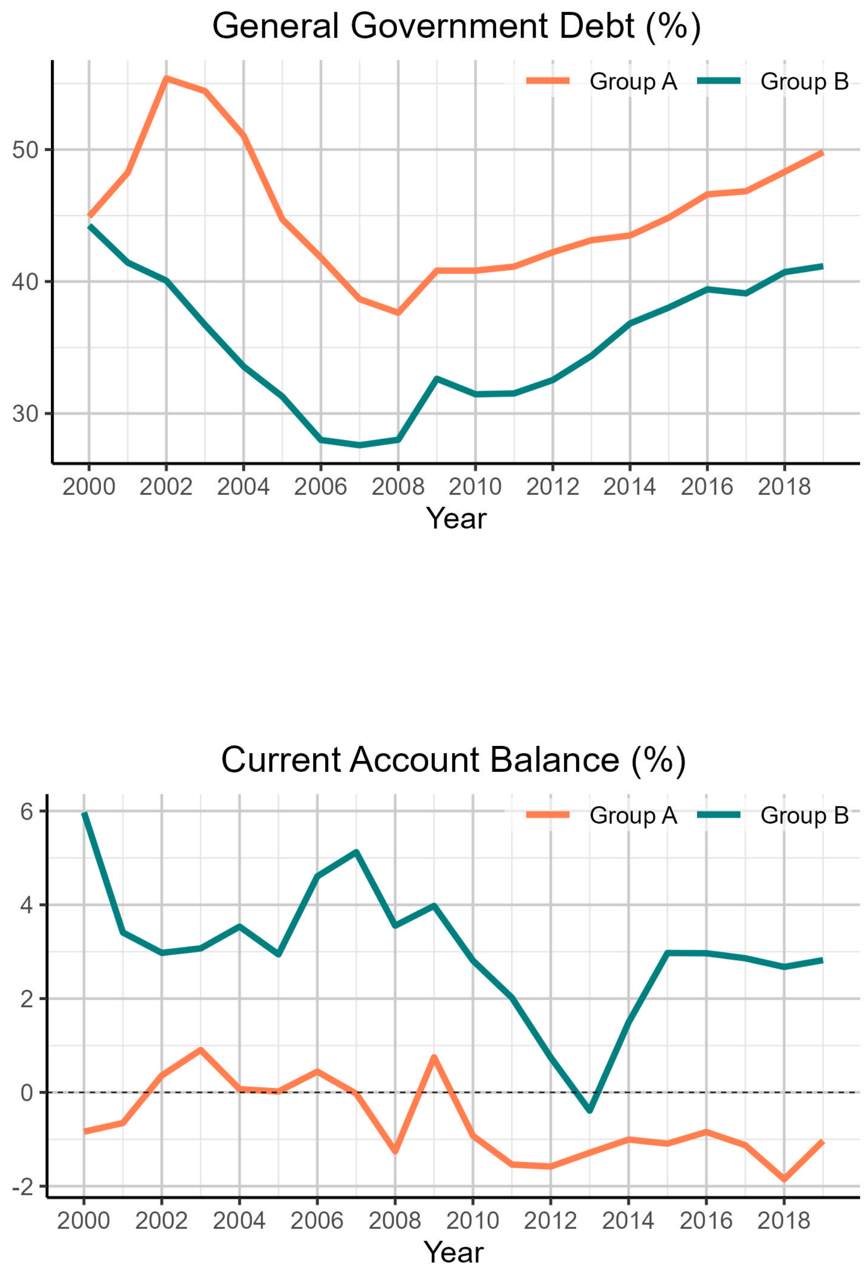
Figure 6 Subsampling Exercise 1: Fiscal Balance and Current Account Balance





Note: The above figure plots the average fiscal balance (*top panel*) and current account balance (*bottom panel*), both shown as per cent of GDP, for countries split into below-median (Group A) and above-median (Group B) performers according to the fiscal balance *plus* current account balance criteria. Country Group A consists of 7 countries that exhibit high levels of fiscal deficits and current account deficits while Group B consists of 4 countries that have low fiscal deficit and current account surpluses.
Source: Authors' calculations.

Figure 7 Subsampling Exercise 2: Growth Effects



Note: The above figure plots the average fiscal balance (*top panel*) and current account balance (*bottom panel*), both shown as per cent of GDP, for countries split into those showing evidence for both growth-enhancing and growth-inhibiting effect (Group A) and those exhibiting only growth-inhibiting effect (Group B). Given the sample split criteria, country Group A consists of 14 countries while Group B consists of 4 countries.
Source: Authors' calculations.

6.2 Tables

Table 1 Country Sample

S. No.	Country Name	Country Code
1	Argentina	ARG
2	Brazil	BRA
3	Chile	CHI
4	China	CHN
5	Colombia	COL
6	Czech Republic	CZE
7	India	INDI
8	Indonesia	INDO
9	South Korea	KOR
10	Malaysia	MAL
11	Mexico	MEX
12	Philippines	PHI
13	Poland	POL
14	Russia	RUS
15	Slovakia	SLO
16	South Africa	SAF
17	Thailand	THA
18	Turkey	TUR

Note: The above table provides the list of emerging market and developing countries (EMDEs) used in this study. Country codes are provided alongside.

Table 2 Financial conditions index: Data and variable construction

Variable Name	Description	Country	Source
Equity Return	Large-cap companies index	ARG, BRA, CHI, CHN, COL, CZE, INDI, INDO, KOR, MAL, MEX, PHI, POL, RUS, SLO, SAF, THA, TUR	Bloomberg
EqVol30	Average 30-day volatility of all large-cap listed companies	ARG, BRA, CHI, CHN, COL, CZE, INDI, INDO, KOR, MAL, MEX, PHI, POL, RUS, SLO, SAF, THA, TUR	Bloomberg
SriskUT	Market capitalization weighted-average S-Risk of the banking sector	ARG, BRA, CHI, CHN, COL, CZE, INDI, INDO, KOR, MAL, MEX, PHI, POL, RUS, SLO, SAF, THA, TUR	V-Lab, NYU
PLR	Corporate sector prime lending rate for banking sector	ARG, BRA, CHI, CHN, COL, CZE, INDI, INDO, KOR, MAL, MEX, PHI, POL, RUS, SLO, SAF, THA, TUR	Bloomberg
OptionVol3m	Implied volatility of USD-EM currency 3-months options contract	BRA, CHI, CHN, COL, CZE, INDI, INDO, KOR, MAL, MEX, PHI, POL, RUS, SLO, SAF, THA	Bloomberg
Term Spread	Difference between 10-year/ 5-year government bond and 91-days T-bill yield as per data availability	BRA, CHI, CHN, COL, CZE, INDI, INDO, KOR, MAL, MEX, PHI, POL, RUS, SLO, SAF, THA	Bloomberg
Corporate Spread	Difference between 3-months CEMBI yield and 91-day T-bill yield	ARG, BRA, CHI, CHN, COL, CZE, INDI, INDO, KOR, MAL, MEX, PHI, POL, RUS, SLO, SAF, THA	Bloomberg
Interbank Spread	Difference between 3-months interbank lending rate and 91-days T-bill yield	BRA, CHI, CHN, COL, CZE, INDI, INDO, KOR, MAL, MEX, PHI, POL, RUS, SLO, SAF, THA	Bloomberg
Credit	Total credit to private non-financial sector	ARG, BRA, CHI, CHN, COL, CZE, INDI, INDO, KOR, MAL, MEX, PHI, POL, RUS, SLO, SAF, THA, TUR	BIS
EMPI	Exchange rate pressure resisted through FOREX intervention, release through exchange rate changes	ARG, BRA, CHI, CHN, COL, CZE, INDI, INDO, KOR, MAL, MEX, PHI, POL, RUS, SLO, SAF, THA, TUR	IMF
Debt-to-GDP	Gross government debt to GDP ratio	ARG, BRA, CHI, CHN, COL, CZE, INDI, INDO, KOR, MAL, MEX, PHI, POL, RUS, SLO, SAF, THA, TUR	IMF
Primary Balance	Revenue net of expenditure (net of interest payments)	ARG, BRA, CHI, CHN, COL, CZE, INDI, INDO, KOR, MAL, MEX, PHI, POL, RUS, SLO, SAF, THA, TUR	IMF
Real-estate prices	Includes both residential property prices (RPP) and commercial property prices (CPP)	ARG, BRA, CHI, CHN, COL, CZE, INDI, INDO, KOR, MAL, MEX, PHI, POL, RUS, SLO, SAF, THA, TUR	BIS
Industrial production	Economic activity measured using industrial production index	ARG, BRA, CHI, CHN, COL, CZE, INDI, INDO, KOR, MAL, MEX, PHI, POL, RUS, SLO, SAF, THA, TUR	IMF

Note: The above table provides a list of variables used for constructing country-level FCI using the DFM framework described in equations (8) and (9). Variable description, country names and data source(s) are provided alongside.

Table 3 Results: Estimated model coefficients with and without covariates

	Baseline	Augmented	
Model Coefficients	**(1)**	**(2)**	**(3)**
B_{ff}	0.91***	0.85***	0.85***
	(0.10)	(0.10)	(0.10)
B_{fg}	-0.46***	-0.41***	-0.41***
	(0.06)	(0.07)	(0.07)
B_{gf}	0.20**	0.27***	0.27***
	(0.09)	(0.09)	(0.09)
B_{gg}	0.56***	0.51***	0.51***
	(0.07)	(0.07)	(0.07)
C_{ff}	–	-0.18**	0.18**
	–	(0.09)	(0.09)
C_{fg}	–	0.14**	-0.14**
	–	(0.06)	(0.06)
AICc	247.29	242.5	242.5
Log-likelihood	-112.91	-108.19	-108.19
Interaction Period	2000-2019	2000-2019	2000-2019
Covariate Period	–	2000-2020	2000-2020

Note: The above table shows the maximum likelihood estimates for the interaction matrix of the state-space MAR model described in equation (5)-(7). The model is estimated at the aggregate EM-level. Estimated standard errors are shown in parentheses. Confidence intervals (CI) at the 5% level of significance and other model diagnostics are provided alongside.
Source: Authors' calculations.

Table 4 Results: Estimated model coefficients with different EM growth measures

Model Coefficients	**Median Growth**	**Equal Weights**	**WB - Weights**	**IMF - Weights**
	(1)	**(2)**	**(3)**	**(4)**
B_{ff}	0.85***	0.86***	0.77***	0.91***
	(0.10)	(0.10)	(0.10)	(0.10)
B_{fg}	-0.41***	-0.32***	-0.18*	-0.31**
	(0.07)	(0.06)	(0.05)	(0.08)
B_{gf}	0.27***	0.35***	0.25**	0.36***
	(0.09)	(0.10)	(0.11)	(0.09)
B_{gg}	0.51***	0.56***	0.81***	0.52***
	(0.07)	(0.06)	(0.07)	(0.09)
C_{ff}	-0.18**	-0.25**	-0.25**	-0.19**
	(0.09)	(0.09)	(0.09)	(0.08)
C_{fg}	0.14***	0.18***	0.06	0.15**
	(0.06)	(0.06)	(0.07)	(0.08)
AICc	242.50	218.33	225.6	272.9
Log-likelihood	-108.19	-96.1	-99.74	-123.39
Interaction Period	2000-2019	2000-2019	2000-2019	2000-2019
Covariate Period	2000-2019	2000-2020	2000-2019	2000-2020

Note: The above table shows the maximum likelihood estimates for the interaction matrix of the state-space MAR model described in equation (5)-(7). The model is estimated at the aggregate EM-level using different measures of annual EM GDP growth. Estimated standard errors are shown in parentheses. Confidence intervals (CI) at the 5% level of significance and other model diagnostics are provided alongside.

Source: Authors' calculations.

Table 5 Results: Model coefficients for different EM growth quantiles

Model Coefficients	Q_{50}	Q_5	Q_{10}	Q_{90}	Q_{95}
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
B_{ff}	0.85***	0.80***	0.82***	0.79***	0.76***
	(0.10)	(0.10)	(0.09)	(0.11)	(0.10)
B_{fg}	-0.41***	-0.28***	-0.33***	-0.19**	-0.12**
	(0.07)	(0.07)	(0.06)	(0.08)	(0.06)
B_{gf}	0.27***	0.27***	0.30***	0.17	0.14
	(0.09)	(0.09)	(0.09)	(0.10)	(0.10)
B_{gg}	0.51***	0.62***	0.60***	0.56***	0.60***
	(0.07)	(0.08)	(0.06)	(0.11)	(0.12)
C_{ff}	-0.18**	-0.21**	-0.22**	-0.16	-0.17
	(0.09)	(0.09)	(0.09)	(0.10)	(0.10)
C_{fg}	0.14**	0.13***	0.15**	0.19**	0.22**
	(0.06)	(0.07)	(0.06)	(0.10)	(0.11)
AICc	242.50	260.54	229.15	303.73	302.81
Log-likelihood	-108.19	-117.21	-101.51	-138.81	-138.35
Interaction Period	2000-2019	2000-2019	2000-2019	2000-2019	2000-2019
Covariate period	2000-2019	2000-2020	2000-2020	2000-2020	2000-2020

Note: The above table shows the maximum likelihood estimates for the interaction matrix of the state-space MAR model described in equation (5)-(7). The model is estimated at the aggregate EM-level using different quantiles for annual EM GDP growth. Estimated standard errors are shown in parentheses. Confidence intervals (CI) at the 5% level of significance and other model diagnostics are provided alongside. **Source**: Authors' calculations.

Table 6 Summary Results: Sign Test

	Growth-inhibiting Effect: B_{fg}	**Growth-enhancing Effect:** B_{gf}	**Covariate Effect:** C_{ff}	**Covariate Effect:** C_{fg}
No. of countries with Expected sign (+/-) and significant	11	8	6	11
No. of countries with Expected sign but insignificant	4	6	4	5
Names of countries without the expected sign	Colombia, Russia and Thailand	China, Mexico, Russia and Thailand	Brazil, Chile, China, Colombia, Czech, Indonesia, Poland and Turkey	Philippines and Russia
Total # countries	18	18	18	18

Note: The above table shows a summary of results based on estimating the state-space MAR model described in equation (5)-(7) at the individual country-level for all EMEs in our data sample. The results are based on inference drawn using a standard 5% level of significance.

Source: Authors' calculations.

Appendices

A Measuring Financial Conditions – Dynamic Factor Model (DFM) approach

This study employs a dynamic factor model (DFM) in the spirit of Giannone *et al.* (2008). Each time-series in a dataset is assumed to be driven by two orthogonal components: a co-movement component, which represents a linear combination of a few common factors $r(r << n)$ and an idiosyncratic component, which is unique to each series. In other words, a DFM assumes that an n-dimensional vector of stationary observed variables $(\lambda_{1,t}, ..., \lambda_{n,t})$ is driven by a vector of r unobserved dynamic factors $(f_{i,t}, ..., f_{r,t})$ as well as some series-specific features, such as measurement errors, captured by idiosyncratic errors $(\varepsilon_{i,t}, ..., \varepsilon_{n,t})$. Empirically, the DFM can be summarised in the following equation:

$$\lambda_{i,t} = \gamma_i' F_t + \varepsilon_{i,t}, \ i = 1, \dots, n, \ t = 1, \dots, T \tag{10}$$

where $(\gamma_{i,t}, ..., \gamma_{r,t})$ is an r - dimensional vector of loadings that does not vary over time. The two components $\zeta_{i,t} = \gamma_i' F_t$ and $\varepsilon_{i,t}$ are orthogonal unobserved stochastic processes. $\zeta_{i,t} = \gamma_i' F_t$ is the linear combination of r unobserved common factors F_t reflecting the bulk of the co-movement in the data. The idiosyncratic component $\varepsilon_{i,t}$, is assumed to follow an AR(1) process:

$$\begin{gathered} \varepsilon_{i,t} = \alpha_i \varepsilon_{i,t-1} + e_{i,t}, \ e_{i,t} \sim \text{iid } \mathcal{N}(0, \sigma_i^2) \\ \mathbb{E}[\sigma_{i,t}, \sigma_{j,s}] = 0 \text{ for } i \neq j \end{gathered} \tag{11}$$

The above system of equations can be represented in a matrix notation as follows:

$$\begin{gathered} X_t = \Gamma F_t + \Pi_t \\ X_t = (\lambda_{1,t}, \lambda_{2,t}, \cdots, \lambda_{n,t})' \\ \Pi_t = (\varepsilon_{1,t}, \varepsilon_{2,t}, \cdots, \varepsilon_{n,t})' \\ \Gamma = (\gamma_1, \cdots, \gamma_r) \end{gathered} \tag{12}$$

The dynamic behaviour of the common factors modelled as an autoregressive process of order one i.e., AR(1) can be shown as follows:

$$F_t = AF_{t-1} + Bu_t \tag{13}$$

After obtaining consistent parameter estimates through asymptotic principal components, we employ the *Kalman* filter to derive more efficient estimates of the common factors. Here, we use the two-step procedure developed by (Doz *et al.*, 2011) to estimate the model parameters. The algorithm is initialised by computing principal components, and the 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. For example, let S be sample correlation matrix of a given dataset:

$$S = \frac{1}{T}\sum_{i=1}^{T} X_t X_t' \tag{14}$$

Then the r largest principal components are extracted from given sample correlation matrix. Let D be the $r \times r$ diagonal matrix with diagonal elements given by the largest r eigenvalues of S. Let V be the $n \times r$ matrix of corresponding eigenvectors such that the normalisation gives $V'V = I_r$. The common factors can be approximated by:

$$\tilde{F} = V' X_t \tag{15}$$

Once we have estimated the common factors $\tilde{F}$, we can estimate the factor loadings Γ and the covariance matrix of the idiosyncratic components Π. This is done by regressing the data series on the estimated common factors as follows:

$$\hat{\Gamma} = \sum_t X_t \widetilde{F}_t' (\widetilde{F}_t \widetilde{F}_t')^{-1} = V \tag{16}$$

The estimated covariance matrix of the idiosyncratic components $\hat{\Pi}$ is as follows:

$$\hat{\Pi} = diag(S - VDV) \tag{17}$$

The dynamic factor equation parameters – A and B, can be estimated from VAR along withe the common factors $\tilde{F}_t$ where $F_t = AF_{t-1} + Bu_t$. These estimates $\hat{\Gamma}, \hat{\Pi}, \hat{A}, \hat{B}$, are consistent as $n, T \to \infty$ (Forni *et al.*, 2000). Given the estimated parameters, in the second step, an updated estimate of the common factors is obtained using the Kalman smoother. The re-estimates of the common factors from the Kalman filter are more efficient than using the principal component method because the filter uses all the information up to the period when the estimation has been made.

B Constructing Financial Conditions Index (FCI) – Role of Financial Stress and Vulnerabilities

The construction of a financial conditions index that combines stress and vulnerability indicators, enables a comprehensive understanding of the financial system's health. Financial stress indicators tend to co-move with actual stress in the system so that they rise/fall as financial stress in the system increases or decreases. On the other hand, vulnerability indicators accumulate slowly in a shock-free environment, providing minimal signalling at the time. When an adverse shock impacts the economy, the vulnerabilities amplify the financial stress, akin to a catalyst. The negative effects of future shocks can be reduced, and the financial system's resilience can be increased, if we monitor and address financial conditions in a way that effectively combines information on stress and vulnerabilities. Similar to Krishnamurthy and Muir (2017), this study categorizes financial indicators into two types: fast-moving stress indicators (e.g., asset prices) and indicators reflecting the gradual build-up of vulnerabilities in the system. These indicators capture the evolving dynamics of financial conditions. In what follows, we discuss and estimate different measures of financial conditions for each country in our EMDE sample. Then, we use these indices to predict country-level GDP growth rates in an out-of-sample forecasting exercise. We use the results derived from this forecasting analysis to show what type of information is useful for constructing a holistic financial conditions index for EMDEs.

Informational contribution of index constituents of Financial STRESS

The financial stress measures, developed through the sequential construction of indexes, provide insight into the impact events reflected in the system. These measures are constructed using a sequential approach, incorporating various indicators to capture different aspects of stress. One such measure is the *domestic price of risk* (DPOR) which includes term spreads, sovereign spreads, and risk spreads relevant to key business sectors, and asset returns and volatility from a financial market point of view. Increasing financial stress is reflected in rising risk spreads, volatility and falling asset returns.

External risk factors circumscribe global financing conditions and the real channel of terms-of-trade and commodities prices. The DPOR-EXT (DPOR-External) index expands on the DPOR by including an additional indicator, implied option volatility on the domestic currency vis-a-vis the US dollar. This extension provides a more comprehensive view of risk indicators in assessing financial stress. Another alternative measure, the DPOR-EMPI index, builds upon the DPOR-EXT by including exchange rate market pressure as an additional component. This index takes into account the impact of exchange rate dynamics on financial stress, providing a better understanding of the interplay between exchange rates and overall market conditions. To further enhance the measurement of financial stress, the DPOR-MF (DPOR-Macro financial) index incorporates real indicators such as the industrial production index (IPI) and housing prices. By including these real indicators, the DPOR-MF index offers a more holistic perspective on the overall stress in the financial system. These alternative measures of financial stress, namely DPOR, DPOR-EXT, DPOR-MF, and DPOR-EMPI, provide nuanced insights into different aspects of stress levels in the financial system.

Informational contribution of index constituents of Financial VULNERABILITIES

To comprehensively assess financial conditions, we consider several alternative measures of financial vulnerabilities encompassing a range of indicators that facilitate a holistic understanding of potential risks within the financial system. One such measure is the DPOR-AGG (DPOR-Aggregate) index, which combines banking indicators, such as systematic risk (S-Risk) and the prime lending rate with the DPOR-EMPI stress index. This augmented index provides further insights into vulnerabilities that may develop in the banking sector and their impact on overall financial conditions.

Furthermore, the DPOR-AGG-FISC index integrates the indicators from DPOR-AGG with fiscal metrics such as the general government balance and debt-to-GDP ratio. By incorporating fiscal variables, this index highlights the interplay between financial vulnerabilities and the fiscal health of the economy. Additionally, the DPOR-AGG-BAL index combines the indicators from DPOR-AGG with balance-sheet metrics like credit growth. This index offers valuable insights into vulnerabilities stemming from imbalances within financial institutions' balance sheets and their potential implications for the broader financial system. Finally, to provide a comprehensive assessment of both stress and vulnerabilities, the DPOR-ALL index amalgamates all the indicators from the stress and vulnerability measures discussed above. This all-encompassing index allows for an evaluation of the overall health of the financial system, capturing both immediate stress events and underlying vulnerabilities.

Should we combine STRESS and VULNERABILITIES into an aggregate Financial Conditions Index?

The question arises as to whether there is merit in combining stress and vulnerabilities into a single aggregate financial conditions measure, or if doing so results in a loss of information on account of aggregation across heterogeneous measures. To address this question, we employ a forecasting exercise based on a bridge equation framework in our analysis. We utilize a parsimonious autoregressive (AR) model of GDP growth augmented with current-period information on the financial conditions index (FCIs). Our analysis focuses on all 18 EMDEs in our sample while using an estimation and forecast sample approach. The training sample covers the period from the first quarter of 2000 to the fourth quarter of 2015, while the forecast sample spans from the first quarter of 2016 to the fourth quarter of 2020. Out-of-sample performance of different measures of FCIs including DPOR, DPORAGG, DPORAGGBAL, DPORAGGFISC, DPORAGGHOUS, DPORAGGR, DPORALL, DPOREMPI, DPOREXT, DPORMF are assessed for a one-quarter ahead horizon across all countries in our sample.[11]

The results obtained from the above forecasting exercise above are presented below. Table 6 summarizes the forecast performance in terms of root mean squared error (RMSE). Interestingly, the DPOR-ALL index consistently outperforms all other indexes for the majority of EMDEs in our sample. This finding suggests that an index that integrates information from both stress and vulnerabilities, encompassing a comprehensive set of indicators, yields the most accurate near-term projections. The DPOR-ALL index demonstrates its superiority in capturing the dynamics of these economies and providing a reliable measure of downside risks to growth. Overall, these results support the efficacy of employing the DPOR-ALL index in the model specification for EMEs, underscoring the significance of incorporating a comprehensive assessment of both stress and vulnerabilities in forecasting GDP growth.

Table 7 Country-wise Out-of-Sample Root Mean Squared Error (RMSE)

	DPOR	DPORAGG	DPORAGGBAL	DPORAGGFISC	DPORAGGHOUS	DPORAGGR	DPORALL	DPOREMPI	DPOREXT	DPORMF	AR1
ARG	4.17	4.84	4.84	4.43	4.81	4.84	4.39	4.40	–	–	4.65
BRA	2.84	2.81	3.01	2.95	2.81	2.80	3.17	2.84	2.84	2.84	2.84
CHI	3.92	3.81	3.85	3.74	3.82	3.81	3.76	3.84	3.85	3.86	3.94
CHN	3.46	3.45	3.38	3.14	3.45	3.45	3.12	3.45	3.46	3.45	3.48
COL	5.16	5.13	5.10	5.10	5.14	5.13	5.04	5.14	5.16	5.16	3.96
CZE	2.71	2.72	2.71	2.71	2.72	2.70	2.68	2.74	2.76	2.74	2.76
INDI	6.54	6.55	6.57	6.51	6.55	6.55	6.51	6.54	6.54	6.54	6.74
INDO	2.34	2.33	2.39	2.47	2.33	2.33	2.59	2.36	2.38	2.39	2.32
KOR	1.36	1.45	1.45	1.39	1.47	1.43	1.38	1.44	1.43	1.44	1.35
MAL	6.17	6.23	6.24	5.38	6.23	6.23	5.48	6.20	6.17	6.18	4.78
MEX	4.20	4.29	4.21	4.10	4.28	4.18	4.08	4.18	4.15	4.02	4.36
PHI	4.33	4.63	4.64	4.60	4.63	4.60	4.41	4.63	4.55	4.52	4.33
POL	2.52	2.59	2.61	2.39	2.59	2.56	2.47	2.51	2.51	2.49	2.60
RUS	3.14	2.78	2.76	2.76	2.78	2.77	2.74	2.77	2.80	2.80	2.29
SLO	4.48	4.52	4.51	4.48	4.52	4.52	4.48	4.49	4.53	4.53	4.68
SAF	2.68	3.50	3.40	3.45	3.48	3.50	3.37	3.03	2.78	3.07	2.68
THA	4.59	4.45	4.51	4.35	4.45	4.45	4.33	4.45	4.47	4.51	3.03
TUR	–	6.19	6.22	6.17	6.18	6.24	6.13	–	–	–	5.35

[11]The model specification includes a parsimonious AR (1) model of GDP growth that includes information from the current period FCIs: $g_t^Q = \mu + \alpha' g_{t-1}^Q + \beta' \mathrm{FCI}_t^Q + \varepsilon_t^Q$.